



# Thèse

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Variable Resolution Transform-based Music Feature Extraction  
and their Applications for Music Information Retrieval

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# Résumé

Dans le secteur de loisirs il y a un nombre considérable d'enregistrements numériques musicaux produits, diffusés et échangés qui favorise la demande croissante de services intelligents de recherche de musique. La navigation par contenu devient cruciale pour permettre aux professionnels et également aux amateurs d'accéder facilement aux quantités de données musicales disponibles. Ce travail présente les nouveaux descripteurs de contenu musical et mesures de similarité qui permettent l'organisation automatique de données musicales (recherche par similarité, génération automatique des playlists) ainsi que l'étiquetage (classification automatique en genres). Ce travail s'intéresse au problème de la construction des descripteurs du point de vue musical en complément des caractéristiques spectrales de bas-niveau. Plusieurs aspects d'analyse musicale, telles que l'analyse du signal où une nouvelle technique de transformation fréquentielle à résolution variable est proposée et décrite. Le traitement de niveau plus haut touche aux aspects de l'extraction des connaissances musicales. Cette thèse présente les algorithmes de détection de coups (*beats*) et d'extraction de  $f_0$  multiples. Les deux algorithmes sont basés sur la transformation à résolution variable proposée. Les informations issues de ces algorithmes sont utilisées dans la construction des descripteurs musicaux, représentés sous forme d'histogrammes (nouvel histogramme rythmique 2D qui permet d'estimer directement le tempo, et les histogrammes de succession et profil de notes). Deux applications majeures qui utilisent les caractéristiques mentionnées sont décrits et évaluées dans cette thèse.

## Summary

As a major product for entertainment, there is a huge amount of digital musical content produced, broadcasted, distributed and exchanged. There is a rising demand for content-based music search services. Similarity-based music navigation is becoming crucial for enabling easy access to the always-growing amount of digital music available to professionals and amateurs alike. This work presents new musical content descriptors and similarity measures which allow automatic musical content organizing (search by similarity, automatic playlist generating) and labeling (automatic genre classification). The work considers the problem of content descriptor building from the musical point of view in complement of low-level spectral similarity measures. Several aspects of music analysis are considered such as music signal analysis where a novel variable resolution transform is presented and described. Higher level processing touches upon the musical knowledge extraction. The thesis presents algorithms of beat detection and multiple  $f_0$  estimation which are based on the variable resolution transform. The information issued from these algorithms is then used for building musical descriptors, represented in form of histograms (novel 2D beat histogram which enables a direct tempo estimation, note succession and note profile histograms etc.). Two major music information retrieval applications, namely music genre classification and music retrieval by similarity, which use aforementioned musical features are described and evaluated in this thesis.

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# Introduction

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# 1. Introduction

## 1.1. Research Topic

As a major product for entertainment, there is a huge amount of digital musical content produced, broadcasted, distributed and exchanged. There is a rising demand for content-based music search services. Similarity-based music navigation is becoming crucial for enabling easy access to the always-growing amount of digital music available to professionals and amateurs alike. A professional user, such as a radio programmer, may want to search for a different interpretation of one song to include in a radio playlist. In addition, a radio programmer has the need to discover new songs and artists to help his listeners to discover new music. The music amateur on the other hand has different needs, ranging from active music discovery for the fans, to the simple seed song playlist generation of similar items. Such ways to organize musical collections as automatic genre classification and titles structuring is important as it facilitates music navigation and discovery.

Manual indexing of audio content is highly time-consuming and usually not compatible with the huge amount of audio data. However, systems that use human expert judgments exist but they are not numerous (e.g. All Music Guide and Music Genome Project). In order to do high quality annotation musical experts are required. The need for music experts combined to the huge amount of data to be annotated makes manual indexing hard to realize

The aim of this work is to develop new musical content descriptors and similarity measures which will allow automatic musical content organizing (search by similarity, automatic playlist generating) and labeling (automatic genre classification). We tried to consider the problem of content descriptor building from the musical point of view in complement of low-level spectral similarity measures.

## 1.2. Problems and Objectives

As compared to vocal signal, music signal is likely more stationary and owns some very specific properties in terms of musical tones, intervals, chords, instruments, melodic lines and rhythms, etc. [TANG 93]. While many effective and high performance music information retrieval (MIR) algorithms have been proposed [CAS 05; LOG 01; MAN 05; MCK 03; MEN 05; SCAR 05; TZAN 02; WEST 04], most of these works unfortunately tend to consider a music signal as a vocal one and make use of MFCC-based features which are primarily designed for speech signal processing. Mel Frequency Cepstrum

Coefficients (MFCC) was introduced in 60's and used since that time for speech signal processing. The MFCC computation averages spectrum in sub-bands and provides the average spectrum characteristics. Whereas they are inclined to capture the global timbre of a music signal and claimed to be of use in music information retrieval [FOOT 97; LOG 00], they cannot characterize the aforementioned music properties as needed for perceptual understanding by human beings and quickly find their limits [AUCO 04]. Recent works suggest combining spectral similarity descriptors with high-level analysis in order to overcome existing ceiling [PAMP 06].

The objective of this work is music retrieval by similarity and automatic labeling (music genre classification) by introducing an approach to high-level musical analysis.

### 1.3. *Our Approach and Contributions*

We propose an approach based on music features and corresponding similarity measures for music information retrieval. While popular spectrum-related techniques tend to characterize music timbre properties, we propose to complete them by musical features which can help to overcome the existing limits and, hence, to enhance the performance of music information retrieval algorithms. In this work, we suggest extracting music properties such as rhythmic, melodic, tonality and timbre fingerprints for automatic music search by similarity as well as automatic classification.

The Fast Fourier Transform and the Short-Time Fourier Transform have been the traditional techniques in audio signal processing. This classical approach is very powerful and widely used owing to its great advantage of rapidity. However, the specificity of musical signals is an exponential law of notes' frequencies. The frequency and time resolution of the FFT is linear and constant across the frequency scale while the human perception of a sound is logarithmic according to Weber-Fechner law (including loudness and pitch perception). As the basis of our work in music feature based MIR, we also propose a new music signal analysis technique by **variable-resolution transform (VRT)** particularly suitable to music signal. Indeed, as it is well known, the frequencies of notes in equally-tempered tuning system in music follow an exponential law (with each semi-tone the frequency is increased by factor of  $2^{1/12}$ ). If we consider a frequency range for different octaves, this frequency range is growing as the number of octave increases. Thus, to cover well with a frequency grid the wide range of octaves, large sized windows are necessary in the case of FFT; this affects the time resolution of the analysis. On the contrary, the use of small windows makes resolving frequencies of neighboring notes in low octaves almost impossible. The ability of catching all octaves in music with the same frequency resolution is essential for music signal analysis, in particular construction of melodic similarity features.

Our VRT is inspired by Continuous Wavelet Transformation (CWT) introduced 20 years ago [KRON 87] and designed in order to overcome the limited time-frequency localization of the Fourier-Transform for non-stationary signals. Unlike classical FFT, our VRT depicts similar properties as CWT, i.e. having a variable time-frequency resolution grid with a high frequency resolution and a low time resolution in low-frequency area and a high temporal/low frequency resolution on the other frequency side, thus behaving as a human ear which exhibits similar time-frequency resolution characteristics [TZAN 01].

The Algorithms proposed in this work are all based on our VRT and can be divided into 3 groups of purposes: spectral features extraction (used in segmentation task in [PAR 05] and music structuring task as well, which are not considered in this thesis), beat detection and automatic F0 estimation. Beat detection algorithm issues beat probability curve which is then transformed into rhythmic similarity features. F<sub>0</sub> estimation algorithm delivers f<sub>0</sub> or note candidates as well as relative amplitudes of their partials. This information constructs melodic, tonality and timbre similarity features. Since these features are presented in a form of histograms, we consider and apply various simple and efficient histogram comparison techniques.

Our similarity measures have been evaluated in several musical information retrieval applications such as automatic genre classification, listening test, reinterpreted compositions search and playlist relevance analysis. In the case of genre classification these similarity measures were combined with classical spectrum-based PGM-MLP [HARB 03] features and have shown a significant improvement of classification rates.

The listening test had as an objective the evaluation of the quality of automatically generated lists of similar musical titles. The overall evaluation score as well as score distribution have been obtained for various musical similarity measures and their combinations.

Playlist relevance analysis and reinterpreted compositions search are a kind of an objective evaluation of the similarity computation approaches. In playlist relevance analysis the number of musical titles in similarity playlists belonging to one artist or one genre were considered.

Our VRT has also been used in other related applications such as audio track segmentation in video content analysis and has shown promising results [PAR 05]. However, the main drawback of VRT is the burden of heavy computation which was partly overcome by using low-level programmed algorithms.

## 1.4. Organization of the manuscript

The thesis is organized into 5 major chapters starting from the definition of the problematic and description of related work in Chapter 2, then ascending different levels of musical signal analysis and finishing by its direct applications.

The Chapter 3 starts from a description of musical signal specificity. In the light of musical signal properties various approaches to signal analysis are discussed. Finally the chapter presents a technique of variable resolution transform which is then used across the whole thesis.

The next Chapter 4 passes from the signal analysis to extraction of rhythmical properties of a music signal. On this stage an algorithm of rhythm detection is presented and partly evaluated. The information issued by the aforementioned rhythmic analysis algorithm is subsequently involved in construction of rhythmical similarity features. A small evaluation of tempo estimation is done in this chapter.

The Chapter 5 touches upon melodic-related similarity aspects. The chapter starts by description of a multiple-f0 extraction algorithm and its evaluation. The algorithm extracts pitch candidates together with their relative harmonic amplitude. Pitch candidates are then forming melodic-related fingerprints such note succession histogram.

The last major chapter - Chapter 6 is dedicated to applications of musical similarity measures. Two of them are considered – automatic music genre classification and music retrieval by similarity. Evolutions of both applications are given.

## 1.5. List of publications

Most of this work is not published yet. The following conference publications only partially cover the various matters presented within this manuscript. Several journal papers are in preparation.

- A Paradzinets, O. Kotov, H Harb, L. Chen., Continuous Wavelet-like Transform Based Music Similarity Features for Intelligent Music Navigation. *Proceedings of CBMI07, Bordeaux, France. 2007.*
- Kotov O., Paradzinets A., Bovbel E. Musical Genre Classification using Modified Wavelet-like Features and Support Vector Machines. *Proceedings of EuroIMSA, Chamonix, France. 2007*
- Paradzinets A., Harb H., Chen L., “Use of Continuous Wavelet-like Transform in Automated Music Transcription”, *Proceedings of EUSIPCO 2006*
- Parshin V., Paradzinets A., Chen L. Multimodal Data Fusion for Video Scene Segmentation, *Proceedings of VIS 2005*
- Paradzinets A., Chen L., Bovbel E. (2004). Histogram-Based Algorithm for Speaker Segments Regroupment in Audio Databases Indexing Applications. *In proceedings of RIAO, pp 793-799, April 26-28, 2004, Avignon – France, 2004*

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## **Chapter II**

### **Problem of music similarity and related work**

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## 2. Problem of music similarity and related work

The ocean of music similarity search application is immense. One can imagine a music expert, or just an amateur, browsing a many-thousand files music collection and wishing to find music of a particular kind or spirit. The meta-data which are present nowadays bring very poor aid in this case. Navigation by an artist or pre-defined genre can hardly cover needs of intelligent navigation. For example, a fan may be looking for music similar to the one he likes but interpreted by a different orchestra or group.

One can imagine a radio-programmer, doing the same work but in different situation – programming playlists which will follow a defined format of music.

A music-selling online store is a direct application, where customers could be proposed to listen to/buy music which is *similar* to the music he or she has just purchased. There are means to use statistical information of a kind “users, who has bought this also has bought that”. These methods need a great amount of transactions in order to obtain meaningful statistics and hence to be effective. Moreover, these methods will tend to be biased towards famous titles.

Search by similarity can have its perfect place in portable mp3 players where it could be found behind an intelligent shuffle function.

In general, similarity of music is based on subjective judgments, making it difficult to define. We can attempt to define the musical similarity as the feature that lets a human subject create a “playlist” of music pieces based on his/her particular taste. Musical similarity can be expressed in musical terms, i.e. musical tones, intervals, chords, instruments, melodic lines and rhythms, etc. Additional music feature which can be mentioned is the timbre. The timbre is defined as the feature that permits humans to discriminate two sound objects having the same pitch.

Automatic music similarity computation can be defined as the problem of musical feature extraction, building models and comparing them.

### 2.1. State of the art

There exists a lot of works in the literature dedicated to automatic computation of music similarity. The most popular approach consists of (Gaussian Mixture Modeling) GMM modeling of several MFCC-like characteristics. *Pachet et al.* within the framework of the CUIDADO project [PACH 03], propose a combination of similarity measurements based on GMM modeling and co-occurrence analysis. [LOG 01] uses MFCC characteristics with GMM modeling and the distance “Earth Moving Distance” to estimate the acoustic similarity between two segments of music. Within a *peer to peer*

framework, [BAUM 03] uses basic characteristics: MFCC and GMM for the music search by similarity.

All the previous works thus build their models over MFCC characteristics which only capture somehow the global timbre property of a music signal while mostly omitting other major music properties such as melody, harmony and rhythm. They differ in the way of computing similarity distances.

In a similar context, [TZAN 03] proposes to describe a segment of music by a texture annotation and values of averages and variances of the traditional characteristics like MFCC, spectral flux, spectral centroid and some musical context characteristics such as beat histogram and histogram of pitch. This approach is an interesting one since it tries combining implicitly spectral and pro-musical features.

Another interesting approach [BERE 03] proposes to make an anchor model for the music. A segment of music is characterized by a vector describing its membership to anchors. The analysis of vectors describing the segments of music makes it possible then to measure the acoustic similarity between two segments. The problem of the approach is that it is still MFCC-based.

*Cheng Yang* presents in [YANG 02] an algorithm for selection of spectrum locations which are most likely to contain relevant information. A spectral signature extracted from these locations is then used as the basis of a signature for the estimation of a similarity between two music segments. The author also shows that the problem of search for various interpretations of a work is a difficult problem which is unsolved by their algorithms.

A pioneer work in this field is MuscleFish [WOLD 96] which make use of averages, variances and correlations of features such as *loudness*, brightness bandwidth and others to characterize a segment of sound. The Euclidian distance is applied to estimate the similarity between two sound segments. The characteristics which are used are purely spectral and hence cannot bring any musical knowledge to similarity models.

In more recent works, [AUCO 05] propose an interesting approach of timbre related music similarity using Gaussian Mixture Models. In this work authors propose to model the global timbre of musical pieces and compute similarity between models. Further evolution of these methods is presented in [PAMP 05]. Authors introduce two new descriptors “Focus” and “Gravity”. However, a detailed consideration of these works confirms that the basic technique behind is always Mel-Frequency Cepstrum Coefficients. The novelty of these works is somehow the way for further processing, i.e. model building and their comparison. Indeed, the first work is a very popular one (based on classical methods). At the same time, the notion of global timbre is rather not clear while the timbre itself is related to the way in which two



instruments sound differently for a human listener. From the point of view of global timbre, a melody played by the same instrument but transposed by some number of intervals will have different timbre while for a human listener it is still the same instrument and the same timbre.

Many other works propose various acoustic measurements to catch the different aspects of music similarity. But the difficulty is always that the perceptive similarity is semantic and holds a good part of subjectivity. It was suggested by authors in [AUCCO 04] the pure acoustic or spectral similarity quickly finds its limits. Authors of state-of-the-art works generally agree that by using the majority of MFCC-based similarity features it is not possible to accurately describe musical similarity aspects [PAMP 06].

During the last few years scarce works appeared which try to describe musical signal using musical context descriptors. One of such works is presented in [GOME 06]. The work considers aspects of high level musical similarity by musical tonality. Algorithms of tonality induction and their evaluation are described. Authors tried to apply methods of tonality comparison to intelligent music navigation problem and confirmed the validity of such application. It reinforces the evidence that classical MFCC-based and other related approaches must be complemented by musical-level descriptors in order to come closer to the human perception of music similarity.

### 2.1.1. Millions of audio features which are ...similar

Let's give now some of the basic spectral features based on the magnitude of the FFT (STFT) spectrum. These features are widely known and their definition can be found in many works (see e.g. [TZAN 02a])

#### **Spectral Centroid**

The spectral centroid is defined as the center of gravity of the magnitude spectrum:

$$C_t = \frac{\sum_{n=1}^N S_t[n] * n}{\sum_{n=1}^N S_t[n]} \quad (2.1)$$

here  $S_t[n]$  is the magnitude of the Fourier transform of the time  $t$  at frequency bin  $n$ . The spectral centroid has been shown to have a relation with musical instrument timbre. It was used for example in [WOLD 96] for sound classification or music genre classification [TZAN 02].

- **Spectral Flux**

Spectral flux is defined as follows:

$$F_t = \sum_{n=1}^N (N_t[n] - N_{t-1}[n])^2 \quad (2.2)$$

It is a squared difference of normalized spectrum  $N_t[n]$  between successive frames  $t$  and  $t-1$ . As the spectral centroid, the spectral flux has been shown to have a relation to the instrument timbre. In [HAWL 93] it was used for harmonic music detection. It was used in music genre classification tasks [TZAN 02] as well.

- **Spectral Rollof**

The spectral rolloff is a measure of spectral shape which denotes a frequency  $R_t$  below which 85% of the spectrum distribution is concentrated.

$$\sum_{n=1}^{R_t} S_t[n] = 0.85 * \sum_{n=1}^N S_t[n] \quad (2.3)$$

- **Zero Crossing Rate**

Zero-crossing rate is the number of times when the signal changes its sign during one time period. It is used for example in such works on music/speech classification [SAUN 96] and in some works dedicated to music classification as well.

- **4Hz Modulation Energy**

This measure is mainly used to characterize speech. Speech has a tendency to have a 4Hz modulation [HOUT 73]. 4Hz modulation energy was found to be useful in speech detection [SCHE 97].

- **Mel-Frequency Cepstrum Coefficients (MFCC)**

We want to mention MFCC individually as nowadays **vast** amount of music information retrieval works are based on them.

Mel-Frequency Cepstrum Coefficients are the most known from the family of cepstral characteristics. These are cepstral coefficients obtained from a spectrum filtered by Mel scale [STEV 40]. The Mel scale is a scale which reflexes characteristics of human perception. It affirms that high frequencies are caught by human's ear with less precision in comparison to low frequencies.

The MFCC are obtained as follows:

1. Divide signal into frames.
2. Compute the FFT to obtain the amplitude spectrum.
3. Take the logarithm.
4. Apply the Mel filter.
5. Take the Discrete Cosine Transform.

The MFCC are widely used in speech modeling and recognition. They also were claimed to be of use in music information retrieval [FOOT 97; LOG 00]. The work [LOG 00] which is always referred as a basic work proving the applicability of MFCC in music modeling stays in the context of speech / music discrimination. It makes a suggestion that the application of Mel scale is at least not harmful for this task.

MFCC was initially designed for speech signal analysis and describes the timbre aspect of a speech signal. As music signal is likely more stationary as compared to speech signals, its application for music analysis certainly also captures some timbre aspects of music signal. However, the other three major properties of a music signal such as rhythm, melody and harmony are not modeled by MFCC based features. As highlighted by several works ([HARB 03; PAMP 06] etc), further advances in music analysis or retrieval clearly needs to go beyond MFCC based features and to consider some other music based features for describing rhythm, melodic line and harmonic properties.

A recent work [PACH 07] proposes a method of automatic construction of well-adapted solutions by using several elementary mathematical and logical operators to combine basic features like pitch, centroid, chroma etc., pointing out the fact that the number of *all possible* acoustic features is hardly calculable. Their proposed algorithms are able to search in a space of  $10^{20}$  features and to construct effective analytical features using samples from training database. However, such search space is constructed of possible combination of a **very limited number** of initial features. By initial feature we mean a characteristic which is extracted directly from the signal or its spectrum (like MFCC). All further derivatives of the kind  $AVG(FFT(FFT(MFCC())))$  are considered to have one origin and hence to be strongly related to it.

### 2.1.2. Spectral similarity

In most of the cases the spectral similarity is calculated in the following ways. First Spectral vectors are extracted by means of the Short Term Fourier Transform. The original spectrum is further filtered by a filter bank containing 20 filters distributed based on the Mel scale.

In the work [HARB 01] the KL distance was used in audio segmentation, and it was found that this distance is suitable for the problem of audio similarities, since the segmentation is a similarity problem between consecutive windows and KL distance enables the measure of dissimilarity between two spectral distributions.

The KullBack-Leibler (KL) distance originates from the information theory [COVE 91]. It is a distance between two random variables. The original KL distance doesn't have the properties of a distance, but the symmetric KL

is a distance. In the case of Gaussian distribution of the random variables the symmetric KL distance is computed by:

$$KL2(X,Y) = \frac{\sigma_X^2}{\sigma_Y^2} + \frac{\sigma_Y^2}{\sigma_X^2} + (\mu_X - \mu_Y)^2 \left( \frac{1}{\sigma_X^2} + \frac{1}{\sigma_Y^2} \right) \quad (2.4)$$

With  $\sigma_X, \sigma_Y, \mu_X, \text{ and } \mu_Y$  are respectively the standard deviation of X and Y and the mean of X and Y.

In the case of audio similarity, X and Y are the set of feature vectors obtained from window X, and window Y (several seconds for the two windows for instance).

The long term similarity or the global similarity can be defined as the similarity that a human subject would find when listening to excerpts of 10 to 20 seconds. Here are some long term similarities proposed by [HARB 03].

Two musical pieces A and B can be segmented to twenty 1-second segments. Any segment from A can be similar to any segment from B, thus the Local Similarity (KL distance) can be calculated between all couples between B and A. However, the problem is how to obtain a global similarity measure between A and B based on their local similarities?

The KL distances between all couples of segments from A, and B, constitute a Local Similarity Matrix:

$$LSM_{A,B} = \begin{matrix} & KL_{1,1}^{AB} & KL_{2,1}^{AB} & KL_{3,1}^{AB} & \bullet \\ & KL_{1,2}^{AB} & KL_{2,2}^{AB} & KL_{3,2}^{AB} & \bullet \\ & KL_{1,3}^{AB} & KL_{2,3}^{AB} & KL_{3,3}^{AB} & \bullet \\ & \bullet & \bullet & \bullet & \bullet \end{matrix} \quad (2.5)$$

Six features from the LSM matrix and other KL-based measures can be extracted. These features are: Homogeneity (H), Local Similarity (LS), Min Distance (MD), Sum Distance (SD), Local Similarity for Low Frequencies (LSLF), and Local Similarity for High Frequencies (LSHF). Each of the features is aimed at providing one aspect of acoustic similarity.

- **Homogeneity (H)**

The aim of the H feature is to measure how much A and B are similar in their homogeneity behavior. For example, theoretically a HipHop music piece will have different homogeneity behavior than a Metal music piece. These measures are computed as follows:

$$H = |H_A - H_B|$$

$$H_A = \frac{1}{M} \sum_{i=1}^M (KL_{i,i+1}^{AA})^2 \quad (2.6)$$

$$H_B = \frac{1}{M} \sum_{i=1}^M (KL_{i,i+1}^{BB})^2$$

- **Matching (M)**

The Matching (M) feature describes the distance between the minimal values and their diagonal counterparts in LSM. For example, if the component  $KL_{i,j}^{AB}$  is the minimal value in row “i”, we measure  $|j-i|$ , and M is the average of  $|j-i|$  for all rows and columns in LSM.

- **Local Similarity (LS)**

The LS measure seeks a dynamic comparison of A and B. It is based on similarities between one block from A (respectively B), with other blocks from B (respectively A), taking the local minimum for 3 neighbors.

$$LS = LS_{A,B} + LS_{B,A}$$

$$\text{With } LS_{A,B} = \frac{1}{M} \sum_{i=1}^M \left| \min_{j=i-1}^{i+1} [KL_{i,j}^{AB}] \right| \quad (2.7)$$

$$LS_{B,A} = \frac{1}{M} \sum_{j=1}^M \left| \min_{i=j-1}^{j+1} [KL_{i,j}^{AB}] \right|$$

- **Min Distance (MD)**

The MD is the sum of the three minimum values in the LSM Matrix. Denote  $MD_{A,B}^1$ ,  $MD_{A,B}^2$  and  $MD_{A,B}^3$  as the three minimal values in the LSM matrix. Thus the MD is simply the sum of these values.

$$MD_{A,B} = MD_{A,B}^1 + MD_{A,B}^2 + MD_{A,B}^3 \quad (2.8)$$

- **Sum Distance (SD)**

The SD measures the similarity based on all the components of the LSM Matrix:

$$SD_{A,B} = \sum_i \sum_j KL_{i,j}^{AB} \quad (2.9)$$

- **Local Similarity for Low Frequencies (LSLF)**

LSLF is the LS feature but based on the KL distance calculation for frequencies below 1 KHz. it is targeted to let to concentrate the similarity toward low frequencies.

- **Local Similarity for High Frequencies (LSHF)**

LSHF is the LS feature but based on the KL distance calculation for frequencies between 1 and 4 KHz. the goal of this measure is to target the similarity in the direction of high frequencies.

## 2.2. Our approach

The number of ways to compute the similarity features of musical compositions is hardly countable. The main goal of constructing similarity features is to come as closer as possible to humans' perception. Instead of turning in all senses the MFCC based features which capture in a certain way the timbre property of a music signal, we propose to complement them by music features characterizing music properties such as rhythm, melody and tonality.

Extraction of several groups of features requires lower-level algorithm of musical content analysis which touches upon all stage of processing. The idea can be visualized by the following schema (Figure 2.1).

Music-based similarity			Classical audio-based similarity		
5	Applications	⇒ playlists, genres	Applications	⇒ playlists, genres	
4	Similarity modeling	⇒ distances	Similarity	⇒ distances	
3	Music features extraction	⇒ chords, tonality, melody lines, tempo, etc	Modeling	⇒ GMM, fluctuation patterns, etc...	
2	Music info computation	⇒ notes, beats	Spectral features extraction	⇒ MFCC, ZCR	
1	Signal processing	⇒ spectrum	Signal processing	⇒ spectrum	

**Figure 2.1.** 5-level music-based similarity analysis dataflow model compared to audio-based similarity dataflow.

On the Figure 2.1 we show our vision of music signal analysis in a music information retrieval process which is represented by 5 levels of treatment. It is compared to an approximate model of popular music analysis known in literature. In this thesis we are interested in all stages of our model starting from signal processing. The classical way of doing it is the use of the FFT in order to obtain spectrum of a signal. Advantages and disadvantages of these two approaches as well as the VRT technique we propose are discussed in Chapter 3.

The next stage is the stage of musical information extraction. In the case of classical way of musical signal analysis the phase of musical information extraction does not have any direct analogue; instead the spectral features are extracted directly. The role of higher-level features in that case is played by descriptive models such as GMM. We focus at the second stage on beat detection and multiple  $f_0$  estimation algorithms we have developed. These lower level algorithms do not provide musical similarity features while they provide information which is necessary for the construction of such features. The process of their computation and comparison is covered by the stages 3

and 4 of the model which chapters 4 and 5 of this thesis are dedicated to. The chapter coverage is illustrated on Figure 2.2.

<b>Music-based similarity</b>		<b>Chapter coverage</b>	
Applications	⇒ playlists, genres	<b>Chapter 6</b>	
Similarity modeling	⇒ distances	<b>Chapter 4</b> (rhythm-related)	<b>Chapter 5</b> (melody-related)
Music features extraction	⇒ chords, tonality, melody lines, tempo, etc		
Music info computation	⇒ notes, beats		
Signal processing	⇒ spectrum	<b>Chapter 3</b>	

**Figure 2.2.** 5-level music similarity analysis dataflow and chapter coverage.

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## **Chapter III**

### **Music signal analysis**

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### 3. Music signal analysis

The primary stage in every kind of audio based music information retrieval is signal data analysis. Some algorithms perform analysis in the time domain as for example several beat detection algorithms. But the majority of music information retrieval algorithms perform their computation in the frequency domain, or a time-frequency representation, to be exact. So, the performance of all further steps of processing is strictly dependent on the initial data representation.

This chapter gives an introduction to signal treatment. It gives a brief excursus into classical FFT-based approach and its drawbacks. In contrast to the FFT, the chapter describes the wavelet transform as a novel and promising instrument in musical signal processing. The chapter explains the main principle of classic wavelet transform. A novel variable resolution transform introduced in this work is also presented in this chapter.

#### 3.1. About music signal

Music is an art form consisting of sound and silence expressed through time. Elements of sound as used in music are pitch (including melody and harmony), rhythm (including tempo and meter), structure, and sonic qualities of timbre, articulation, dynamics, and texture.<sup>1</sup>

Melodies are usually sequences of pitches which are created in Western music in respect to scales and modes and having a certain rhythm. Scales and modes are notions of music theory which describe a set of notes involved in the play. In Western music there are 12 notes. An interval between neighbor notes is called *semitone*.

For better understanding of particularity of music signal, let's consider the following Figure 3.1 containing a musical excerpt expressed in a form of pattern.

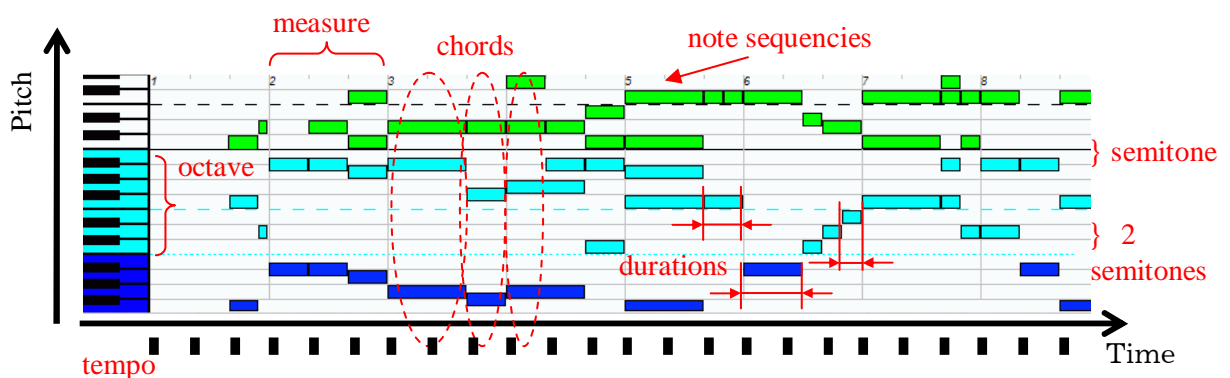


Figure 3.1. Typical music pattern.

<sup>1</sup> <http://en.wikipedia.org/wiki/Music>

The term *pitch* is directly related to frequency, the higher is the pitch – the higher is the frequency. The relation between pitch and frequency is logarithmic.

$$p = 69 + 12 \cdot \log_2 \left( \frac{f}{440\text{Hz}} \right) \quad (3.1)$$

In music, pitch is the perceived *fundamental frequency*. Sounds of real instruments do not have single frequency in their spectrum, but a packet of frequencies – fundamental and its harmonics. The Figure 3.1 would represent a spectrogram of a musical signal if instruments in it had a single frequency in their spectrum.

As we have noticed, musical signal have two main properties – temporal and frequency granulation. In reality, we don't speak about frequency granulation of musical signal since there could be signing voice or percussion instruments in it. Speeding up or slowing down the signal also leads to shifts of note frequencies from their theoretical values corresponding to integer pitches.

In comparison to speech signals music signals can be assumed to be more stationary (during one note or one chord the spectrum of the signal does not change much). Duration of notes can be considered to be around 120-250 ms for 1/8 - 1/16 (quaver - semiquaver) at the most popular tempo of 120 BPM (the minimal duration of a note which could be found in music at 120 BPM is then 65 ms for 1/32). Nevertheless, music signals may contain percussion instruments rapidly changing in time or of a very short duration. Signing voice of one or many persons may be also present. The second grand specificity of a musical signal is *multipitch*. Music is usually represented by multiple simultaneous note events, such as chords. A chord may contain from 2 to many (>10) pitches at the same time. Some instruments may already contain multiple pitches in one note. These facts make musical spectrum much more complicated in the meaning of frequency contents in comparison to speech signals. Such complexity can be referred to *timbre* of the musical sound. Timbre characterizes each voicing instrument defined by its spectrum (presence of harmonic and inharmonic components) and envelop. Timbre allows us to distinguish different instruments.

Unlike voicing instruments, percussion instruments in music may not have its fundamental frequency. Thus, they are undetermined-frequency instruments (no pitch can be perceived). As an example we can mention snare drums, hi-hats and cymbals. These instruments have mainly noisy components in their sound which are then superposed to voiced instruments and form more complex spectrum.

We have briefly described some specificities of a musical signal. In order to be able to extract its musical properties, a well adapted analysis tool is

required which will resemble somehow the human auditory system. Human perception of pitch is linear, thus, the tool should have a logarithmic frequency scale. It is also known, that human ear is more sensitive to rapid changes in high frequencies and less sensitive to rapid changes in low frequencies. A tool owning similar characteristics might be better suited for analysis of musical signals.

In this work we are passing by different level of analysis, starting from obtaining a musical spectrum, extraction of musical features and finishing by building similarity models for different musical features and applying them to high-level music analysis such as automatic classification or similarity search. In this context, we are interested to have a tool with both frequency sampling suitable for analyzing notes in equal tempered note system and good frequency resolution in high frequency area since harmonic resolution is important as well. The tool must also provide acceptable time resolution, suitable for beat/onset detection.

### **3.2. Related work**

There are plenty of works in the literature dedicated to musical signal analysis. The common approach is the use of FFT (Fast Fourier Transform) which has become a de-facto standard in music information retrieval community. The use of FFT seems straightforward in this field and relevance of its application for music signal analysis is almost never motivated.

There are some works in music information retrieval attempting to make use of wavelet transform as a novel and powerful tool in musical signal analysis. However, this new direction is not very well explored. [TZAN 02] proposes to rely on discrete wavelet transform for beat detection. Discrete packet wavelet transform is studied in [GRIM 02] to build time and frequency features in music genre classification. In [KADA 92], wavelets are also used for automatic pitch detection.

Spectrum analysis tools with geometric frequency spacing are well known. One of classic examples is Constant Q transform, considered further. Many other custom filterbank techniques have been proposed in literature. These are bounded versions of constant Q transform [KASH 85], fast filter banks [LIM 92] having the goal of minimizing frequency bins dispersion, bounded constant Q filter banks [DINI 07]. In fact, there is no universal analysis tool with ideal frequency grid. It is either fast transform with linear or quasi-linear (linear within octaves) frequency grid or it is logarithmic frequency heavy computational solutions. Depending on target application, different solutions may perform better.

Another class of approaches to signal analysis is an analysis by modeling. The aim of these approaches is to approximate a multi-sinusoidal model to the signal issuing frequencies and phases of separate harmonic components.

An example of such approach is described in [BADE 02]. Although these methods represent a great interest in musical signal analysis, we are concentrated on spectrum based approaches in our work.

### 3.2.1. Fourier transform

As it is well known, Fourier transform enables a spectral representation of a periodic signal as a possibly sum of a series of sines and cosines. While Fourier transform gives an insight on spectral properties of a signal, its major disadvantage is that a decomposition of a signal by Fourier transform has infinite frequency resolution and no time resolution. It means that we are able to determine all frequencies in the signal, but without any knowledge on where they are situated. This drawback makes Fourier transform to be perfect for analyzing stationary signals but unsuitable for irregular signals whose characteristics change in time. To overcome this problem several solutions have been proposed in order to represent more or less the signal in time and frequency domains.

One of these techniques is windowed Fourier transform or short-time Fourier transform. The idea behind is to bring time localization into classic Fourier transform by multiplying the signal with an analyzing window:

$$X(\tau, \omega) = \int_{-\infty}^{\infty} x(t)w(t - \tau)e^{-j\omega t} dt \quad (3.2)$$

where  $w(t)$  – is a windowing function (usually Gauss window, Hamming or Hann function and many others. The same principle is applied in **discrete** short-time Fourier transform.

$$X(m, \omega) = \sum_{n=-\infty}^{\infty} x[n]w[n - m]e^{-j\omega n} \quad (3.3)$$

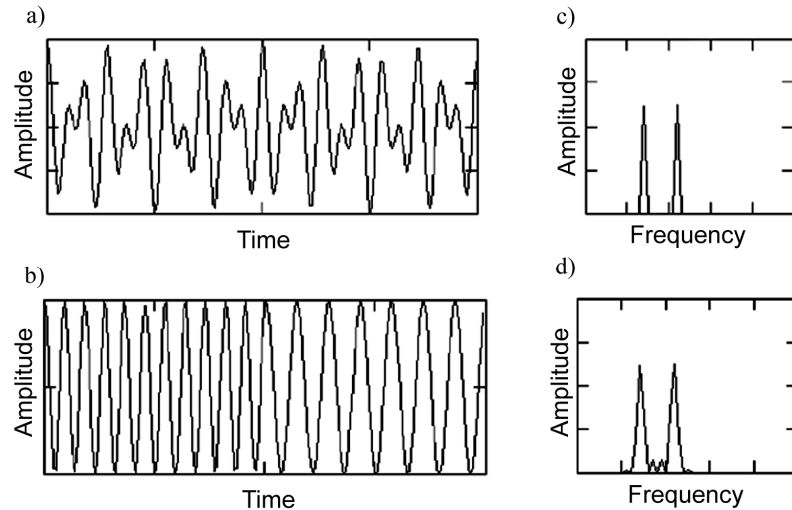
The problem here is that the short-time discrete Fourier transform has fixed resolution. The width of the windowing function determines whether it is good frequency resolution transform or good time resolution transform. Shorter window leads to smaller frequency resolution but higher time resolution while larger window leads to greater frequency resolution but lower time resolution. This phenomena is related to Heisenberg's uncertainty principle which says that

$$\Delta t \sim \frac{1}{\Delta f} \quad (3.4)$$

where  $\Delta t$  is a time resolution step and  $\Delta f$  is a frequency resolution step.

A classical example illustrating weakness of Fourier transform is two signals with two sine waves in it (Figure 3.2). The signal on figure a) is a sum

of two sine waves while figure b) represents a signal where two sine waves follow each other. It can be noticed that their Fourier transforms (figures c and d correspondingly) have very few differences enabling discrimination of these two signals.



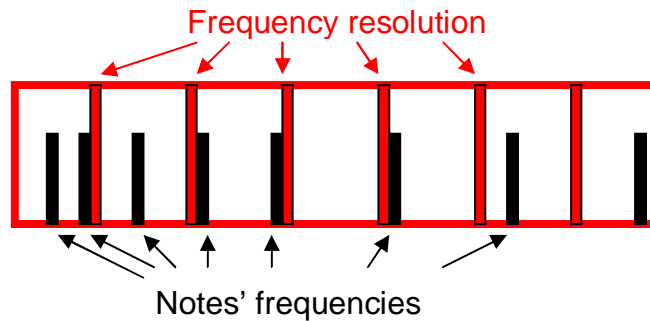
**Figure 3.2.** Fourier transform of two test signals. The signal a) is composed with two superposed waves with different frequencies, b) the same waves, but concatenated one after another, c) d) their Fourier spectrum

Of course, this example cannot be used to illustrate the weakness of the Fast Fourier Transform in music analysis applications (Fast Fourier Transform – a fast version of the discrete Fourier transform). For example, a 512-sample window in FFT applied on 16kHz-sampled signal gives about 30ms of time resolution which is sufficient for most of music applications where duration of notes can be considered to be around 50-200 ms. However, the frequency resolution step of 512-sample FFT is about a semi-tone in the 3<sup>rd</sup> octave, what is obviously not enough. Usually short notes are notes which are involved in melodic lines (average-to-high frequencies) while long notes stand more often for bass lines (low frequencies).

Recall, that in our work the main goal is music analysis. In this respect, we consider rather music-related example which illustrates specificities of musical signals. As it is known, the frequencies of notes in equally-tempered tuning system in western music follow a logarithmic law, i.e. adding a certain interval (in semitones) corresponds to multiplying a frequency by a given factor. For an equally-tempered tuning system a semitone is defined by a frequency ratio of  $2^{1/12}$ . So, the interval between two frequencies is

$$n = 12 \cdot \log_2 \left( \frac{f_2}{f_1} \right) \quad (3.5)$$

If we consider a frequency range for different octaves, it is growing as the number of octave is higher. Thus, applying the Fast Fourier Transform we either lose resolution of notes in low octaves (Figure 3.3) or we are not able to distinguish high-frequency events which are closer in time and have shorter duration.



**Figure 3.3.** Mismatch of note frequencies and frequency resolution of the FFT.

Time-frequency representation, which can overcome resolution issues of the Fourier transform is **Wavelet transform**. Wavelets (literally “small waves”) are a relatively recent instrument in modern mathematics. Introduced about 20 years ago, wavelets have made a revolution in theory and practice of non-stationary signal analysis [KRON 87; MALL 99]. Wavelets have been first found in the literature in works of Grossmann and Morlet [GROS 84]. Some ideas of wavelets partly existed long time ago. In 1910 Haar published a work about a system of locally-defined basis functions. Now these functions are called Haar wavelets. Nowadays wavelets are widely used in various signal analysis, ranging from image processing, analysis and synthesis of speech, medical data and music [KADA 92; LANG 98].

### 3.2.2. Wavelet transform

Wavelet transform is a form of time-frequency representation. It is divided into continuous and discrete subclasses.

Reference fundamental works on wavelets are [COHE 92; DAUB 92; GROS 84; MALL 89] and many others.

A work, explaining the use of the continuous wavelet transform in signal analysis is, for example [LANG 98].

Wavelets are functions satisfying certain mathematical rules which are used to represent data or other functions as it was done by Joseph Fourier, who has proposed to represent all periodic functions from  $0$  to  $2\pi$  with an infinite sum of sines and cosines.

For many decades researchers wanted more appropriate functions than sines and cosines – the basis of the Fourier analysis – to approximate choppy

signals and functions. Wavelets are localized functions and therefore well-suited for approximating data with sharp changes.

### 3.2.2.1 Continuous wavelet transform

Continuous wavelets transform of a function  $f(t) \in L^2(\mathbb{R})$  is defined as follows:

$$W(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) \psi^* \left( \frac{t-b}{a} \right) dt \quad (3.6)$$

where  $a, b \in \mathbb{R}, a \neq 0$ .

In the equation (3.6)  $\psi(t)$  is basic wavelet or mother wavelet function (\* stands for complex conjugate). Parameter  $a$  is called wavelet scale. It can be considered as analog to frequency in the Fourier transform. Parameter  $b$  is localization or shift. It has no correspondence in the Fourier transform.

The wavelet transform, primarily, is a correlation of a signal being analyzed with mother wavelet function, which is shifted and zoomed on its time axis. Mother wavelet function usually, but not necessarily, looks like a wave, faded to zero on its sides. Therefore, the window of short-time Fourier or Gabor transform is somehow included.

Inverse integral wavelet transform is defined as

$$f(t) = C_{\psi}^{-1} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W(a,b) \psi \left( \frac{t-b}{a} \right) \frac{1}{\sqrt{a}} \frac{dad b}{a^2} \quad (3.7)$$

where  $C_{\psi}$  - is a normalizing factor defined as follows:

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{|\Psi|^2}{|\omega|} d\omega < \infty \quad (3.8)$$

Inequality (3.8) is a condition for the existence of the inverse transform. Here  $\Psi(\omega)$  stands for the Fourier transform of  $\psi(t)$ . To satisfy the aforementioned expression, the Fourier transform of  $\psi(t)$  at zero frequency must be equal to zero. Hence, we can rewrite it as follows:

$$\int_{-\infty}^{\infty} \psi(t) dt = 0 \quad (3.9)$$

In other words,  $\psi(t)$  must be a wave, i.e. it must satisfy to **zero mean condition**.

It is sometimes necessary that wavelet function satisfy an equality to zero of higher moments:

$$\int_{-\infty}^{\infty} t^m \psi(t) dt = 0 \quad (3.10)$$

Center  $\langle t \rangle$  and radius  $\Delta_t$  of a function can be used in order to estimate its localization.

$$\langle t \rangle = \frac{1}{\|\psi\|^2} \int_{-\infty}^{\infty} t |\psi(t)|^2 dt \quad (3.11)$$

$$\Delta_t^2 = \frac{1}{\|\psi\|^2} \int_{-\infty}^{\infty} [t - \langle t \rangle]^2 |\psi(t)|^2 dt \quad (3.12)$$

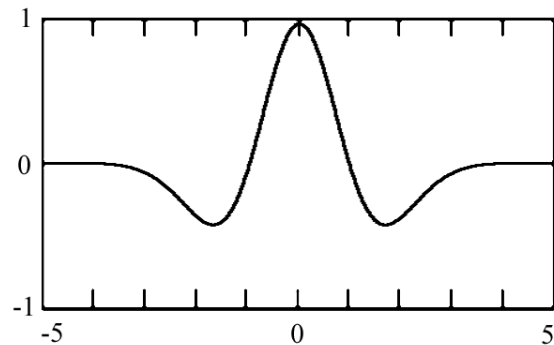
Effective width of a wavelet is usually taken as  $2\Delta_t$ . The same expressions are also true for the frequency axis:

$$\langle \omega \rangle = \frac{1}{2\pi} \int_{-\infty}^{\infty} \omega |\Psi(\omega)|^2 d\omega \quad (3.13)$$

$$\Delta_\omega^2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} [\omega - \langle \omega \rangle]^2 |\Psi(\omega)|^2 d\omega \quad (3.14)$$

Let's consider now some examples of wavelets functions.

- Mexican Hat wavelet

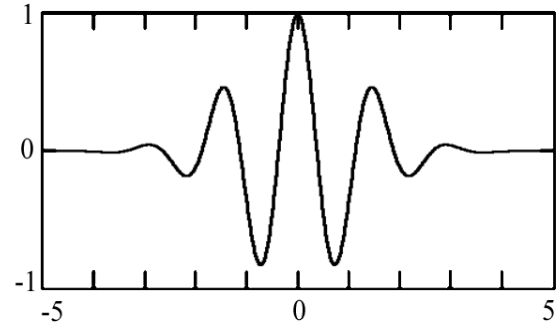


$$\psi(t) = (1 - t^2) e^{-t^2/2} \quad (3.15)$$

The name of this wavelet comes from its form. This kind of wavelets is obtained by differentiation of Gaussian exponents. MHAT wavelets are well localized in time and frequency domain.



- Morlet wavelet



$$\psi(t) = e^{-t^2/\alpha^2} \left( e^{ik_0 t} - e^{-k_0^2 \alpha^2 / 4} \right) \quad (3.16)$$

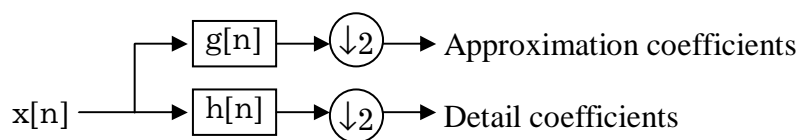
Morlet wavelet is a Gaussian-modulated flat wave. Parameter  $\alpha$  defines Gaussian's width and  $k_0$  stands for frequency (usually taken  $k_0 = 2\pi$ ). Parameter  $\alpha$  adjusts time-frequency localization and hence time-frequency resolution scale of the transform.

### 3.2.2.2 Discrete wavelet transform

Discrete wavelet transform is a sampled version of the wavelet transform where sampling points are selected following the system  $(a^m, na^m b)$  with integers  $m, n \in \mathbb{Z}$ .

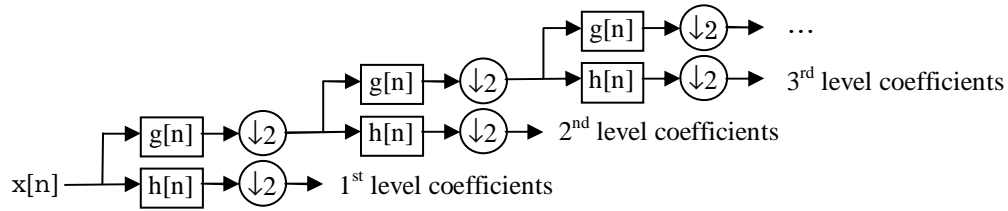
The discrete wavelet transform is often calculated by a *pyramidal algorithm* by passing a signal  $x(t)$  through a series of low-pass (g) and high-pass (h) filters related to each other. The filter outputs are then downsampled by factor 2.

$$\begin{aligned} y_{low}[n] &= \sum_{k=-\infty}^{\infty} x[k] g[2n-k] \\ y_{high}[n] &= \sum_{k=-\infty}^{\infty} x[k] h[2n-k] \end{aligned} \quad (3.17)$$



**Figure 3.4.** Block diagram of DWT filter cascade.

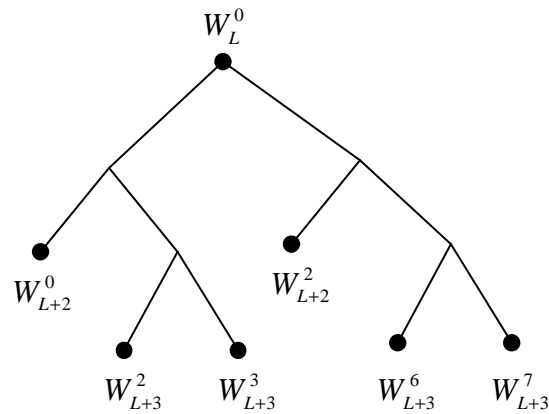
The decomposition is repeated by cascading filter pairs in a form of binary tree for further increase of frequency resolution. This tree is also called a filter bank.



**Figure 3.5.** Example of DWT filterbank.

Discrete wavelet transform is mostly used in signal coding and data compression.

A variety of discrete wavelet transform is *wavelet packet transform* (see e.g. [CODY 94; MALL 99]). Wavelet packet transform can tile the frequency space in a discrete number of intervals. It can be represented as a binary tree, defining subspaces of details  $W_L$ , as illustrated in Figure 3.6.



**Figure 3.6.** Example of a valid wavelet packet tree.

Wavelet packets can be adapted for music analysis for example by defining Heisenberg boxes matching musical octaves and musical notes [GRIM 02].

### 3.2.3. Other transforms and filter banks

#### 3.2.3.1 Constant Q transform

The idea to adapt the time/frequency scale of a Fourier-related transform to musical applications is not completely novel. A technique called **Constant Q Transform** [BROW 91] is related to the Fourier transform and it is used to transform a data series to the frequency domain. Like the Fourier transform a constant Q transform is a bank of filters, but in contrary to Fourier transform it has geometrically spaced center frequencies  $f_k = f_0 \cdot 2^{\frac{k}{b}}$  ( $k = 0; \dots$ ), where  $b$  is the number of filters per octave. In addition it has a

constant frequency resolutions ratio  $R_{f/\Delta} = \left(2^{\frac{1}{b}} - 1\right)^{-1}$ . Choosing appropriately  $k$  and  $f_0$  makes central frequencies to correspond to frequencies of notes.

In general, the transform is well suited to musical data (see e.g. [NAWA 01], in [ESSI 05] it was successfully used for recognizing instruments), and this can be seen in some of its advantages compared to the Fast Fourier Transform. As the output of the transform is effectively amplitude/phase against log frequency, fewer frequency bins are required to cover a given range effectively, and this proves useful when frequencies span several octaves. The downside of this is a reduction in frequency resolution with higher frequency bins.

The transform mirrors the human auditory system, whereby at lower frequencies spectral resolution is better, whereas temporal resolution improves at higher frequencies, and so for musical signal this kind of analysis makes sense.

In addition, the harmonics of musical notes form a pattern characteristic of the timbre of the instrument in this transform. Assuming the same relative strengths of each harmonic, as the fundamental frequency changes, the relative position of these harmonics remains constant. This makes identification of instruments much easier. In this extent it is similar to log-sampled continuous wavelet transform with sinusoid mother function. Its advantages and disadvantages we described in section 3.3.

### 3.2.3.2 Other filter banks

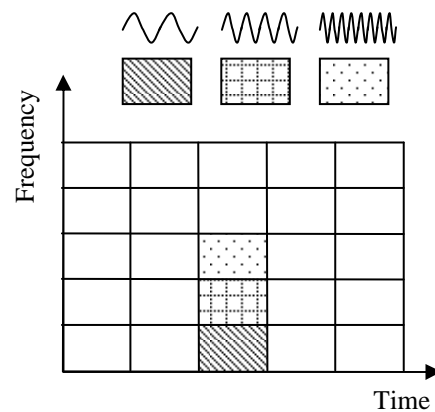
Besides constant Q transform there are bounded version of it (BQT) which use quasi-linear frequency sampling when frequency sampling remains linear within separate octaves. This kind of modification allows construction of medium complexity computation schemes in comparison to standard CQT. However, making the frequency sampling quasi-linear (within separate octaves) renders the work of harmonic structure finding to be more complex task.

Fast Filter Banks are designed to deliver higher frequency selectivity maintaining low computational complexity. This kind of filter banks inherit all disadvantages of FFT in music analysis applications (discussed in §3.2.4).

More advanced techniques, described for example in [DINI 07] are medium-complexity methods which aim to overcome disadvantages of FFT and try to follow note system frequency sampling. However, octave-linear frequency sampling keeps the same disadvantage as in the case of bounded Q transforms.

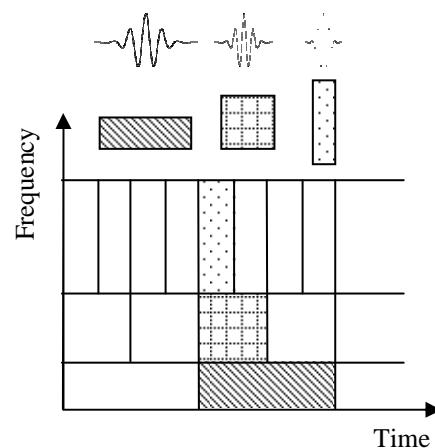
### 3.2.4. Discussion: FFT vs WT for music signal analysis?

Let's consider the windowed Fourier transform and the wavelet transform. One way to see the time-frequency resolution differences between the Fourier transform and the wavelet transform is to look at the basis function coverage (tiling) of time-frequency plane. Figure 3.7 shows a windowed Fourier transform. The window is square and it truncates the sine and cosine function of the transform by a particular width. Because the STFT uses the window of the same size for all frequencies, the resolutions is the same at all locations in the time-frequency plane.



**Figure 3.7.** Fourier basis functions, time-frequency tiles, and coverage of the time-frequency plane.

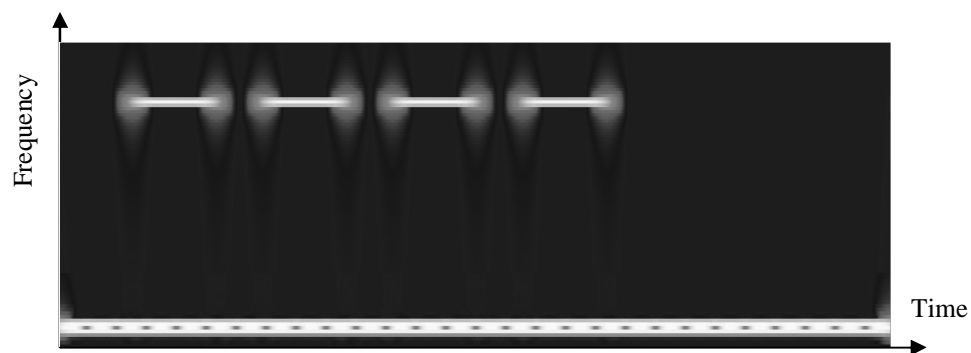
The main advantage of the wavelet transform is that the window size is not constant. It changes across the frequency axis. Figure 3.8 shows the coverage in the time-frequency plane with a wavelet mother function, namely Morlet wavelet.



**Figure 3.8.** Morlet wavelet basis functions and time-frequency coverage.

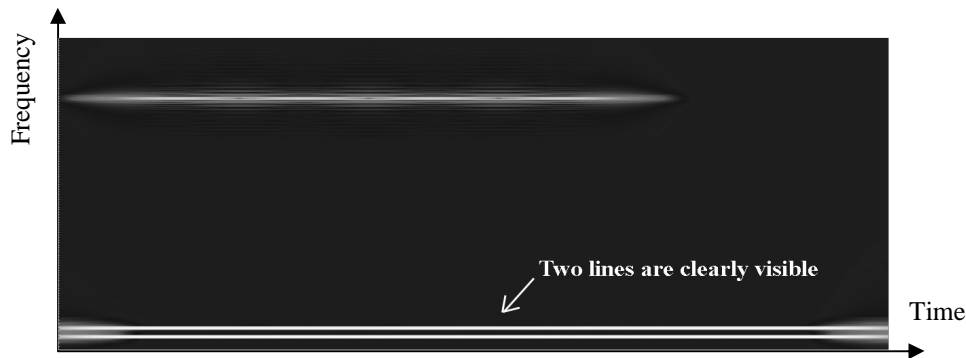
One important thing is that the wavelet transform does not have a single set of basis functions like the Fourier transform. Instead, the wavelet transform utilizes an infinite set of possible basis functions. Thus, it has an access to a wide range of information including the information which can be obtained by other time-frequency methods such as Fourier transform.

As explained in brief introduction on music signal, a music excerpt can be considered as a sequence of note (pitches) events lasting certain time (durations). Beside beat events, singing voice and vibrating or sweeping instruments, the signal between two note events can be assumed to be quasi-stationary. The duration of a note varies according to the main tempo of the play, type of music and type of melodic component the note is representing. Fast or short notes usually found in melodic lines in high frequency area while slow or long notes are usually found in bass lines with rare exceptions. Let's consider the following example in order to see the difference between the Fourier transform and wavelet one. We construct a test signal as containing two notes E1 and A1 playing simultaneously during the whole period of time (1 second). These two notes can represent a bass line, which, as it is well known, does not change quickly in time. At the same time, we add 4 successive notes B5 with small intervals between them (around 1/16 sec). These notes can theoretically be notes of the main melody line. Let's see now the Fourier spectrogram of the test signal with a small analyzing window.



**Figure 3.9.** Small-windowed Fourier transform (512 samples) of the test signal containing notes E1 and A1 at the bottom and 4 repeating B5 notes at the top.

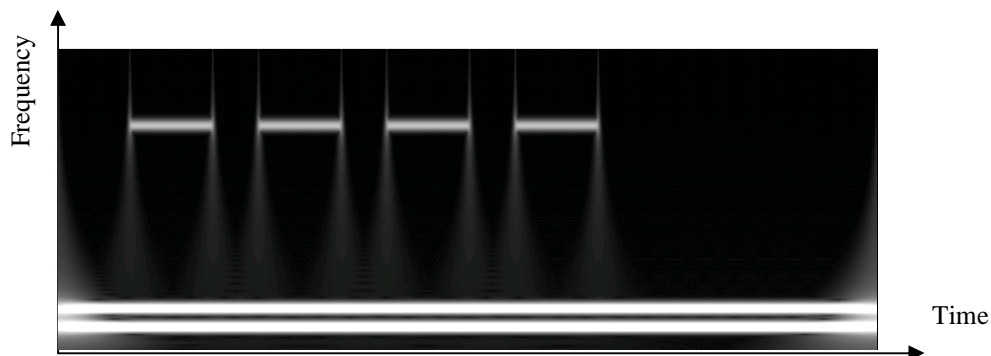
As we can see from Figure 3.9, while high-octave notes can be resolved in time, two bass notes are irresolvable in frequency domain. Now we increase the size of the window in the Fourier transform. Figure 3.10 illustrates the resulting spectrogram.



**Figure 3.10.** Large-windowed Fourier transform ( $\geq 1024$  samples) of the test signal containing notes E1 and A1 at the bottom and 4 repeating B5 notes at the top.

As we can see, two lines at the bottom of the spectrogram are now clearly distinguishable while the time resolution of high-octave notes has been lost.

Finally we apply wavelet transform to the test signal. Figure 3.11 shows such Morlet-based wavelet spectrogram of our test signal.



**Figure 3.11.** Wavelet transform (Morlet) of the test signal containing notes E1 and A1 at the bottom and 4 repeating B5 notes at the top.

Of course, the given example is quite artificial; however it explains well our motivation for a wavelet like time-frequency representation of a signal. It is also known, that human ear exhibits time-frequency characteristic closer to that from wavelet transform [TZAN 01].

Crucial disadvantage of the wavelet transform is its heavy computations. There are fast algorithms for wavelet transform computation (E.g. [RIOU 91]). They are based on self-similarity of wavelets at different scales or on the fact of particular sampling of the scale axis of the wavelet. We overcome this problem by manually programming wavelet-like transform algorithms (including our implementation of VRT on which our work is based on) using fast vector arithmetic of modern CPUs (MMX/SSE instruction sets), which is usually never done automatically by high-level languages compilers.

### 3.3. Variable Resolution Transform

In this section, we introduce our Variable Resolution Transform (VRT) specifically designed for music signal analysis. Inspired by the wavelet and constant Q transforms, our VRT is a set of specially crafted filters with central frequencies following a logarithmic scale which only “resembles” a wavelet transform and in reality does not appear to be a true wavelet transform (generally, all kinds of transforms as for example FFT, CQT can be considered as filter sets [SMIT 07]). Our VRT is a fundamental tool for music signal analysis in our work as it is used for deriving music features such as beat detection, multiple  $F_0$  estimation etc. which, in turn, enable construction of melodic, tonality and timbre similarity features. There are no “universal” and 100% efficient filterbanks, suitable for all kinds of applications. Our tool is one of numerous possible solutions which we position to be better adapted for harmonic structure extraction owing to its higher frequency resolution in upper frequency area.

#### 3.3.1. Building Variable Resolution Transform

Our Variable Resolutions Transform (VRT) is first derived from the classic definition of Continuous Wavelet Transform (CWT) given in §3.2.2.1 in order to enable a variable time-frequency coverage which should better fit to music signal analysis. The consideration of specific properties of music signal finally leads us to change also the mother function and thus our VRT is not a true CWT but a filter bank.

##### 3.3.1.1 The basis

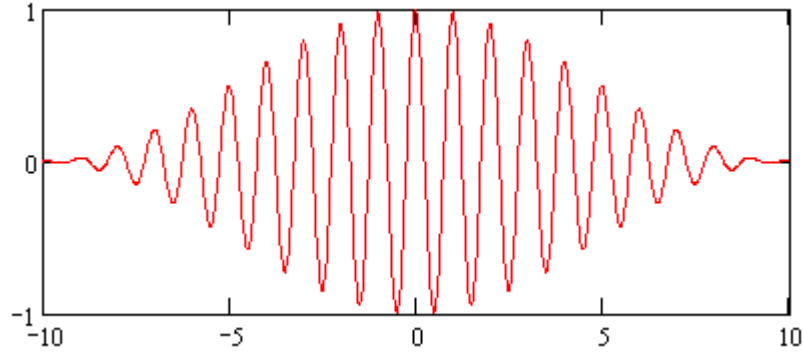
We start the construction of our VR Transform from Continuous Wavelet Transform defined by (3.6). Thus, we define our mother function as follows

$$\psi(t) = H(t, l) e^{j \cdot 2\pi \cdot t} \quad (3.18)$$

where  $H(t, l)$  is Hann window function of length  $l$  with  $l \in \mathbb{Z}$  as defined by (3.19). In our case  $l$  will lie in a range between 30-300 ms. Notice that using different different length values  $l$  amounts to change the mother wavelet function  $\Psi$ .

$$H(t, l) = \frac{1}{2} + \frac{1}{2} \cos \frac{2\pi t}{l} \quad (3.19)$$

Once fixed the length  $l$ , function (3.18) looks like much similar to Morlet wavelet. It is an oscillating function, a flat wave modulated by Hann window. The parameter  $l$  defines the number of periods to be present on the wave. Figure 3.12 illustrates such a function with  $l=20$  waves.



**Figure 3.12.** Our mother wavelet function. A flat wave modulated by Hann window with  $l=20$ .

We can write according to the definition of the function (since  $l < \infty$ ):

$$\int_{-\infty}^{\infty} |\psi(t)| dt < \infty \quad \text{and} \quad \int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \quad (3.20)$$

The function is oscillating symmetrically around its 0 value, hence

$$\int_{-\infty}^{\infty} \psi(t) dt \rightarrow 0 \quad (3.21)$$

Using (3.6) we write a discrete version of the transform for a sampled signal between instant of time form  $t-l/2$  to  $t+l/2$ . Applying the wavelet transform to the signal, we are interested in spectrum magnitude

$$W(a,b) = \frac{1}{\sqrt{a}} \sqrt{\left( \sum_{t=-l/2}^{l/2} s[t+b] \cdot H\left[\frac{t}{a}, l\right] \cdot \cos\left(2\pi \frac{t}{a}\right) \right)^2 + \left( \sum_{t=-l/2}^{l/2} s[t+b] \cdot H\left[\frac{t}{a}, l\right] \cdot \sin\left(2\pi \frac{t}{a}\right) \right)^2} \quad (3.22)$$

Where  $W(a,b)$  is magnitude of spectral component of the signal  $s[t]$  at time instant  $b$  and wavelet scale  $a$ .

The value of  $W(a,b)$  can be obtained for any  $a$  and  $b$  provided that  $b$  does not exceed the length of the signal. The equation (3.22) thus defines a Continuous Wavelet Transform for a discrete signal (in the meaning of time).

The scale of wavelet  $a$  can be expressed in terms of central frequency corresponding to it since our mother function is a unit oscillation:

$$a = \frac{f_s}{f} \quad (3.23)$$

Where  $f_s$  is the sampling frequency of the signal.

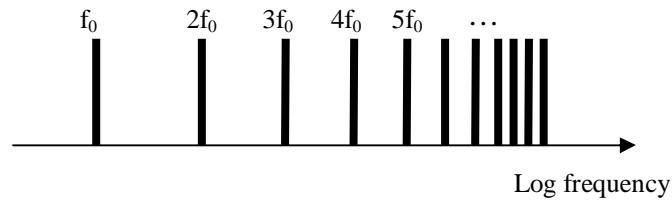
A higher value of  $a$  stands for a lower central frequency inversely to the sampling frequency.



### 3.3.1.2 Logarithmic frequency sampling

First of all, the sampling of the scale axis is chosen to be logarithmic in the meaning of frequency. It means, that each musical octave, or each note will have equal number of spectral samples. Such choice is explained by properties of music signal, which is known to have frequencies of notes to follow a logarithmic law (following the human perception). Logarithmic frequency sampling simplifies also harmonic structure analysis and economizes the amount of data necessary to cover effectively musical tuning system.

Voiced signal with single pitch is in general case represented by its *fundamental frequency* and fundamental frequency's *partials (harmonics)* with the frequencies equal to the fundamental frequency multiplied by the number of partial. Since distances between partials (harmonic components) and  $f_0$  (basic frequency) in logarithmic frequency scale are constant independently from the  $f_0$ . Such harmonic structure looks like a fence, depicted on Figure 3.13.



**Figure 3.13.** Harmonic structure in logarithmic frequency scale.

In order to cover now the frequency axis from  $f_{min}$  to  $f_{max}$  with  $N$  frequency samples with a logarithmic law we define a discrete function  $a(n)$  which denotes the scale of wavelet and where  $n$  stands for wavelet bin number ranging in the interval  $0..N-1$ .

$$a(n) = \frac{f_s}{f_{min} e^{\frac{n}{N} \ln \left( \frac{f_{max}}{f_{min}} \right)}} \quad (3.24)$$

Now the transform (3.22) sampled in both directions gives

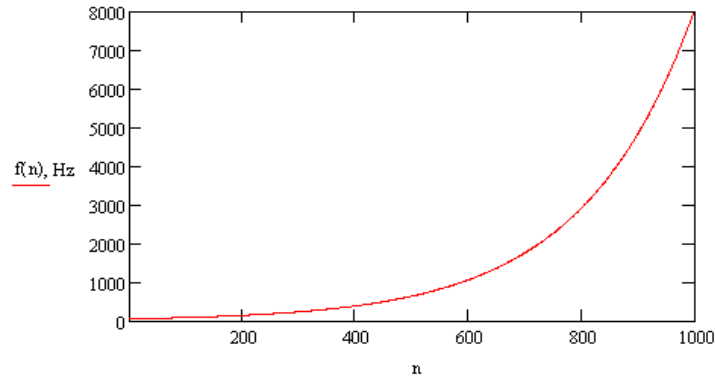
$$W(n, b) = \frac{1}{\sqrt{\frac{f_s}{f_{min} e^{n \cdot C}}}} \left| \sum_{-l/2}^{l/2} s[t+b] \cdot H \left[ \frac{t \cdot f_{min} \cdot e^{n \cdot C}}{f_s}, l \right] \cdot e^{-i \frac{t f_{min} \cdot e^{n \cdot C}}{f_s}} \right| \quad (3.25)$$

Where constant  $C = \frac{1}{N} \ln \left( \frac{f_{max}}{f_{min}} \right)$ .

Expression (3.25) is the basic expression to obtain  $N$ -bin spectrogram of the signal at time instant  $b$ . Thus, for a discrete signal of length  $S$ , expression (3.25) provides  $S \times N$  values for each instant of time,  $N$  being the number of frequency samples. The expression (3.25) is still a sampled version of the Continuous Wavelet Transform where the sampling of the scale axis has been chosen logarithmic for  $N$  samples.

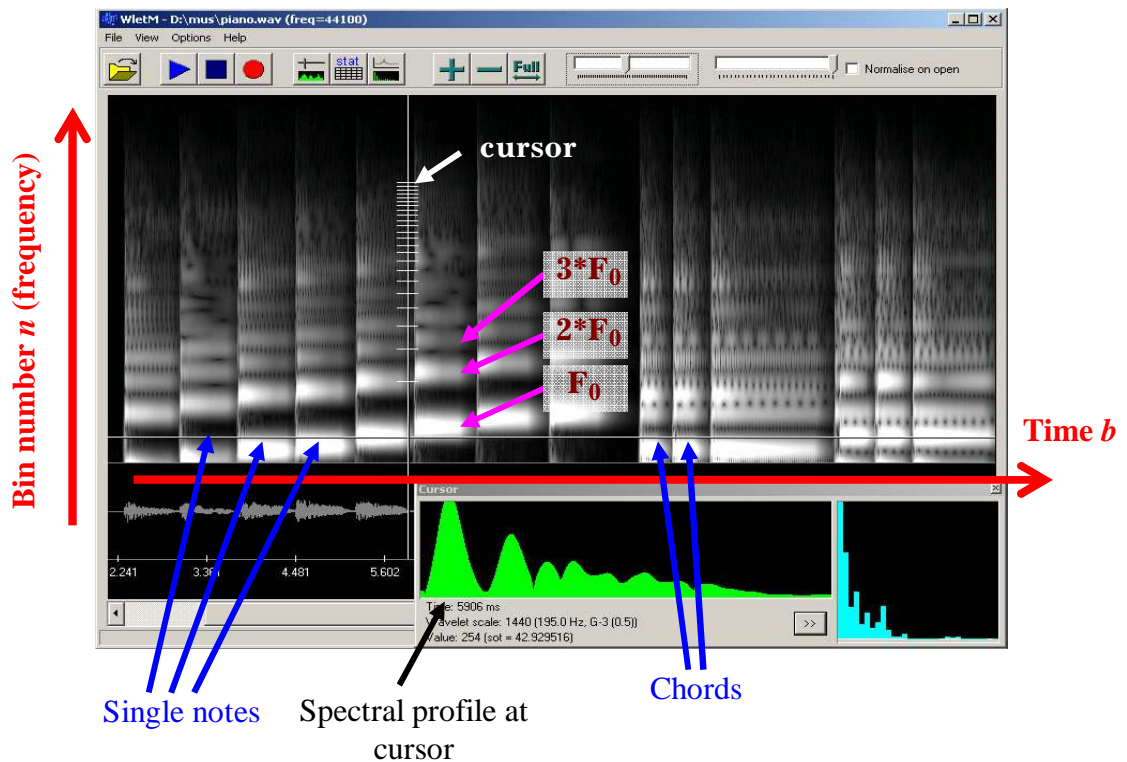
Frequency dependency from the bin number has the following form (with  $f_{min}=50$ ,  $f_{max}=8000$ ,  $N=1000$ ).

$$f(n) = f_{min} e^{\frac{n}{N} \ln\left(\frac{f_{max}}{f_{min}}\right)} = f_{min} e^{nC} \quad (3.26)$$



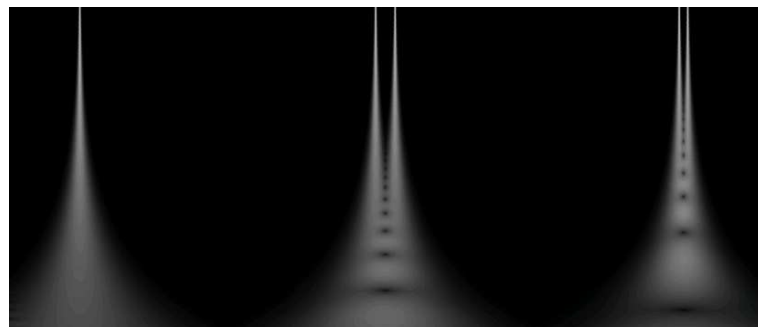
**Figure 3.14.** Equivalent central frequency of wavelet according to its bin number.  $f_{min}=50$ ,  $f_{max}=8000$ .

In order to depict the time/frequency properties of music signals by this discretized wavelet transform with a fixed length value ( $l=20$ ), let's consider wavelet spectrograms of several test signals. Figure 3.15 shows wavelet spectrogram  $W(n,b)$  of a piano recording. One can observe single notes on the left and chords on the right. Fundamental frequency ( $F_0$ ) and its harmonics can be observed in the spectrum of each note. As we can from the Figure 3.15, up to 5 harmonics are resolvable. Higher harmonics after the 5<sup>th</sup> one become indistinguishable especially in the case of chords where the number of simultaneous frequency components is higher.



**Figure 3.15.** Wavelet spectrogram of a piano recording (wavelet (3.18)). Single notes on the left and chords on the right. Up to 5 harmonics are resolvable. Higher harmonics after the 5<sup>th</sup> one become indistinguishable especially in the case of chords where the number of simultaneous frequency components is higher. The main window illustrates our wavelet analysis tool developed within this thesis work.

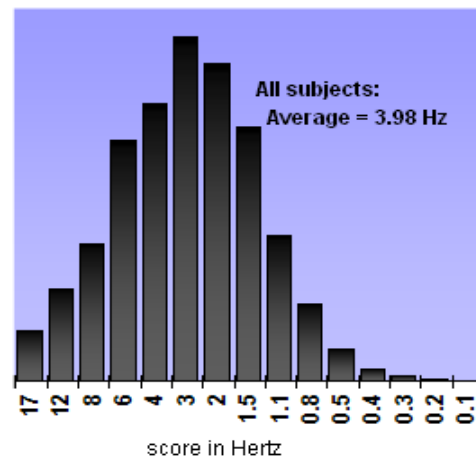
Good time resolution is important in such tasks as beat or onset detection for music signal analysis as we will see in the next chapter. The next example serves to illustrate time resolution properties of the Variable Resolution Transform we are developing. In this example we examine a signal with a series of delta-impulses (Dirac) as illustrated in Figure 3.16 which is a wavelet spectrogram of 5 delta-impulses (1 on the left, 2 in the middle and 2 on the right). As we can see from this figure, Delta-impulses on the picture are still distinguishable even if the distance between them is only 8 ms (right case). In the case of FFT one need 64-sample window size in order to obtain such time resolution.



**Figure 3.16.** Wavelet transform of a signal containing 5 delta-impulses. The distance between two impulses on the right is only 8 ms.

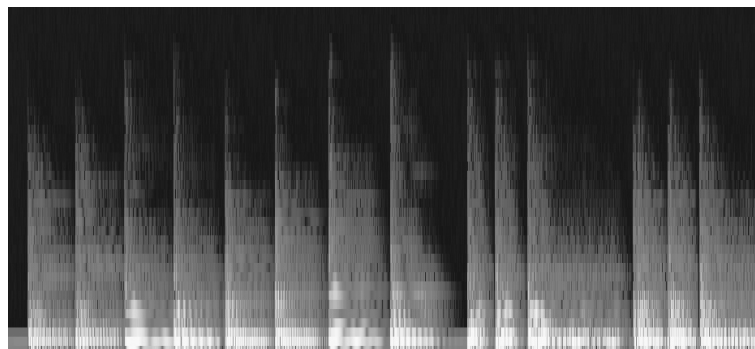
A quite straightforward listening experiment that we have carried out reveals that the human auditory system is capable to distinguish delta-impulses when a distance between them is around 10 ms. On the other hand, the human auditory system is also able to distinguish very close frequencies - 4Hz in average<sup>1</sup>, and down to 0.1Hz (see the following figure).

*Data was generated from 11,761 subjects*



**Figure 3.17.** Human auditory system frequency resolution histogram for frequencies around 500Hz.

To maintain a time resolution around 5-10 ms, the FFT requires a window size around 64-128 samples. Figure 3.18 illustrates a Fast Fourier transform spectrogram with 64-sample window of the same piano recording which clearly contrasts to the spectrogram in Figure 3.15. Neither fundamental frequencies nor partials can be extracted in this case.



**Figure 3.18.** Fourier transform of the signal with notes played by a piano (the same signal with was used in previous wavelet experiment on Figure 3.15). Neither fundamental frequencies nor partials can be extracted.

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<sup>1</sup> <http://tonometric.com/adaptivepitch/>

### 3.3.1.3 Varying the mother function

However, music analysis requires good frequency resolution as well. As we can see from the spectrogram in Figure 3.15, high-order partials are not resolvable neither close notes because the spectral localization of the used wavelet is too wide. Increasing the length parameter  $l$  in (3.18) or (3.25) of Hann window would render our wavelet transform unusable in low-frequency area since the time resolution in low-frequency area would raise exponentially. Thus, we propose in this work to make dynamic parameter  $l$  **with** a possibility to adjust its behavior across the scale axis. For such a purpose we propose to use the following law for parameter  $l$  in (3.25) instead of applying scale  $a(n)$  to parameter  $t$  in  $H(t,l)$ :

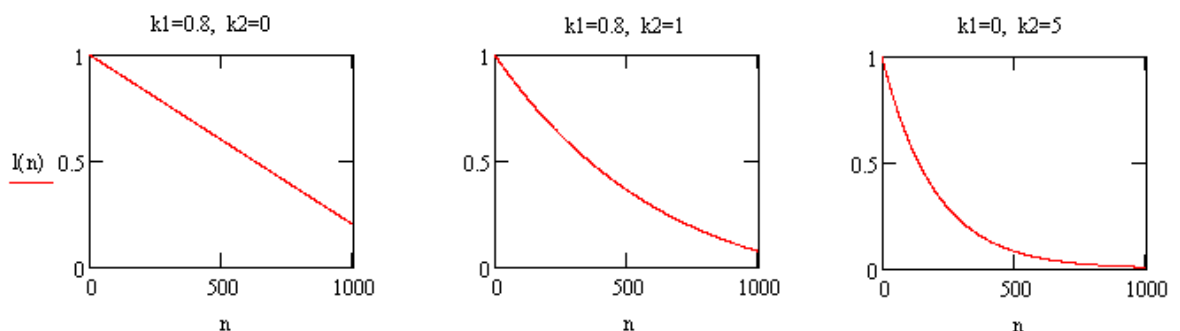
$$l(n) = L \cdot \left(1 - k_1 \frac{n}{N}\right) \cdot e^{-k_2 \frac{n}{N}} \quad (3.27)$$

where  $L$  is the initial window size,  $k_1$  and  $k_2$  – adjustable parameters

The transform (3.25) becomes:

$$W(n,b) = \frac{1}{\sqrt{\frac{f_s}{f_{\min}} e^{n \cdot C}}} \left| \sum_{-l/2}^{l/2} s[t+b] \cdot H \left[ t, L \cdot \left(1 - k_1 \frac{n}{N}\right) \cdot e^{-k_2 \frac{n}{N}} \right] \cdot e^{-i \frac{t f_{\min} \cdot e^{n \cdot C}}{f_s}} \right| \quad (3.28)$$

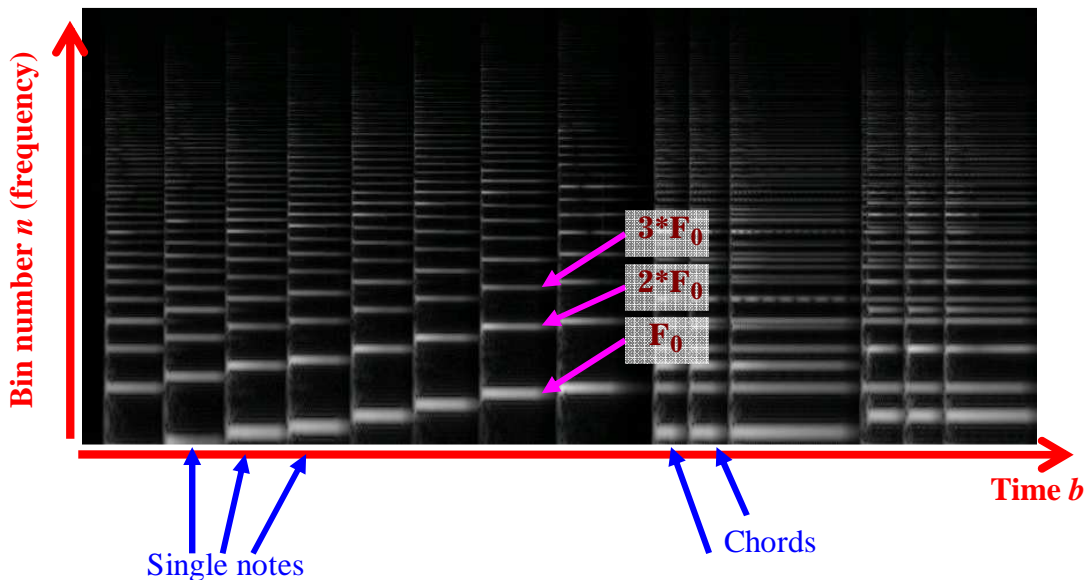
The expression (3.27) allows the effective "wavelet" width to vary in different ways: from linear to completely exponential to follow the original transform definition. When  $L = \frac{f_s}{f_{\min}}$ ,  $k_1=0$  and  $k_2=C \cdot N$ , (3.28) is equivalent to (3.25).



**Figure 3.19.** Various  $l(n)$ , depending on parameters. From linear (left) to exponential (right).

Doing so, we are now able to control the time resolution behavior of our transform. In fact, such transform is not anymore a **wavelet transform** since the mother-function changes across the scale axis. For this reason we call the resulted transform as **variable resolution transform (VRT)**. It can be also referred as a custom filter bank.

As the effective mother-function width (number of wave periods) grows in high-frequency relatively to the original mother-function, the spectral line width becomes more narrow, and hence the transform allows to resolve harmonic components (partials) of the signal. An example of the spectrogram with new variable resolution transform is depicted in Figure 3.20.



**Figure 3.20.** Piano recording VRT spectrogram where fundamental frequency and partials are distinguishable ( $k_1=0.8$ ,  $k_2=2.1$ ).

### 3.3.2. Properties of the VR transform

Recall, that the aim of this work is music analysis. Let's study properties of our VR transform regarding music signals.

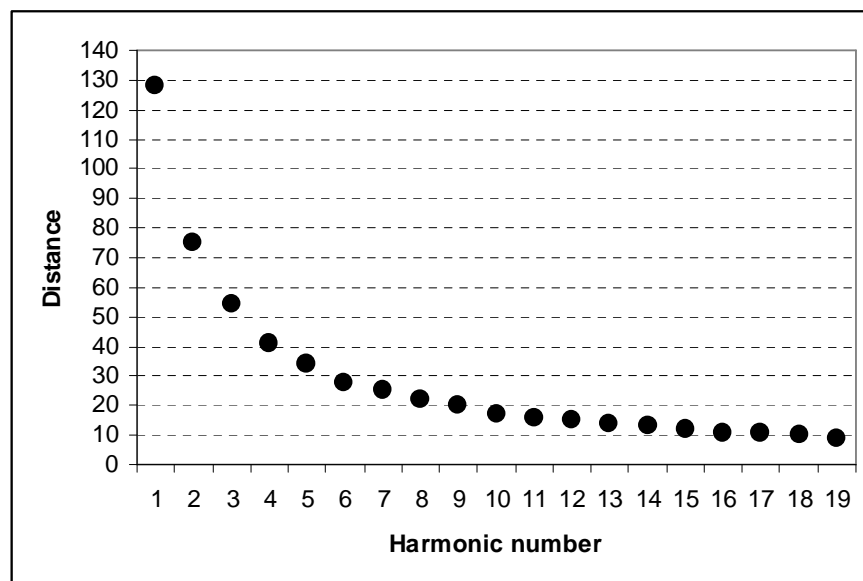
A music signal between 50 and 8000 Hz contains approximately 8 octaves. Each octave consists of 12 notes, leading to a total number of notes around 100. A filterbank with 100 filters would be enough to cover such octave range. In reality, frequencies of notes may differ from the theoretical note frequencies of equal-tempered tune because of recording and other conditions. Therefore for music signal analysis considered here, we are working with spectrogram size of 1024 bins – 10 times the amount necessary which covers the note scale by 10 bins per note. It is important to know the size of the spectrogram because all spectral graphs and their derivatives are represented in terms of *spectral bin number  $n$* , which has a logarithmic relation with frequency behind it. The other reason of increasing the number of bins comes from the necessity to distinguish high-order partials. However, there is a tradeoff to be found as further increase of the number of bins renders the computation much too heavy.

Timbre is a one of major properties of music signal along with melody and rhythm. Let's consider now a structure of partials of a harmonic signal (harmonic structure). In Figure 3.13 we have depicted an approximate view of such structure in logarithmic frequency scale. According to the definition of the function  $f(n)$  (3.26), the distance between partial  $i$  and partial  $j$  in terms of number of bins is **independent** from the absolute fundamental frequency value.

Indeed, according to (3.26)  $n(f) = \frac{1}{C} \ln \frac{f}{f_{\min}}$  and taking into account  $f_i = i \cdot f_0$  and  $f_j = j \cdot f_0$  we obtain:

$$n(f_j) - n(f_i) = \frac{1}{C} (\ln(f_0 \cdot j) - \ln f_{\min}) - \frac{1}{C} (\ln(f_0 \cdot i) - \ln f_{\min}) = \frac{1}{C} (\ln(f_0 \cdot j) - \ln(f_0 \cdot i)) = \frac{1}{C} \ln \frac{j}{i}$$

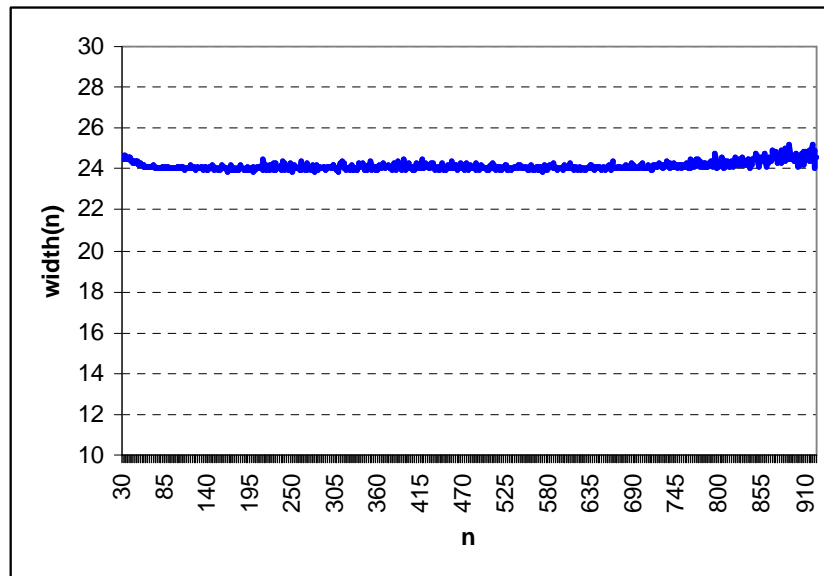
Figure 3.21 illustrates these decreasing distances between neighboring partials  $i$  and  $i-1$  when harmonic component number  $i$  increases, covering the first 20 harmonics. As we can see, the number of bins between the two first partials  $f_0$  and  $f_1$  are relatively high (128 bins). However, when the partial number of the harmonic increases, the number of bins decreases quickly but stays around 10 bins for high-order harmonics.



**Figure 3.21.** Dependency of the distance between partials form partial number.

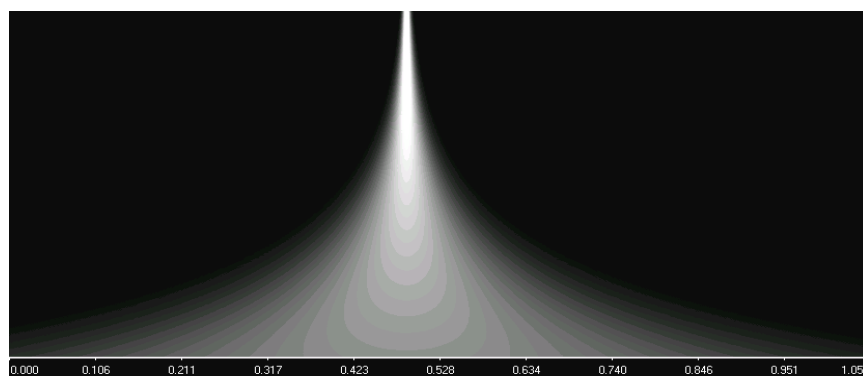
An accurate harmonic analysis of music signal implies that frequency resolution in terms of spectrogram bin number, as expressed by the spectral dispersion (3.14), should be always below the distance between decreasing distance between neighboring components which need to be considered. Figure 3.22 illustrates an example of spectral dispersion for a wavelet transform (e.g. Morlet or another one defined in (3.18)). It is computed by sweeping a sine

wave by all frequencies across the wavelet scale axis and calculating the dispersion.



**Figure 3.22.** Spectral dispersion for a **wavelet** transform. It is taken in terms of wavelet number  $n$  on  $x$  axis.

This flat dispersion comes from the fact that the frequency axis is in a logarithmic scale. As we saw in Figure 3.15, such a constant frequency dispersion over the frequency axis leads the situation where only 5 partials of a harmonic signal can be distinguished without peak intersection by such wavelet transform which is obviously not enough for majority of applications (higher order harmonic might be still resolvable while the step of the frequency resolution is still lower than the dispersion). Further improving frequency localization of such wavelet transform (lowering the dispersion) decreases dramatically its time resolution making the maximum time localization to grow exponentially. In the Figure 3.23 we can observe the result of such manipulation with Morlet wavelet which was used to transform a delta-impulse.

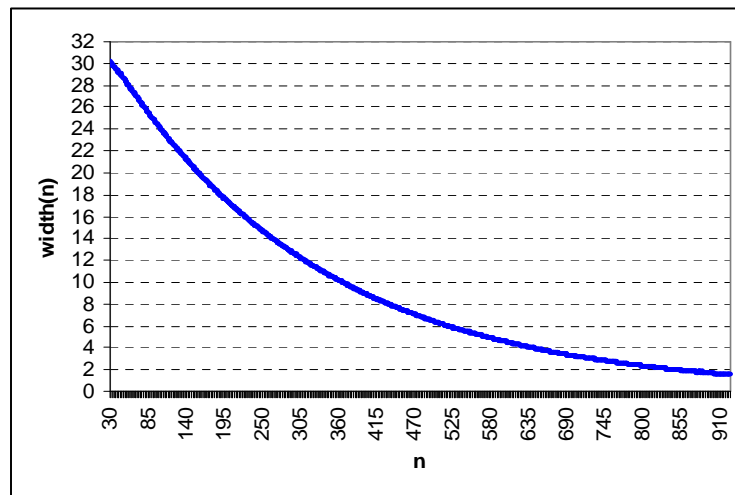


**Figure 3.23.** Morlet wavelet transform with  $\alpha^2=200$  of a delta-impulse. The maximum time localization **exceeds one second bounds**.



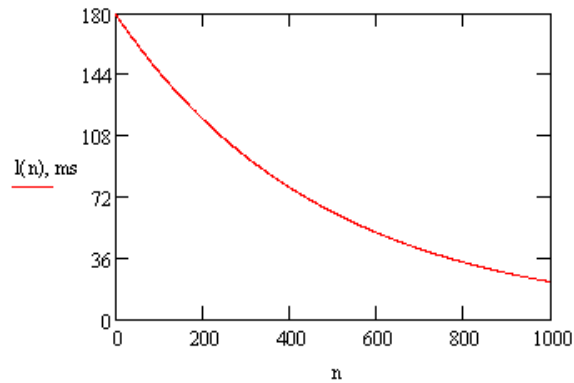
Despite an unacceptable time localization at low frequencies, classical wavelet transform in logarithmic scale stays to be an attractive tool in analyzing rapidly changing signals. Together with impressive time resolution in high-frequency area it has constant frequency localization because of the frequency axis sampling we have chosen is logarithmic.

Let's return to our variable resolution transform. As it was described in §3.3.1.3, we can vary the effective window size using different laws independently from the main scale of the mother-function. With  $k_2=2.1$  and  $k_1=0.8$  we obtain the following spectral dispersion distribution as illustrated in Figure 3.24.



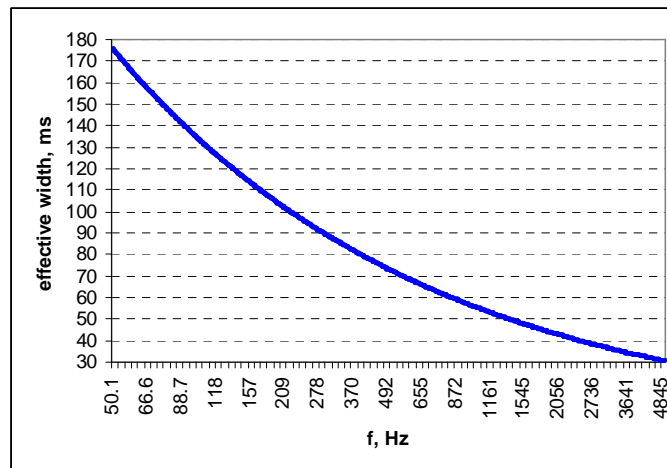
**Figure 3.24.** Spectral dispersion graph of VR transform with  $k_2=2.1$  and  $k_1=0.8$  for bins numbers from 30 to 900.

Having the total width of 20-partial harmonic structure to be a constant which is around 600 points in terms of number of bins ( $n(f_{20}) - n(f_0)$ ), we can establish the fact that the frequency resolution of the obtained transform is largely enough to resolve high-order partials we are interested in at all positions of the VRT spectrogram, especially for low octave notes. It means that a 20-partial harmonic structure starting from the beginning of the spectrogram will lie always *above* the dispersion curve. If we consider now the time resolution of the transform, we must recall Figure 3.19, where various dependencies of the effective width of filter were given. If we define the maximum effective window size to be 180ms (recall our musical signal properties) we obtain the following time resolution grid as illustrated in Figure 3.25.

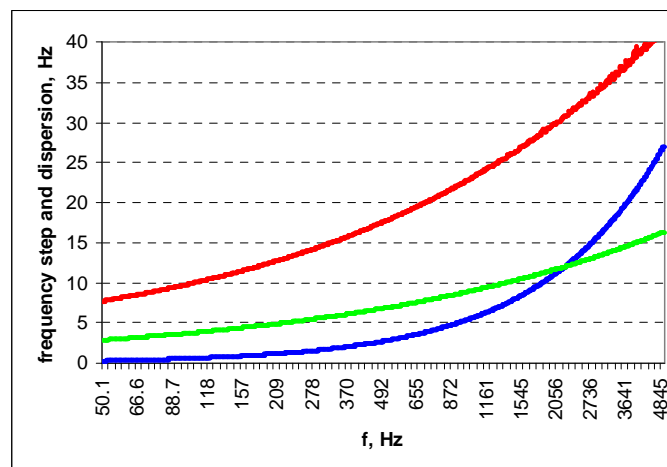


**Figure 3.25.** Time resolution dependency of VR transform with  $k_2=0.8$ ,  $k_2=2.1$ .

Final resolution plots of our variable resolutions transform is given in Figure 3.26 and Figure 3.27 in terms of frequency in Hz and time in milliseconds (given for frequencies between 50 and 5000Hz where the most of notes frequencies are found).

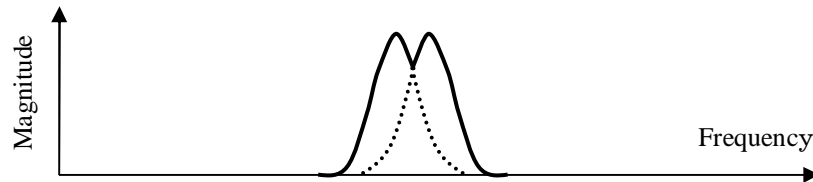


**Figure 3.26.** Practically calculated time resolution grid of our VR transform ms/Hz.



**Figure 3.27.** Practically calculated frequency resolution grid of our VR transform. The red trace stands for dispersion graph according to frequency; blue graph signifies a frequency step (Hz/bin) of the transform. Green curve on the picture stands for equivalent FFT frequency resolution (Hz/sample) as if it would have window size equal to that one from VRT (from Figure 3.26).

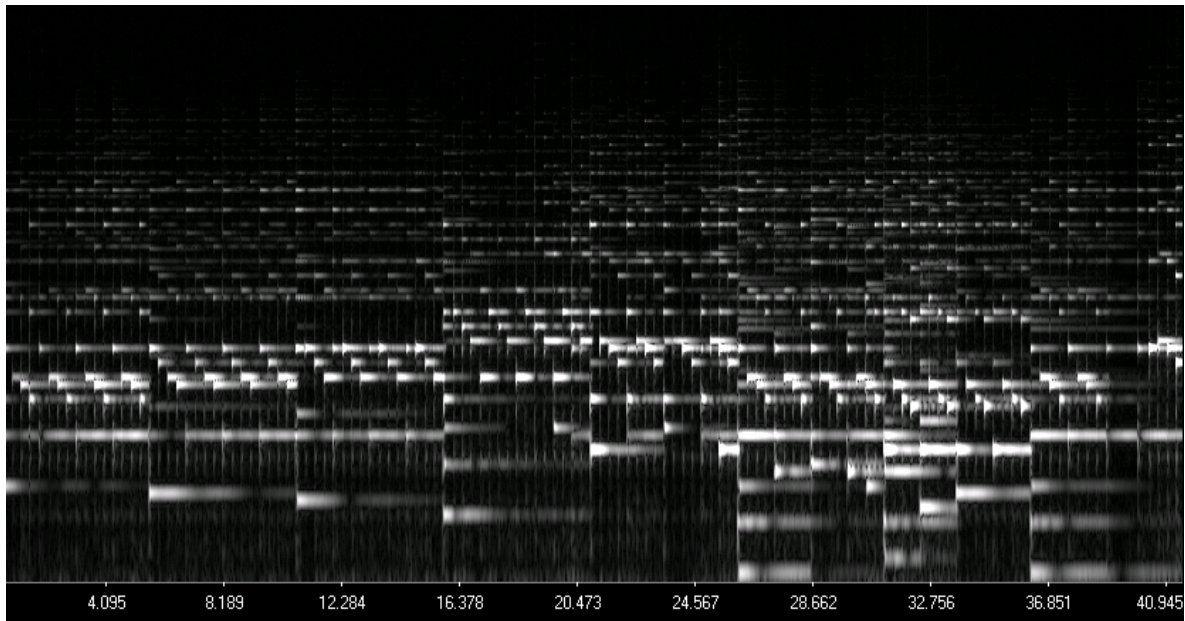
To better understand the previous figures, let's consider an example. The blue curve in Figure 3.27 corresponds to a spectral step size – the difference of equivalent frequencies of  $n^{\text{th}}$  and  $n-1^{\text{th}}$  filter. Taking as example 500Hz, we obtain frequency step size around 3Hz. The same equivalent characteristic can be calculated for an FFT. What does it mean? If we take 500Hz and look at Figure 5.5, we get an effective window size of VR transform to be approximately 70ms. If we imagine then an FFT with window size of 70ms (with 16kHz sampling rate it is going to be close to 1024 samples). The size of frequency step in 1024-sampled FFT is 8Hz, what can be observed by the green curve in Figure 3.27. It means that for an FFT with 1024-sample window, frequencies of 500Hz and 508Hz cannot be resolved unlike the case of the VR transform, where the size of frequency step at 500Hz was equal to 3Hz. However, the VR transform has considerable frequency dispersion – around 18Hz at 500Hz point. Therefore, on the spectrogram, two frequencies of 500 and 508Hz will have an intersection as illustrated in Figure 3.28.



**Figure 3.28.** Intersection of two close frequencies on VR spectrogram.

The main point of the VRT is nonlinearity of time-frequency tiling which renders possible to resolve rapidly changing high-frequency events and at the same time to have constant number of spectral steps per semitone in all octaves in order to be well adapted to music analysis.

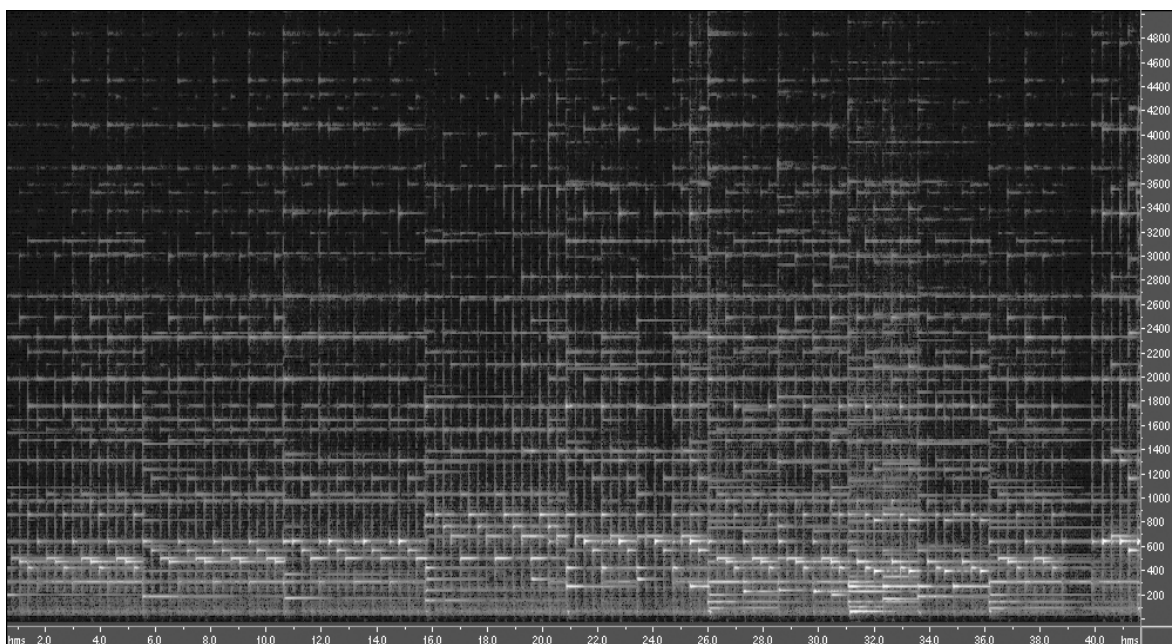
Now let's consider some wavelet spectrogram examples of real music excerpts.



**Figure 3.29.** VRT spectrogram of an excerpt from *Era – Flowers of the Sea*, piano.

Figure 3.29 is a VRT spectrogram for an excerpt from “Era – Flowers of the Sea”. In this excerpt only one instrument is present – a piano. Bars, measures and note events are distinguishable. As we can see, positions of notes on the frequency axis looks like (and it is!) linear. This example contains about 800 frequency planes (calculation points), with 50ms step. Computing time on a *PentiumM-1.4GHz* was around 3 seconds.

The same excerpt was studied in a known sound edit software. The result is given in Figure 3.30. In this example the window size of the FFT was 2048 points. Calculation time is also around 3 seconds.



**Figure 3.30.** 2048-point FFT spectrogram of the excerpt from *Era – Flowers of the Sea*.

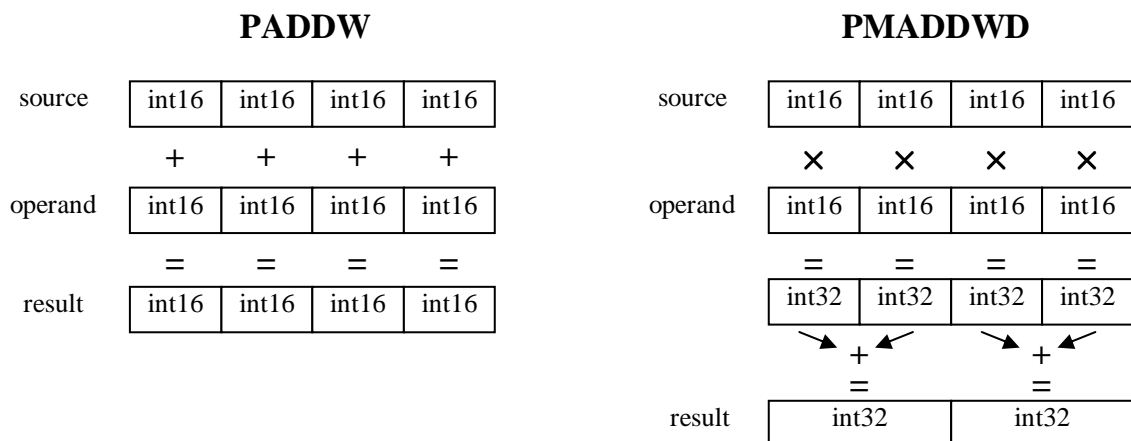
As we can see from the figure, the main melody notes are crowded at the bottom of the spectrogram, but the “forest” of partials is very distinct.

Another interesting fact is that frequencies of partials are not necessarily linear as  $n*f_0$ . (See e.g. [KLAP 99]). Regarding to this aspect, our VR transform might be more advantageous as the logarithmic frequency scale most probably “eat” non-linearity of partials’ frequencies, and hence, non-linear partials will be situated not far in terms of spectral bin number from their linear theoretical positions.

### 3.3.3. Computation

Regardless of the existence of relatively fast algorithms of continuous wavelet transform computation as for instance octave algorithm, we implement a direct scheme of computation as the most precise one. The choice of direct computation is imposed also by an absence of self-similarities in wavelet-like functions introduced in this work, and therefore, an absence of fast algorithms of computation.

However, several efforts have been made in order to accelerate the computation procedure. First of all, we store previously crafted values of wavelet functions for all frequencies in memory arrays. Avoiding the sine and cosine calculation every time during wavelet analysis computation significantly increases the overall speed. Finally the procedure of computation is done via vector arithmetic of modern processors where a SIMD instruction can operate many data at the same time (*SIMD – Single Instruction Many Data*) (see [Intel 03]). Each integer 64-bit MMx register may contain 8 bytes (char), 4 words (short), 2 double words (int) or 1 quad word (int64 or longlong). SIMD instructions make arithmetic operations on all operands stored in MMx register simultaneously. More recent instruction sets manipulate 128-bit registers with packet integers or floating points. Some examples of packed arithmetic instructions are given on figure.



**Figure 3.31.** Example of integer SIMD instruction from Intel’s MMX instruction set.

Using Intel MMX technology it looks like

```
movq MM2, qword ptr [esi]      // take 4 samples of the signal
movq MM3, MM2
pmaddwd MM2, qword ptr [edi]  // multiply and add pairs, real part
padd MM0, MM2                  // accumulate
pmaddwd MM3, qword ptr [ebx]  // compute complex part
padd MM1, MM3                  // accumulate
```

The example of the computation code provides a gain of performance about 5-8 times in comparison to standard C++ implementation.

### 3.3.4. Discussion

Our Variable Resolution Transform is derived from the classic definition of Continuous Wavelet Transform given in 3.2.2. In our previous work, we referred our VRT as “Wavelet-Like” or “Pseudo-Wavelet” transform [PARA 06; PARA 07]. Actually, our VRT is not a CWT even they have many similarities. The main difference between VRT and CWT resides in the frequency axis sampling, and in the mother wavelet function which is changing its form across the scale (or frequency) axis in the case of VRT in order to have enough resolution details for high order frequency partials. This last property is not a wavelet transform, because in the true wavelet transform the mother function is only scaled and shifted making a discrete tiling of the time-frequency space in the case of DWT or infinite coverage in the case of CWT. Our VRT can be also referred as specially crafted filter bank. Major differences between our VRT and a wavelet transform are:

- no 100% space tiling
- no 100% signal reconstruction (depending on parameters)
- mother function changes

Major similarities between our VRT and a wavelet transform are the following:

- They are based on specially sampled version of CWT
- with certain parameters they can provide 100% signal reconstruction
- low time resolution and high frequency resolution in low frequency area and high time with low frequency resolution in high frequency area

Comparison of our VRT to other techniques can be summarized by the following table.

**Table 3.1.** Comparison of VRT to other approaches according to their properties

Technique	Frequency sampling	Frequency bin dispersion	Computational complexity	Note resolution	Harmonic resolution	Temporal resolution
FFT (small window)	Linear	High	Low	Very low	Low	Very high
FFT (large window)	Linear	High	Low	Low	High	Low
FFB	Linear	Low	Low	Same as FFT	Same as FFT	Same as FFT
CQT	Log	High	High	Very high	Low	High
CWT (general)	Variable	Variable	High	High	Low	High
BQT	Linear in octaves	High	Medium	High	Medium	High
BQFFB	Linear in octaves	Low	Medium	High	Medium	High
VRT	Log	High	High	High	High	Medium

Another comparison table we provide to summarize various approaches according their applicability in different applications.

**Table 3.2.** Comparison of VRT to other approaches according their applicability

Technique	Beat detection	Note detection	Spectral features
FFT (small window)	++	--	+ -
FFT (large window)	--	+ -	++
FFB	Same as FFT	+ -	Same as FFT
CQT	++ / --	+ - / ++	++
CWT (general)	++ / --	+ - / ++	++
BQT	++	+ -	++
BQFFB	++	+ ±	++
VRT	++	++	++

Generally, BQFFB approach could be used for our music similarity retrieval application, but due to its specific frequency sampling, it complicates spectral modeling (distances between harmonic are not constant).

### 3.4. Application to spectral similarity

The following spectral similarity measure was proposed in one of our previous works – spectral ratio coefficients matrix. Coefficients are computed in the following way. First, the signal spectrum is obtained from the VR Transform. Then the filterbank of MEL frequencies is applied to absolute values of the spectrum (it is directly mapped to the VRT spectrogram). The spectral descriptor is then represented in a form of matrix  $N \times N$  which is constructed as follows:

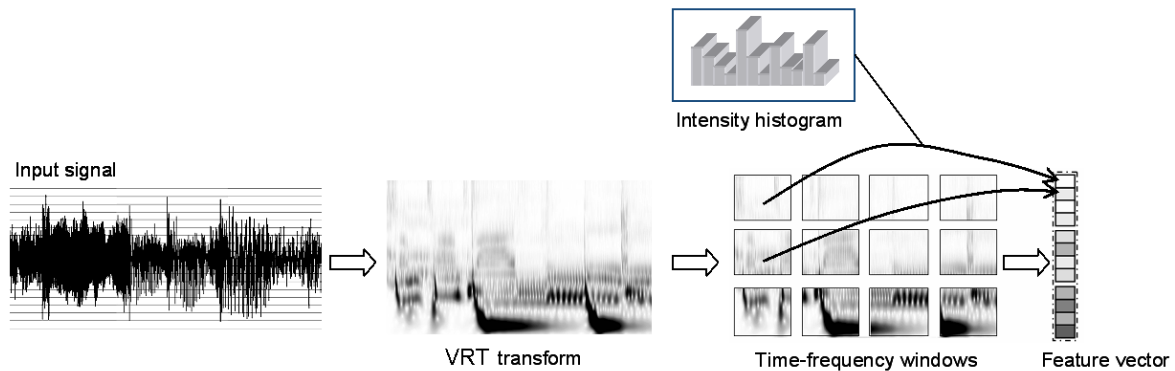
$$M_{i,j} = \begin{cases} \log\left(\frac{B_i}{B_j}\right), & \text{when } B_i \neq 0 \text{ and } B_j \neq 0 \\ -CONST, & \text{when } B_i = 0 \\ +CONST, & \text{when } B_j = 0 \\ 0, & \text{when } B_i = B_j = 0 \end{cases} \quad (3.29)$$

Where  $N$  is total number of spectral bands,  $B_i$  is energy in the  $i^{\text{th}}$  band.

The matrix  $M$  is used as initial spectral feature. A sequence of them can then be modeled by a set of Gaussian distributions (each element independently). The distance between two sound excerpts is calculated as a sum of KL distances for distributions of each  $M_{i,j}$ .

The feature we have presented does not have disadvantage of volume dependency because only energy ratios are taken so it is more robust in acoustic similarity and it showed better results in audio segmentation issue of video segmentation context [PAR 05].

A second spectral feature we have proposed is based on cutting the VRT spectrum into time-frequency rectangles (with the following dimensions:  $25\text{ms} \times 1/8$  of total frequency range) and computing histograms of values in each obtained rectangular area. The main principle is shown on Figure 3.32.



**Figure 3.32.** Spectral feature extraction procedure. Wavelet or VRT spectrum is divided into time-frequency tiles. Histograms of values are computed in each tile. Histograms are then serialized in form feature vectors.



Bins of obtained histograms are then serialized and concatenated into one feature vector. The usage of this spectral similarity characteristic was found in genre classification problem [KOTO 07] where histogram is summarized by the mean values.

### **3.5. Conclusion**

In this chapter we have introduced our Variable Resolution Transform as a novel signal processing technique specifically designed for music signal analysis. A music signal is characterized by four major properties: melody, harmony, rhythm and timbre. The classic Fast Fourier transform, a de-facto standard in music signal analysis in the current literature, has its main drawback of preceding a uniform time-frequency scale which makes impossible to perform efficient spectrum analysis together with good time resolution. The wavelet transform overcomes this limit by varying the scale of mother-wavelet function and, hence, the effective window size. This kind of transform keeps frequency details in low-frequency area of the spectrum as well as time localization information about quickly changing high-frequency components. However, the dramatic decrease of frequency resolution of the basic wavelet transform in high-frequency area leads to confusion in high order harmonic components whose resolution is necessary for the analysis of harmonic properties of a music signal. We have thus introduced our Variable Resolution Transform in varying mother-function. The law of variation is controlled by two parameters, linearity and “exponentiality”, which can be carefully chosen in order to adjust frequency-time resolution grid of the VRT. Hence, our VRT takes advantage of the classic continuous wavelet transform and the windowed or short-time Fourier transform by diminishing frequency dispersion in high-frequency area and therefore keeping the frequency resolution in high-frequency area to be good enough to resolve harmonic components of musical instruments. As compared to time-frequency characteristic of the Fourier and the wavelet transform, the major advantage of the VRT is the dynamic variability of time-frequency tiling in contrast to constant tiling in the case of the STFT. This ability to change the tiling allows a better description of a music signal while keeping a fixed number of frequency samples by octave and a good time resolution where it is necessary, i.e. in high-frequency area, where all rapid changes usually take place.

As we will see in the next chapters, the families of music analysis algorithms introduced in this thesis are exclusively based on the aforementioned VR transform and their influence on the performance of MIR algorithms are also discussed.

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## **Chapter IV**

### **Rhythm-related similarity features**

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## 4. Rhythm-related similarity features

Rhythm is one of four major music properties along with melody, harmony and timbre. Automatic extraction of rhythmic pulse from musical excerpts has been a topic of active research in recent years. Also called beat-tracking and foot-tapping, the goal is to construct a computational algorithm capable of producing behaviors that correspond to the experience of beat or pulse in a human listener. Rhythm as a musical concept is intuitive to understand, but somewhat difficult to define.

Let's define beats as a sequence of pulses and accents over a musical composition issued either by percussion instruments or by note onsets. In general, beats are forming musical tempo which is measured in *beats per minute* (BPM). While characterizing the rhythmic feature of a music excerpt, the tempo in BPM may not be enough in music classification and similarity search. For example a classical composition and at the same time a rock composition may have 140 beats per minute while these two compositions are from very different genres. On the other side, the perception of the tempo (foot-tapping) is ambiguous [MOEL 04] it may usually have an error of 2 or other multiples.

### 4.1. Related work

Detection-related or tempo estimation-related algorithms have found many implementations. They can be divided into two groups treating different problems: beat/onset detection algorithms and periodicity search algorithms.

The first group of algorithms is destined to detect rhythmic activity such as percussion instrument beats, note onsets, accents, etc. Sounds of percussion instruments are generally non-voiced strong attack noisy instruments (although they can contain harmonic components), leaving considerable noisy traces in spectrum. Note onsets are less remarkable events and according to instrument, may be rather smooth. Figure 4.1 depicts an energy envelope example of a note onset.

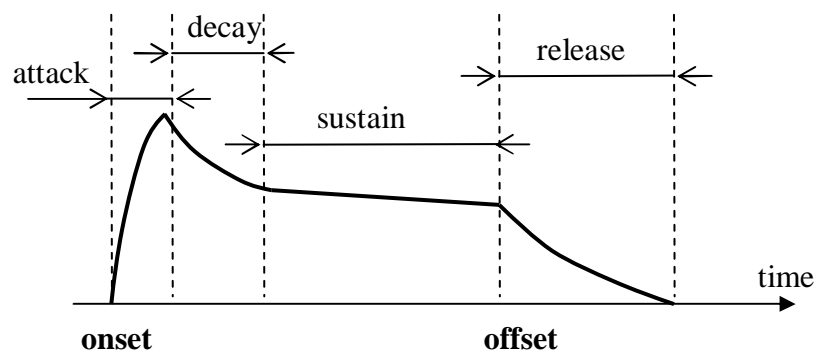
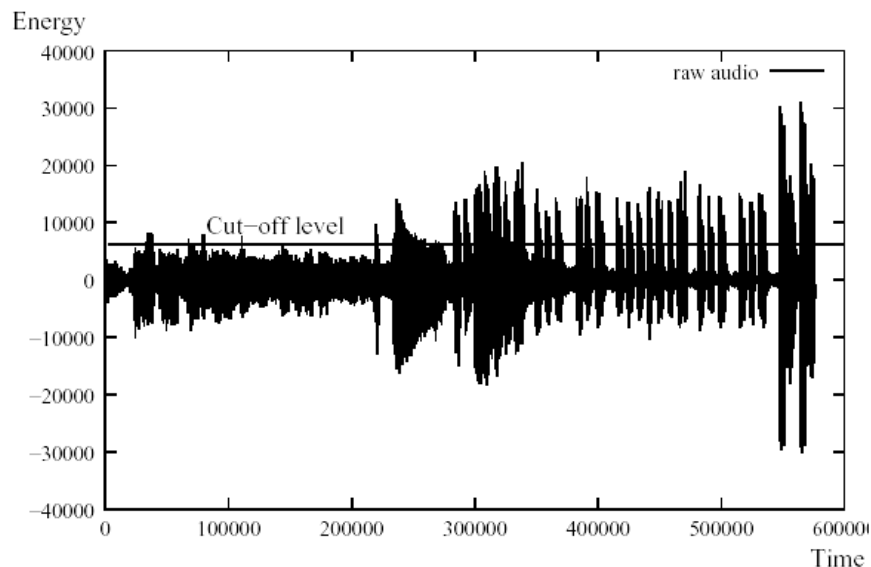


Figure 4.1. Typical energy envelop of a note (piano-like instrument)

The easiest way to extract beats events – is to use energy envelop directly from the raw signal with automatically adjusted threshold (Figure 4.2). This method is very fast and can be used as the first approximation in beat detection or for example visualizing applications. Unfortunately this method is very sensitive to the musical content – there must be really strong beats represented by percussion instruments with light music on background. Moreover it does not fit to onset detection which has equal importance in rhythmical analysis of a musical composition.



**Figure 4.2.** Beat detection from the raw WAV. The signal's waveform is cut at certain energy level. Obtained peaks are considered as detected beat or high-energy events.

Other deterministic methods are working with time-frequency representation of the signal such as STFT spectrogram (e.g. [COLL 05]) and filter banks (e.g. [KLAP 99a]). An approach of beat detection using image treatment techniques applied on spectrogram is presented in [NAVA 04]. An interesting work is presented in [ALON 03]. In their work authors decomposes the signal into 12 subbands, each subband is processed separately by representing it in bi-component form containing sinusoidal signal + noise (using Exponentially Damped Sinusoidal, described in [BADE 02]). Attacks extraction and periodicity detection is done separately in these subbands.

Another kind of methods - statistical methods are based on assumptions that the music signal can be described by some probabilistic model trying to guess locations in the signal where a potential accentuation event may occur. Obviously, the detection performance of these methods is strongly dependent on musical content and on training data.

The approach we present in our work is a deterministic one. It analyses the musical signal directly using VR Transform and processing the resulting spectrogram as a grayscale image. No assumption on music nature or theoretic beat positions is made.

The second group of algorithms concerns higher level processing in order to find periodicities. These algorithms can be divided into some sort of general classes:

- Autocorrelation-based. This class of algorithms is based on computing of one or multiple autocorrelation functions from the signal, its spectrum or on sequence of feature vectors in order to find the most salient period and mainly used for tempo estimation. Such works can be mentioned as [BROW 93; ECK 05; GOUY 03; PAUL 02]. In [PEET 05] authors proposed a method for the automatic estimation of the tempo based on the reassigned spectral energy flux, a combination of DFT and Frequency Mapped autocorrelation function and a Viterbi decoding algorithm.
- Based on a mathematical model of resonators set (e.g. [KLAP 06; SCHE 97a]). The idea behind these methods is to find the most probable periodicity using multiple resonators or oscillators. Each oscillator has its own frequency and produces a probability output (resonance). Non-linear resonators are also known, e.g. [LARG 94].
- Histogram building. One of rhythmical information representation is the beat histogram as used for example by *George Tzanetakis* [TZAN 02]. In his work the beat histogram accumulates peaks of autocorrelation function over the whole sound. Each bin of the beat histogram corresponds to the peak lag (i.e. the beat period in BPM – beat per minute). This kind of representation is quite useful for example for genre classification as it carries information about number of beats with different periods or tempo determination by finding a maximum. There are other works known in the literature which are based on histogramming. The work [AREN] proposes a simple time-domain method in order to extract the tempo in BPM.

Other methods of periodicity detection are known. Authors of the work [ALON 06] use frequency domain methods, such as spectral sum and spectral product for periodicity analysis.

Autocorrelation and resonator-based approaches are not suitable for music similarity analysis since they operate with periodicity detection and issue the main tempo of the play. We are interested in representing of rhythmic structure, thus we need a mechanism of periodic and non-periodic beat and also onset detection together with rhythmic fingerprint computation.

Non-periodic beat tracking and rhythmic-structure representation is described in the work [TZAN 02a]. In this work beat periods are organized in form of beat histogram allowing their rhythmic comparison. The

disadvantage of the proposed method is an absence of beat strength information included into rhythmic-structure representation.

Rhythm-related similarity characteristics are among the few numbers of semantic features which are quite well explored in literature. For instance, in the work of *Eric Scheirer* [SCHE 00], the question of beat related characteristics holds a dominant part. There are many other works on rhythm analysis in the context of automatic music retrieval. The work in [ALGH 99] proposes to achieve beat tracking and their hierarchical organization in order to obtain periodicity patterns. The beat tracking is done in low frequency area, therefore, not all beat events are theoretically detected since instruments like hi-hats or cymbals do not have low-frequency components. Another beat tracking system is presented in [GOTO 01] which describes a real-time system able to detect different rhythm-forming events such as beats, onsets or chord changes and to organize them hierarchically. Sound signal in this work does not require drum instruments in it.

More recent works discuss questions of rhythmic similarity. The work in [FOOT 02] is based on “beat spectrum” extraction and comparison. The goal of the work is automatic retrieval of musical pieces with similar rhythm. Some theoretical evaluation is also provided on a very small corpus. A theoretical aspect of rhythmic similarity is given in [HOFM 02].

In our work we focus on construction of rhythmic similarity feature which consists of two parts:

- a) beat detection
- b) fingerprint extraction

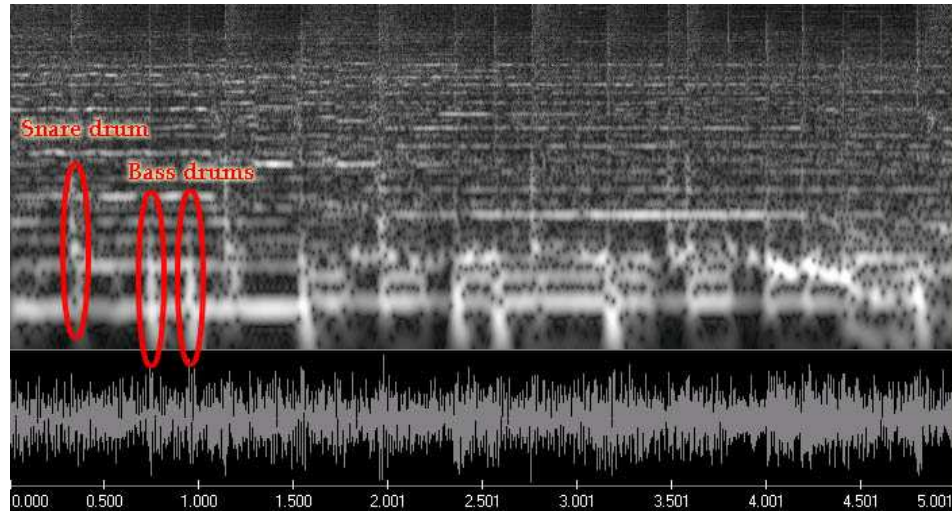
Additionally, the fingerprint we obtain allows doing tempo estimation which is then evaluated and compared with other works.

## **4.2. Our VRT based approach for beat curve extraction**

In our work, the beat detection relies on our previously defined VRT giving a time-frequency (spectral) representation of the signal.

### **4.2.1. An intuitive approach**

Let’s consider a music excerpt as represented by our VRT. Figure 4.3 is a spectrogram of a musical segment obtained using the VR transform as described in paragraph 3.3. The musical segment comes from meal music with noisy instruments, distortion guitars etc. *a priori*, contrast between beats and the rest of the music is rather low.



**Figure 4.3.** VR transform representation of a musical excerpt (of metal genre).

However, as we can discover from Figure 4.3, the VRT based spectrogram has remarkable elements in a form of vertical spots. These are drum events (bass drums and snare drums). In high frequency area they stand out against the background in a form of thin vertical lines.

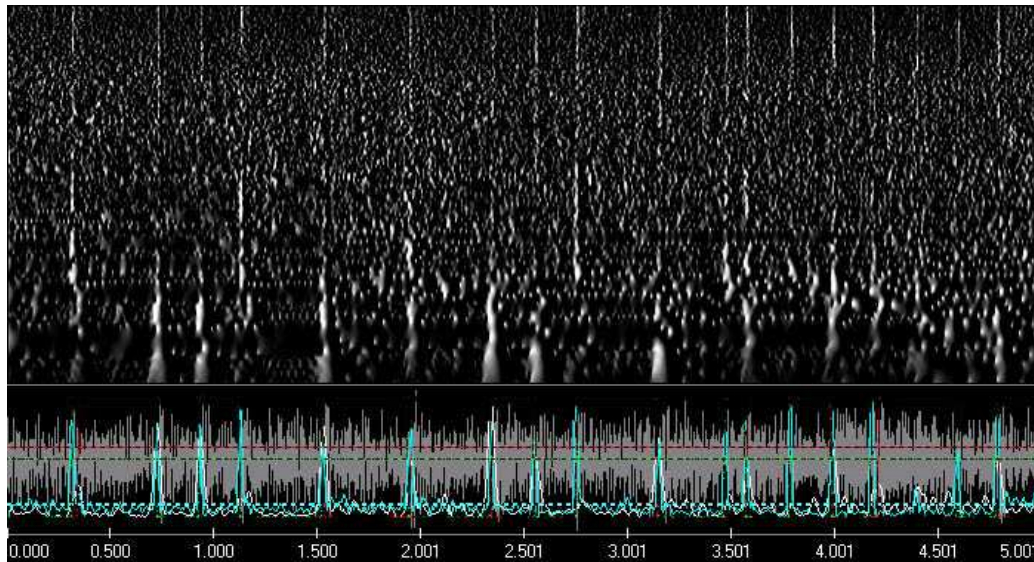
Since the information about beats and offsets is concentrated on vertical constituent, it is possible to make use of image processing technique, such as gradient filters, to mark out all fragments of this “spectral image” more or less interesting in the meaning of beats and onsets. We thus propose to apply Sobel operator in horizontal plane [SOBE 90], with its mask depicted on the next image.

-1	0	1
-2	0	2
-1	0	1

**Figure 4.4.** Sobel gradient operator in horizontal plane.

The central horizontal line in the mask is directly responsible for emphasizing vertical lines and may be adjusted in order to give more importance to horizontal gradient. Values -5 0 5 are found during experiments to be more appropriate for further beat detection.

The result of such treatment is shown in Figure 4.5.

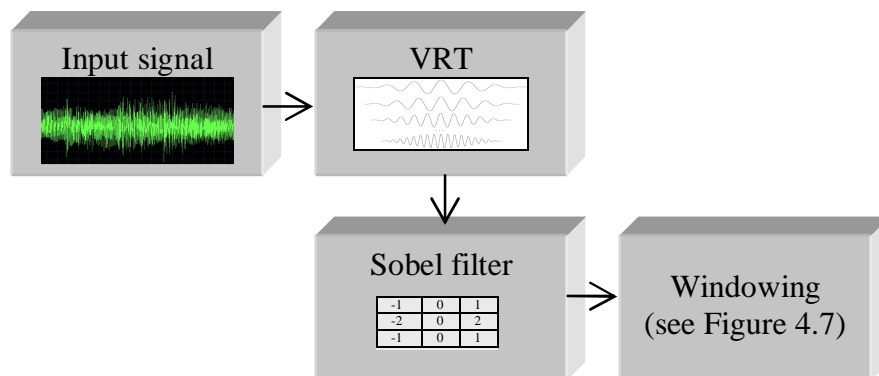


**Figure 4.5.** Sobel-filtered VRT spectrogram for a musical excerpt with detected beat strength curve at the bottom.

After image enhancement all events we are interested in are now much clearer. Subsequently, the enhanced (Sobel-filtered) spectrogram  $W^*(b, a)$  is treated by calculating a beat curve in the following way. A small window together with a large one is moved across the enhanced spectrogram. The value of the beat curve in each time moment is the number of points in the small window with values higher than a threshold which is obtained from the average value of points in the large window. Numerous beat curves may be computed separately by dividing the spectrum into bands. For the general question of beat detection the only one beat curve is used.

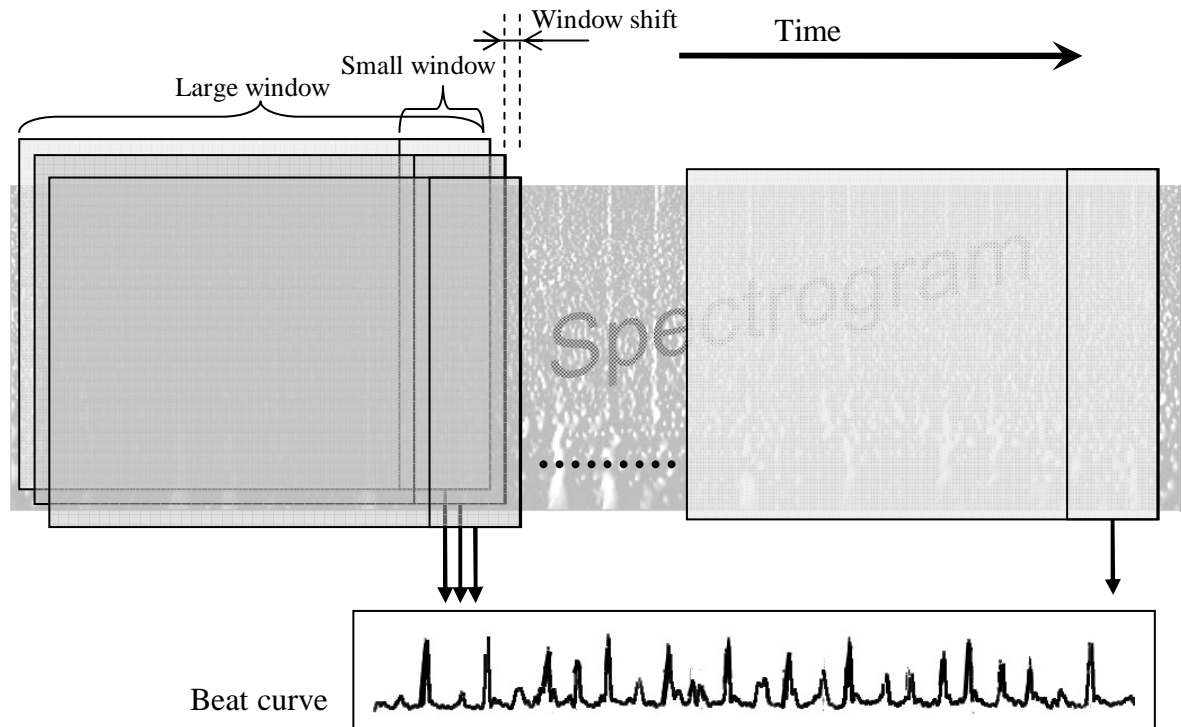
#### 4.2.2. Procedure of beat curve extraction

Figure 4.7 and Figure 4.6 summarize our procedure of beat curve extraction.



**Figure 4.6.** Beat curve extraction procedure diagram.



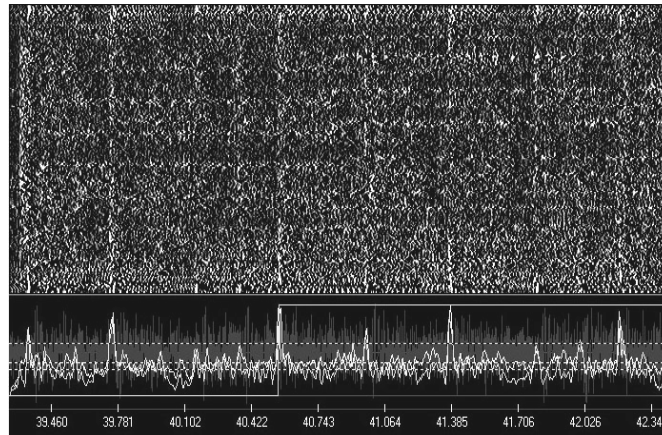


**Figure 4.7.** Beat detection windowing procedure. Beat probability or beat strength curve (at the bottom) is obtained by moving a sliding window and calculating number of spectrum points whose values are higher than the average value for bigger one.

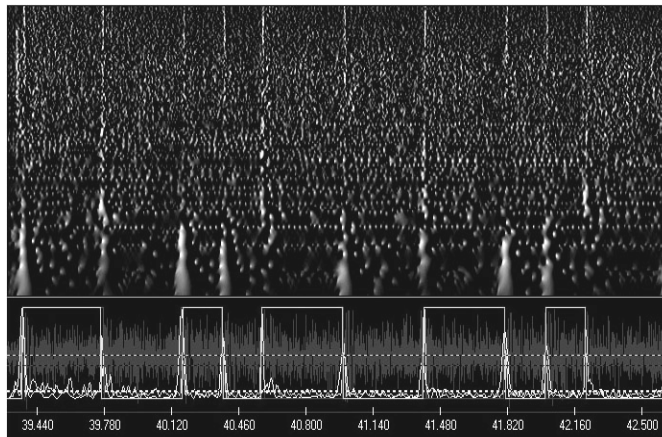
Sizes of windows as mentioned in our procedure are chosen in the following way. The small window should cover well a snare drum beat or tom. Its size was selected to be 50-100ms (depending on analysis step size). The length of the large window was chosen to be 20 times the size of the small window, i.e. 1-2 seconds. As the beat curve extraction procedure is aimed to be volume-independent, we thus assume that a music excerpt has a relatively constant volume during each interval of 1-2 seconds which appears quite reasonable. Moreover, these two windows are shifted every 10 to 30 ms, producing thus beat curve values accordingly.

#### 4.2.3. Discussion: VRT versus FFT based techniques

Instead of VRT based spectrogram, we may also apply our beat curve extraction technique on a Sobel-filtered image from the FFT transform. Figure 4.8 illustrates the result obtained from a FFT spectrogram that can be compared with the one processed by our VRT on the same musical excerpt (Figure 4.9).



**Figure 4.8.** FFT spectral image (excerpt from “Nightwish – Come Cover Me”)



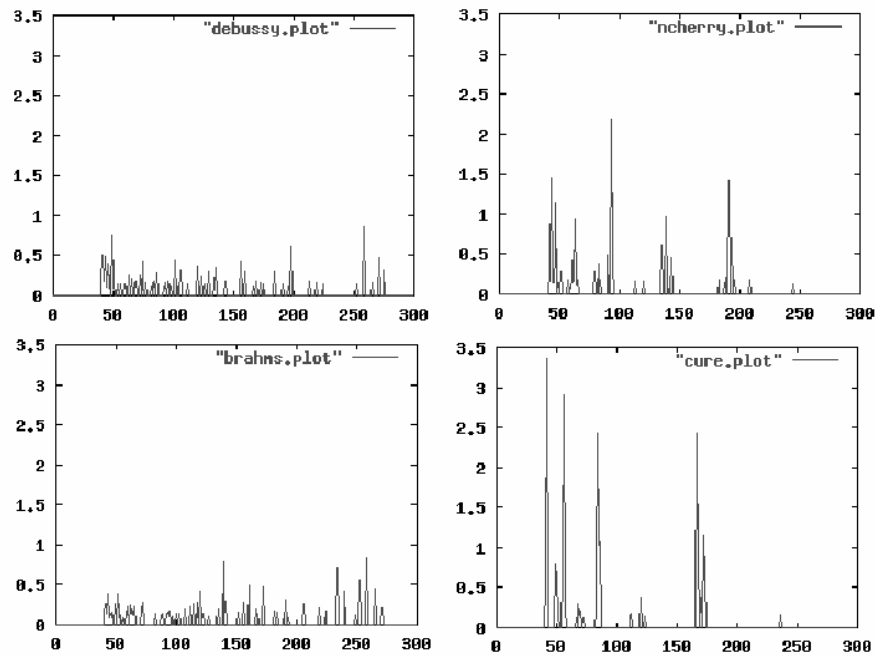
**Figure 4.9.** VRT spectral image (excerpt from “Nightwish – Come Cover Me”)

As we can see, VRT based beat curve extraction shows 100% detection of percussion instrument beats in the test excerpt. This example suggests that VRT tend to be better suited than FFT for beat detection.

### **4.3. Rhythmic fingerprint**

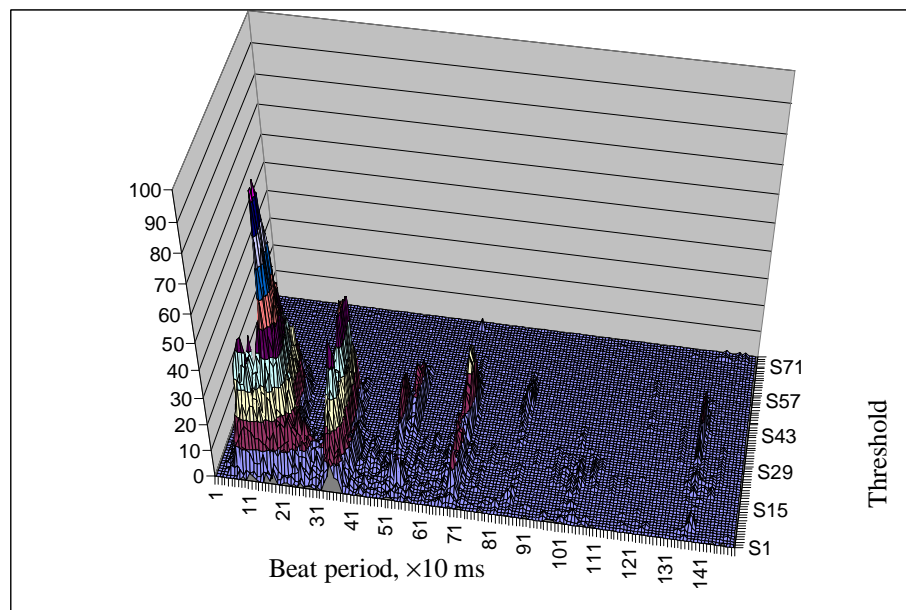
#### **4.3.1.2D beat histogram**

In our work, we propose to improve beat histogram representation for a better characterization of rhythmic property of a music signal. Indeed, classical one-dimensional beat histogram (Figure 4.10) only provides some knowledge about the different beat periods while the distribution of beats in the meaning of their strength is not clear. At the same time beat detection algorithm and its parameters affect the form of the histogram.



**Figure 4.10.** Classical one-dimensional beat histogram from the work of *G. Tzanetakis*.

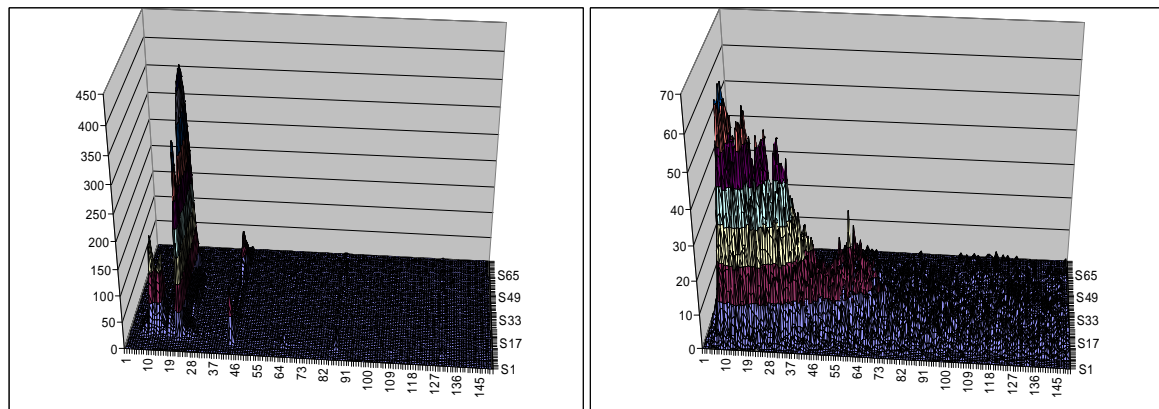
A more accurate rhythmic property representation of a music signal should thus bring some knowledge about the strength of beat periods into the histogram and avoid the dependency from the beat detection algorithm parameters. In this work, we propose a 2D form histogram which can be built with a beats period on the X axis and with amplitude (strength) of a beat on the Y axis (Figure 4.11). The information about beat strength in our histogram is represented since the histogram is computed upon the threshold varying in Y axis. It is hence possible to avoid the disadvantage of recording conditions dependency (e.g. volume) and peak detection method. The range of threshold variation is taken from 1 to the found maximum-1. Thus, the beat strength is taken relatively and the volume or recording level dependency is avoided



**Figure 4.11.** Example of two-dimensional beat histogram. Here the x axis represents beat period, y axis stands for threshold value used in peak detection on the beat curve.

As we can see, the histogram in Figure 4.11 contains several peaks. One of these peaks can be considered as main tempo peak, and the strongest peak is likely to represent *tatum* – the pulse of the lowest metrical level.

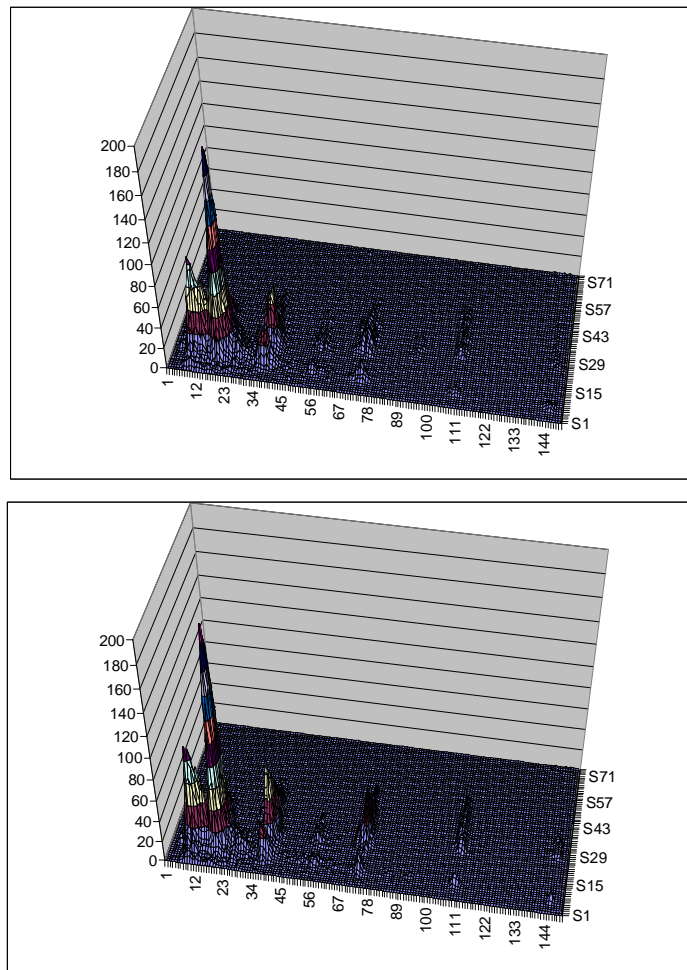
Such histogram characterizes rhythmic property of a music signal. It can thus be used as feature vector in music analysis applications such as genre classification or music matching. Figure 4.12 illustrates two 2D beat histograms for a dance composition (left) and a classical composition (right).



**Figure 4.12.** Two-dimensional beat histograms for dance (left) and classic (right) musical pieces.

As we can see in Figure 4.12, the top histogram has sharp hills, indicating that the rhythmic structure of the play contains strong rhythmic beats. The bottom histogram, on the contrary, is an evidence of absence of strong periodic events as expected since classical composition does not contain neither percussion instruments nor strong attack instruments. The difference in 2D beat histogram shapes expresses different rhythmic properties of music signals and can then be used for music analysis applications such as music genre classification.

The following experiment tends to prove the independency of our 2D beat histogram from recording conditions. A musical composition is filtered with treble and bass cut filters (telephone filter 300-3000Hz). As we can see in Figure 4.13, the resulting histograms of beats still have the same shape and peaks. Moreover, the absolute difference between these two 2D histograms is under 10%.



**Figure 4.13.** Beat histogram for “Rammstein – Mein Herz Brennt” without filtering (top) and after bass/treble cut filter (bottom).

Our 2D beat histogram is used in our work as rhythmic feature vector. The size of the 2D histogram in our case is  $70 \times 150$  bins where 150 bins are devoted to beat period axis in order to maintain high temporal accuracy whereas 15 bins has been observed enough for the details of strength axis.

#### 4.3.2. Rhythmic similarity measure

Rhythmic similarity of two music pieces is then based on comparison of their beat histograms. Several measures can be used for similarity comparison of two histograms  $H=\{h_i\}$  and  $K=\{k_i\}$ . They are classified into two categories: bin-by-bin similarity and cross-bin similarity measures. The bin-by-bin similarity measure only compares contents of corresponding histogram bins while cross-bin similarity measure includes a comparison of non-corresponding bins. Naturally, bin-by-bin similarity measures are more sensitive to slight variations of neighboring bins.

In the family of bin-by-bin similarity measures, several distances can be mentioned:

- **Minkovsky-Form Distance**

$$d(H, K) = \left( \sum_{i=1}^N |h_i - k_i|^r \right)^{1/r} \quad (4.1)$$

- **Histogram Intersection**

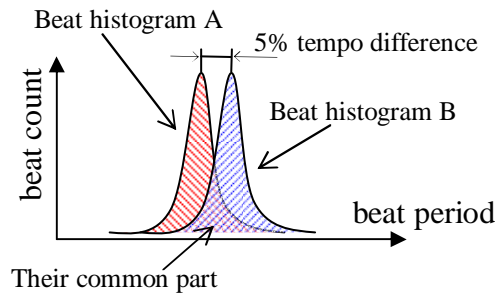
$$d(H, K) = 1 - \frac{\sum_{i=1}^N \min(h_i, k_i)}{\sum_{i=1}^N k_i} \quad (4.2)$$

- **Jeffrey Divergence**

Jeffrey divergence is a symmetric form of Kullback-Leibler divergence.

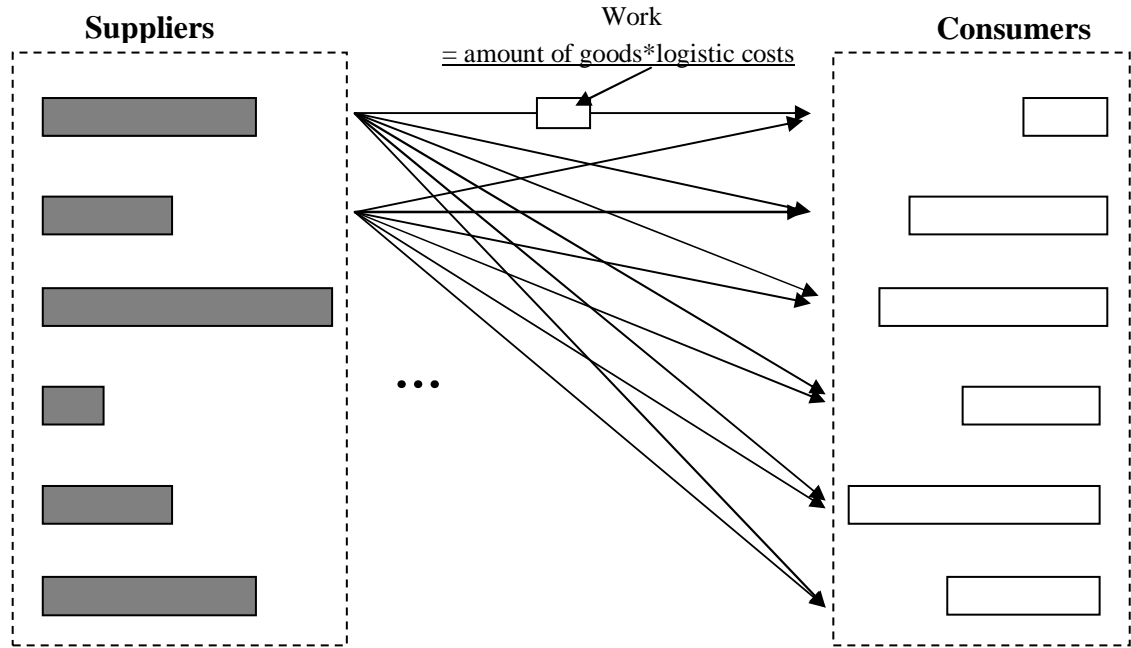
$$d(H, K) = \sum_{i=0}^N \left( h_i \log \frac{2h_i}{h_i + k_i} + k_i \log \frac{2k_i}{h_i + k_i} \right) \quad (4.3)$$

The main disadvantage of bin-by-bin similarities is their sensitivity to slight variations in neighboring bins. In the case of beat histograms, small changes in rhythm may result in vast modifications in the distance between two histograms as we can see in Figure 4.14.



**Figure 4.14.** Small rhythmic changes lead to large bin-by-bin beat histogram distance (at strength plane).

A well known cross-bin similarity measure is the Earth Mover's Distance (e.g. [RUBN 00]). The Earth Mover's Distance (EMD) is based on a solution of transportation problem. It is a problem of suppliers and consumers where goods are to be transported from suppliers to consumers according to logistic costs. Stocks of suppliers are limited as well as consumers' appetites. Thus, the EMD can be used to measure the necessary effort or cost to transform one thing (histogram, image, signature etc.) into another one. Figure 4.15 illustrates its basic principle.



**Figure 4.15.** Illustration of EMD between suppliers and consumers.

Transfer of goods from a supplier to a consumer has a transportation cost. The work done on the transportation is amount of goods transferred from supplier  $X$  to consumer  $Y$  multiplied by the cost of transportation. The goal of EMD computing is to minimize the total cost. It can be formalized as the following linear programming problem: Let  $A = \{(a_1, w_{a1}), \dots, (a_m, w_{am})\}$  be the supplier grid with  $m$  suppliers (or histogram with  $m$  bins). Where  $a_i$  is a bin representative (coordinate or bin number etc.) and  $w_{am}$  is the weight of the bin.  $B = \{(b_1, w_{b1}), \dots, (b_n, w_{bn})\}$  is the second signature with  $n$  elements.  $D = [d_{ij}]$  is the ground distance matrix where  $d_{ij}$  is distance between elements  $a_i$  and  $b_j$  (transportation cost).

The question is to find a flow  $F = [f_{ij}]$  where  $f_{ij}$  is the flow between  $a_i$  and  $b_j$  that minimizes the total cost

$$Work(A, B, F) = \sum_{i=1}^m \sum_{j=1}^n d_{ij} f_{ij} \quad (4.4)$$

with the following constraints:

$$f_{ij} \geq 0 \quad 1 \leq i \leq m, \quad 1 \leq j \leq n \quad (4.5)$$

$$\sum_{j=1}^n f_{ij} \leq w_{a_i} \quad 1 \leq i \leq m \quad (4.6)$$

$$\sum_{i=1}^m f_{ij} \leq w_{b_j} \quad 1 \leq j \leq n \quad (4.7)$$

$$\sum_{i=1}^m \sum_{j=1}^n f_{ij} = \min \left( \sum_{i=1}^m w_{a_i}, \sum_{j=1}^n w_{a_j} \right) \quad (4.8)$$

Once the minimization problem is solved, the Earth Mover's Distance is defined as normalized total cost:

$$EMD(A, B) = \frac{\sum_{i=1}^m \sum_{j=1}^n d_{ij} f_{ij}}{\sum_{i=1}^m \sum_{j=1}^n f_{ij}} \quad (4.9)$$

The advantage of the EMD to allow all possible variations of rhythms in our case is “compensated” by the cost of EMD computation. Complexity of EMD computation is polynomial ( $\sim n^3$ ), it makes it quite few applicable for comparing large histograms having in our case  $70 \times 150$  bins and building complete similarity matrix of many-thousand musical files collection.

While all the previous similarity measures can be used for comparing our 2D beat histogram and outputting a rhythmic similarity, we propose in our work a tradeoff between computation efficiency and robustness of similarity measure to slight tempo variation. Indeed, we assume that two songs having similar rhythmic structure is likely to have similar beat histograms except small tempo variations. On the other hand, a music retrieval system by similarity needs to give the impression of being real time: once fingerprints are calculated for the musical collection, the algorithm of similarity search should perform quickly to issue the complete similarity matrix or to give a list of similar songs to a query song. We thus propose a modified version of bin-by-bin similarity measure so that it is insensible to slight histogram changes while keeping its advantage of low computation cost.

Our rhythmic similarity measure base on 2D beat histogram is defined as follows:

$$Dist_{H1, H2} = \sum_{x=1, y=1}^{N, M} \frac{1}{2} \left( \min_R \left( |H1_{x,y} - H2_{(x,y)+R}| \right) + \min_R \left( |H1_{(x,y)+R} - H2_{x,y}| \right) \right) \quad (4.10)$$

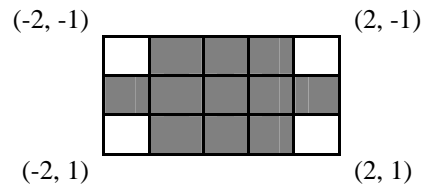
where

$H1, H2$  – beat histograms to compare

$N, M$  – beat histogram size

$R$  – tolerance area as for instance of the following form (Figure 4.16)





**Figure 4.16.** Tolerance area used in the similarity computation of two beat histograms.

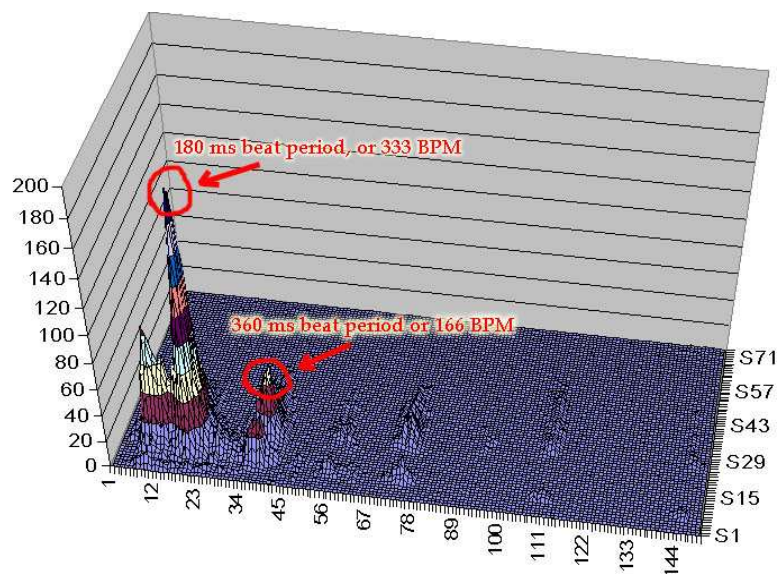
As we can see from Figure 4.16, the tolerance area  $R$  defines thus slight histogram shifts in beat period axis  $X$  and beat strength axis  $Y$ .

#### 4.4. A 2D beat histogram based tempo estimation algorithm and its evaluation

While general evaluation of our 2D beat histogram and the associated rhythmic similarity measure will be made through their applications, namely automatic genre classification and music similarity search, which are described in chapter 6, we describe in this section a sideways product of our 2D beat histogram, namely a tempo estimation algorithm and also propose an evaluation of our algorithm as a first validation of our VRT-based beat curve extraction procedure.

##### 4.4.1. A 2D beat histogram based tempo estimation algorithm

As we can see from Figure 4.17, peaks on our 2D beat histogram correspond to the tempo of the piece or its multiples like  $2x$ ,  $3x$ ,  $4x$ , or  $1/2x$ ,  $1/3x$ ,  $1/4x$ . We thus derive from this 2D beat histogram a tempo estimation algorithm.



**Figure 4.17.** A 2D beat histogram. Main tempo and its  $2x$  alias are marked on the image.

The basic assumption is that the true tempo can have its BPM value ranging from 65 to 200 (rarely past 200 and fewer than 60, see e.g. [ALON 03]). Our algorithm proceeds first by seeking the maximal peak on the 2D beat histogram. If the value of its period hit the range of possible tempos, then the peak is considered as the found tempo. Otherwise, its multiples are examined in the following manner:

- 1) find the first multiple with significant (non-zero) amplitude
- 2) check if its period lies in the tempo acceptance range
- 3) if in acceptance range – return the obtained tempo, else find the next multiple

#### 4.4.2. Experimental evaluations

Two evaluations of this simple tempo estimation algorithm have been driven using different databases.

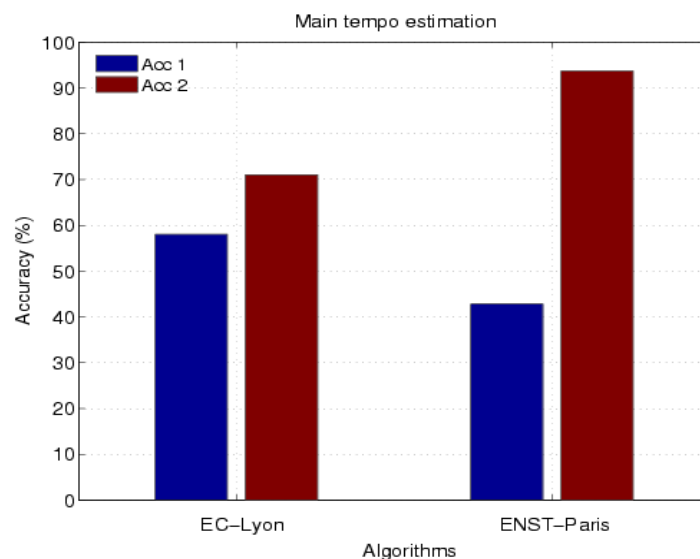
A detailed evaluation of our tempo estimation (and hence, beat detection) was conducted by Miguel Alonso from the research team of ENST Paris in the context of **MusicDiscover** project. Evaluation methods they used were pretty much the same as in known tempo induction contests (e.g. MIREX) with 8% of confidence window. The dataset which was used is the dataset of 474 30-sec. pieces annotated by Anssi Klapuri from Tampere University (Finland).

Here are the results (algorithm from this work is referred as EC-Lyon in the tests).

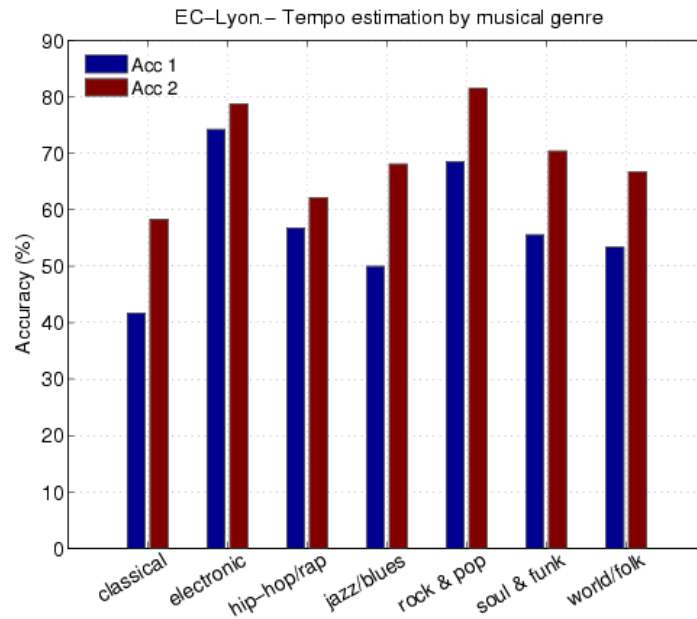
Acc1 – exact tempo estimation within acceptance window

Acc2 – tempo with 2x and 3x multiples

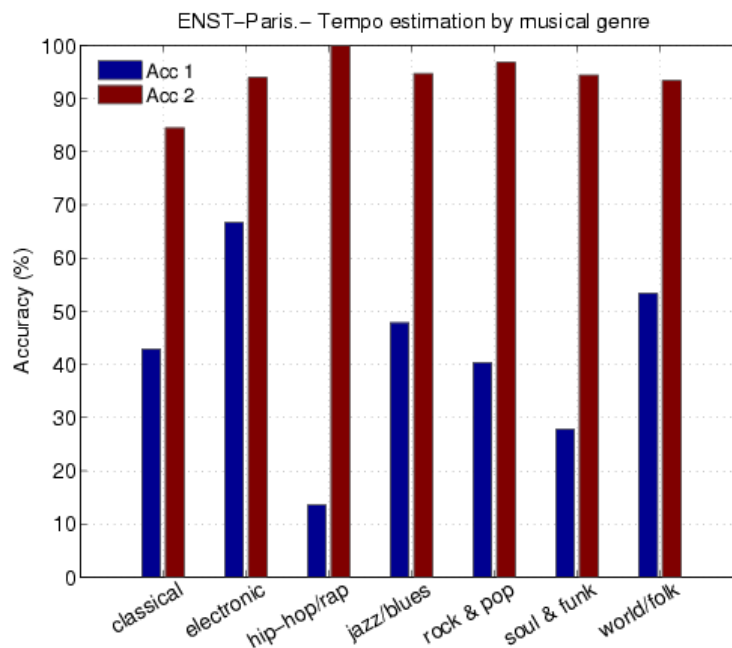
Acc3 – tempo with 1/2x and 1/3x multiples.



**Figure 4.18.** Performance comparison of two tempo estimation algorithms – EC-Lyon and ENST-Paris.

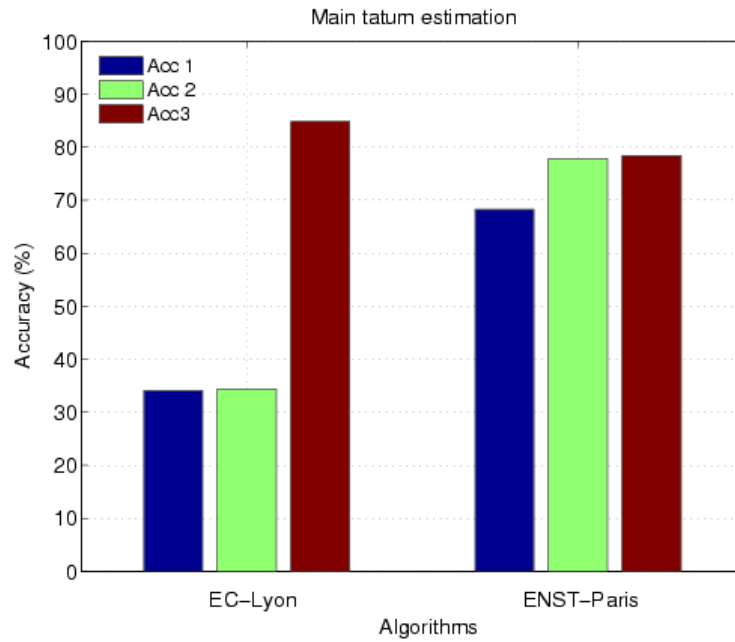


**Figure 4.19.** Distribution of the tempo estimation accuracy as function of genre for ECL algorithm.



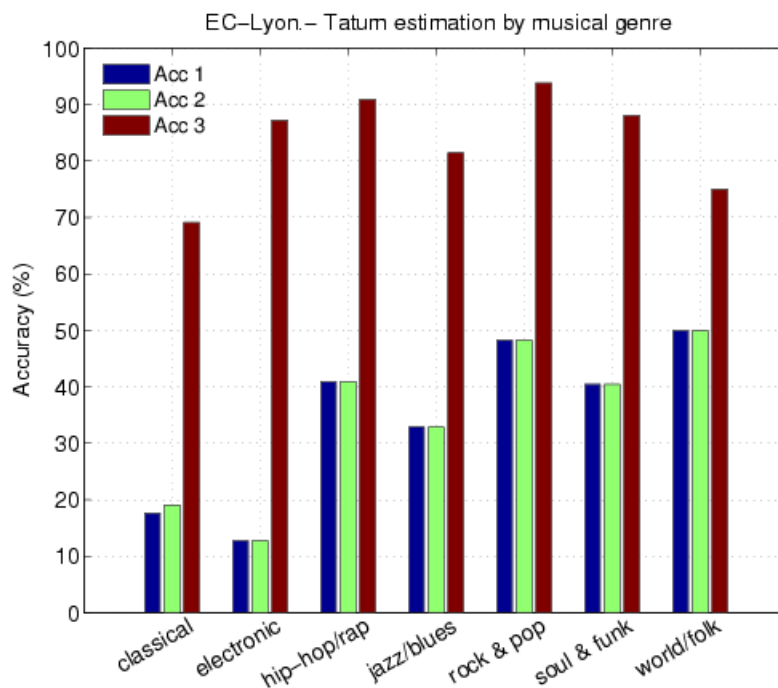
**Figure 4.20.** Distribution of the tempo estimation accuracy as function of genre for ENST algorithm.

The following figures concern tatum estimation. The tatum may be established by the smallest time interval between two successive notes, but is in general best described by the pulse series that most highly coincidences with all note onsets.

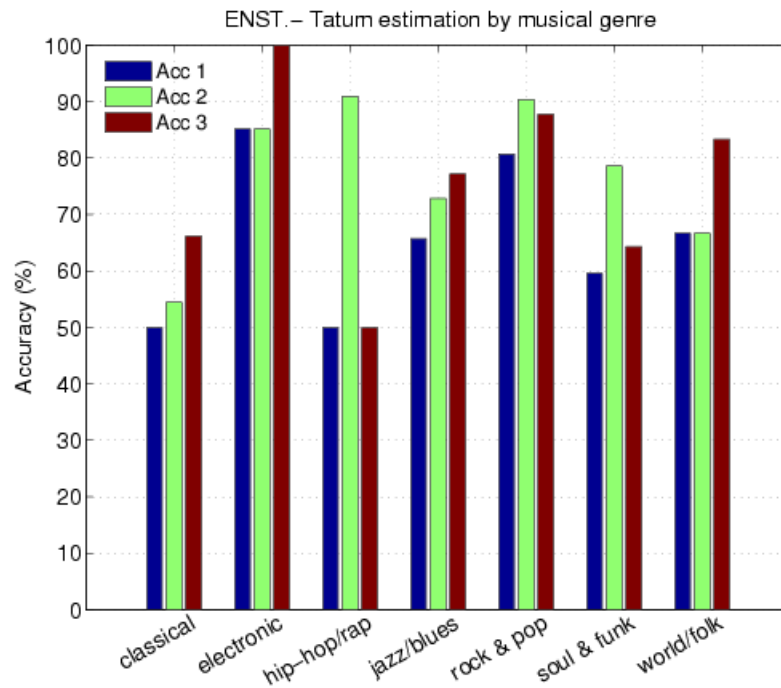


**Figure 4.21.** Tatum estimation accuracy of two algorithms.

The picture above shows an overestimation of tatum by our algorithm. It was extracted by our algorithm as a period of maximal peak on the beat histogram. The true tatum appeared to be two or three times the period obtained by our algorithm, according to the image since the measure Acc 3 takes into account these multiples.



**Figure 4.22.** Tatum estimation performance by musical genre. EC-Lyon algorithm.



**Figure 4.23.** Estimation performance by musical genre. ENST-Paris algorithm.

As we can see from the previous figures, our tempo estimation algorithm has outperformed the algorithm of ENST-Paris more than 10 points in exact tempo estimation accuracy. However, in the case of tatum estimation, our algorithm underestimates the exact tatum frequency and delivers values two or three times less than the actual tatum. This problem comes from the confusion between tatum and the declared tatum by our algorithm, i.e. the detected maximum peak in 2D beat histogram which is not necessarily tatum. For a better discrimination between tempo and tatum, a learning scheme on 2D beat histogram might be used to improve the previous result.

The second experiment was based on database which consisted of a subset of musical files used in *ISMIR2004* tempo estimation contest. Musical segments were selected from *BallroomDancers* collection. There were about 100 30-second files in 6 genres: Cha-Cha, Quickstep, Salsa, Samba, Tango and Waltz. All files are sampled at 16kHz 16 bit.

Precision metric A was taken as a percentage of correctly estimated tempos within 4% of absolute error. Precision metric B was a percentage of correctly estimated tempos within 4% of absolute error and have its close multiples, i.e. 2x, 3x, 4x, 1/2x, 1/3x and 1/4x to be also a correct estimation is it is done at common tempo estimation contests.

The following results were obtained for 3 analysis window shifts - 10, 15, 30ms (Table 4.1 - Table 4.4). The last table is shown here to indicate the fact that increasing the confidence area influences strongly on results.

**Table 4.1.** Tempo estimation results for 10ms analysis window shift.

	ChaCha	Quickstep	Salsa	Samba	Tango	Waltz	Average
A	100	0	66.7	0	33.3	0	33.3
B	100	60	66.7	60	33.3	21.4	56.9

**Table 4.2.** Tempo estimation results for 15ms analysis window shift.

	ChaCha	Quickstep	Salsa	Samba	Tango	Waltz	Average
A	100	0	55.6	0	60	35.7	41.9
B	100	86.7	55.6	66.7	60	57.1	<b>71.0</b>

**Table 4.3.** Tempo estimation results for 30ms analysis window shift.

	ChaCha	Quickstep	Salsa	Samba	Tango	Waltz	Average
A	92.9	0	22.2	66.7	66.7	28.6	<b>46.2</b>
B	92.9	66.7	33.3	86.7	66.7	42.9	64.8

**Table 4.4.** Tempo estimation results for 30ms analysis window shift, 10% confidence area.

	ChaCha	Quickstep	Salsa	Samba	Tango	Waltz	Average
A	100	0	78.8	66.7	93.3	78.6	69.4
B	100	93.3	88.9	86.7	93.3	92.9	92.5

The best result known in the literature for the complete *BallroomDancers* database (~3200 musical excerpts) is 67% (measure A) and 84% (4% accuracy and 2x, 1/2x etc. tempos taken into account, measure B). All results of ISMIR 2004 tempo induction contest is given in the Table 4.5.

**Table 4.5.** Complete table of reference results from ISMIR2004 tempo estimation contest.

4% accuracy	4% accuracy, w/ alias tempos
1. Klapuri 66.91%	1. Klapuri 84.36%
2. Uhle 46.26%	2. Dixon_auco 81.74%
3. <b>ECL 46.2%</b>	3. McKinney 80.68%
4. McKinney 44.89%	4. Dixon_trac 74.14%
5. Dixon_auco 38.66%	5. Dixon_indu 72.98%
6. Scheirer 37.70%	6. <b>ECL 71.0%</b>
7. Alonso_sppr 35.98%	7. Alonso_sppr 69.30%
8. Dixon_indi 31.60%	8. Uhle 68.02%
9. Tzan_medsumbands 30.94	9. Scheirer 67.73%
10. Tzan_medmultibands 30.72%	10. Alonso_auco 56.92%
11. Alonso_auco 27.38%	11. Tzan_medsumbands 55.17%
12. Dixon_trac 26.53%	12. Tzan_medmultibands 50.48%
13. Tzan_histsumbands 22.42%	13. Tzan_histsumbands 49.87%

The experiment shows that our tempo estimation algorithm achieves comparable results since exact tempo estimation performance displayed by our tempo estimation algorithm shared the second place in total rank while we didn't make use of any training scheme.

These two experiments, while displaying acceptable performance of our simple 2D beat histogram tempo estimation algorithm, tend thus to show the soundness of our VRT-based beat extraction curves as they characterize rhythmic events in music signal. The relevance of the derived rhythmic similarity measure for music genre classification or music retrieval by similarity will be further studied in chapter 6 dedicated to applications.

## **4.5. Conclusion**

In this chapter, we have proposed some VRT-based solutions for characterizing rhythmic property of music signal and its similarity. Rhythmical features are first extracted from a VRT spectrogram as a beat curve using some basic image enhancing algorithms. The resulted beat strength curve can be assumed to be a beat probability-related curve. This beat curve is further summarized by a beat histogram in two-dimensional space. There are two advantages of such representation. First, the histogram is built with the second axis covering a range of thresholds in beat detection algorithm, so the necessity of threshold choosing is omitted. The second advantage is that this histogram is therefore volume-independent as the range of thresholds is taken from 0 to maximum.

The rhythmical similarity has been defined as the distance between two 2D beat histograms. The main question is how to compare two beat histograms? Several most popular approaches to histogram comparison have been studied in this chapter – from bin-by-bin to complete cross-bin comparison algorithms. We have proposed an intermediate solution which keeps the rapidity of bin-by-bin methods and add a liberty to slight neighbor bin variations.

Based on our 2D beat histogram, we have also proposed a simple tempo estimation algorithm which has displayed, when evaluated by two experiments, comparable performance to other tempo estimation algorithms known in the literature.

Our 2D beat histogram and its associated rhythmic similarity measure will be further used as rhythmic features in music genre classification and music retrieval by similarity as we will see in chapter 6.

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## **Chapter V**

# **Melody-related similarity features**

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## 5. Melody-related similarity features

We call *melody-related similarity features* a series of similarity measures based on melodic and harmonic properties of a music signal. The true melodic similarity metrics are used to compare melodies upon their score representation like MIDI (Musical Instrument Digital Interface). The question of score-based melodic similarity is well known and well explored in the literature (see e.g. [TOIV 02; TYPK 03]). A work providing a comparison of different approaches is for example [GRAC 02].

Unfortunately, working with raw signal makes useless symbolic similarity algorithms since general 100% effective signal to score translation is not yet available. Therefore, we do not focus here on score-based melodic similarity but rather on signal-based one. We propose in this chapter a VRT-based approach for approximate extraction of multiple fundamental frequencies with relative amplitudes of their harmonics from the signal. Furthermore, based on these estimated multiple  $f_0$  and their harmonics we also derive several melody related similarity measures within the framework of music information retrieval.

### 5.1. Related work

A melody-related characteristic currently used in the MIR community is *pitch*. The notion of pitch is often related to monophonic pitch obtained using autocorrelation-based algorithms (see e.g. [MCKI 03]). However, this definition of pitch is not equivalent to converting a polyphonic music signal into note score. Pitch in musical signal is defined as fundamental frequency ( $f_0$ ) of a sounding voiced instrument.

Early works on automatic pitch detection were developed for speech signal. (see e.g. [ABE 96; HU 01]). Much literature nowadays treats the ***monophonic*** case (only one  $f_0$  present and detected) of fundamental frequency estimation. In the monophonic case several approaches are well known. Autocorrelation based algorithms are among the most frequently used approach for  $f_0$  estimation (e.g. [CHEV 02; TALK 95]). Operating directly in the time-domain, zero-crossing rate based methods are the simplest techniques for fundamental frequency estimation. Other techniques operate in frequency domain. For instance, harmonic matching methods propose to extracting peaks in the spectrum which are further compared to predicted harmonics of each  $f_0$  candidate (see e.g. [DOVA 91; PISZ 79]).

The previous works are mostly destined to speech signal analysis. Unfortunately, it is admitted that algorithms designed for monophonic or speech case are rarely usable for multi-pitch detection.

There exist also works studying the polyphonic case of music signal in the literature. However, the polyphonic music signal is usually considered in most of these works with a number of restrictions such as the number of notes played simultaneously or hypothesis on instruments involved.

The work [KLAP 99] presents a pitch detection technique using separate time-frequency windows. Both monophonic and two-voice polyphonic are studied. Multiple-pitch estimation in polyphonic single-instrument case is described in [LAO 04] where authors propose to apply a comb-filter mapping linear frequency scale of FFT into logarithmic scale of notes frequencies. As the method is FFT-based, the technique inherits drawbacks of FFT for music signal analysis as we highlighted in Chapter 3, namely requiring large FFT analysis windows thus leading to low time resolution.

An advanced  $f_0$  detection algorithm is presented in [GOTO 01a] which is based on finding frequencies which maximize a  $f_0$  probability density function. The algorithm is claimed to work in general case and tested on CD recordings.

We can mention also many other recent works for multiple fundamental frequency estimation, for instance the ones in [LI 07; YEH 05]. Both these two works are probabilistic methods. The first one uses a probabilistic HMM-based approach taking into account some a priori musical knowledge such as tonality. Variable results from 50% to 92% of recognition rates for different instruments in MIDI synthesized sequences are reported. The second algorithm is evaluated on synthetic samples where each file contains only one combination of notes (1 note or 1 chord).

It is not evident to compare these different multiple  $f_0$  estimation algorithms as assumptions or models on the polyphonic music signal are often not explicitly stated. On the other hand, there is no single evident way of multiple  $f_0$  detection. Some algorithms are strong in noisy environment; some algorithms require a priori training; others are able to detect inharmonic tones etc. The most popular approach to  $f_0$  estimation is harmonic pattern matching in frequency domain. Our multiple- $f_0$  estimation algorithm makes use of this basic idea and relies on our VRT specifically designed to music signal analysis.

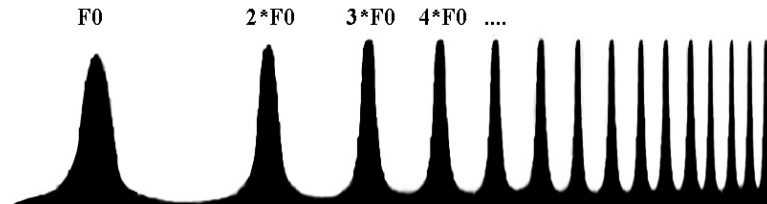
## **5.2. Our VRT-based multiple $f_0$ estimation algorithm**

### **5.2.1. Principle and procedure**

The basic principle of the  $f_0$  estimation algorithm consists of modeling of our VRT spectrum with harmonic models. Real musical instruments are known to have inharmonic components in their spectrum [KLAP 04]. It means that the frequency of the  $n^{\text{th}}$  partial can be not strictly equal to  $f_0 * n$ .

The algorithm we describe does not take such inharmonic components into account, but it tolerates some displacement of partials in natural way.

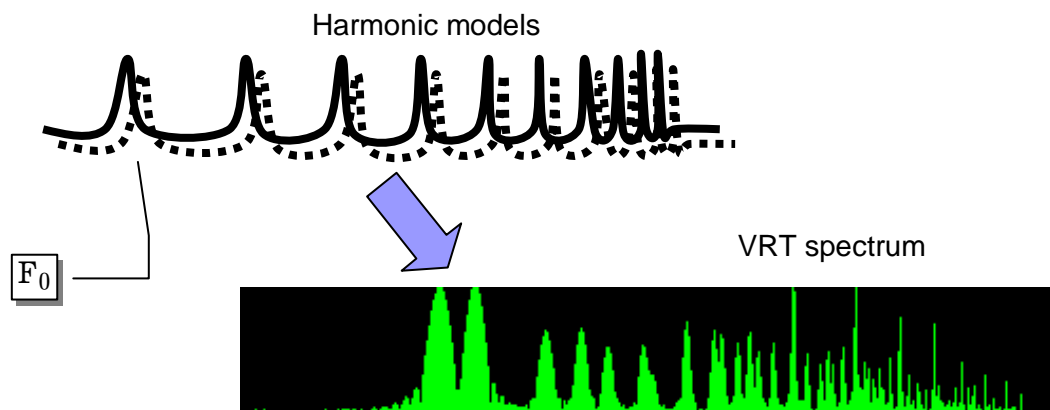
Typical “flat” harmonic structure used to model the spectrum is depicted in the Figure 5.1.



**Figure 5.1.** Harmonic structure.

This fence is a vertical cut of VRT spectrogram calculated from a synthetic signal representing an ideal harmonic instrument. Width of peaks and space between them is variable because the VR transform has a logarithmic frequency scale.

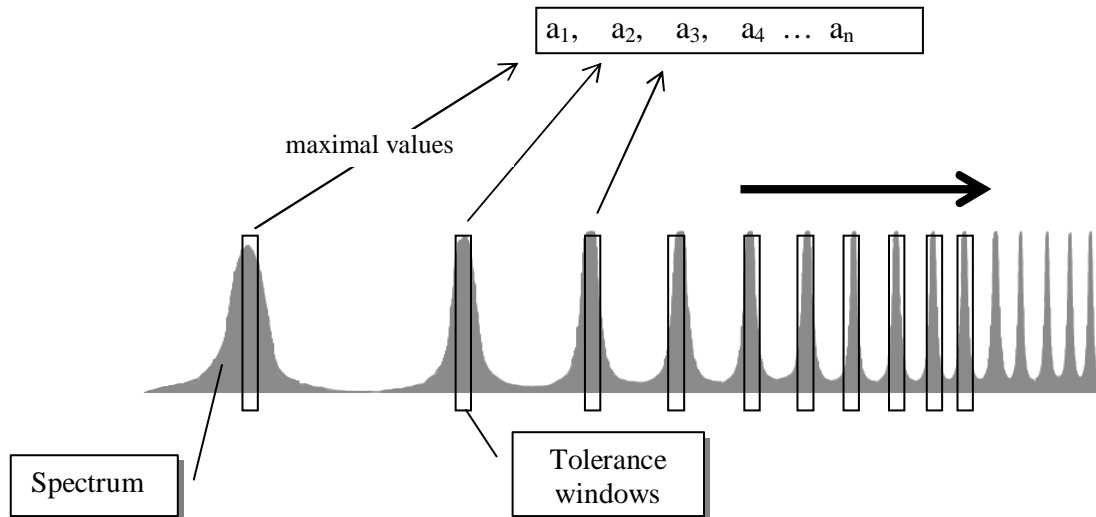
In the next step, these models are used to approximate the spectrum of the signal being analyzed in order to obtain a list of  $f_0$  candidates.



**Figure 5.2.** Matching of harmonic models to spectrum.

During every iteration of the algorithm, such harmonic fence is passed lengthwise the frequency axis of the spectrogram and matched at each starting point with it.

The matching of the harmonic model is done as follows. At every harmonic their amplitudes  $a_i$  are taken from values of the spectrogram for the frequencies of  $i^{\text{th}}$  harmonics. As frequencies of harmonics have not necessarily integer ratios to the fundamental frequency, we take maximal amplitude in a close neighborhood, as it is explained in Figure 5.3.



**Figure 5.3.** Procedure of extraction of harmonic amplitude vector.

This passage forms a function  $A(f)$  which is a norm of the vector  $\mathbf{a}$  for the frequency  $f$ . The value of frequency for which the function  $A$  takes its maximum value is considered as an  $f_0$  candidate.

Further, the obtained  $f_0$  candidate and the corresponding vector  $\mathbf{a}$  of amplitudes of harmonics is transformed into a spectrum slice like in Figure 5.1. The form of hills is taken from the form of VRT spectrum of a signal with a sine wave with corresponding frequency. This slice is then subtracted from the spectrum under analysis. The iterative process is repeated until currently harmonic structure has the value of  $A(f)$  inferior to a certain threshold or the maximum number iterations has been reached. We limit the maximal number of iterations to 4, and therefore the maximal number of notes which can be simultaneously detected is 4. As it was observed in preliminary experiments, increasing the number of simultaneously detected notes doesn't improve significantly the  $f_0$  detection performance for high-polyphonic music, because after 3<sup>rd</sup> or 4<sup>th</sup> iteration the residue of spectrum is already quite noisy as almost all harmonic components have been already subtracted from it due to harmonic overlaps. The procedure of multiple  $f_0$  estimation can be depicted by the following algorithm:

```

max_match = 0
model_width = number_of_bins taken by N-harmonic model
for starting_point = 0 to spectrum_size - model_width {
    A[starting_point] = match model with the spectrum at starting_point;
    if max A[starting_point] then max_match = starting_point;
}
f0_candidate = convert to pitch (max_match);
subtract the model from spectrum at max_match;
if spectrum is not empty and max iterations is not reached then continue
iterations;

```

Where the matching algorithm can be described by the following function:

```

Function match (starting_point)
{
  for i = 0 to number_of_harmonics_in_model {
    y = starting_point + disp[i]; // disp - an array of relative harmonic positions,
disp[0]=0
    a[i] = max(W[y-1], W[y], W[y+1]); // W[0...spectrum_size] - current spectrum slice
// a tolerance window size of 3 bins is applied
here
  }
  match = norm (a[...]);
}

```

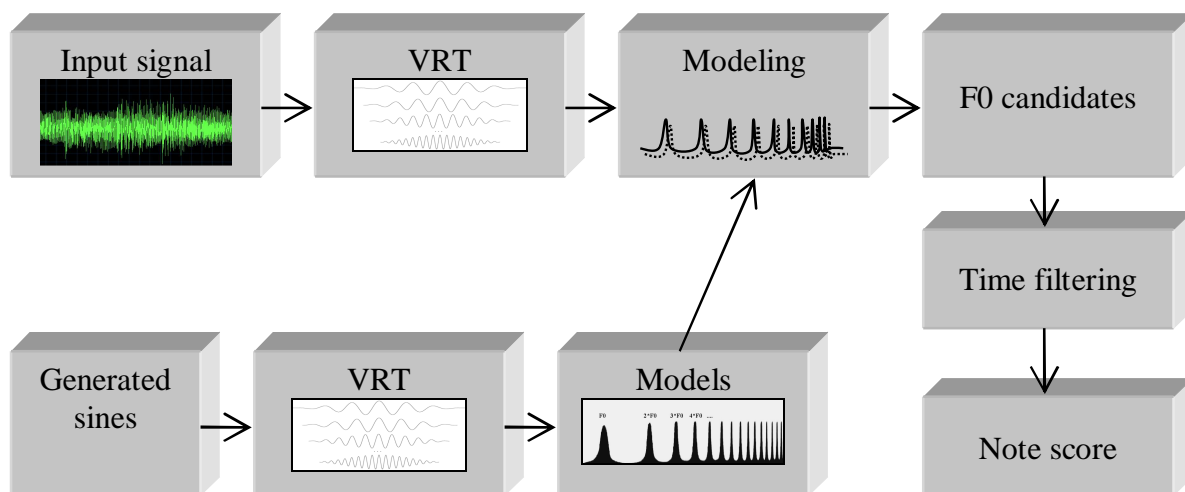
The procedure of note extraction is applied each 25 ms to the input signal sampled at 16 kHz 16 bits. Hence, for the shortest notes with duration around 50-70 ms we obtain note candidates at least twice in order to be able to apply filtering techniques. Every slice produces a certain number of  $f_0$  candidates; then,  $F_0$  candidates are filtered in time in order to remove noise and unsure notes. Time filtering used is nearest neighbor interframe filtering. It takes 3 successive frames and  $f_0$  candidates in the middle frame are changed according to  $f_0$  candidates in side neighbors. The filter removes noisy (false detected)  $f_0$  candidates as well as holes in notes issued by misdetection; it can be explained by the following algorithm:

```

for all  $f_0$  candidates at time t-1 {
  if candidate absent at t-2 or candidate absent at t the remove candidate at
t-1
}
for all  $f_0$  candidates at time t-2 {
  if candidate present at t then add candidate at t-1
}

```

Block diagram of the note detection algorithm is shown in Figure 5.4.



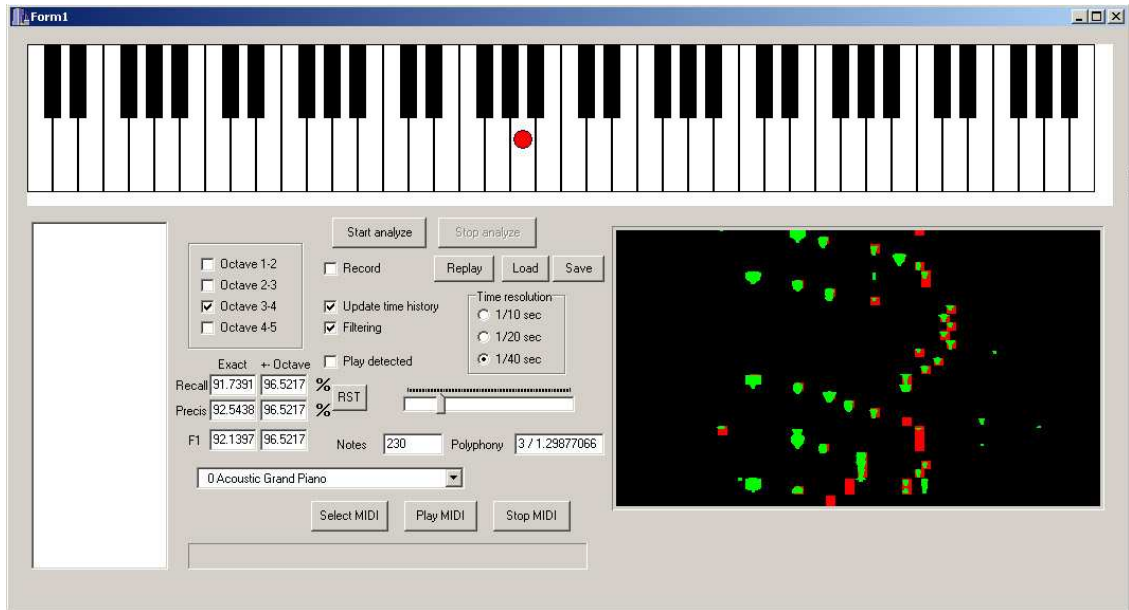
**Figure 5.4.** Block diagram of note detection procedure.

### 5.2.2. Experimental evaluation

The easiest way to make basic evaluation experiments in automated music transcription is to use MIDI files (plenty of them can be freely found in Internet) rendered into waves as input data and MIDI events themselves as ground truth. However, the real life results must be obtained from recorded music with true instruments and then transcribed by musical educated specialists.

In our work we used wave files synthesized from MIDI using hardware wavetable synthesis of Creative SB Audigy2 soundcard with high quality freely available in Internet 140Mb SoundFont bank “Fluid\_R3”. In such wavetable synthesis banks all instruments are sampled with good sampling rates from real ones: the majority of pitches producible by an instrument are recorded as sampled (wave) block and stored in the soundfont. In the soundfont we used, acoustic grand piano, for example, is sampled every four notes from a real acoustic grand piano. Waves for notes which are in between these reference notes are taken as resampled waves of closest reference notes. Therefore, signal generated using such wavetable synthesis can be considered as real instrument signal recorded in ideal conditions. And a polyphonic piece is an ideal linear mixture of true instruments. To make the conditions closer to reality in some tests we passed the signal over speakers and record it with a microphone.

Figure 5.5 is a screen-shot of our note detection program which is used for note detection. With a capability of real-time input signal processing, our note detection program achieves candidate f0 detection and time filtering with 25 ms interframe time. It is capable to parse and play MIDI files and compare the result of note detection with the original music score.



**Figure 5.5.** Note recognition and evaluation program.

Recall and Precision measures are used to measure the performance of the note detection. Recall measure is defined as:

$$\text{Recall} = \frac{\text{the number correct notes detected}}{\text{the actual number of notes}} \quad (5.1)$$

Precision is defined as following:

$$\text{Precision} = \frac{\text{the number correct notes detected}}{\text{the number of all notes detected}} \quad (5.2)$$

For the overall measure of the transcription performance, the following *F1* measure is used

$$F1 = \frac{2 \cdot \text{Recall} \cdot \text{Precision}}{\text{Recall} + \text{Precision}} \quad (5.3)$$

All falsely detected notes also include those with octave errors. For some tasks of music indexing as for instance tonality determination, what is important is the note basis and not the octave number. For this reason, the performance of note detection without taking into account octave errors is estimated as well.

Our test dataset consists of 10 MIDI files of classical and pop compositions containing 200 to 3000 notes. Some other test sequences are directly played using keyboard. The following tables (Table 5.1 - Table 5.4) display precision results of our multiple pitch detection. Perf.Oct column stands for performance of note detection not taking into account notes' octaves (just the basic note is important). The *polyphony* column indicates the

maximum and the average number of simultaneously sounding notes found in the play.

**Table 5.1.** Note detection performance in monophonic case. Sequences are played manually using keyboard.

Name	№ of notes	Polyphony max / avg	Performance			Perf. Oct
			Recall	Prec	F1	F1
Piano Manual	150	1 / 1	100	100	100	100
Violin Manual	160	1 / 1	100	97	98.5	100

**Table 5.2.** Note detection performance in polyphonic case. Sequences of chords are played manually using the keyboard.

Name	№ of notes	Polyphony max / avg	Performance			Perf. Oct
			Recall	Prec	F1	F1
Piano Manual	330	2 / 1.8	98.5	100	99.5	99.7
Piano Manual	214	5 / 2.2	95.8	100	97.8	99.1
Flute Manual	174	4 / 2	97.7	97.7	97.7	99.7

**Table 5.3.** Note detection performance in polyphonic case. Classical music titles (single- and multi-instrument, no percussion).

Name	№ of notes	Polyphony max / avg	Performance			Perf. Oct
			Recall	Prec	F1	F1
Fur_Elize	924	6 / 1.6	91.1	88.7	88.9	95.6
Fur_Elize w/ microphone	924	6 / 1.6	88.1	86.9	87.5	95.4
Tchaikovski 01	177	4 / 3.5	84.7	95.5	89.8	95.4
Tchaikovski 16	186	4 / 2.6	86.5	100	92.8	97.2
Bach 01	687	5 / 1.7	91.1	88.7	89.9	98.2
Bach 03	549	5 / 2.1	98.9	91.9	95.2	96.8
Bach Fugue	252	5 / 2.4	83.7	76.1	79.8	93.2
Vivaldi Mandolin Concerto	1415	6 / 2.9	70.1	74.8	72.4	91.5

**Table 5.4.** Note detection performance in polyphonic case. Popular and other music (multi-instrument with percussion).

Name	№ of notes	Polyphony max / avg	Performance			Perf. Oct
			Recall	Prec	F1	F1
K. Minogue	2545	10 / 4.7	40.6	37.1	38.8	64.3
Madonna	2862	8 / 3.9	43.9	56.9	49.5	66.4
Soundtrack f/ Godfather	513	9 / 4.1	88.7	67.2	76.5	90.4

As we can see from these tables, our algorithm performs quite well in monophonic case. Good results are also obtained in polyphonic case with classical music having a low average level of polyphony (number of notes simultaneously played). More complex musical compositions which include percussion instrument and have high polyphony rate have produced lower recognition rates. In our note detection algorithm, we have limited the maximal detectable polyphony to 4 while the maximal and average polyphony in the case of popular and other music is 10 and 4.7

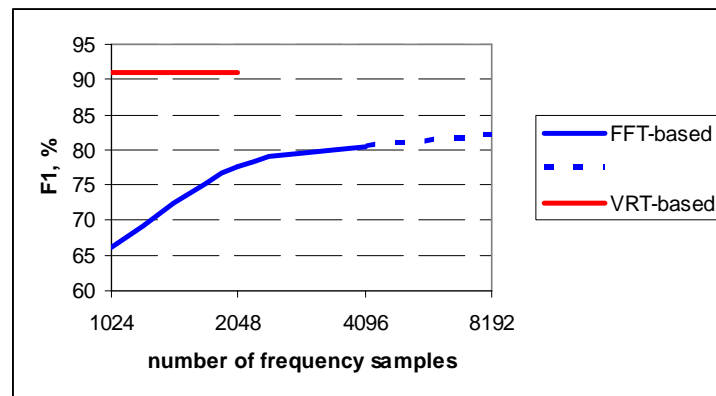


correspondingly. The octave precision, however, stays high (perf. Oct F1 field).

For comparison purpose, we also implemented our note detection algorithm based on FFT with different window size instead of our VRT. We carried out an experiment with a set of polyphonic classical compositions (~1000 notes) using this FFT-based note detection algorithm. Table 5.5 and Figure 5.6 summarize the experimental results.

**Table 5.5.** Comparison of transcription performance based on different time-frequency transforms (the FFT with various window sizes versus VRT).

Transform	FFT	FFT	FFT	VRT
FFT size or number of VRT frequency samples	1024	2048	4096	1024
Result (F1)	66.2	77.6	80.5	<b>91.3</b>



**Figure 5.6.** Note detection algorithm performance according to underlying spectral analysis approach.

Further increase of the FFT window size lowers down the time resolution to 0.5-1 seconds so that note changes quicker than 0.5 seconds cannot be resolved anymore.

These experimental results show the advantage of our VRT and its simple use performs quite well multiple note detection in the case of low average polyphony rate.

### 5.3. Melody-related similarity features

Recall that the main goal of this work is music retrieval by similarity which is quite subjective, a 100% accurate note detection algorithm may not be necessary. In the following, we thus assume that our VRT-based note detection algorithm delivers *partial transcription* of a music signal on which we can build melody-related similarities. The basic idea is that our multiple  $f_0$  detection algorithm issues for each window a list of detected  $f_0$ 's together with relative amplitudes of their partials. This information is then used for building several kinds of statistical characteristics (histograms).

### 5.3.1. Note profile histogram

The simplest way to calculate a similarity distance is to calculate a distance between note histograms. Note histograms, or *chroma profiles* and *chromagrams* [PAUW 04] are well known and they are computed across the whole musical file or its part and serve for estimation of musical similarity by tonality as well as tonality estimation (musical key) itself.

Tonality is a musical term denoting a system of relationships between a series of pitches (notes), which are forming melodies and chords. In simple words, tonality can be referred as describing a collection of pitches, used to build musical piece. A tonality has a *tonic* – a central note as its most stable element. Besides the tonic, one of the most important notes of a tonality is the dominant (the 5<sup>th</sup> note) and subdominant (the 4<sup>th</sup> note).

Besides the tonic tonalities are distinguished by *modes* – major and minor (natural, harmonic, melodic). Each of them has different musical characteristics regarding the position of tones and semitones. Figure 5.7 gives an example of two tonalities – do-major and do-minor.

#### C-major

Tonic					Subdominant				Dominant				
Do (I)	Do#	Re (II)	Re#	Mi (III)	Fa (IV)	Fa#	Sol (V)	Sol#	La (VI)	La#	Si (VII)		
1	2	3	4	5	6	7	8	9	10	11	12		



#### C-minor

Tonic					Subdominant				Dominant				
Do (I)	Do#	Re (II)	Mib (III)	Mi	Fa (IV)	Fa#	Sol (V)	Lab (VI)	La	Sib (VII)	Si		
1	2	3	4	5	6	7	8	9	10	11	12		

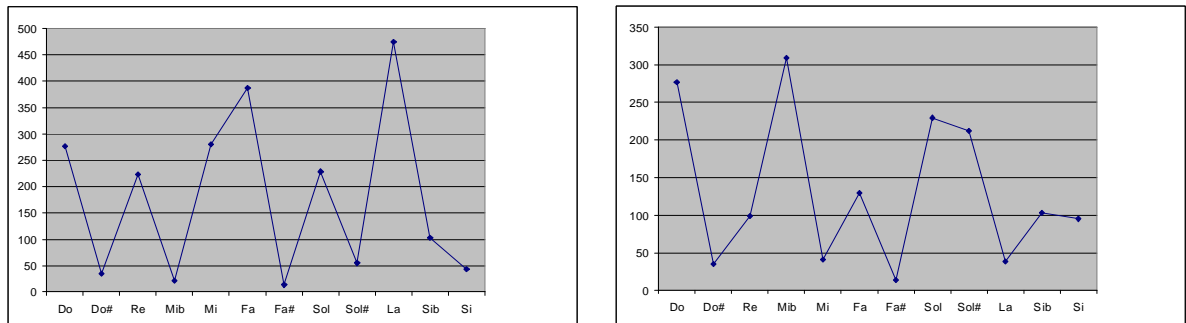


Figure 5.7. Tonality. Do-Major and Do-Minor (natural) tonalities.

These are parallel tonalities in respect of the tonic. There are also parallel tonalities in the meaning of notes used. For do-major it is la-minor.

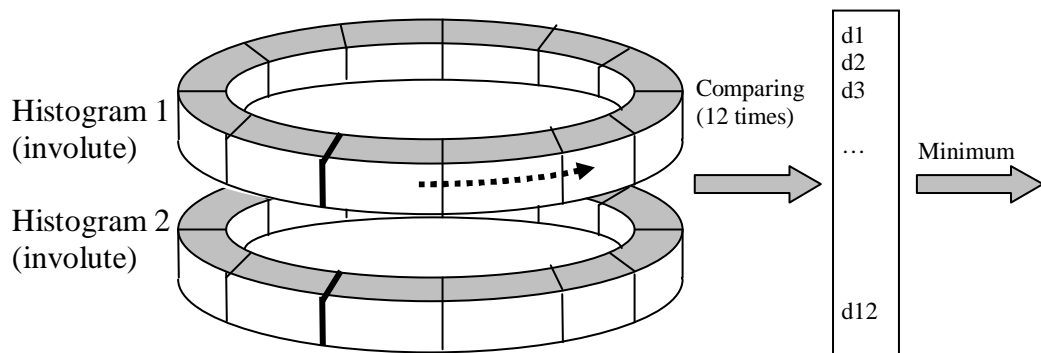
The note histogram or tonal profile has close relationship with tonality as tonality and its mode (minor/major) are related to probabilities of notes which can be observed in the play. For example, for a song in Do-major it is few probable to find Do# in it. An example of two such tonal profiles (for C-dur and C-mol) is given in Figure 5.8. In music analysis applications the

tonality can be inducted using note histogram of the musical piece [CHUA 05; PEET 06].



**Figure 5.8.** Note profiles for major (C-dur, left) and minor (C-mol, right) tonalities (approximate).

In our work, we propose to utilize note profile histogram as a measure in order to characterize a tonal similarity between two musical compositions using Minkovsky-form distance (4.1). Since a transposition in music does not change perception of melody, the distance must be computed taking into account all possible transpositions. An illustration of the process is given in Figure 5.9. The algorithm makes a rotation of one of the two histograms. As the number of notes in histograms is 12, the rotation produces 12 variants. These variants of the first histogram are compared to the second histogram by computing a distance between histograms. The minimum value of obtained distances is used as the measure of tonal distance.



**Figure 5.9.** Comparison of note histograms taking into account all possible transpositions.

This tonal distance is assumed to be useful in finding of musical pieces which are similar in tonality, and therefore, probably mood as music in a minor key is often claimed to sound sad, whereas music in a major key is typically viewed as sounding cheerful (see e.g. <http://en.wikipedia.org/wiki/Major-Minor>).

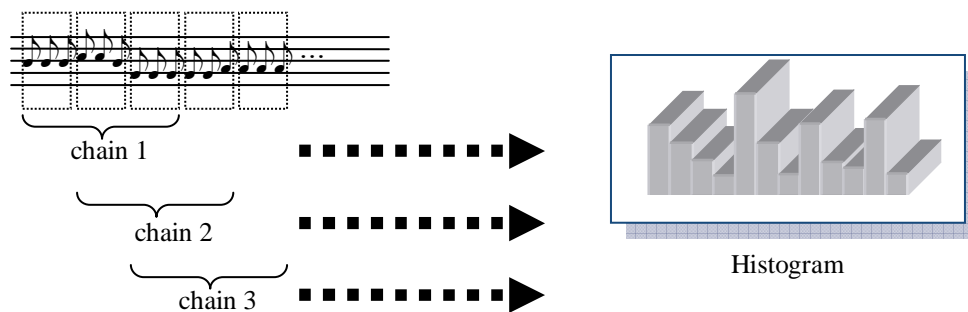
A variant of note histogram which we use is multi-octave note histogram. In this type of tonal profile, octaves are not rolled up into one to produce a histogram, but histogram is produced from the absolute height of notes. Comparison of such multi-octave histograms can be done by shifting

them by up to  $\pm S$  octaves with one semi-tone shift (melodies can be transposed and we want to accept such transpositions within one octave). Multi-octave tonal profile is mostly indicating the total distribution of notes in the spectrum, for example a balance between bass and melody lines can be extracted, etc.

### 5.3.2. Note succession histogram

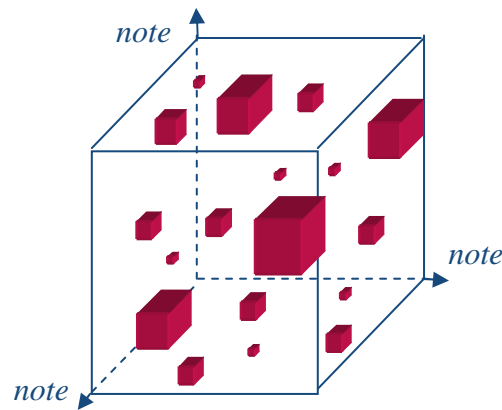
Another musical similarity measure studied in this work is a similarity based on note successions histogram. Here the probability of 3-note chains is collected and its histogram is then used as a “fingerprint” of musical title. A musical basis of such similarity measure is that if same passages are frequent in two musical compositions, it gives a chance that these two compositions have similarities in melody or harmony.

The note successions histogram extracted from a music signal is computed as follows. First, note extraction over the whole piece is carried out. Then detected notes are grouped in local note histograms in order to find a dominating note in each grouping window. The size of the grouping window may vary from 100ms to 1 sec. Finally, all dominant notes are extracted from local histograms and their chains are collected in the note successions histogram. The process is depicted in Figure 5.10.



**Figure 5.10.** Procedure of note succession histogram calculation.

The resulting histogram is 3-dimensional histogram where each axis is one note of 3-note chain found in the musical piece under analysis. Figure 5.11 illustrates such a histogram where



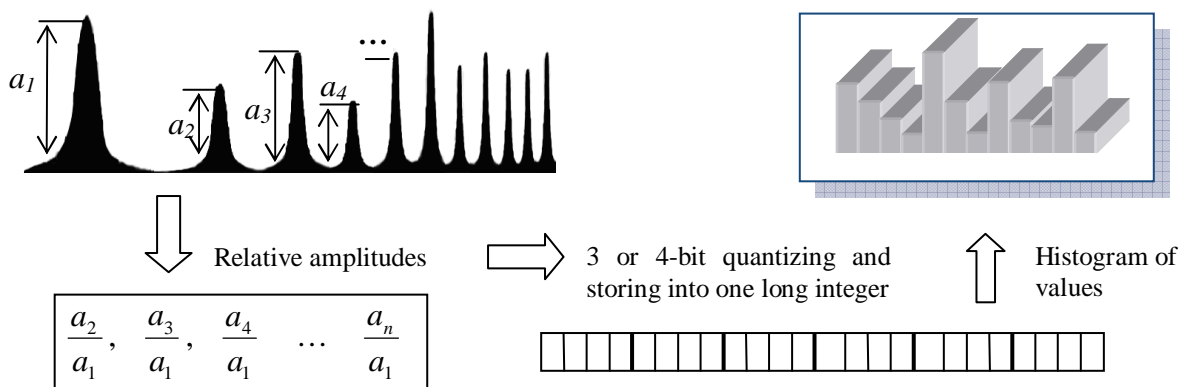
**Figure 5.11.** 3D note successions histogram example.

Figure 5.11 illustrates such a histogram where red cubes represent histogram bins. The bigger is the cube – the higher is the value of the corresponding histogram bin. Bins are depicted in three-dimensional space since the histogram is three-dimensional. As each note axis 12 positions (corresponding to notes), the whole histogram therefore possesses  $12^3$  bins. In the case of 4-note succession histogram, it contains  $12^4$  bins which would be too large and too sparse for good comparison as few notes in one play would fill the histogram.

To compare the note succession histograms we apply the same principle as for one-dimensional note histograms. All rotations around 3 axes simultaneously of the histogram are considered and the minimum distance value is taken.

### 5.3.3. Timbre histogram

The third characteristic we extract from a musical piece is the timbre histogram. In general, “voiced” instruments differ from each other also by their timbre – profile of their partials. In our work we collect all detected notes with relative amplitude of their harmonics. Further, relative amplitudes of harmonics are reduced to 3-4 bits and attached together in order to form an integer number. Histogram of these numbers is then computed.



**Figure 5.12.** Computing of timbre histogram.

Unlike the classical approach which consists of describing the timbre globally, our timbre features are first defined on separate notes isolated by the multiple-f<sub>0</sub> estimation algorithm and then they are summarized in a histogram. Comparing such histograms gives a similarity measurement which is supposed to be somehow instrument-related.

## **5.4. Conclusion**

In this chapter we have presented a VRT-based multiple-f<sub>0</sub> estimation algorithm which is characterized by its simplicity, its rapidity and high temporal resolution unlike FFT-based methods. It performs pretty well in detection of multiple pitches with non-integer rates. However, as other similar algorithms, our VRT-based multiple f<sub>0</sub> estimation algorithm does not solve the following problem: two notes with a distance of an octave can hardly be separated, because the second note does not bring any new harmonics into the spectrum, but changes the amplitude of existing harmonics of the lower note, so some knowledge of instruments involved in the play or instrument recognition techniques and multi-channel source separation is necessary to resolve the problem.

Our note detection mechanism was evaluated in its direct application – musical transcription from the signal. In this evaluation ground truth data was taken as note score files – MIDI. These files from various genres (mostly from classic) were rendered into waves using high-quality wavetable synthesis. The resulting wave files were passed as input for the transcriptions algorithm. The result of the transcription and ground-truth data was compared and performance measure calculated showing a result which is correct enough to be able to use this partial transcription in similarity metrics.

Several musical features and corresponding similarity measures have been proposed in this chapter. Some of them were already known in literature (pitch class or note profile), some of them are newly presented in this thesis (note succession histogram, timbre histogram). All these music features are closely related to musical content. As we will see in the next chapter on music genre classification and music retrieval by similarity, they are precious complementary features of previous pure spectral or timbre similarity features so far developed in the literature.

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## **Chapter VI**

### **Applications and evaluation**

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## 6. Applications and evaluation

Recall that our basic assumption when starting this thesis work was, as also suggested by many works in the literature [AUCO 04], that music signal analysis within MIR framework needs to go beyond pure acoustic or spectral features and consideration of some music features in complement of popular acoustic and spectral features can improve performance of music information retrieval algorithms, in particular music genre classification and music retrieval by similarity.

In our work we consider the task of automatic genre classification *as a tool of an objective* (in some extent) *evaluation* of our previously defined music features and the associated similarity measures.

While evaluation of the first application is rather clear, the second application presents a certain difficulty caused by an absence of objective ground truth data since the question of musical similarity is a subjective one. Of course, the ground truth data can be found in some extent in the meaning of genre classification or artist identification. In this chapter we will speak about it in details.

### 6.1. Automatic genre classification

Music genres are categories used by music editors and distributors. These categories facilitate the navigation into a physical music collection. Genres are naturally used to categorize digital music collections. To date, genres are manually associated by music editors, distributors and aggregators. Associating genres automatically to music titles is becoming important for several reasons. First, in the digital era the music unit is the title in contrary to the album in the physical era, meaning a clear increase in the number of units to be categorized.

#### 6.1.1. The problem

The main practical difficulty in the problem of automatic genre classification is the absence of reliable ground-truth data. Definitions of genres are often ambiguous and unclear. Moreover, even if genres are well defined, their borders are still a question to discuss. There exist many musical pieces with transitional genres sharing multiple classes.

The fact, that human genre classification does not give 100% of classification rates is known. The work [PERR 99] has provided 72% of classification that agrees with genres among 10 attributed by record companies. Another study [LIPP 04] has found inter-participant genre agreement rates of only 76%. With these facts one can assume an existence of unavoidable ceiling on automatic genre classification performance.



Another fact which makes ground-truth data for automatic genre classification less reliable is that genres are often attributed to artists or albums while in general artists have songs belonging to different genre even within the same album. An example is easy to find. Quite large number of *Rock (Metal)* albums can contain calm and romantic compositions which can be closely related to *Ballad* or *Power Ballad* to be exact. From listener's point of view these songs are different from the original artist's genre and the absence of detailed per-song genre attribution is sometimes confusing. From the point of view of automatic genre classification algorithms such exception songs may produce big disturbances in classification models since these songs will generate descriptors far away similar to those from the principal attributed genre.

The aforementioned facts and small performance gains during last years render the task of automatic genre classification out of precise definition and hence utility of the automatic genre classification can be argued. However, there are works in literature which provide arguments in favor of using genre (see e.g. [MCKA 06]).

The automatic genre classification may be useful with re-defining the genres as sub-clusters of some low-level meta-genres which are closely related to *styles* of music instead of genres. In this case genres would be presumably better defined in the meaning of acoustic or perception. At the same time musical files from the same genre would produce more homogeneous audio descriptors. So, this will increase classification rates as well. But this would also require detailed manual labeling of every song with new genre taxonomy which is sometimes a time consuming procedure, especially in the case of large music collections.

As we stated at the beginning of this chapter, we consider the task of automatic genre classification *as a tool of an objective* (in some extent) *evaluation* of our previously defined music features and the associated similarity measures. The goal here is thus to show that our previously defined music features and the associated similarity measures bring performance gain when they are used in complement to pure acoustic or spectral based features, even in the case of simple classifiers.

### 6.1.2. Related work

Several systems for automatic genre classification have been proposed. In their majority, these systems are an adaptation of a general audio classifier to the task of music genre classification. They use a signal-only analysis.

[TZAN 02] uses frequency centroid, spectral flux, zero crossing rate, cepstral characteristics as well as characteristics of musical rhythm and other aspects. Proposed features are classified by GMM classifier. For six musical

genres: Classic, Country, Disco, Hip Hop, Jazz and Rock the results in terms of average classification precision were of 62% for 30-second segments.

[DAN 02] proposes to use peak valleys of spectral characteristics coupled with GMM for genre classification. For five genres of music: baroque, romantic, pop songs, jazz, and rock a precision of classification of 82% was reported for 10-second segments of their proprietary database constructed from 1500 pieces.

A classical approach of genre classification, based on cepstral features (MFCC and delta MFCC) and GMM classifier was used in [PYE 00]. The author reports a precision of 92% in classification of entire songs (musical titles) of the following genres: Blues, Easy Listening, Classic, Opera, Techno and Indy Rock.

An original approach of temporal structure modeling of musical signals using neural networks is introduced in [SOLT 98]. This approach was evaluated in genre classification of four genres: Rock, Pop, Techno and Classic. Authors provide an average precision of 70% for 4-second segments.

Recent approaches presented in literature use spectral features such as MFCC, ZCR etc. together with support vector machines [MAN 05] and AdaBoost methods [BERG 06]. They reported nearly 64% and 69.5% correspondingly of normalized raw classification accuracy on *Magnatune* database at MIREX2005 Genre Classification Contest.

Direct comparison of algorithms found in literature is quite a complicated question since they were often evaluated on **different databases with different genres**. For example, similar approaches used correspondingly in [TZAN 02] and [PYE 00] have produced precision rates rather different as 64% and 92%. In addition, length of segments used for classification also has an influence on the results. It is very probable, for example, that one song could be correctly classified by major vote over all segments of the song when only 30% of its duration is classified correctly.

### 6.1.3. Principle and architecture of our classification system

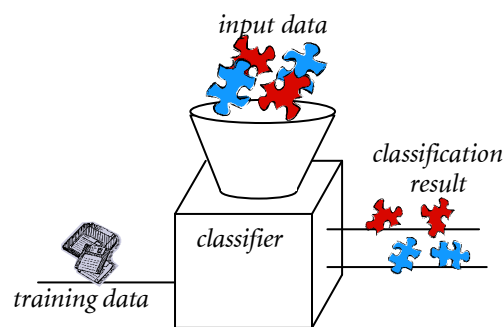
The idea we present here is to apply musical similarity measures to the automatic genre classification problem. It is supposed that songs from the same genre should induce resemblances in musical and acoustic properties. Precisely, songs from the same genre must sound similarly to some extent (timbre, rhythm, melody, etc.). This conjuncture forms the basis of our genre classification system.

In our work, two kinds of classifier are considered. They are described in the following two sections. A single classifier is first investigated using some specific music feature and correlated similarity measure previously defined. This respectively leads to four different experts, namely acoustic

expert, rhythmic expert, timbre expert and tonality expert. Starting from the assumption that each expert get to an extent insight into the genre according to its specific feature, we also investigate a multi-expert classification system which further synthesizes these individual expert decisions into a global classification decision, thus making use of all acoustic and music features so far developed.

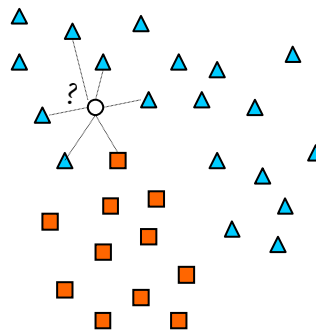
### 6.1.3.1 Single-classifier system

The single classifier version of our genre classification system uses classical architecture where a universal supervised classifier which is trained on learning partition of the dataset produces  $n$  outputs equivalent to probabilities of classes.



**Figure 6.1.** General principle of classification

For our system we have chosen the k-NN (k-Nearest Neighbors) classifier [AHA 91]. K-Nearest Neighbor classification is a very simple, yet powerful classification method. The main idea behind the k-NN is that similar observations belong to similar classes. Thus, one simply has to look for the class designators of a certain number ( $k$ ) of the nearest neighbors of an unknown sample and weigh number of their classes' appearance in order to assign a class to the unknown sample (Figure 6.2).



**Figure 6.2.** The k-NN classification principle.

The choice of naïve k-NN classifier is induced by its simplicity and the fact that our subsequent multi-expert system requires a class probability

made by each individual expert that each music excerpt belongs to one of six genres according to its specific expertise. Alternatively, popular classifiers such as neural networks with an appropriate architecture or SVM may also be used.

Of course, we are aware that, as opposition to its needless for learning, the major drawback of k-NN classifiers is its heavy computation cost during classification as it requires all the available learning dataset. Alternative classification strategies may trade off learning complexity against classification cost.

Since the k-NN classifier does not need any special training, for each song to be classified it looks through the training data set, counts a distribution of classes of  $k$  closest samples and attributes the resulting class according to the most representative class of the closest samples.

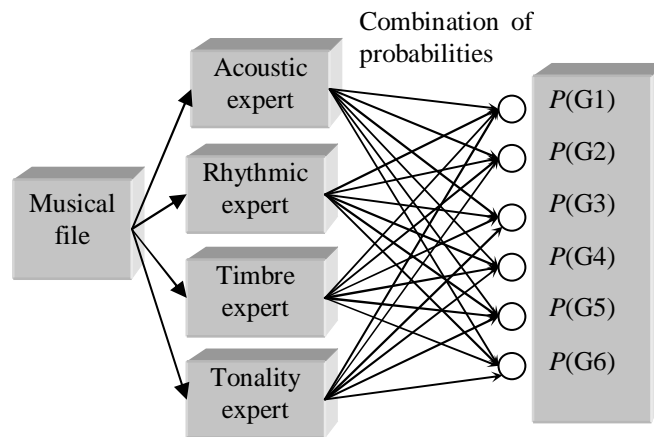
Here is the list of single classifiers:

- Rhythmic classifier or *rhythmic expert* is a k-NN classifier which uses 2D beat histograms of musical pieces as feature vector and (4.10) as similarity measure.
- *Timbre expert* is a k-NN classifier fed by timbre histograms (§5.3.3) as feature vectors. Minkosvky-form distance (4.1) is used in quality of distance measure.
- *Tonality expert* is much like the other experts, taking note profile histograms (§5.3.1) as feature vectors and wrapped-around Minkovsky-form distance using the principle described by Figure 5.9.
- The acoustic classifier we used in our work is PGM-MLP (Piecewise Gaussian Model – Multi Layer Perceptron) audio classifier [HARB 05]. PGM models the context effect by an auditory memory supposes that the classification of a stimulus at time instant  $t$  is based on the status of the memory at time instant  $t$ . The auditory memory is supposed to be a Gaussian distribution of the spectrum in the past time window, called the Integration Time Window ITW. The auditory memory is therefore modeled by one Gaussian distribution for each frequency band. The frequency bands are chosen according to the MEL psychoacoustic scale in order to model the frequency resolution of the human ear. The auditory memory model is updated continuously by a new acoustic observation and hence by new spectral features. For the sake of simplicity it was supposed that the duration of the memory model is constant, which means that the ITW is constant. Also, the Gaussian distributions are described by their mean and diagonal covariance. The PGM features are then coupled to a Multi Layer Perceptron (MLP) trained using the error back-propagation algorithm. The MLP has 40 input neurons corresponding to the 20 mean values and the 20 variance values obtained from each ITW window. The MLP has 1 hidden layer with

100 hidden nodes, 6 output neurons according to number of genres. The MLP estimates, after a training phase using the gradient descent algorithm, the probability of the audio classes given the PGM features of the ITW window.

### 6.1.3.2 Multi-expert classification system

As our previous single classifier makes use of different music features for music genre classification, we further consider the conjunction of these different music features by fusing the outputs of these single classifiers into a final classifier, thus leading to a *multi-expert* system. The intuition behind such architecture is that each single classifier using its specific music feature is more suitable for characterizing music genre according to its input music feature and a final classification result is needed to fuse these very complementary single expert decisions.



**Figure 6.3.** Multi-expert architecture of the classification system. Individual experts issue genre probabilities which are then mixed using the final combining expert.

The usage of mixture of experts is not entirely new. The theory properties of mixtures of experts have been investigated in [JORD 94]. They have been successfully applied in a general audio classification system in Hadi Harb's thesis work [HARB 03; HARB 05]. Multi-expert systems have shown good results in music genre classification (see e.g. [SCAR 05a]). They are known to divide the problem into sub-problems and to reduce their complexity improving the global accuracy.

One of the experts constituting our multi-expert classification system is the expert of classification by acoustic analysis (the first expert on Figure 6.3). This expert is a classifier presented in [HARB 05] is one or several Multi Layer Perceptrons (MLPs) having the perceptually motivated PGM (Piecewise Gaussian Model) features as input characteristics. Each MLP of this expert is trained independently on the entire learning dataset or on a part of it.

All the other individual experts are naïve k-NN classifiers used in single-expert version of the system where they were applied on similarity

measures like rhythmic, melodic (note profile and note succession histograms) and similarity by timbre. Since the k-NN classifier produces one class designator as a classification result, it was adapted to produce multiple probabilistic outputs standing for probabilities of a song being analyzed to belong to the corresponding class.

$$P_i = \frac{C_i}{\sum_{j=1}^N C_j} \quad (6.1)$$

In previous works by our team a weighted sum of individual classifiers was used for producing resulting probabilities [HARB 04] however a contribution of each classifier is not necessarily linear. Hence in this work we used a combining method based on MLP as a generic non-linear classifier with the following architecture. Normalized outputs of individual classifiers form the input for the MLP. Six outputs of the MLP are probabilities that a song belongs to six genres. The MLP is trained on the testing set where target vectors for training are formed with one member value equal to 1 for the genre in question and 0-values for all the rest. The MLP which was used has one hidden layer with 24 neurons. Further increase of the number of neurons in hidden layer leads to augmenting of complexity of the network and requires more training data and therefore can result in overtraining with bad generalization.

The training algorithm used for the neuron network is back error propagation [RUME 86]. The function of activation was the sigmoid function.

#### 6.1.4. Experimental results

One important difficulty to overcome in the development of an automatic music genre classification system is the constitution of a reference database. A reference database that is sufficiently representative of the real world situation in order to draw reliable conclusions on system architecture, features, classifiers etc. The database must also reflect the real needs in real world applications, especially in the definition of genres and the variability of music excerpts for each genre. In the following, we first introduce and discuss ECL-Music genre dataset which is used as reference database in complement of Magnatune dataset. Then, performances by single classifiers and multi-expert classifier are presented and discussed.

##### 6.1.4.1 Reference database

One important difficulty to overcome in the development of an automatic music genre classification system is the constitution of a reference database. A reference database that is sufficiently representative of the real world situation in order to draw reliable conclusions on system architecture,

features, classifiers etc. The database must also reflect the real needs in real world applications, especially in the definition of genres and the variability of music excerpts for each genre.

We have chosen six music genres for the reference database. The genres were chosen as being the six genres we generally found on several online music stores. The selected list of genres includes: Rock (Pop), Rap (HipHop, R&B), Jazz (Blues), Classic, Dance (Disco, Electro, House), Metal (Hard Rock, Heavy Metal)

Each of these “general” genres consists of several sub-genres which have more precise definition. For example, the Rap genre consist of such sub-genres as Rap, HipHop, R&”, Soul etc... each sub-genre corresponds to a specificity which means that two songs of the given sub-genre are closer at least from musical edition’s point of view than two songs from different sub-genres. Unfortunately, detailed genre taxonomy can be defined in multiple ways [PACH 00] which is a limit for the definition of universal musical genres taxonomy. Hence, we propose to choose from each “general” genre a well defined sub-genre which represents the main genre. The choice of sub-genres lies on the most representative sub-genre in the meaning of number of songs associated to it by a musical distributor, for instance *fnacmusic*. E.g. Rock  $\cup$  Pop rock, Metal  $\cup$  Hard rock, etc.

For each representative sub-genre we have selected the list of artists associated to it on the music distributor store. This list was then used to capture music from webradios<sup>1</sup>. The musical segments were captured as 20-seconds records starting from the 50<sup>th</sup> second of the play and saved as PCM 8KHz 16bit Mono files. In total the reference database consists of 1873 titles from 822 artists which make 37480 seconds in total.

It is crucial to note an important variability of musical titles in this reference database owing to an important number of artists (see Table 6.1). As far as we know, this is the first reference database where the attribution of genres to each title is not made in subjective manner by one person but takes into account the musical distribution’s attribution. Also, in comparison with other freely available databases like *magnatune* (see Table 6.2) used in ISMIR 2004 genre classification contest<sup>2</sup>, the current reference database is better balanced in the meaning of representation of classes (640 classic songs vs. 52 jazz songs in the case of *magnatune*).

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<sup>1</sup> [www.shoutcast.com](http://www.shoutcast.com)

<sup>2</sup> [http://ismir2004.ismir.net/genre\\_contest/index.htm](http://ismir2004.ismir.net/genre_contest/index.htm)

**Table 6.1.** Database details – number of songs per class, number of various artists per class etc.

Genre	Titles	Artists	Duration (seconds)
Classic	214	113	4280
Dance	335	226	6700
Jazz	305	104	6100
Metal	324	105	6480
Rap	311	152	6220
Rock	384	122	7680
Total	1873	822	37480

For the reason of comparison we also provide some results conducted on the *magnatune* (ISMIR 2004) database which is a known reference database. The *magnatune* database contains 1458 files of 6 genres and 138 artists. The database is heavily unbalanced – there are 12 times less songs in Jazz genre than in Classic genre (see Table 6.2 for details). Better balanced datasets allow better training of classification models. An important matter of the *magnatune* database requiring discussing is the genre “World” which has collected wide are of genres not very well defined in musicological way which doesn’t mention the acoustic definition. “*World*” is a common “catch-all” for ethnic/folk music that is not easily classified into another group and can contain such diverse music as Indian tabla and Celtish rock”.<sup>1</sup>

**Table 6.2.** *Magnatune* database details.

Genre	Titles	Artists
Classic	640	40
Electronic	230	30
Jazz_Blues	52	5
Metal_Punk	90	8
Pop_Rock	202	36
World	244	19
Total	1458	138

#### 6.1.4.2 Experimental results by single classifiers

In this series of experiments we apply separately single music feature-based classifiers to make genre classification. The aim here is to show the relative performance achieved by individual music feature and the associated similarity measure related to music genre classification.

<sup>1</sup> [http://www.music-ir.org/mirex2005/index.php/Audio\\_Genre\\_Classification](http://www.music-ir.org/mirex2005/index.php/Audio_Genre_Classification)



In the case of rhythmic and timbre classifiers every musical title in the testing set is compared to all titles in the learning set by the distance between their histograms. The learning set is taken as 50% of the entire database. The classifier used is the k-NN classifier with  $k=10$ .

First we consider the *Magnatune* reference database for which there exist classification results in the literature. We got the classification accuracies as follows. For the single classifier the best two musical descriptors in the meaning of their importance in genre classification were rhythmic similarity and timbre similarity. Note profile descriptors applied single do not distinguish well between genres since tonality cannot be related to a specific genre, thus we do not provide its classification confusion matrix; its mean classification accuracy was around 28%. For the classification by rhythmic similarity the result obtained was 68.1% of raw classification accuracy which means that 496 songs from 729 were classified correctly. The result normalized with respect to the probability of classes is 54.6%. The confusion matrix of the classification result is presented in Table 6.3.

**Table 6.3.** Beat expert classification result on *Magnatune* (normalized mean accuracy **54.6%**, raw accuracy **68.1%**)

	Classic	Electronic	Jazz-Blues	Metal	Rock-Pop	World
Classic	<b>89.7</b>	0.6	0.6	0.3	3.1	5.6
Electronic	6.1	<b>56.8</b>	1.7	3.1	13.1	19.2
Jazz-Blues	11.5	1.9	<b>30.8</b>	0	3.8	51.9
Metal	4.4	3.3	0	<b>46.7</b>	30.0	15.6
Rock-Pop	10.8	7.4	1.0	13.3	<b>52.7</b>	14.8
World	23.0	9.0	0	0.4	16.8	<b>50.8</b>

It can be noticed, relatively high recognition rate for classic songs. This result is expectable since classical music naturally does not have strong rhythmic structure and high rhythmic dissimilarity with all the other classes except World. Regarding the class World one can conclude a significant confusion with other classes, especially with Classic and Pop. These results tend to show that this class actually contains different types of music. Among the other classes, Metal and Rock-Pop have high cross-confusion rates as well.

These experimental results, while displaying comparable ISMIR 2004 genre classification contest results, thus tend to show that rhythm based music features impact on music genre classification, and appear particularly efficient for discriminating classic from the rest of music genres.

The second experiment concerns another musical similarity metric – the timbre distance. A k-NN classifier based on this distance has performed with lower but still correct results. The raw classification accuracy obtained was 52.2% which makes 380 songs from 729 to be classified exactly. The

normalized mean accuracy was 39.6%. The whole confusion matrix is given in Table 6.4.

**Table 6.4.** Timbre expert result (normalized mean accuracy **39.6%**, raw accuracy **52.2%**)

	Classic	Electronic	Jazz-Blues	Metal	Rock-Pop	World
Classic	<b>75.6</b>	1.9	0	2.5	5.0	15.0
Electronic	16.6	<b>17.0</b>	0.4	14.0	15.3	36.7
Jazz-Blues	19.2	0	<b>5.8</b>	3.8	13.5	57.7
Metal	10.0	2.2	0	<b>58.9</b>	18.9	10.0
Rock-Pop	23.2	2.0	0.5	24.1	<b>30.5</b>	19.7
World	27.5	9.0	0	5.3	7.4	<b>49.6</b>

As we can see from this table, the best distinguished classes are Classic and Metal owing to the characteristic nature of instruments involved. The percentage of recognition of Metal genre is even higher than in the case of classification by rhythmic distance. However, classes where songs are characterized mostly by their rhythmical structure such as Jazz-Blues and Electronic have weak classification rates. These results tend thus to suggest that our timbre feature and associated similarity measure are useful for distinguishing the kinds of music genres clearly characterized by the involved instrumentations such as classic and metal.

Our baseline music genre classification system is the acoustic PGM-MLP-based system [HARB 05]. When applied to Magnatune dataset, the acoustic PGM-MLP-based system has produced the following classification performance (Table 6.5). The raw classification accuracy was 53.6% with 390 correctly classified songs of 729. The normalized mean accuracy obtained was 49.6% which is higher than in the case of timbre distance-based classification but lower than in the case of rhythmic similarity classifier. However, the acoustic classifier has outperformed both rhythm and timbre classifiers in Metal genre.

**Table 6.5.** Acoustic expert on *Magnatune* (normalized mean accuracy **49.6%**, raw accuracy **53.6%**)

	Classic	Electronic	Jazz-Blues	Metal	Rock-Pop	World
Classic	<b>69.6</b>	3.4	6.9	0	3.8	16.3
Electronic	6.6	<b>33.6</b>	5.7	11.4	28.4	14.4
Jazz-Blues	11.5	3.8	<b>53.8</b>	0	15.4	15.4
Metal	3.3	7.8	6.7	<b>61.1</b>	20	1.1
Rock-Pop	9.9	14.3	10.3	11.3	<b>44.3</b>	9.9
World	26.6	11.1	7.8	4.1	15.2	<b>35.2</b>

It can be observed from these experimental results that each classifier-expert is strong in classifying certain genres and rather weak in classifying the others which can be better classified by other experts. That reinforces

our hypothesis of necessity of multi-expert system and fits the assumption that non-linear combination of classifiers can improve global classification accuracy.

For the purpose of comparison we provide here the best and the worst result of the ISMIR2004 genre classification contest<sup>1</sup>.

The system of Dan Ellis & Brian Whitman has produced the following classification accuracy: raw accuracy of 64% and normalized 51.48% (Table 6.6).

**Table 6.6.** Dan Ellis & Brian Whitman's system classification result (51.48% mean and 64% raw).

	Classic	Electronic	Jazz-Blues	Metal	Rock-Pop	World
Classic	<b>97.8</b>	0.9	0.3	0	0	0.9
Electronic	36.2	<b>33.8</b>	0.8	4	15.3	9.6
Jazz-Blues	18	1.6	<b>21.3</b>	8.1	31.1	19.6
Metal	2.2	11.1	0	<b>51.1</b>	35.5	0
Rock-Pop	19.8	18.8	1.9	7.9	<b>51.4</b>	0
World	62.6	9.7	0	0.8	4.8	<b>21.9</b>

Another classification system from the ISMIR2004 we reference here is the system of Elias Pampalk ([PAMP 06]). The system has shown very high classification accuracy (84.07% of correctly classified songs and 78.78% of normalized rate). The confusion matrix is given in (Table 6.7).

**Table 6.7.** Classification accuracy by a reference system (E. Pampalk) (78.78% normalized accuracy and 84.07% raw).

	Classic	Electronic	Jazz-Blues	Metal	Rock-Pop	World
Classic	<b>97.8</b>	0.3	0	0	0.6	1.2
Electronic	0.7	<b>62.2</b>	0	16.2	14.8	5.9
Jazz-Blues	7.6	3.8	<b>80.7</b>	0	3.8	3.8
Metal	0	4.4	0	<b>75.5</b>	20	0
Rock-Pop	2.9	9.9	0	4.9	<b>77.2</b>	4.9
World	14.6	6.5	0.8	0	9.7	<b>68.2</b>

The ECL\_database described in §6.1.4.1 was also examined. For this database the obtained classification rates were higher than in the case of the Magnatune database. It can be explained by better quality of the ECL\_database where all classes are nearly equal in terms of representation and better defined (no such classes as World).

<sup>1</sup> [http://ismir2004.ismir.net/genre\\_contest/results.htm](http://ismir2004.ismir.net/genre_contest/results.htm)

Both rhythmic and timbre k-NN classifiers were applied and following results were observed. Table 6.8 gives the class recognition confusion matrix for the rhythmic classifier.

**Table 6.8.** *ECL\_genres* database classification results with rhythmic classifier (normalized mean accuracy 71.4%)

	Classic	Dance	Jazz	Metal	Rap	Rock
Classic	<b>82.8</b>	0.5	4.4	5.4	1.0	5.9
Dance	0.3	<b>76.8</b>	2.1	4.6	7.9	8.2
Jazz	5.5	3.8	<b>68.9</b>	1.4	10.0	10.4
Metal	8.3	3.5	8.0	<b>69.7</b>	2.2	8.3
Rap	0.0	6.0	10.7	3.3	<b>75.7</b>	4.3
Rock	7.4	3.6	15.3	8.2	11.2	<b>54.4</b>

As it was noticed before, the rhythmic classifier is stronger in classifying rhythmically bright genres of music such as Dance, Rap. Classic genre lies in this category since it doesn't have strong rhythmic patterns. An absence of strong rhythm is a rhythmic descriptor as well.

**Table 6.9.** *ECL\_genres* database classification results by timbre (normalized mean accuracy 42.4%)

	Classic	Dance	Jazz	Metal	Rap	Rock
Classic	<b>49.3</b>	3	13.8	17.7	4.4	11.8
Dance	7.9	<b>19.8</b>	5.8	30.8	7.6	28.0
Jazz	8.0	11.4	<b>31.5</b>	14.9	9.0	25.3
Metal	5.1	3.2	1.6	<b>85.7</b>	0.3	4.1
Rap	5.3	12.0	15.0	23.0	<b>28.3</b>	16.3
Rock	12.3	7.9	6.0	30.6	3.6	<b>39.6</b>

**Table 6.10.** *ECL\_genres* database classification results by acoustic expert (normalized mean accuracy 49.3%)

	Classic	Dance	Jazz	Metal	Rap	Rock
Classic	<b>53</b>	5	12	2	5	10
Dance	3	<b>40</b>	7	7	11	8
Jazz	23	4	<b>38</b>	2	6	21
Metal	7	24	15	<b>75</b>	16	19
Rap	2	16	12	7	<b>55</b>	7
Rock	12	11	16	7	7	<b>35</b>

The classification by timbre and by acoustic classifier again shows a superiority of Metal recognition rate owing to a specific instrumentation used.

#### 6.1.4.3 Experimental results by Multi-expert system

As explained in the section on architecture of classifiers, our multi-expert system aims at fusing single music feature based-experts into a global

one for music genre classification. As the goal of this thesis work is the use of music features in complement to pure acoustic features, we have also included a pure acoustic feature based classifier as one of our single classifiers as a baseline music genre classifier. Recall also that the fusion strategy is a Multi-Layer Perceptron having one hidden layer which synthesizes a global classification result from the outputs of single classifiers. The following Table 6.11 shows the result obtained for combinations of all experts on the Magnatune dataset.

**Table 6.11.** All experts combined by MLP, (normalized mean accuracy 66.9%, raw accuracy 74.2%)

	Classic	Electronic	Jazz-Blues	Metal	Rock-Pop	World
Classic	<b>88.7</b>	0.6	0	0.6	1.2	8.9
Electronic	3.5	<b>58.8</b>	9.6	3.5	7.9	16.7
Jazz-Blues	7.7	3.8	<b>57.7</b>	0	11.5	19.2
Metal	0	8.9	0	<b>66.7</b>	22.2	2.2
Rock-Pop	1	11.8	2	10.9	<b>64.7</b>	9.8
World	13.9	8.2	2.5	0.8	9.83	<b>64.6</b>

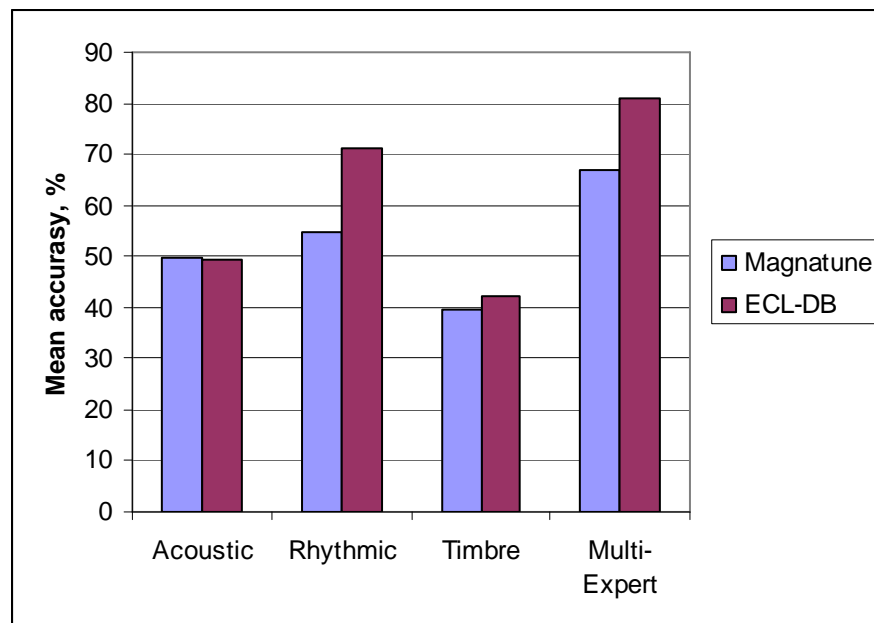
As it can be seen from the table, with a normalized mean accuracy rate up to 66,9%, the combination of experts, using thus music features in complement to pure acoustic feature based PGM-MLP expert, brings significant improvement of classification precision as compared to the normalized mean accuracy rate of 49,6% achieved by the single PGM-MLP expert. Our multi-expert system outperforms the single acoustic feature based PGM-MLP expert in each of considered six genres, with the best improvements achieved on Electronic and World genres, respectively passing from an accuracy rate of 33,6% and 35,2% in the case of single PGM-MLP to 58,8% and 64,6% in the case of multi-expert system. These two music genres probably need more music features for better discrimination for reason of their varieties.

With the ECL Music genres dataset which has higher artist variability and where genres are generally better defined, our multi-expert system achieves even better results. Table 6.12 gives the classification results by our Multi-expert system. Indeed, our multi-expert system displays a normalized mean classification accuracy rate up to 80.9% as compared to 49.3% achieved by the single PGM-MLP expert.

**Table 6.12.** *ECL\_genres* database classification results (normalized mean and raw accuracy 80.9%)

	Classic	Dance	Jazz	Metal	Rap	Rock
Classic	<b>91.6</b>	0	2	0	0	6.2
Dance	0	<b>69.2</b>	1	3.2	6.5	19.7
Jazz	1.1	8	<b>71.2</b>	0	3.4	16
Metal	0	1	0	<b>89.2</b>	2.1	7.5
Rap	0	4.6	2.3	4.6	<b>80.2</b>	8.1
Rock	1.7	4.4	2.6	5.3	1.7	<b>83.9</b>

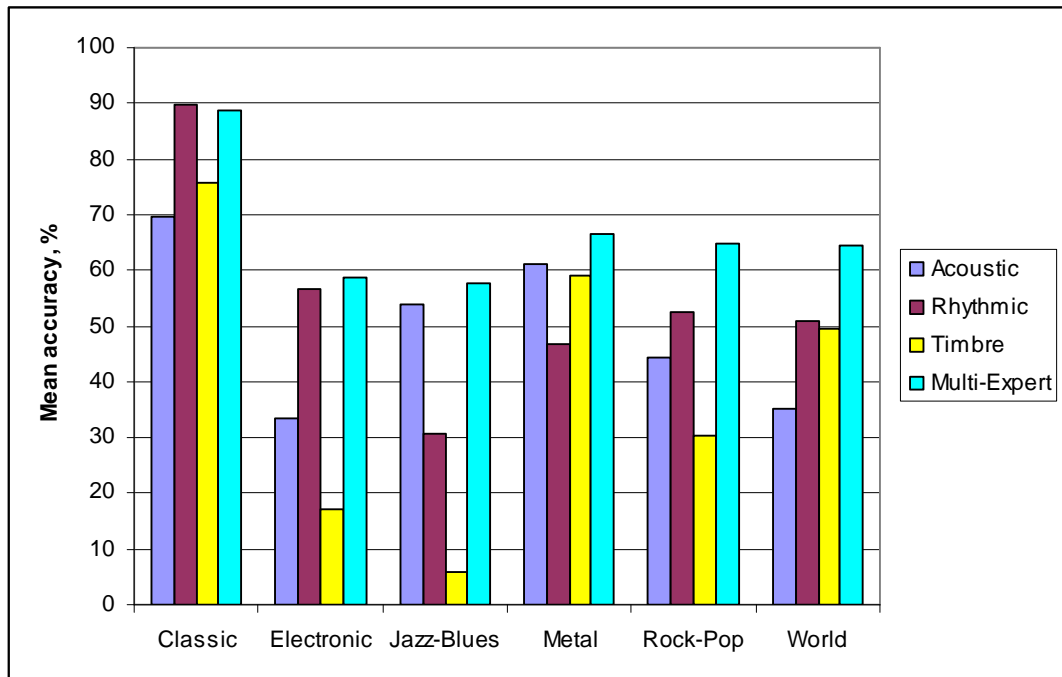
Experimental results and final comparison can be summarized by the following figures. Figure 6.4 depicts a comparison of classification accuracies of separate classifiers and their multi-expert combination for both databases.



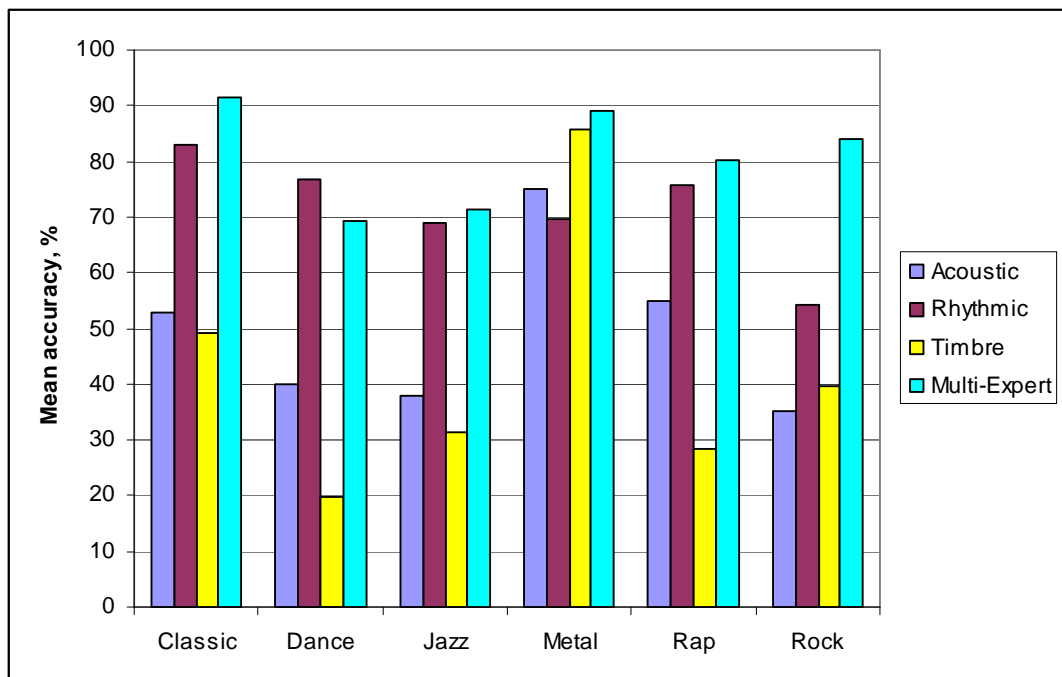
**Figure 6.4.** Comparison of classification results issued by different classifiers and their multi-expert combination for both databases.

All classifiers behave quite similarly in the case of both databases except the rhythmic classifier which performed better on the ECL database. In both cases there is a significant increase of classification rates with combined experts.

The next two figures (Figure 6.5 and Figure 6.6) show performances of separate classifiers and their combinations for both databases according to genre.



**Figure 6.5.** Performance of separate classifiers and their combination according to genre in the case of Magnatune database.

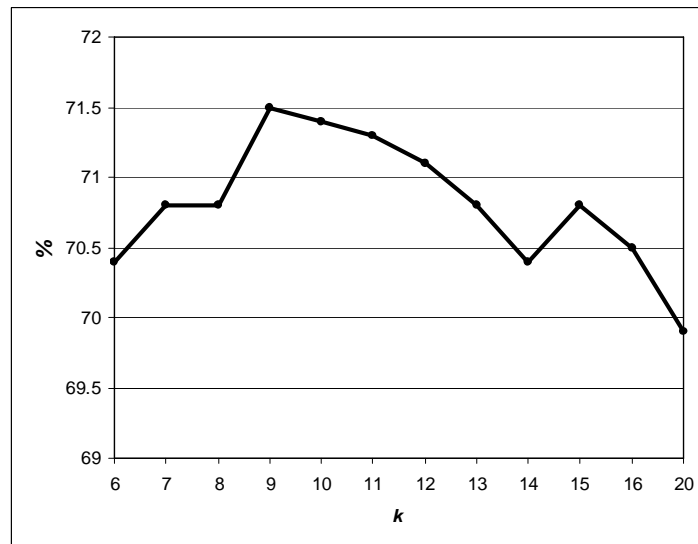


**Figure 6.6.** Performance of separate classifiers and their combination according to genre in the case of ECL database.

Generally a superiority of Multi-Expert classification results is observed for majority of classes except two cases – Classic of Magnatune database and Dance of ECL database. It can be explained by a tendency of the Multi-Expert configuration to average per-class accuracies together with high Dance-to-Rock confusion in the second case.

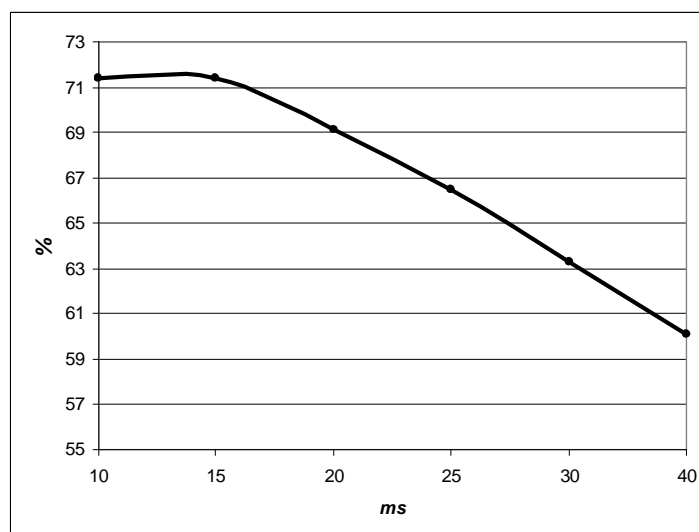
#### 6.1.4.4 Discussion

In the previous experiments, some parameters need to be tuned in order to achieve the best genre classification accuracy. Using the ECL music genres dataset and the rhythmic similarity measure, we studied the impact of two particular parameters on the classification accuracy, namely  $k$  in the  $k$ -NN classifier and window moving step in beat detection algorithm. Figure 6.7 illustrates the classification accuracy curve using different  $k$  values. As we can see, the best classification accuracy was achieved with  $k=9$ .



**Figure 6.7.** Dependency of the classification accuracy from the size of cluster in the  $k$ -NN.

On the other hand, when studying the size of shifting window, we can see from Figure 6.8 that the best classification rate was obtained for the shift equal to 15 ms and further increased shift size almost linearly decreases the classification performance.



**Figure 6.8.** Dependency of the classification accuracy from the window shift in beat detection algorithm.



However, these experimental results can be considered as very primary ones showing utility of music based features in music genre classification in complement to pure acoustic based features. Several directions need to be further investigated. Indeed, while simple k-NN classifiers are used in these experiments, one can also consider some other popular classifier such as SVM, neural networks and Bayesian classifiers, etc. which may display better classification accuracy when using appropriate learning scheme. Moreover, we also need to deepen the study on the fusion strategy. In the previous experiments, the outputs of single classifiers are fused by a neural network into a global classifier. However, other fusion strategies might give better results.

## **6.2. Music search by similarity**

Search for music by similarity is an interesting but difficult direction of the music information retrieval research. It is at the heart of such applications as intelligent music navigation automatic playlist composition, music recommendation and others.

### **6.2.1. The problem**

Unfortunately, music similarity is rather subjective and personal according to cultural background. Precise definition of music similarity is thus impossible. Unlike well-defined task with ground truth data, such as for example automatic classification of audio signal, the task of intelligent playlist composition by musical similarity lacks for the reliable ground truth. Therefore, construction of 100% ground-truth data cannot be possible.

However, several attempts on evaluating the musical similarity algorithms have been made. In their work on artist similarity [ELLI 02] authors have constructed ground-truth data by artist survey. Visitors of their web site were proposed to find similar artist for a given one. Authors in another work [PAMP 03] have used statistical information such as ration between average distance between all musical pieces and average distance in groups (artist, genre, album, etc.). In that way a large-scale evaluation was performed without involving listening tests. MIREX evaluation contest<sup>1</sup> uses listening test together with statistical information analysis in order to evaluate various musical similarity retrieval algorithms.

In our work we based our evaluation on listening tests and analysis of statistical information. Reinterpreted compositions search was also performed and used as an objective evaluation.

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<sup>1</sup> [http://www.music-ir.org/mirex2006/index.php/Audio\\_Music\\_Similarity\\_and\\_Retrieval](http://www.music-ir.org/mirex2006/index.php/Audio_Music_Similarity_and_Retrieval)

### 6.2.2. Principle and architecture of our combination system of similarity measures

While pure similarity metrics could be interesting for exact matching of musical pieces by certain criteria, a combination of similarities have in goal of building “general” similarities like human listener could do (e.g. finding a piece with the same rhythm and key type could issue two slow sad melodies which are judged similar by a human listener).

In the case of genre classification tests, the final combination was done by multi-expert system where the combining system was operating on class probabilities. In the case of similarity search, distances must be fused in order to get the overall similarity score including various aspects.

- **Fusing similarities by a Linear combination**

To combine 4 distances (rhythmic, tonality, timbre and note succession) obtained with algorithms described in Chapters 4 and 5, we use a liner combination which is used in many other works.

$$D = \sum k_i d_i \tag{6.2}$$

Alternatively, in the case when source distances have incongruous physical nature another version of liner combining could be applied - a weighted sum of ratings where for every kind of similarity being combined its rating or position in a sorted list of similar titles is obtained. Final distance is computed as a weighted sum of ratings. In our experiments, these two kinds of linear combination are studied and compared.

- **Fusing Similarities by a Multi-layer perceptron**

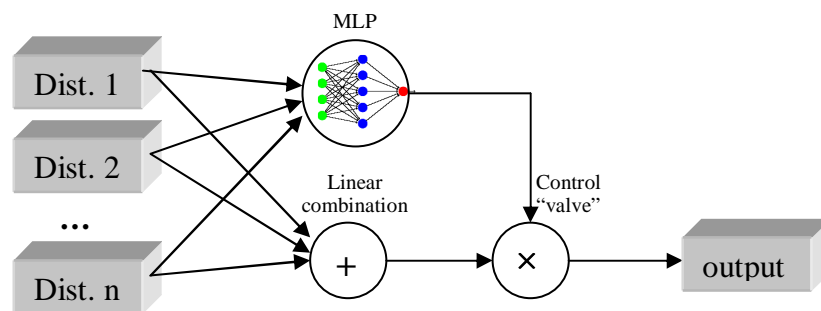
These methods are non-linear methods which involve a neuron network trained on user feedback data. The choice of MLP is motivated by its relative simplicity and ability to approximate multi-variable functions. In our case the target function is a function of 4 distances described in previous paragraphs between any couple of music excerpts and the target values are similarity ratings (from 0 to 1) provided by listeners.

The MLP used in our work had 4 input neurons (the number of input variables) and 4 neurons in hidden layer. Training and testing sets consisted of approximately 800 listeners’ votes. Training of the MLP was performed in two ways:

- 1) direct training with target values of listeners’ votes;
- 2) threshold training when listeners’ votes on similarity were divided into two category – similar ( $\geq 0.5$ ) and non-similar ( $< 0.5$ ) and target values for the MLP were 1 and 0 correspondingly.

In both cases a difference in classification results on the testing set was not statistically significant. The total error rate in both cases was around 20%. Further increase of number of neurons in hidden layer provoked instabilities in classification of the testing set and led to increasing classification errors.

The disadvantage of the MLP combining is its observed irregularity. Songs can hardly be sorted upon similarity measurement issued by the neural network having high error rate. In order to overcome this problem we propose to use multi-cascade system where the linear similarity measurement is controlled by MLP. The principle is the following: similar songs are searched using linear combination of distances and the final list is filtered by an MLP which drops all non-similar songs according to its decision. In this case thresholds of decision-making must be adjusted to have minimal false rejection rate. The principle of such architecture is depicted on Figure 6.9.



**Figure 6.9.** Architecture of the combining system with linear distance combination controlled by neuron network.

## 6.2.3. Experimental results

### 6.2.3.1 Evaluation method

We carried out preliminary experiments on musical similarity search. They consisted of three evaluation parts – listening test, statistical analysis and reinterpreted pieces search.

A database of approximately 1000 musical compositions of different artists, genres and rhythms has been collected. It was taken from private collections of music and contained musical pieces of various genres and different languages. The crucial point is to ensure existence of various close groups of music within the dataset. A small database containing musical pieces which are too different may result in unreliable evaluation results due to an absence of similar music excerpts. For this purpose the Magnatune database could be used.

The evaluation proceeds as follows. For each type of similarity metric (rhythmic, tonality, timbre and melodic) a similarity matrix 1000x1000 has been computed. Then the system retrieved 5 most similar songs from the

database for a given example by different combinations of similarity metrics. People from our laboratory and third-party people (men and women, not necessarily working with music) were asked as listeners. A dedicated website was build which enables listeners to rate queries from the database with scores from 0 (not similar) to 5 (very similar) according to similarity type shown (for example, in the case of similarity by tonality, listeners had to indicate if tonalities (tonality modes) of proposed songs were sounding similar or not). Neither songs' titles nor artist names were provided to listeners. Also with a probability of 50% listeners were provided with random and not similar music pieces and listeners were not notified of this fact in order to avoid prejudgments. Listeners had to rate the similarity for those random propositions as they were retrieved by true similarity algorithm. Further comparing of vote distributions of both true and random similarities allows to rate the quality of search algorithms. The result is supposed to be reliable since such evaluation technique cannot be "tricked".

In our experiments we have used 4 pure similarity metrics: rhythmic, tonality, timbre and melodic; and 4 mixtures where **comb1** was a combination of tonality and rhythm metrics, **comb2** – timbre and rhythm, **comb3** – tonality + melody + rhythm, **comb4** – timbre + melody + rhythm. For the mentioned mixtures two types of combinations were applied. They are: linear combination and combination by rating. We didn't use a linear combination of all 4 distances because it is quite difficult to say in advance if mixing coefficients should be equal for all distances or not since these 4 distance have different nature. In the case of Multi-layer perceptron combination all 4 similarity measures were used.

While the previous experiment is rather a subjective evaluation, the following ones are objective evaluations. Our second evaluation is reinterpreted pieces search. The aim of this experiment was the evaluation of melodic similarity measures. The test was based on composing of similarity playlists for musical titles that have multiple reinterpretations. For this purpose we have injected several musical pieces with multiple representations. The following reinterpreted pieces are included into the dataset.

1. Ennio Morricone – "Chi Mai", 3 interpretations
2. Roxette – "Listen to Your Heart", DHT – "Listen to Your Heart", DHT – "Listen to Your Heart" (dance)
3. Rednex – "Wish You Were Here", Blackmore's Night – "Wish You Were Here"
4. Tatu – "Not Gonna Get Us" (Eng), Tatu – "Nas Ne Dogonyat" (Rus)
5. Tatu – "All the Things She Said" (Eng), Tatu – "Ya Soshla s Uma" (Rus), Tatu – Remix
6. Tatu – "30 minutes" (Eng), Tatu – "Pol Chasa" (Rus)
7. Archie Shep, Benny Golson, Dexter Gordon, Mike Nock Trio, Ray Brown Trio – "Cry Me a River" (ver.1 jazz instrumental)
8. Diana Krall, Tania Maria, Linda Ronstadt, Bjork, Etta James, July London – "Cry Me a River" (ver. 2. vocal)

In this experiment the different interpretations of the same title are considered as “similar”. Playlists with 30 similar titles corresponding to each musical title from the list above were built. Appearance of “a priori” similar titles at the top of playlist was considered as successful similarity output.

Finally as a third evaluation of our similarity system, we proceeded on analysis of relevance of top 5 songs in playlists. We considered two types of relevance: number of songs from the same genre and number of songs from the same artists. As the database we took the ISMIR2004 genre classification database based on *Magnatune* collection since musical pieces are classified by genres and there is no high variability in artist. The database contains totally 729 titles of 128 artists in 6 genres.

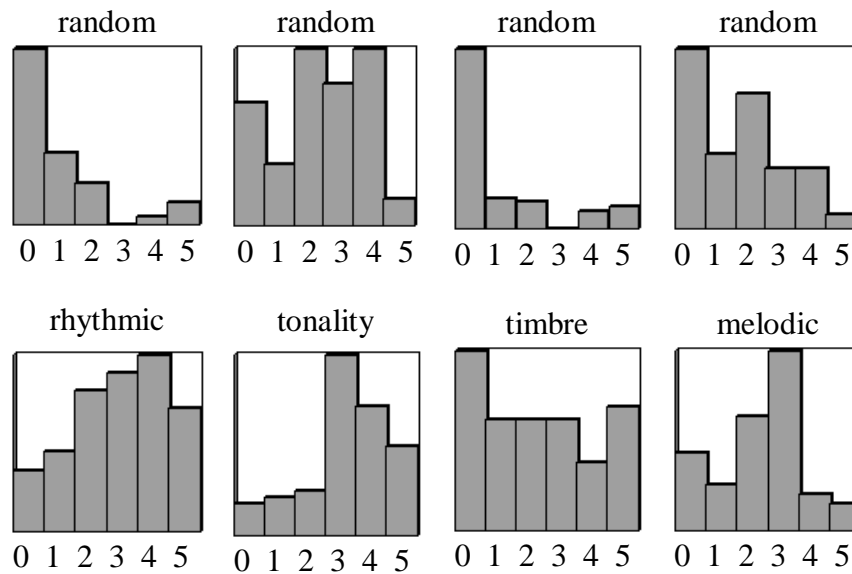
### 6.2.3.2 Listening test evaluation

Evaluation results obtained in our listening test experiments are presented in the Table 6.13. Here for each similarity type there is mean and median value of totality of votes. The column “corresponding random” shows the mean and median of listeners’ votes for those cases when listeners were proposed random songs as similar. Since listeners were not notified about this fact, they still had to evaluate how similar were the proposed songs. These data are used as background un-truth. All found multiple interpretations of songs were not filtered out and considered as 5 – very similar.

**Table 6.13.** Listening test results (mean / median).

Similarity type	Linear combination or single	Rating combination	Corresponding random
rhythmic	2.92 / 2	n/a	0.40 / 0
tonality	3.16 / 3		2.41 / 3
timbre	2.16 / 2		0.81 / 0
melodic	2.23 / 2		1.60 / 2
comb1	3.55 / 4	2.06 / 3	0.94 / 1
comb2	2.78 / 3	3.75 / 4	0.97 / 0
comb3	3.85 / 5	1.80 / 1	0.75 / 0
comb4	2.49 / 3	2.26 / 3	1.01 / 0

Figure 6.10 shows normalized distributions of votes for mentioned single similarity metrics. The upper histograms stand for distributions of votes for “random” similar songs.

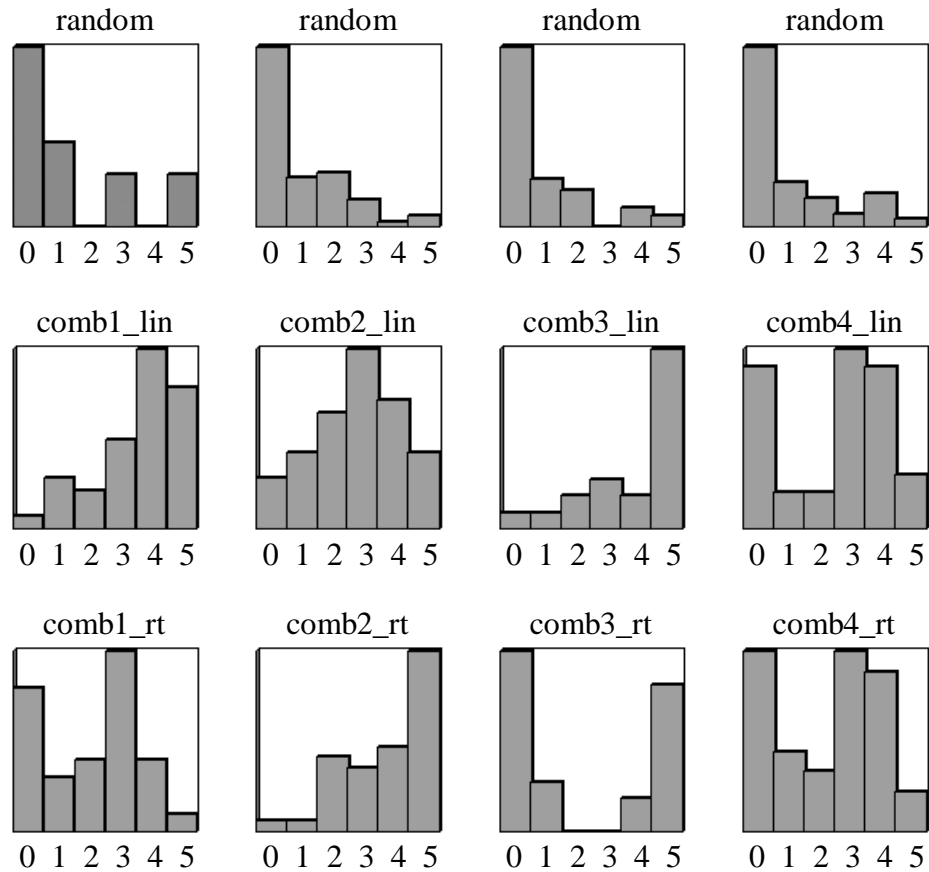


**Figure 6.10.** Histograms of listeners' votes for pure similarity metrics. The upper row contains histograms of votes for corresponding randoms.

Notice, that in the case of random similarity generation all histograms are different. It means that the notion of similar tonality class is not evident for all listeners. In addition, the mean error in the case of random should be around 50% since there are only two modes of tonalities – minor / major. The difference in melodic similarity voting against corresponding random is not significant which makes not evident the immediate judgment of its performance. Some of similarity measures perform quite well as for example rhythmic one.

Examining true similarity votes' histogram one can observe an evident positive bias on average vote. It is also evident for the tonality case.

On the next figure normalized histograms of votes for composite similarities are depicted. Here the upper row is showing histograms of votes for random songs. Two other rows include results for linear (lin) and rating (rt) combinations. Figure 6.11 shows vote histograms for MLP combinations. Here **comb1** is the combination of tonality and rhythm metrics, **comb2** – timbre and rhythm, **comb3** – tonality + melody + rhythm, **comb4** – timbre + melody + rhythm.



**Figure 6.11.** Histograms of listeners' votes for linearly and rating combined similarity metrics.

Considering the Figure 6.11 the following conclusion can be made:

- There is a remarkable positive bias of votes in the case of combined (we can call them general or true) similarities, which is in fact higher than in the case of pure similarity measures. This can be seen by comparing `comb3_lin` versus pure rhythmic similarity rating histograms.
- Certain instability of results according to the type of combination is observed
- The hypothesis that the combination of various similarity types by its rating in generated sub-playlists could be better adapted for measures of different nature did not find confirmation (except the case of `comb2` combination)
- In some cases of similarity combination as for instance `comb3_rt`, `comb4_rt`, a big number of completely dissimilar (voted as completely unsimilar) songs in resulting playlists were observed in comparison to pure similarity measures where this fact only presents in timbre similarity. This can be an evidence of nonapplicability of linear or rating combinations of various similarity types. Example: two musical

pieces close in the meaning of tonality of melodic passages may have a certain difference in their rhythmic structure. Since one of similarity measures issues very low value of distance, the second similarity measure may not bring any significant dissimilarity. So, the pair of songs is considered to be close to each other. However, a human listener may not pay attention to the melodic aspect of similarity, but to be attached only to the rhythmic aspect (which is in fact has closer relation with genre of music). As the result, the vote provided by the listener is considerably low.

- It can be declared, that the best two combinations for this particular dataset are `comb3_lin` and `comb2_rt`. The first case is a linear combination of rhythmic, tonal and melodic distances; the second case is a rating combination of rhythmic similarity and similarity by timbre. This can be explained by instability of combination of timbre similarity measure with all other measures.

Two other similarity fusing configurations are also experimented. The first one consists of using a MLP for a non linear combination of similarity measures. The second configuration is the one with the neuron network used as an agent for ensuring quality of similarity measure from the best linear combination `Comb3` previously studied, i.e. outputs from the linear combination `Comb3`, thus using tonality, melody and rhythm similarity measures, are further controlled by a MLP discarding dissimilar music excerpts. Table 6.14 shows votes distributions for multi-cascade configuration and a single MLP. As we can see, no big statistical difference in results was observed for these two configurations.

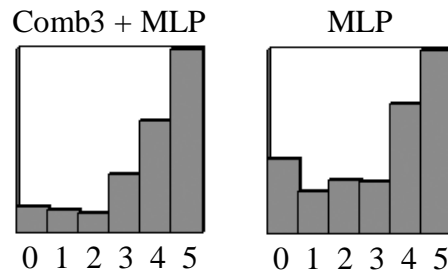
**Table 6.14.** Listening test results for MLP combinations.

Combination Type	Score
Comb3 + MLP	3.80 / 4
MLP	3.25 / 4

The decrease of the average similarity search quality in the case of pure MLP can be an evidence of a lack of statistical training data which makes the neuron network to behave in an unstable manner. The second source of instability is the subjectivity of listener's votes. Having multiple listeners voted differently for the same titles in the same playlist leads to ambiguities in training data.

Histograms of votes' distributions are depicted on Figure 6.12.





**Figure 6.12.** Histograms of listeners' votes for MLP combined similarities.

The configuration with neuron network as a quality agent controlling the output of linear combination is more preferable in comparison to the single NN mixing agent.

### 6.2.3.3 Objective evaluation

In the objective evaluation experiment performed we have generated 30-title playlists for each musical piece in the database. Appearance of “a priori” similar titles (see §6.2.3.1 for the list) at the top of playlist was considered as successful similarity output. The following Table 6.15 shows the result of playlist composition. It gives the information about position of appearance of similar titles in the associated playlist (1 – is the original music file at the top of playlist).

**Table 6.15.** Objective evaluation results of music comb3\_lin similarity measurement.

Original music composition	Positions of appearance of similar titles
Chi Mai	(1), 2, 3
Listen To Your Heart	(1), 3, 12
Wish You Were Here	(1), 2
Not Gonna Get Us	(1), 2
All the Things She Said	(1), 2, 3
30 minutes	(1), 2
Cry Me a River (ver. 1)	(1), 2, 3, 4, 6
Cry Me a River (ver. 2)	(1), 2, 4, 7, 8, n/a (not appeared)

As we can see from the table, all interpretation of songs are taking first positions in corresponding playlists regardless of the fact that some of song groups had quite distant versions like dance versions (Listen To Your Heart), or different artist and instrumentation (Wish You Were Here, Cry Me a River).

The second part of the objective evaluation consisted of playlist relevance analysis. For that purpose we proceeded on analysis of relevance of top 5 songs in playlists generated for seed songs. We considered two types of relevance: number of songs from the same genre and number of songs from

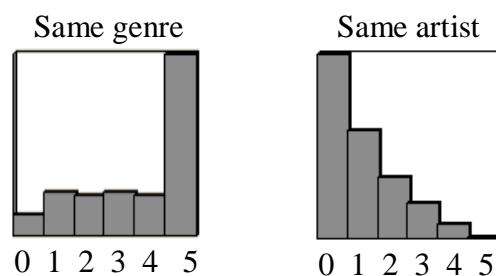
the same artists. For the database we took ISMIR2004 genre classification database based on *Magnatune* collection. The database contained totally 729 titles of 128 artists in 6 genres.

The obtained results are as following (Table 6.16).

**Table 6.16.** Average number songs in the same genre or from the same artist.

Similarity type	Same genre	Same artist
Comb2_lin	3.58	0.99
Comb2_rt	3.48	0.89
Comb3_lin	3.07	0.86

The next picture (Figure 6.13) depicts distribution histograms of number of songs in the same genre and from the same artist for the best combination which in this case is *comb2\_lin*.



**Figure 6.13.** Histogram of number of songs in the same genre in TOP-5 (left), and histogram of number of songs from the same artist in (TOP-5) (right).

Results of relevance analysis reported in literatures includes such numbers as average 1.43 songs in TOP-5 with the same genre as the query [AUCO 02], average 3.44 of similar genres and 1.17 of similar artist [LOG 01]. A result obtained from the same ISMIR'2004 database found in literature is an average 3.4 songs (67.9%) in TOP-5 with the same genre [POHL 06].

#### 6.2.3.4 MIREX2007 Audio Music Similarity and Retrieval

Having 7000 30-second audio clips drawn from 10 genres (700 clips from each genre) the MIREX evaluation contest<sup>1</sup> has run the audio music similarity and retrieval evaluation among the other MIR tasks. Two distinct evaluations were performed

- Human Evaluation
- Objective statistics derived from the results lists

<sup>1</sup> [http://www.music-ir.org/mirex2007/index.php/Main\\_Page](http://www.music-ir.org/mirex2007/index.php/Main_Page)

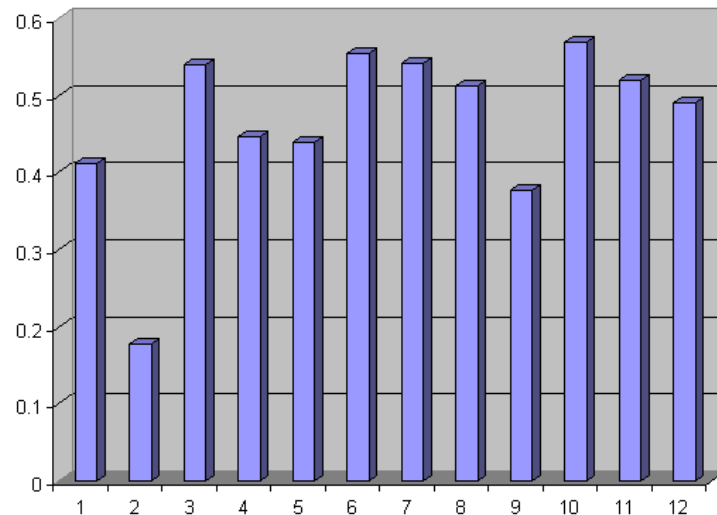
The primary evaluation involved subjective judgments by human evaluators of the retrieved sets. Given a search based on randomly selected queries, sets of results returned by all systems were provided to listeners. They had to rate the results by one of three classes (not similar, somewhat similar, very similar) and provide an indication on a continuous scale of 0 - 10 measuring how similar the track is to the query. The songs by the same artist as the query were filtered out of each result list (artist-filtering) to avoid colouring an evaluator's judgment.

The second evaluation was the objective statistics derived from the distance matrix which is:

- Average % of Genre, Artist and Album matches in the top 5, 10, 20 & 50 results - Precision at 5, 10, 20 & 50
- Average % of Genre matches in the top 5, 10, 20 & 50 results after artist filtering of results
- Average % of available Genre, Artist and Album matches in the top 5, 10, 20 & 50 results - Recall at 5, 10, 20 & 50 (just normalizing scores when less than 20 matches for an artist, album or genre are available in the database)
- Always similar - Maximum # times a file was in the top 5, 10, 20 & 50 results
- % File never similar (never in a top 5, 10, 20 & 50 result list)
- % of 'test-able' song triplets where triangular inequality holds

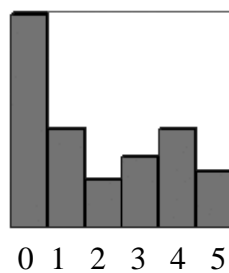
The algorithm we have submitted to the MIREX evaluation intended to be linear combination similarity algorithm. Due to a pity mistake, the mixing matrix combining various similarity measures was defined incorrectly and only rhythmical distance was taken into account. That made the submitted system to be pure rhythmic similarity system.

The final subjective judgment results are provided on Figure 6.14 where the system #9 is the system we have presented.



**Figure 6.14.** MIREX 2007 Audio Music Similarity and Retrieval subjective evaluation results (x-axis – team number, y-axis – average vote divided by 10).

The histogram of listeners' votes expanded to fit 5-level scale as we used in our work is given on the Figure 6.15



**Figure 6.15.** Histogram of listeners' votes resulted by our system at MIREX contest.

The experiment shows that rhythmic similarity plays an important role in global music similarity. However, the both experiments (see also §6.2.3.2) prove that perceptual similarity is not limited to rhythmic similarity.

Another observation was made from the MIREX results. For certain genres the rhythmic similarity was more important than for other genres. These genres are for example Jazz/Blues and Country. The complete ratings by genre of algorithms presented at MIREX are given on the Figure 6.16.

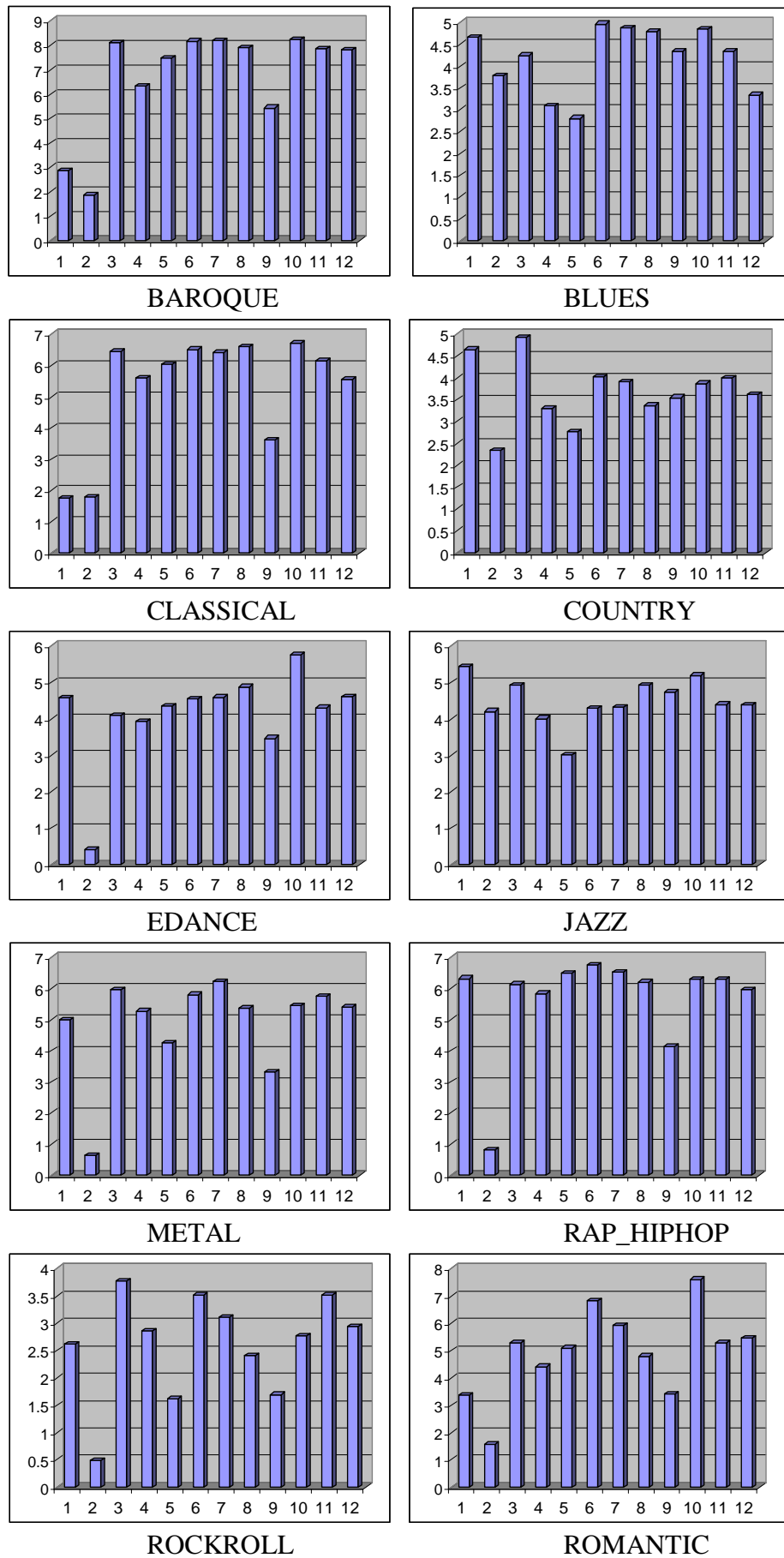
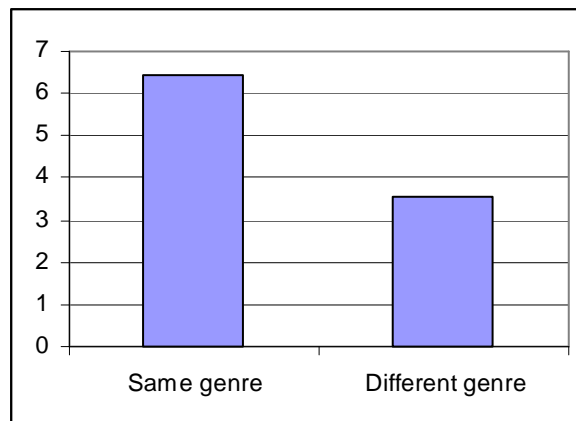


Figure 6.16. MIREX similarity contest result distribution by genres.

We have analyzed the correlation between equality of genres of query and retrieved samples and users votes. The average of users' votes for those queries which returned a piece of the same genre was 6.42 while the average of votes for non-similar genres was 3.55 (Figure 6.17).



**Figure 6.17.** Average vote for query and result of the same or of different genres.

According to our observation (6000 queries from all algorithms have been analyzed), the correlation between genre and similarity is quite strong, but the average of votes for non-similar genres in query/result pairs is high enough to conclude that the perceptual similarity is not only limited to similarity of genre.

#### 6.2.3.5 Discussion

The problem of “hubs” described in numerous works [AUCO 04; PAMP 06a] was also analyzed for the proposed similarity metrics. A hub is a song which appears to be similar to a large number of other songs. In the results obtained by our similarity combination algorithm no extreme hubs were observed. The following Table 6.17 presents the maximum number of appearances of a song in TOP-5 rankings of all other songs showing the issue of “hubs” non critical for our similarity measurements.

**Table 6.17.** Maximum number of appearances of a song in top-5 rankings

Similarity metric	Rhythmic	Tonality	Timbre	Melodic
<b>Number of appearances</b>	24	19	124	101
Similarity metric	Comb1	Comb2	Comb3	Comb4
<b>Number of appearances</b>	25	41	39	66

Maximum number of song appearance reported at MIREX'06 was 24 to 61 [PAMP 06a], one irregular result of 1753 appearances was also reported for one of algorithms indicating the presence of hubs.

### **6.3. Conclusions**

In this chapter we have described two direct applications of music features and the associated similarity measures. The first application consisted of automatically classifying songs by genres. We have shown that single application of acoustic similarity or musical similarity features issues quite low classification accuracies while combination of both approaches leads to a significant gain of classification performance.

The second application – music search by similarity was based solely on musical similarity features. The evaluation we have carried out consisted of subjective judgment (human feedback) and objective evaluation such as relevance analysis. Objective evaluation showed quite good, but unstable results while using linear or rating combination of similarity measure. We have found also the best two combinations which were combinations of rhythm/tonality/melody and rhythm/timbre. A surprising result was observed when putting timbre similarity measure instead of tonality in the first combination. However, putting all distances together in a neuron-network combination mechanism showed stable results but not higher than in the case of linear combinations.

The objective analysis of similarity retrieval algorithm have shown very good similar genre rate – 3.58 against the best rate found in literature 3.4 in TOP-5 playlists analysis based on the ISMIR'04 corpus. Promising results were also achieved in search for pieces with multiple interpretations.

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## **Conclusions and Outlook**

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## 7. Conclusions and outlook

In this thesis we have touched upon the question of automatic music analysis within such music information retrieval applications as music search by similarity (intelligent navigation) and automatic genre classification. We have started in the Chapter 3 by defining an appropriate tool of musical signal analysis. In this chapter we presented the *variable resolution transform* as a tool which better suited for such applications from our point of view. The goal we had is to obtain a single transform which can cover at one time the time-frequency scale in a way allowing catching pitch and rhythm information at the same time. The advantage of the tool we have proposed is that it has logarithmic frequency sampling in order to follow musical notes, but in comparison to classical approaches where the frequency sampling is also logarithmic, we improved frequency resolution in high frequency area to distinguish better high-order harmonics of the signal.

Starting from Chapter 4 questions of music similarity measures were discussed. In Chapter 4 we have presented and described an algorithm of beat and strong note onset detection based on the VRT and image treatment technique. In comparison to classical resonator-based or autocorrelation-based approaches, our algorithm is destined to detect any kind of beats with or without periodicities. Extracted beat information served to construct a rhythmic similarity measure in a form of 2D beat histograms allowing their direct comparison as well as tempo induction.

In the next chapter we have described an algorithm of multiple  $f_0$  estimation based on the VR Transform. As majority of classical approaches this algorithm was based on harmonic pattern matching. Our contribution in this case is an application of note-adapted variable resolution transform. An evaluation of the aforementioned algorithm was performed on wavetable synthesized musical signals. The chapter is also discussing aspects of musical similarity. For this purpose various  $f_0$ -estimation derived or melodic features such as note succession histogram, note profile or timbre histogram were proposed.

Direct applications of musical similarity features and estimation of their performance is presented in Chapter 6. It was proved in the case of automatic genre classification that combining of musical and spectral similarity features leads to a considerable performance gain. The objective of the second application was an automatic construction of similar music playlists. The algorithms were based only on musical features and were evaluated by human feedback.

Techniques we have described in the thesis are mostly ready to be implemented and deployed in real-life applications. Music similarity search produces acceptable results and can be integrated in online music stores or

media players. However, the work opens a large number of scientific questions. Of course, the first research direction is improvement of musical similarity features as well as methods of their combination. For instance, the kNN classifier we applied in the problem of genre classification is very content-dependent and requires training data to be available all the time. Another disadvantage of the kNN classifier is its increasing complexity with increasing training data set size. Thus, an important direction for future work is to employ other type of classifiers which are able to produce better and more stable results. This concerns also the use of neuron network in combining of different experts in both genre classification and music similarity problem. A direction of stochastic approaches is a promising one in all kind of algorithms we have presented.

Improving the musical features may require such algorithms as automatic instrument recognition which we didn't touch in our work.

Another question remaining open is the invention of truly efficient transcription algorithms working well with all kinds of music. As a subject of future work we can envisage development of musical object detection-based approaches which would enable high semantic modeling and analysis, like it is done in image and video processing.

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