CONTINUOUS WAVELET-LIKE TRANSFORM BASED MUSIC SIMILARITY FEATURES FOR INTELLIGENT MUSIC NAVIGATION

Aliaksandr Paradzinets¹, Oleg Kotov², Hadi Harb³, Liming Chen⁴

Ecole Centrale de Lyon
Département MathInfo
{¹aliaksandr.paradzinets,³hadi.harb,⁴liming.chen}@ec-lyon.fr, ²elfsoft@tut.by

ABSTRACT
Intelligent music navigation is one of the important tasks in today’s music applications. In this context we propose several high-level musical similarity features that can be used in automatic music navigation, classification and recommendation. The features we propose use Continuous Wavelet-like Transform as a basic time-frequency analysis of a musical signal due to its flexibility in time-frequency resolutions. A novel 2D beat histogram is presented in the paper as a rhythmic similarity feature which is free from dependency on recording condition and does not require sophisticated adaptive algorithms of threshold finding in beat detection. This paper also describes a CWT based algorithm of multiple F0 estimation (note detection) and corresponding melodic similarity features. Evaluation of the both similarity measures is done in automatic genre classification context and playlist composition.

1. INTRODUCTION
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. Also, 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 music discovery for the geeks, to the simple seed song playlist generation of similar items.

In this context we present in this paper different similarity measures capturing the rhythmic and the melodic information. The algorithms are evaluated using two similarity experiments: genre classification and reinterpreted compositions search. For all our features we use algorithms based on Continuous Wavelet Transform (CWT).

There are actual works which propose a series of various acoustic measurements to catch the different aspects of perceptive similarity of the music [1][2][3][4]. But the difficulty is always that the perceptive similarity is semantic and holds a good part of subjectivity.

The rhythmic aspect of a music piece may be considered as a crucial component in a perceptive similarity measure. Considering the problem of rhythmic similarity we can refer to the following works. [5] describes a method for describing the rhythm and tempo of music as well as a rhythmic similarity measure based on the beat spectrum. Another work [6] presents the similarity of rhythmical patterns. In the current paper one of acoustic features we propose is a representation of rhythmic image.

Extraction of melodic characteristics is based on automatic approximate transcription. The question of automated music transcription is the question of multiple F0 (pitch) estimation. Being a very difficult problem and being not resolved for the general case it is widely addressed in the literature. Lots of works are dedicated to the monophonic case of pitch detection in singing/speech [7][8]. The polyphonic case is usually considered with a number of limitations like the number of notes played simultaneously or an assumption of instruments involved [9][10]. The general case, for example, CD recordings [11] remains less explored.

2. ACCOUSTIC SIMILARITY FEATURES
The most known acoustic characteristics generally used for audio similarity measures are Mel Frequency Cepstral Coefficients (MFCC). In a previous work [12] we have proposed the use of the statistical distribution of the audio spectrum to build feature vectors in what we call the Piecewise Gaussian Modeling (PGM) features. PGM features constitute an interesting alternative for the MFCC features. In this paper we propose several new acoustic features – 2D beat histogram and note succession histogram. Unlike simple spectral features, these new
measures take into account semantic information such as rhythm, tonality etc.

2.1. Continuous wavelet transform vs. FFT

The Fast Fourier Transform and the Short-Time Fourier Transform have been the traditional techniques in signal analysis for detecting pitches. However, the frequency and time resolution is linear and constant across the frequency scale (Figure 1) while the frequency scale of notes as well as human perception of a sound is logarithmic.

Figure 1. Time-frequency resolution of the Fourier Transform

The rule of calculating the frequencies of notes is well-known. So if we consider a frequency range for different octaves, it is growing as the number of octave is higher. Thus, to cover well with 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 impossible to resolve frequencies of neighboring notes in low octaves.

The Continuous Wavelet Transformation (CWT) was introduced 15 years ago in order to overcome the limited time-frequency localization of the Fourier-Transform (FFT) for non-stationary signals and was found to be suitable in a lot of applications [13]. Unlike the FFT, the Continuous Wavelet Transformation has 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. In that respect it is similar to the human ear which exhibits similar time-frequency resolution characteristics [14].

Also the scale of frequencies can be chosen as logarithmic which fits well for the note analysis. In that case the number of frequency bins is constant for each octave.

In our works an experimental “wavelet-like” function with logarithmic frequency scale was used to follow the musical note system:

$$\psi(x, a^*) = H_{x,m(x^*)} e^{jw(a^*)}$$

where $a^*$ – relative scale of wavelet, $H(x,m)$ – function of Hanning window of length $m$.

$$m(a^*) = L_{max} k_1 e^{-k_2 a^*}$$

$$w(a^*) = L_{max} a^*/L_{min} a^*+1$$

Here $k_1, k_2$ – time resolution factors, $L_{max}$ and $L_{min}$ – range of wavelet absolute scales.

We have chosen this function because it has elements of windowed Fourier transform (with Hanning window) and classical wavelets. The frequency scale here is always logarithmic while the time resolution scale can be adjusted to be from linear to logarithmic. Time/frequency scale of the transform is shown on the Figure 2.

Figure 2. Time-frequency resolution of the Transform used in our work

The use of CWT, however, has a negative point of costly computations.

2.2. Beat detection and rhythmic similarity features

Existing approaches of beat detection can be divided into some sort of general classes, such as signal energy envelope-based, signal autocorrelation-based [15][16], based on a mathematical model of resonators set [17], non-linear resonators [18] etc. In the work [17] there is a comparison of autocorrelation and resonators set approaches in tempo and beat analysis. An approach of beat detection using image treatment techniques is presented in [19].

These methods are aimed to detect periodicities in order to determine the main tempo of the composition (in BPM). However a global view on the rhythmical image or pattern is required. One of such view is the beat histogram, proposed by [20]. Example of application of musical knowledge in the issue of beat tracking is given in [21]. Theoretical aspects of rhythmic similarity issue are mentioned in [22].

The beat/onset detection algorithm being described in this paper is based on Continuous Wavelet-like Transform described in the previous chapter.

An example of the wavelet representation of a musical excerpt is depicted on Figure 4.
Since the information about beats and onsets is assumed to be concentrated in vertical constituent of wavelet spectrogram, an image treatment technique can be applied to mark out all fragments in this “spectral image” connected with beats and onsets.

Usage of image treatment technique has been described in literature by few works. In their work [19] the authors apply edge enhancement filter on the Fast Fourier Transform (FFT) image in the preprocessing phase.

In the current work, preliminary experiments with wavelet spectrum showed good results with the use of Sobel X operator.

The result of an enhancement by Sobel operator is depicted on Figure 5. All beats in that musical excerpt are now clearer.

The enhanced spectrogram \( W^*(t,\text{scale}) \) is treated by calculating a small-windowed sum to obtain one or more beat curve(s) with time resolution of 10 ms.

\[
    c(t) = \sum_{i=0}^{3} \sum_{\text{scale}=0} \sum_{t=0}^{N} W^*(t + i, \text{scale})
\]  

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.

The probable beats are situated in beat curve’s peaks. However, the definition of a threshold for beat detection is problematic. Adaptive and none-adaptive algorithms for peak detection may be unstable. Many weak beats can be missed while some false beats can be detected. Later it is shown how we can overcome this difficulty in a manner which is compatible to our aim: rhythmical music similarity.

We have applied the same technique of image treatment on FFT in order to compare the efficiency of CWT. The following example will show the difference in enhanced spectral image and obtained beat curve.

Enhanced spectral images from FFT and CWT are shown on Figure 6. In the second case, implementation of Continuous Wavelet Transform is showing 100% detection of percussion instrument beats in the test excerpt. This example suggests that the CWT is better suited than the FFT for beat detection.

Recall that our aim is the use of the rhythmical information for music similarity estimation. One of rhythmical information representation is the beat histogram. Beat histograms were presented in [20] and [23]. 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. Further evolution of beat histogram is being investigated and described in the current work.

A classical one-dimensional beat histogram provides some knowledge only 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.

It is evident to be of use to bring some knowledge about the strength of beat periods into the histogram and avoid the dependency from the beat detection algorithm parameters. Thus, a 2D form histogram can be built with a beats period on the X axis and with amplitude (strength) of a beat on the Y axis (Figure 7). The information about beat strength in the proposed histogram is implicit since the histogram is computed upon the threshold used in beat detection. 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 dependency is avoided.

Such histogram can likely be a feature vector for example in genre classification or music matching. The main tempo is easily found from the histogram. In the case of Figure 5 it is equal to 34 “points” (means 340 ms) and in BPM it makes 176 while the strongest peak with 170ms (352 BPM) presents the most probable beat period which is out of usual tempo range. However, for “beat-less” musical pieces like classic or new age without clear beat or onset accents the tempo estimation is not evident.

To prove the independency from recording conditions another set of experiments with beat histogram has been carried out. For this purpose a musical composition has been filtered with treble and bass cut filters. The resulting histograms of beats still had the same forms and peaks. Comparison of histograms showed only 10% of relative difference.

The described rhythmical image representation foresees a resemblance measure of two musical compositions in the meaning of rhythm. As the 2D beat histogram is not affected neither by volume of music nor by conditions of recording (e.g. frequency pass band), it can be used directly in a distance measure.

The measure of rhythmic distance can be defined in numerous was. In our experiments we have found the following equation which takes into account slight variation of rhythm of musical pieces being compared.

\[
\text{Dist}_{H_1,H_2} = \sum_{x_1,y_1} \frac{1}{N,M} \left[ \min \left( H_1(x_1,y_1) - H_2(x_1,y_1) \right) + \min \left( H_1(x_1,y_1) - H_2(x_1,y_1) \right) \right]
\]

where

\( H_1, H_2 \) – beat histograms to compare
\( N, M \) – beat histogram size
\( R \) – an area of the following form

\[
\begin{array}{c|c}
(-2,-1) & (2,-1) \\
(2,1) & (2,1) \\
\end{array}
\]

2.3. Melodic similarity

This chapter covers aspects of melodic similarity measures. Algorithms described in the chapter are based on automated transcription (multiple F0 estimation) of polyphonic music with the use of Continuous Wavelet-like Transform.

Numerous algorithms for F0 estimation (pitch detection) exist in the literature. [11] describes an advanced method PreFEst. Using EM algorithm, it basically estimates the F0 of the most predominant harmonic structure in the input sound mixture; it simultaneously takes into consideration all the possibilities of F0 and peak detection method. Another pitch model based system is presented in [9].

In the paper [10], authors describe a computationally inexpensive scheme of transcribing monophonic and polyphonic music produced from a single instrument. The scheme is based on two steps (track creation and grouping) and uses discrete variable window-size comb-filter together with sharpening filter.

We use a technique inspired by harmonic pitch models. The analysis procedure is divided into two parts (its diagram is shown on Figure 5). The first part consists of
model generation. The model is simply a “fence” of peaks situated at the places where F0 and its harmonics 2*F0, 3*F0… etc. can be found on a CWT spectrogram. Recall that our CWT spectrogram has a logarithmic frequency scale, so the distances between corresponding harmonics on such spectrogram remain constant with the change of absolute value of F0. Only the forms of each peak are changing over the frequency scale due to the change of frequency and time resolution of wavelets. To obtain these forms we are using the CWT applied on sine waveforms with appropriate frequencies.

The shape of the harmonic model—“fence” may be used either flat where all amplitudes are similar for all the harmonics or with raised low harmonics part (ratios 3 2 1.5 1 1 etc… for corresponding harmonics) which actually gives better results in general case. In particular, the shape of the harmonic model can be adjusted to the instrument assumed to be used in the play. In general case such assumption cannot be made.

The second part of the analysis lies in analyzing of input wave signals for transcription. The input signal (16KHz, 16bit PCM) is processed by the CWT which has 1024 bins for frequencies lying in the range of 34-5500Hz every 25 ms. Obtained spectrum slices are analyzed in the following way. The above-mentioned harmonic structure is moved across the frequency scale of the CWT spectrogram slice and the correlation between the model and the spectrogram is computed. The place where the correlation has a maximum value on the spectrogram is assumed to be an F0 candidate. As it is found, the harmonic “fence” is subtracted from the currents slice of the spectrogram with the values on its peaks being taken from the actual values on the spectrogram. The procedure is repeated until no more harmonic-like structures are found in the spectrum (above the certain threshold) or the maximum number of harmonic structures to be searched defined in the algorithm is reached. We limit the maximum number of notes searched to four in our works.

The described algorithm has an advantage of its rapidity and it is working well in detection of multiple pitches with non-integer rates. However, there is a disadvantage of such algorithm. Notes with F0s being in integer rates whose partials intersect are rarely can be completely detected together. At the same time, two notes with a distance of an octave hardly can be separated, because the second note does not bring any new harmonics into the spectrum, but changes the amplitude of existent harmonics of the lower note, so some knowledge of instruments involved in the play might be necessary to resolve the problem.

Another possibility of the search for F0 candidates has been studied. Instead of successive subtractions of dominant harmonic structures found, one can use a local maximums search on the correlation curve. Every peak above a defined threshold is considered as an F0 candidate. Such approach can partly solve the problem of notes with overlapping partials while it generates “phantom” notes in one octave down to the note which actually present. With subtracting algorithm such notes never appear. Finally, all pitch candidates are filtered in time in order to remove any noise notes with duration below a defined threshold.

Further, several melodic similarity measures can be proposed. The simplest way to calculate such distance is to calculate a distance between note profiles (histograms). Note profile (histogram) is computed across the whole musical title and serves for estimation of musical similarity by tonality as well as tonality (musical key) itself.

Tonality in music is a definition of note set used in a piece which is characterized by tonic or key note and mode (e.g. minor, major). Each tonality has its own distribution of notes involved in a play and it can be obtained from the note histogram [24] (Figure 11).

To compare two musical titles in the meaning of tonal similarity we calculate a similarity of two note profiles. These profiles must be either aligned by the detected tonality’s key note (e.g. by Re for D-dur or D-mol) or a maximal similarity across all possible combinations of tonalities must be searched.

Another musical similarity measure studied in the current 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 procedure is note successions histogram calculation is following. First, note extraction over the whole piece is carried out with a step of 320 samples (20ms). Then detected notes are grouped in local note histograms in order to find a dominant note in each grouping window. The size of the grouping window may vary from 100ms to 1 sec. Finally, all loudest notes are extracted from local histograms and their chains are collected in the note successions histogram. The resulting histogram is 3-dimensional histogram where each axe is a note of 3-note chain found in the musical piece being analyzed (Figure 12).

![Note successions histogram example](image)

## 3. EXPERIMENTS

Recall, that that our paper is dedicated to similarity estimation of musical pieces. In developing beat and note detection algorithms we do not aim to achieve 100% accuracy, however experiments on evaluation of the algorithms have been carried out. Our main experiments have in aim an estimation of musical similarity accuracy. They consist of two evaluation parts – subjective and objective.

### 3.1. Subjective evaluation

Preliminary experiments with musical similarity search were carried out. A database of 1000 musical composition of different genres, rhythms and types has been processed. Then series of playlists have been created using following two laws:

- 1st group of playlists: each next composition in playlist is the nearest in the meaning of rhythmical distance to the previous
- 2nd group of playlists: each next composition in playlist is the most distant from the previous.

Comparison of two groups of playlists by a human listener showed resemblance of compositions in the first group and dissemblance in the second. In playlists of the first group classical compositions were mainly put together with other classical compositions, dance music was together with other dance music, slow melodic pieces were near other pieces of such kind and mood.

### 3.2. Objective evaluation

In the case of rhythmical similarity an objective evaluation would be an experiment with genre classification. Notice that a music title from one genre has more probability of being rhythmically similar to another title from the same genre. We have built fro this task a reference database of 1873 musical excerpts containing musical titles of 6 genres from 822 different artists. 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&B, 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 [25] which is a limit for the definition of a 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.

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 [www.shoutcast.com]. The musical segments were captured as 20-seconds records starting from the 50th 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. 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 attribution. Also, in comparison with other databases like [magnatune](https://www.magnatune.com), the current reference database is better balanced in the meaning of representation of classes (~1000 classic vs. ~70 for jazz in the case of [magnatune](https://www.magnatune.com)).

The algorithm of classification by rhythmical analysis is a basic kNN classifier based on the 2D beat histogram and
the rhythmical similarity measure described in this paper. The rhythmical distances between musical files to be classified and musical files from the test set are calculated. The probability of belonging of the file in question to a class (genre) is proportional to the number of files of the same class returned in the top 15. Hence, this is a 15-NN classifier.

The results of the classification using 2D beat histogram are presented in the following table.

Table 1. Genre classification confusion matrix (average 52.7%)

<table>
<thead>
<tr>
<th></th>
<th>Classic</th>
<th>Dance</th>
<th>Jazz</th>
<th>Metal</th>
<th>Rap</th>
<th>Rock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classic</td>
<td>89</td>
<td>5</td>
<td>20</td>
<td>36</td>
<td>8</td>
<td>12</td>
</tr>
<tr>
<td>Dance</td>
<td>0</td>
<td>57</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Jazz</td>
<td>3</td>
<td>12</td>
<td>53</td>
<td>11</td>
<td>22</td>
<td>15</td>
</tr>
<tr>
<td>Metal</td>
<td>6</td>
<td>8</td>
<td>4</td>
<td>31</td>
<td>6</td>
<td>19</td>
</tr>
<tr>
<td>Rap</td>
<td>0</td>
<td>11</td>
<td>13</td>
<td>7</td>
<td>55</td>
<td>20</td>
</tr>
<tr>
<td>Rock</td>
<td>2</td>
<td>7</td>
<td>8</td>
<td>13</td>
<td>4</td>
<td>31</td>
</tr>
</tbody>
</table>

In fact, comparing these results with classification rates, obtained using acoustic features based classifier [26] we got the following confusion matrix and average rate:

Table 2. Genre classification confusion matrix using PGM-MLP (average 49.3%)

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

With the object of an objective comparison of the 2D and 1D beat histograms as well as comparison of FFT and CWT transforms for music classification, a series of experiments with genre classification have been made using the same database and classification algorithm. The use of CWT instead of FFT and proposed 2D instead of 1D beat histogram showed an increase of average classification rates by 8.4% and 3.3% respectively.

Evaluation of melodic similarity measures was based on composing of similarity playlists for musical titles that have multiple reinterpretations. The database of these titles used in this work is a certain number of musical files in MP3 format. The list is as follows.

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”.

In the experiment playlists with 30 similar titles corresponding to each musical title in the database were built. Appearance of “a priori” similar titles at the top of playlist was considered as successful similarity output. The following table 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).

Table 3. Objective evaluation results of music similarity measures.

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

Presence of similar songs in first positions of playlists signifies good performance of given melodic similarity measure. Further combinations of various similarity measures can be helpful in task of intelligent music navigation and recommendation, automatic classification and categorization.

4. CONCLUSION

In this paper we described CWT-based approaches of automated music analysis. Rhythmic and melodic similarity measures have been proposed and evaluated. Brief comparison of proposed CWT-based algorithms with the same algorithms but based on FFT transform showed an important results improvement.

REFERENCES


