Fourier Principles for Emotion-based Human Figure Animation

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Abstract

This paper describes the method for modeling human figure locomotions with emotions. Fourier expansions of experimental data of actual human behaviors serve as a basis from which the method can interpolate or extrapolate the human locomotions. This means, for instance, that transition from a walk to a run is smoothly and realistically performed by the method. Moreover an individual's character or mood, appearing during the human behaviors, is also extracted by the method. For example, the method gets "briskness" from the experimental data for a "normal" walk and a "brisk" walk. Then the "brisk" run is generated by the method, using another Fourier expansion of the measured data of running. The superposition of these human behaviors is shown as an efficient technique for generating rich variations of human locomotions. In addition, step-length, speed, and hip position during the locomotions are also modeled, and then interactively controlled to get a desired animation.

CR Categories and Subject Descriptors: I.3.3 [**Computer Graphics**]: Picture/Image Generation; I.3.7 [**Computer Graphics**]: Three-dimensional Graphics and Realism, Animation; I.6.3 [**Simulation and Modeling**]: Applications

Additional Keywords and Phrases: Human figure animation, Fourier analysis, Emotion

1. Introduction

Human or more generally articulated figure animations have been seen in a variety of application fields including advertising, entertainment, education, and simulation. The primary research goal now to further the animations is providing a system which allows animators to easily and interactively design and get desired movements. Many approaches to this goal are available, including key-framing[8], physics or robotics based methods [1, 3, 6, 11], and space-time control [5]. However many open problems remain and the required reality or complexity of the human animation may be rather different according to its application.

In a general system for articulated figure animations, an articulated body is modeled with a hierarchy of rotational joints each of which may have up to three degrees of freedom. Moreover, motion control of the model is also hierarchically prescribed, such as script-based specifications at the highest level of control and key-framing for joint angles control at the lowest. By the use of higher level control, the system should reduce the user's load of direct specifications for the desired movement [7, 9]. This heavy task would be reducible by introducing into the system a knowledge database about the variety of movements. A basic problem is then how to get and construct the database, which is particularly crucial for describing human behaviors. In other words the problem is how to *model* the behaviors, since we cannot measure all kinds of human behaviors in advance. We also note that human behavior is usually affected by an individual's emotion or character (to some extent), which must therefore be modeled.

In this paper we consider the problem of how to model human behaviors with emotions for the purpose of advertising or entertainment use. Therefore the solution of the problem should allow interactive and real-time control, while providing variations of movements, including cartoon-like exaggerations or expressions. The database of the human behaviors should then be concise and small enough for quick response and for needing limited storage in the computer's memory. In existing methods to tackle the problem, dynamic simulation [3, 11] or procedural models [2, 4] often have been used. However, dynamic simulation techniques require experiments (usually off-line) from the animator to get the desired result, whereas procedural approaches employ trial and error steps for suitable choice of the parameters involved. These inconveniences may occur particularly when animating individualized behaviors (such as with mood, characters or emotions). This is mainly because the existing methods do not directly deal with "emotion" or "mood" appearing with the human behavior. For instance, in making a "brisk" walk with a physics-based approach, if the animator wants to change the degree of briskness of the human model, then he has to adjust the parameters which are physically meaningful but do not directly prescribe nuances of emotion or mood.

The method we propose in this paper is for making "emotion-based" human animations. Characteristics of human behaviors are extracted in the method simply from the empirical data of actual human movements, without any physics-based simulations. Based on the Fourier series expansion of the original measured data, a functional model is defined for generating a rich variation of movements, far from the original. A prototype of the functional model was originally introduced in our former work [10], where the prototype was used only for describing the emotional aspect of human locomotions through the Fourier analysis and synthesis. In making a human figure animation, however, we

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must treat not only the emotional aspect but also the kinematic aspect. Therefore the functional model in this paper is further extended to provide intuitive parameters for simultaneously controlling emotional and kinematic human locomotions, where the kinematic control, for example, prescribe speed and step-length of the human figure model. In addition real-time and interactive control is performed with the functional model and this consequently provides wider variations of human figure animations than previous approaches.

2. Functional Models for Human Locomotions

2.1 Preparation

We first prepare a skeleton model represented with a hierarchical structure of rotational joints. The number of joints of the model and the degrees of freedom depend largely on the desired reality or quality. In this paper we employ a relatively simple model with nineteen joints which are hierarchically defined in Fig. 1. As shown in Fig. 2, each joint then has three degrees of freedom for rotation around x, y and z axes in the local coordinate system at each joint, where the y-axis is in the same direction as the stick direction of the previous joint.

Now we assume that the rotational joint angles $\Theta^m{}_x$, $\Theta^m{}_y$ and $\Theta^m{}_z$ at the m-th joint are measured for all the joints except when m = 8 and 9, with a motion capturing system. The eighth and ninth joint angles' data are not used in our method (see Fig.1(a)), since tiptoe's landing is treated differently than other parts of the body (see **3.1**). The obtained data set of the m-th joint is then of a form like $\{(\Theta^m{}_x(i\Delta t), \Theta^m{}_y(i\Delta t), \Theta^m{}_z(i\Delta t)) \mid i = 1, 2,..., n\}$, where Δt denotes the time interval specified in measuring with the capturing system, and $m \neq 8$ or 9. In addition, we assume that the obtained data set represents an (almost) periodic behavior, such as walking and running.

2.2 Rescaled Fourier Functional Model

Based on the discrete data of the m-th joint angle, let us first construct a functional model with continuous parameter of t, which represents the periodic behavior of the joint angle. In general, however, the period of the functional model is rather hard to estimate from the measured data of the joint angle, since the original data may be "noisy". Then we employ the Fourier series expansion (approximation) of the joint angle as the functional model. For simplicity, hereafter, Θ_m (t) denotes $\Theta^m{}_x$ (t), $\Theta^m{}_y$ (t), or $\Theta^m{}_z$ (t). The period of Θ_m (t) for each m is originally the same value T_Θ, and the Fourier coefficients are obtained with the sample values $\Theta_m(t_p)$, $t_p \in [-T_\Theta/2, T_\Theta/2]$. In practice, however, we can estimate these coefficients, based on the sample values in a larger interval. After rescaling time parameter t, we may suppose that the period of Θ_m (t) is normalized to be 2π . Thus we have the following expressions, which we call a *rescaled Fourier functional model*:

$$\Theta_m (t) = A_{m\,0} + \sum_{n \geq 1} A_{m\,n} \sin(n\,t + \phi_{m\,n}). \quad (1)$$

Similarly, based on the discrete sample data of the joint angles for another periodic behavior, we have

$$\Pi_m (t) = B_{m\,0} + \sum_{n \geq 1} B_{m\,n} \sin(n\,t + \psi_{m\,n}). \quad (2)$$

We use, again by rescaling, Π_m (t) as described in (2), whereas the original period of Π_m (t) may be different from that of Θ_m.

As explained later, the effect of "rescaling" in the above functional models occurs typically when we make a transition animation between two different locomotions, such as "from walking to running".

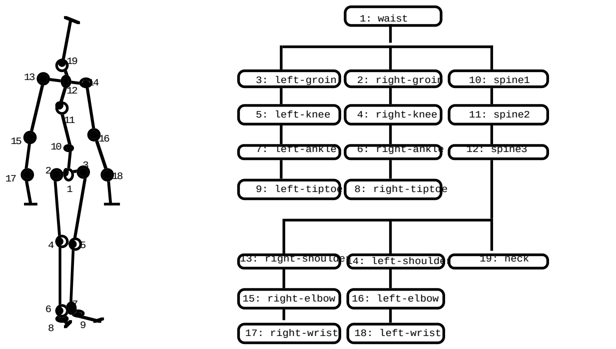
2.3 Interpolation, Extrapolation, and Transition

We show, in this section, how the rescaled Fourier functional models are effectively used in making variations of human behaviors.

Let us consider the following function of two variables s and t:

$$\Xi_m (s, t) = \{(1- s)A_{m\,0} + sB_{m\,0}\} + \sum_{n \geq 1}\{(1- s)A_{m\,0} + sB_{m\,0}\}\sin\{n\,t +(1-s)\phi_{m\,n} + s\psi_{m\,n}\}. \quad (3)$$

In (3), if we suppose that $0 \leq s \leq 1$, Ξ_m is then an interpolant



(a) Rotational joints considered. (b) Connection of human joints.
Figure 1. Skeleton model used.

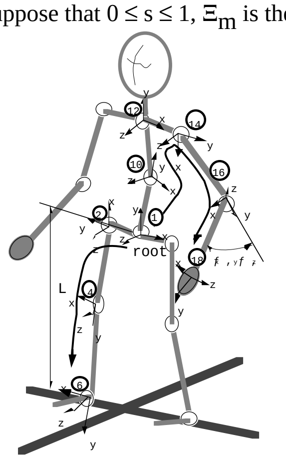


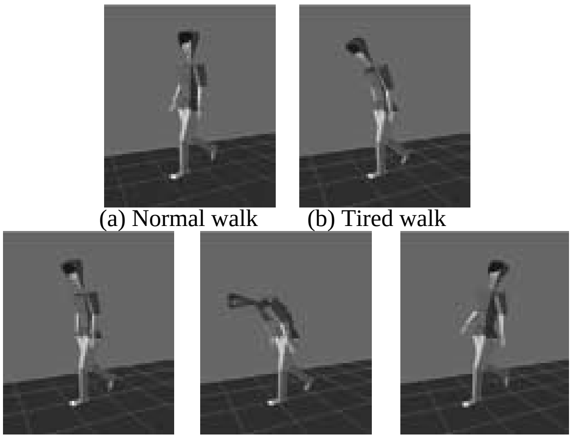
Figure 2. Local coordinate system of the model.

between Θ_m and Π_m in the mathematical sense that, as s varies from 0 to 1, Ξ_m continuously changes from Θ_m to Π_m. Moreover, in the context of human animations, we see that Ξ_m not only interpolates Θ_m and Π_m, but also extrapolates them. This means that the animations obtained from Ξ_m still provide realistically human movements as the interpolant, while expressing exaggerated behaviors as the extrapolant.

Fig. 3 shows an example; $\Theta_m(t)$ (= $\Xi_m(0, t)$) represents a "normal" walk (Fig.3(a)) and $\Pi_m(t)$ (= $\Xi_m(1, t)$) shows a "depressed" or "tired" walk (Fig.3(b)). If $0 < s < 1$, we see "a little tired" walk (Fig.3(c)). If $s > 1$, then we see that the degree of being "tired" is amplified (Fig.3(d)). On the other hand, if s becomes less than 0, the model looks rather brisk (Fig.3(e)). A smooth transition from walk to run is also obtained, if we get $\Pi_m(t)$ from the measured data of a run, with $\Theta_m(t)$ being the above walk function. The interpolant $\Xi_m(s, t)$ $(0 < s < 1)$ then gives the smooth transition.

These examples illustrate well the rescaling effect involved in a rescaled Fourier functional model. For example, if we want to make the transition animation from walking to running by a traditional method, a skilled animator is required to consider many parameters, such as, speed, step, or one locomotion cycle. In particular the original data sets $\{\Theta_m(t)\}$ and $\{\Pi_m(t)\}$ have to be carefully synchronized. This means, for instance, that the arms must reach their furthest swinging position at the same time in both data sets, before making the transition animation. Once we get the "rescaled" Fourier expressions as described in (1) and (2), the synchronization of the data sets are automatically made and the desired animation is easily obtained. Finally we also note that the number of sine functions (n in (1) - (3)) is rather small (our experiments show that n is usually 3, and 7 at most). This implies that human locomotions are characterized with the small number of Fourier coefficients and phases in the Fourier functional model.

We have used Ξ_m (s, t) in (3) as an inter/extrapolant and for making a transition animation, based on the two different measured data. In this case parameter s travels in the frequency-phase domain. An alternative of Ξ_m (s, t) may be defined as $(1- s)\Theta_m(t) + \Pi_m(t)$, where s moves in the joint angle (time) domain. In both cases similar variations of human behaviors may be synthesized as long as we employ the rescaled Fourier functional models.



(a) Normal walk (b) Tired walk

(c) s = 0.5 (d) s = 2.0 (e) s = - 0.5

Figure 3. Interpolation and extrapolation of "tired" walk - (a) and (b) are obtained directly from the measured data sets, while (c) - (e) are by the method.

3. Fourier Characterizations for Human Animation

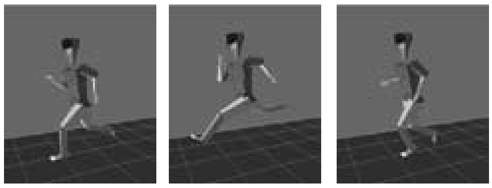
3.1 Step-Constraints Parameters

Next we see that the rescaled Fourier functional model is endowed with the "step-constraints" parameters, which control kinematic aspects of human locomotions: step length, speed, hip position, etc. In the following, italics denote parameters' names appearing on the screen of the prototyping editor (see **3.3**).

Step: The step length is specified in the Fourier domain by adjusting the spectrum component. For example, when using $\Theta_m(t)$ in (1), replace $A_{m\,n}$ by *step*$A_{m\,n}$. Then *step* is controlled. If *step* becomes larger, the step length is longer (Fig. 4).

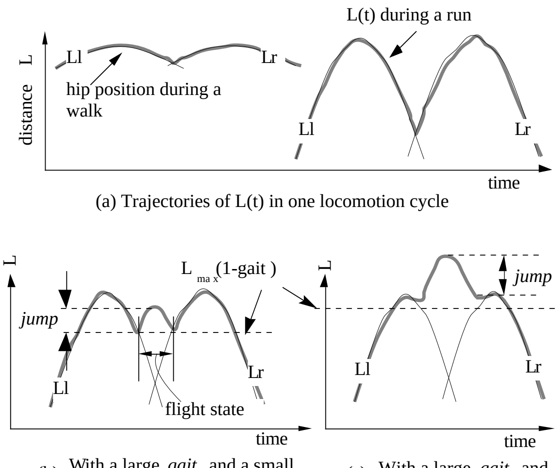
Speed: Time-interval *speed*(= $\Delta\tau$) can be independently specified. Based on the discrete values $\{\Theta_m(k\Delta\tau)\}_k$, the human animation is made. If *speed* tends to 0, then the human model smoothly stops walking.

In particular we note that the above parameter *step* is easily introduced, because of the (rescaled) Fourier expressions of a measured data set.



(a) *Step* = 1.0 (b)*Step* = 1.8 (c) *Step* = 0.5

Figure 4. "Step" effect.



(a) Trajectories of L(t) in one locomotion cycle

(b) With a large *gait* and a small *jump*

(c) With a large *gait* and a small *jump*

Figure 5. Definition of hip position.

The next two parameters, *gait* and *jump*, relate to the hip position. To explain them, we must consider a human walking for a moment. Since one foot is always on the ground during the walk, we may assume that the following function L (t) is equal to the hip position L_{Walk} (t):

$$L(t) = \max(L_l(t), L_r(t)), \quad (4)$$

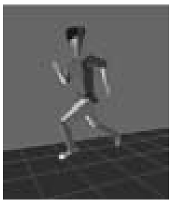
where $L_l(t)$ or $L_r(t)$ means the vertical length of the left or right groin from the ground, respectively. Since locomotion is a periodic activity with a basic pattern of one locomotion stride, we need to observe only one step of the locomotion, as shown in Fig.5(a). Then we consider the case of running, in which L (t) is shown like Fig.5(a), and it does not express the hip position anymore. A run actually involves a flight state. Therefore, to define the hip position L_{Run} (t) in the running case using L (t), we introduce the following parameters:

Gait: The parameter prescribes the time of the flight state, taking values from 0 to 1. At every frame during the animation, the normalized value N(t) is compared with the value of *gait*, where $N(t) = \{L_{max} - L(t)\}/L_{max}$ and $L_{max} = \max_t\{L(t)\}$. If *gait* ≥ N(t), then we set $L_{Run}(t) = L(t)$. Otherwise we define

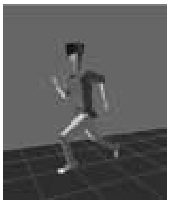
$$L_{Run}(t) = L(t) + jump\sqrt{L_{max} - L(t)}, \quad (5)$$

where *jump* is another parameter described next. Intuitively, if *gait* becomes larger, the running movement looks more like a walk (Fig.6).

Jump: This controls the height during the flight. Figs.5(b) and (c), for example, show typical cases. If *jump* is much larger 1.0, the flight state is rather exaggerated.



(a) *gait* = 0.06



(b) *gait* = 0.5

Figure 6. "Gait" ef fect.

3.2 Superposition of Human Behaviors

In section **2.3**, we showed experimentally that the rescaled Fourier functional models successfully provide smooth transition of two different (measured) human movements. More generally, in this section, *superposition* of the functional models is used as an efficient technique for making emotion-based human figure animations.

Let $\{\Phi^1_m(t)\}$ and $\{\Phi^2_m(t)\}$ be the rescaled Fourier functional models of two different measured data sets:

$$\Phi^1_m(t) = A^1_{m\,0} + \sum_{n \ge 1} A^1_{m\,n} \sin(n\,t + \phi^1_{m\,n}), \quad (6\text{-}1)$$

$$\Phi^2_m(t) = A^2_{m\,0} + \sum_{n \ge 1} A^2_{m\,n} \sin(n\,t + \phi^2_{m\,n}). \quad (6\text{-}2)$$

Then we consider the following differences of the above Fourier coefficients:

$$A^{12}_{mn} = A^1_{m\,n} - A^2_{m\,n}, \quad (7\text{-}1)$$

$$\phi^{12}_{m\,n} = \phi^1_{m\,n} - \phi^2_{m\,n}. \quad (7\text{-}2)$$

The pairs $\{(A^{12}_{m\,n}, \phi^{12}_{m\,n})\}_n$ (n = 0, 1, 2, ...) are called the *Fourier characteristics* of the two measured data sets. As mentioned earlier, we may assume n is in practice rather small. Therefore it is believed that the Fourier characteristics provide a small and concise database of human behaviors. For example we can have the Fourier characteristics of "briskness", which are obtained from the two rescaled Fourier functional models of a normal walk and a "brisk" walk.

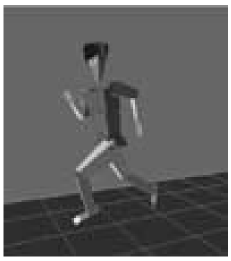
Associated with these Fourier characteristics, we can define the *Fourier characteristic function* as

$$\Psi_m(t) = A^{12}_{m\,0} + \sum_{n \ge 1} A^{12}_{m\,n} \sin(n\,t + \phi^{12}_{m\,n}). \quad (8)$$

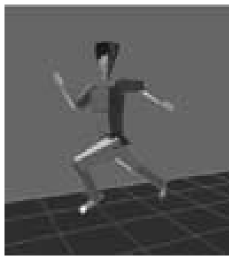
The superposition of human behaviors by our method is then stated as:

Suppose that we have the Fourier characteristic function $\Psi_m(t)$ *in* (8), *and that we have another measured data set with its rescaled Fourier functional model* Π_m (t) *in* (2). *Then,* Ψ_m *and* Π_m *give a rich variation of human behaviors through linear interpolation, extrapolation, and transition, if* Ψ_m *and* Π_m *express mutually meaningful human behaviors*.

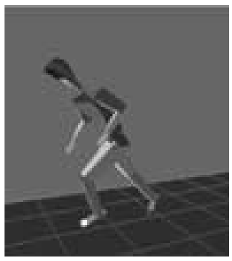
Fig. 7 shows examples of this technique. In this case Π_m (t) in the above statement expresses the running data for Fig. 7(a), while the Fourier characteristic function $\Psi_m(t)$ describes "briskness" which is extracted from the data of a walk and of a "brisk" walk. Then we get a "brisk" run as shown in Fig. 7(b), where we employ $\Xi_m(s, t)$ in (3) for linear transition. Similarly we have a "tired" or "depressed" run from the data of a run and "tiredness" in Fig. 7(c). In this way our experimental results assert that the superposition works well.



(a) a run



(b) a "brisk" run



(c) a "tired" run

Figure 7. Superposition of human behaviors - "briskness" and "tiredness" are extracted from the measured data sets of walking.

Formally, if we assume that $\Phi^2{}_m(t)$ in (8) is identically zero, the techniques described in section **2.3** can be regarded as a special case of the superposition technique. In such a case, the rescaled Fourier functional model of a measured data set simply equals its Fourier characteristic function.

3.3 Results and Discussion

The demonstration editor in Fig.8 is used for real-time previewing. The method runs in almost real-time (about 10 frames per second) on a R4000 workstation. The step-constraints parameters and the Fourier characteristics, such as of briskness, tiredness, or a run, are therefore interactively specified with the editor.

Figs. 9 and 10 show examples of the effects of these parameters and characteristics. We note that consistency of the parameters and characteristics observed in Fig. 9 is also derived from the rescaled Fourier functional models. The two still images in Fig. 10 are taken from an animation example, featuring the "TV robo". Combined with additional stage effects, such as a flash in Fig. 10(a), the proposed method succeeded in making the TV robo perform well on the bright and dark side of life. An additional feature of the rescaled Fourier functional model is demonstrated with Fig. 10(b), where a shivering walk is made. This is easily achieved by adding randomized higher frequency terms to the Fourier functional model. Adding noise as higher frequency terms to a rescaled Fourier functional model is useful for such dramatization. We also note that the generated animations show a wider variation than existing physics-based or procedural approaches.

Currently the proposed method is not invertible. This means that the transition from running to walking by the method is unnatural, while the realistic transition from walking to running is made by the method. This problem must be addressed. The very limitation of the superposition technique in **3.2** will be clarified under more explicit formulation.

4. Conclusion

Based on the experimental data set of a few different human movements, the proposed method allows human movements to be interactively designed and generated in a wider variety. The key idea in the method is the use of Fourier series expansions of the measured data sets. Then smooth interpolation, extrapolation, and transition between different types of movements were made. In addition mood or characteristics of the human behaviors, such as "tiredness", and "briskness", were successfully extracted by the method.

A promising direction of future research involves extensions of the method in order to describe non-periodic human behaviors and to model a crowd or throng of people. In addition, the integration of the proposed method and dynamics techniques will be indispensable for further applications.

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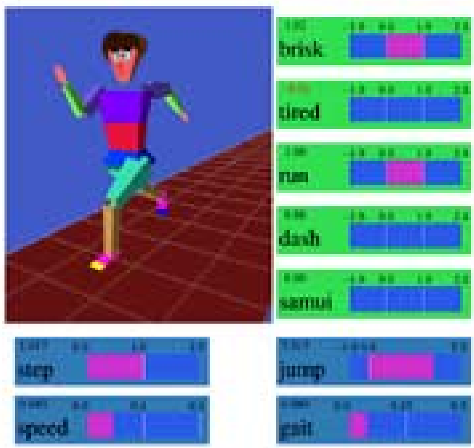

Figure 8. Demonstration editor.

(a) *run* = 1.0; *jump* = 5.0

(b) *run* = 1.0, *jump* = 5.0, *brisk* = 1.37; *step* = 1.8, *gait* = 0.5

(c) *run* = 1.0, *jump* = 5.0, *brisk* =1.3 *step* = 1.8, *gait* = 0.06

Figure 9. Emotion-based running examples with step-constraints.

(a) "Light"

(b) "Shade"

Figure 10. Stills from animation example.
(Courtesy NTV Corp.)