Motion Cyclification by Time $\times$ Frequency Warping

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Abstract. This paper presents a new algorithm for the cyclification of 1D signals, based on a time $\times$ frequency warping. The main goal is to preserve the basic characteristics of the signal, such as low and high frequency regions. The application outlined in this work is the cyclification of motion captured joint curves (near–periodic signals). Also, a method for cyclification of articulated figure motion is presented.

keywords: motion capture, computer animation, motion processing techniques, motion control, digital signal processing, audio and video synchronization.

1 Introduction

The data generated by a motion capture device is formed by a set of samples which represents the position and global orientation of a real object at uniformly spaced instants of time. In the case of human motion capture, the position and orientation of several joints of an actor are recorded, generating a set of 1D signals also known as motion curves. These curves are then processed and mapped onto a skeleton hierarchy which will drive a virtual actor in the computer [5]. This signal–like nature of the captured data suggests that it should be treated using the paradigms of signal processing theory [1].

Motion capture data processing has become an important field of research in recent years [4]. The crescent demand of powerful tools for motion editing has led to the development of several techniques such as warping [12], blending [14], concatenation [16] and reparametrization [6]. In all cases, the main goal is to reduce the overall time and, consequently, cost of the capturing process. Animators should be able to manipulate and reuse the captured data in order to achieve the desirable effect, even when the recorded motion is not as good or precise as expected.

Another example of motion processing is cyclification. This technique scales the motion length in time while preserving its basic characteristics. Several important applications arise from the use of this method. In the entertainment industry, computer games such as FIFA99 [33] use cyclification to create transitions between basic pieces of motion according to user interaction. Cyclification/expansion methods are also used for synchronization purposes in digital sound+video processing and motion control theory [9].

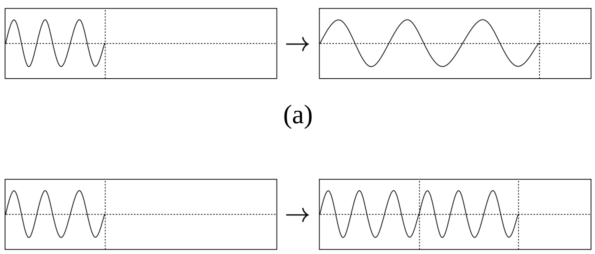
This paper presents a novel approach for motion cyclification. We use a time warping algorithm [17], initially developed for audio signals, to generate seamless transitions between motion loops. The motion curves are warped in the time $\times$ frequency domain, thus preserving the characteristic of frequency components of the original signal. The techniques presented here work well with motion capture data, but would work equally well with any other animation parameter like trajectories, velocities or forces.

The organization of the paper is as follows: Section 2 briefly reviews previous work in the area of motion cyclification; Sections 3 and 4 present our method, discussing the representation and warping of 1D signals in time $\times$ frequency domain; Section 5 applies our method to motion captured joint curves; Section 6 presents a method for cyclification of articulated structures using our algorithm. Finally, section 7 concludes the paper and presents some future work.

2 Previous Work

Motion expansion can be performed by using two different approaches: reparametrization or cyclification.

In the first method, regions of the motion curves are reparametrized using resampling techniques. This operation changes the number of samples at those selected regions, resulting in a expansion (warping) of the signal in time domain, as shown in Figure 1 (a). Note that this transformation changes the overall characteristic of the movement, because the frequency components of the original motion curve are also being "deformed". In [6], a discrete motion reparametrization technique was proposed to produce effects such as slow–motion and accelerated–time in captured data. A local resampling process is performed, expanding or compressing regions of the motion curves according to a user–defined velocity function.



(a)

(b)

Figure 1: (a) - Expansion of a periodic signal in time domain; (b) - Concatenation of a periodic signal.

The second approach attempts to preserve the frequency components of the original signal. This can be done naively by concatenating the motion curves several times, one after another. Observe that this process works very well for perfectly periodic motions, where the beginning and end of the curves match precisely so that a smooth transition is guaranteed between the loops of the concatenated sequence, as shown in Figure 1 (b). Moreover, the overall "shape" of the movement is preserved since there is no change in the frequency contents of the motion curves (they are simply being repeated along the time axis).

However, due to the nature of human locomotion, it is very unlikely that a perfectly periodic motion will occur. Small variations in phase components of a "potentially periodic" human motion signal are caused by a series of factors, including oscillations of torque forces in muscles, uneven terrain and other external factors. Moreover, these biomechanic and external factors introduce an important noise component in the signal, which is a fundamental aspect of natural–looking motion. In fact, Perlin [18] has pointed out that human motion synthesis should incorporate some kind of "texture" so that this stochastic characteristic is simulated. We will call a motion with these properties as *near–periodic*. An example of such kind of motion signal is shown in Figure 2.

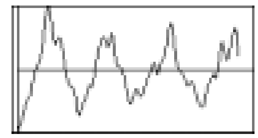


Figure 2: Motion captured joint curve: a near–periodic signal.

In the cyclification process of near–periodic motions, there is a boundary problem that should be addressed in order to guarantee a correct transition between the movements (see Figure 3). Smoothing methods can be used to blend the regions between motion cycles, but this may cause undesirable features in the final animation, such as self–intersection of body segments and joint constraint violations. Another important issue regarding this problem is the detection of cycles. For near–periodic motions this usually requires a complicated analysis of the motion curves, making the process very time consuming and, consequently, not suitable for interactive applications.

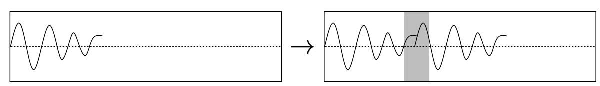


Figure 3: Boundary problem on near–periodic curve cyclification.

Cohen et al. [16] propose a semi–automatic method for motion cyclification based on minimization criteria. The algorithm requires user interaction in order to specify the approximate length of a cycle. The discontinuities existing when the motion cycles are reduced by minimizing kinematic parameters of the articulated structure. Moreover, the end points of the cycle are deformed so that they match exactly. At the end of the process, a C^2 motion curve is generated by fitting a least squares cyclic B-spline approximation to the modified motion. Using a similar approach, Sudarsky and House [15] generate motion cycles by fitting nonuniform B–splines to captured data. Such interpolation reduces the natural noisy behavior of captured motion curves, but provides an easy way to generate cycles by using blending operators based on the B–splines construction scheme.

Working on the frequency–phase domain, Unuma et al. [13] developed a method to generate transitions by using a Fourier expansion of the motion curves. Periodic motions are interpolated by an automatic synchronization of phases based on "rescaled" Fourier expressions.

Our approach is novel in two ways. First we use a discrete transform, which allows fast and efficient implementation. Second, by the choice of this transform: local cosine basis, which is a real orthonormal transformation (perfect reconstruction) that achieves window overlapping and dismisses the care in the “phase” component. Moreover, the fine structure (that is, the natural “texture”) of the movement is preserved, since we are not deforming the frequency contents of the original motion curves.

3 Lapped Cosine Representation of 1D Signals

Since a motion curve is a 1D signal, it seems natural to use time $\times$ frequency transforms to analyze it. Fourier and Wavelets transforms have been widely used for this task. There is vast signal processing literature concerning this theory, such as [21], [22] and [23]. In particular, [25] and [26] describe warping techniques on the frequency and space–frequency domain, respectively.

In order to achieve the purpose of developing a time warping of a motion path without changing the frequency components, we need a transform that could break the frequency spectra into wave packets of different sizes. In fact, using such a transform, when scaling the path we replicate the packets without changing its frequency contents. The well known process of constructing those wave packets is the windowing technique, as illustrated in Figure 4.

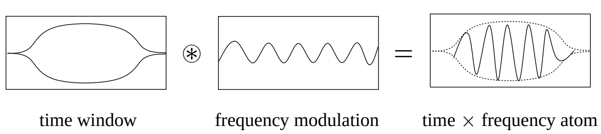


Figure 4: Windowing of a periodic function.

By carefully choosing the window, H. Malvar, Coifman and Y. Meyer were able to construct an orthonormal transform, so called *Lapped Cosine Transforms* (LCT). For a detailed discussion on the construction of the orthonormal basis using the windowing process, see [27]. We have chosen the LCT to represent the motion signal in time $\times$ frequency domain. The LCT have two relevant advantages:

1. It is a real transform based on the Discrete Cosine Transform-IV [28]. This avoids the need for special care of the phase component.

2. It is an orthogonal transform, whose basis are differentiable and have compact support. Also, its windows overlap.

The overlapping is responsible for the elimination (or considerable reduction) of the undesirable clicking, that usually appears after synthesis and manipulation using the WFT representations. This is a boundary problem, and happens due to discontinuities in the boundaries of adjoining windows (see Figure 5).

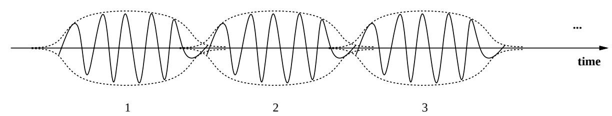


Figure 5: Basis elements: orthonormality with overlap.

The forward transform is accomplished in two steps: first a “folding” operation is done on each segment, which will in some sense add the neighbors’ border information to each window; then, a normal DCT-IV is executed. This folding operation must be carefully projected such that an orthonormal transformation is achieved at the end.

The inverse transform is also done in two steps: the normal DCT-IV (which is it own inverse), followed by the unfold operation.

Some of the different elements of this basis can be seen in Figure 6. They are carefully constructed such as to preserve orthonormality.

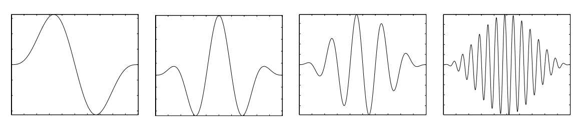


Figure 6: Four different elements of the basis.

The representation of a signal in time $\times$ frequency domain creates a finite partition of the time $\times$ frequency plane. In the vertical axis (frequency axis) there are all the frequency elements of the transform basis, while in the horizontal axis (time axis) the overlapped time windows are placed. The time $\times$ frequency localization is done by a convolution of each frequency element with its corresponding time window, thus creating a partition of atoms in the time $\times$ frequency plane, as shown in Figure 7.

4 Time $\times$ Frequency Warping of 1D Signals

When a 1D signal (f) is represented in a time $\times$ frequency domain, it can be regarded as a continuous 2D image. The support is a rectangle whose horizontal axis represents the time support of the phenomenon, and whose vertical axis represents the frequency axis (from 0 to π).

The time warping operation (W) in the frequency domain uses an affine dilation on the time axis of the time

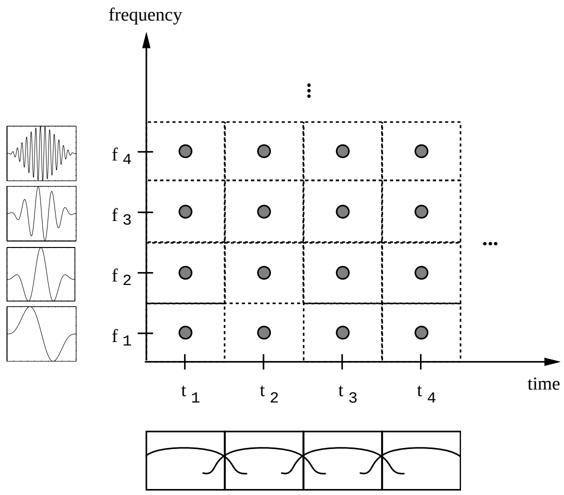


Figure 7: Time × frequency representation.

× frequency representation (i.e., we scale the image on the time axis). This results in a replication of the atom elements of the representation, as shown in Figure 8. We transform the 1D signal, $T(f)$; apply the time scaling (dilation or compression), $W(T(f))$; and reconstruct the curve in the time domain using the inverse transform, $T^{-1}(W(T(f)))$. Since regions of the image represent the presence of certain frequency components in the time segment limited by its boundaries, its stretching is responsible for a replication of the oscillations (prolonging the phenomenon in the expansion case). This sequence of transformations is presented in Figure 9.

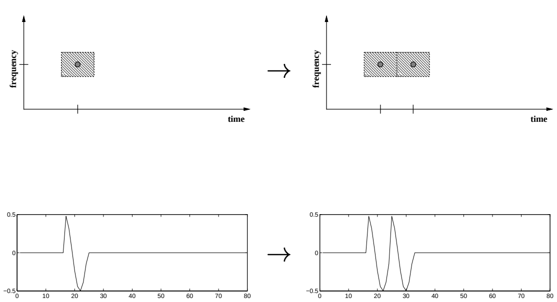


Figure 8: Time dilatation in time × frequency domain.

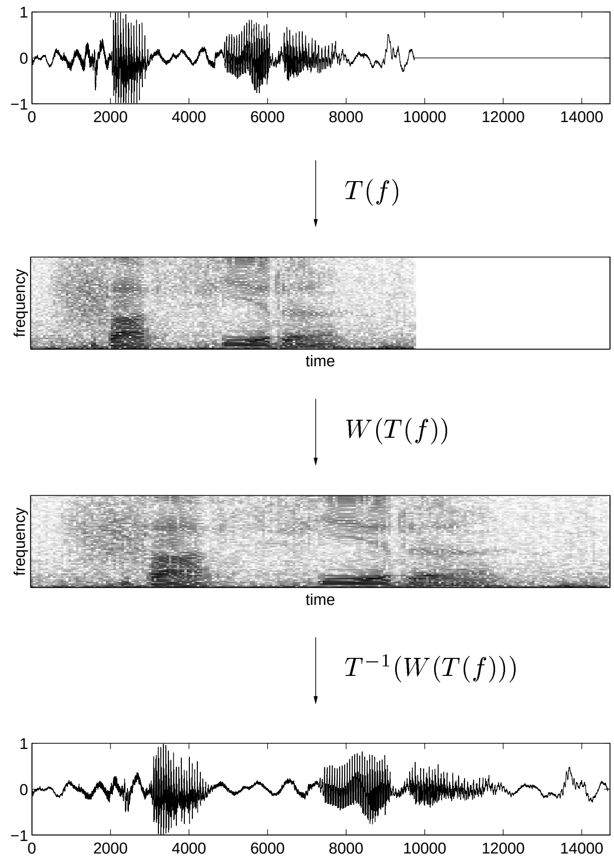


Figure 9: Time × frequency representation and warping of a signal f (top). (from Goldenstein et. al [17])

5 Warping of Joint Motion Curves

An articulated object consists of rigid bodies connected by joints. These joints are geometric constraints which allow relative movement between segments of the structure[1]. Such relative movement is called a Degree of Freedom (DOF).

In traditional animation, the movement of an articulated object is performed by varying the angle of joints in time. Depending on the control method used to drive the objects, this angular variation may be produced by kinematic or dynamic constraints imposed to the structure. The resulting sequence of angular values is known as a motion curve, and can be represented in the computer as a 1D discrete signal. Figure 10 presents a simple articulated object (a pendulum with one DOF) and a motion curve (that is, values of θ) generated by releasing the pendulum from point A until it reaches the rest position in B.

In human motion capture animation, the angular displacement of joints is recorded directly from the move-

[1]There are three types of joints: revolute, spherical and prismatic. The first two are the most used for representing complex structures such as the human body [4].

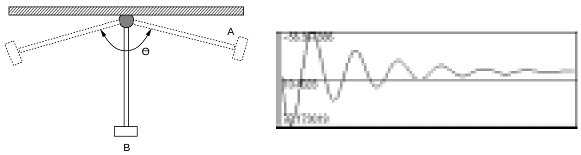


Figure 10: Motion curve of a pendulum.

ment of body segments. Due to biomechanic characteristics of human locomotion, its motion curves are highly complex. General, basic motion patterns are represented by low frequencies components of the curves. This is called the "shape" of the motion. On the other hand, high frequencies contain detail, subtleties and noise artifacts which are responsible for the "texture" of the movement. Although there are innumerous possibilities for human motions, it is observed that a predominant set is formed by motions with periodic or near–periodic characteristics. Daily actions such as walking, running and eating have a periodic behavior. Even variations of a same movement, such as "fast walk" or "brisk walk", have a common periodic shape on their motion curves (a detailed discussion on this topic can be found in [1], [13] and [18]). Figure 11 presents a near–periodic captured curve containing the angular displacement of the left upper arm joint of an actor executing a walking movement.

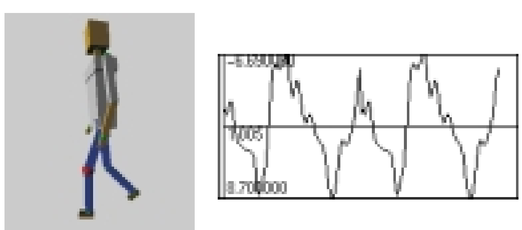


Figure 11: Motion captured curve (left upper arm joint) from a walking sequence.

For best results, a cyclification algorithm must extend the motion curve in time while preserving both its shape and texture. In order to accomplish this task, the first step is the detection of the fundamental cycle, which is equivalent to the lowest frequency present in the signal (Figure 12).

Our algorithm employs an autocorrelation method, and the fundamental cycle is given by the distance between consecutive maximum points of the correlated signal. The circular autocorrelation function can be used to

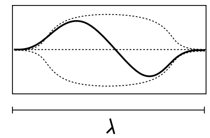


Figure 12: The fundamental cycle: a low frequency signal.

measure the similarity between translated versions of a signal:

$$\rho(i) = \sum_{\tau=0}^{N/2} x(i) + x((i+\tau) mod N). \qquad (1)$$

Observe that $|\rho(i)| \leq \rho(0)$, since $\rho(0)$ is the signal energy. Through the use of a smooth window in the signal before calculating the circular autocorrelation, we give more weight to the central part of the data, farther from the border effects, as well as increase the likelihood of smaller periods. This is extremely important because in periodic or near–periodic functions, there will exist at least one maximum at each multiple of the fundamental cycle. However, there is no guarantee that other (lower) local minima will also exist. Without the windowing, all maxima concerning the multiples of the fundamental cycle will have amplitude similar to $\rho(0)$, which makes difficult the task of choosing the fundamental cycle. With the windowing process, the function is smoothed and the selection of the fundamental cycle is taken by choosing the greater maximum, excluding $\rho(0)$.

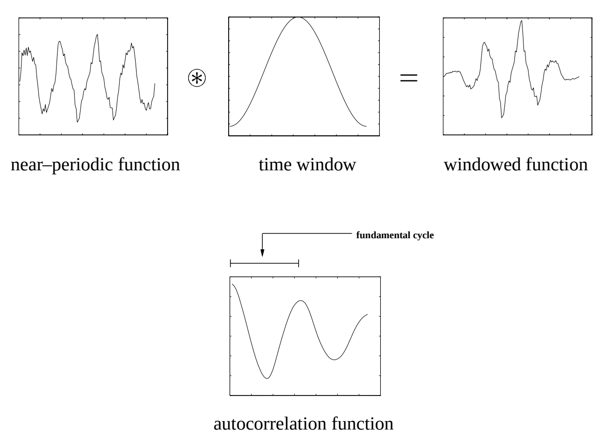


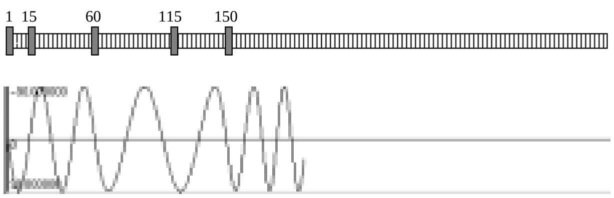
Figure 13: The process of autocorrelation.

5.1 Some Examples

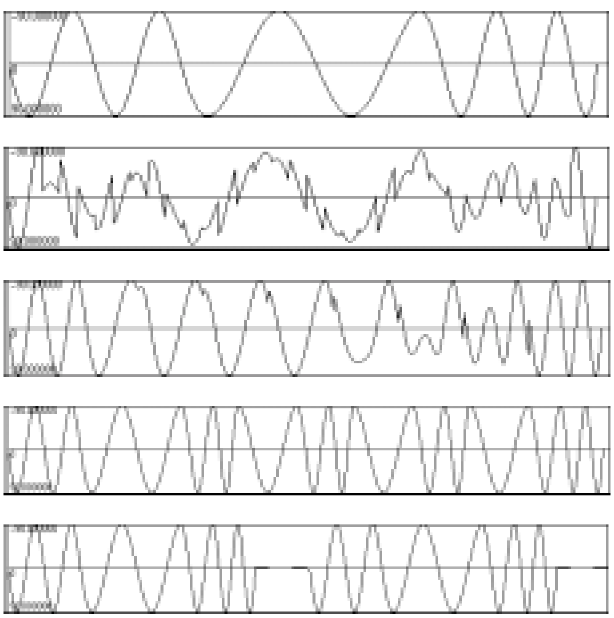
The following examples illustrate the application of our method to several individual motion curves. In all examples, the window size (that is, the fundamental cycle) detected by the algorithm is represented as a gray rectangle in the original signal, which is placed at the top. A warp factor of two was applied in all examples.

$Sine$ with variable period and window size

Figure 14 (a) shows a signal which is a combination of $sine$ functions with different periods. Also, a frame ruler was placed at the top of the image, showing all the window sizes *(WS)* used with the algorithm in order to observe the effects on the resulting signal.



(a)



(a)

Figure 14: (a) - Original $sine$ function; (b) - Warping of $sine$ function with variable period (warp factor = 2.0). From top do bottom, window size of 1, 15, 60, 115 and 150.

In Figure 14 (b), the first signal represents a warping with *WS=1*. Note that in this case the result is equivalent to a reparametrization (that is, expansion in the time domain). This happens because with *WS=1* each frequency of the original signal is repeated along the time axis. The second signal shows a warping with *WS=15*. This time, noisy artifacts were introduced because the window size is smaller then the fundamental cycle (the algorithm tries to replicate frequencies that doesn't match). The third signal shows the application of our method with *WS=60*. Note that there are still noisy artifacts in the resulting signal, specially in the high frequency regions. The forth signal presents a warping with the fundamental cycle detected by the algorithm *(WS=115)*. Observe that in this example there is a perfect replication of low and high frequencies of the original signal. Finally, the last signal shows a warping with *WS=150*. In this case, since the window size is greater than the fundamental cycle, some discontinuities were introduced during the cyclification process.

$Sine$ with fixed period

Figure 15 shows the application of our algorithm to a $sine$ function with fixed period. Note that, although the $sine$ function is periodic, in this example the beginning and end of the signal doesn't match, and therefore a simple concatenation would not generate good results. By applying our algorithm, the resulting signal is a perfect cyclification, and there are no discontinuities in the boundaries of the cycle.

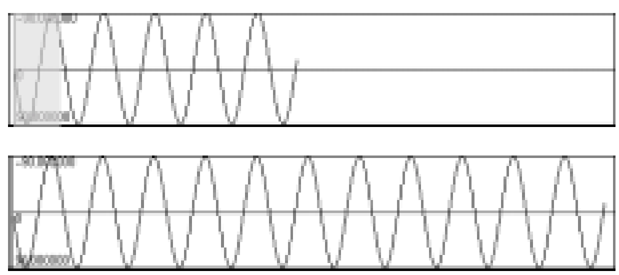


Figure 15: Warping of $sine$ function with fixed period (warp factor = 2.0).

Pendulum

In Figure 16 the pendulum function was used as input to our method. It is important to notice that in this case there is only a basic frequency which is repeated along the curve, but its amplitude decreases quadratically with time. The resulting signal shows a replication of the frequency component, while preserving the quadratic decaying of its amplitude.

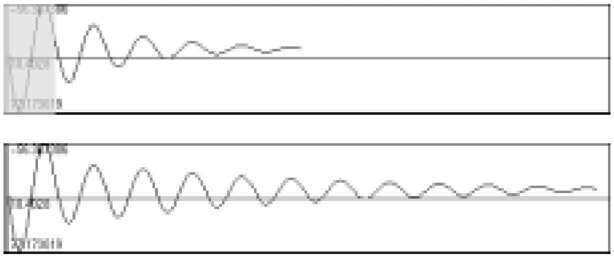


Figure 16: Warping of pendulum motion curve (warp factor = 2.0).

$Sine$ with variable period and noise

Figure 17 presents an example with a $sine$ function with variable period and random noise. Our algorithm has produced a signal that preserves both the fundamental cycle and the higher frequencies of the original signal.

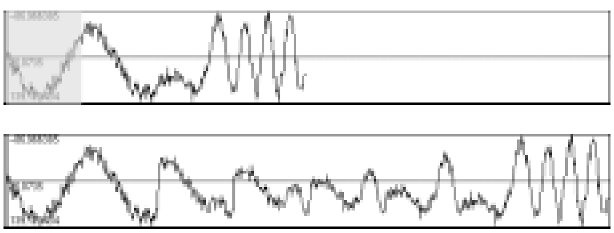


Figure 17: Warping of $sine$ function with variable period and random noise (warp factor = 2.0).

Left upper arm joint curve

In the last example of this section (Figure 18), we have used the motion captured curve of the left upper arm. Note that the resulting signal is a perfect cyclification of the original one, with no discontinuities during the motion loops.

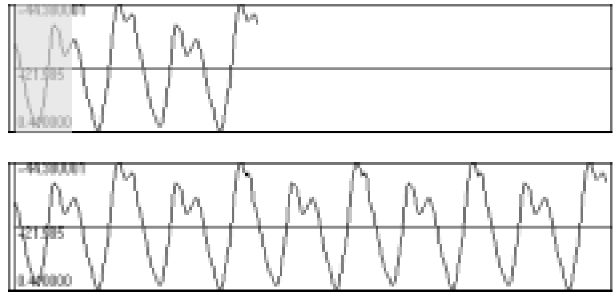


Figure 18: Warping of left uparm motion curve (warp factor = 2.0).

6 Cyclification of Articulated Figure Motion

In the previous section of this paper, we employed the time warping algorithm to transform motion curves of simple articulated structures in time. These structures consisted of only one joint with a single DOF. One of our goals is to extend the method to work with objects of higher complexity, such as articulated structures that represent the human body. This is a very difficult task, mainly because of two aspects:

- To represent the movements of a human body with exactness, an articulated structure must have a large number of segments and joints, each with two or three DOF's. This results in a large amount of data to process and control simultaneously.
- For near–periodic motions, such as walking, there is synchronism between segments of the human body. This synchronism should be preserved by the warping algorithm in order to generate a dynamically plausible movement.

The literature of motor control techniques for character animation has several examples of methods to deal with the problem of generating periodic human motion ([9], [10] and [11]).

Motions with periodic or near–periodic characteristics have a coupling between the movements of joints or groups of joints. Depending on the type of motion that is being executed, these joints may have a strong or weak dependence on their phases. A strong dependence within a group of joints means that their motion curves have a common periodic behavior, with phases that are multiples of a predominant fundamental cycle. In a weak dependence, the motion curves of joints are being influenced by the movement of other joints or groups of joints. To illustrate this problem, we will analyze the walk movement.

In a walk movement, the motion of knees, feet, elbows and hands is strongly influenced by the motion of upper arm and upper leg joints. This happens due to the structural relationship existing between these joints and also due to the nature of the walk motion. Events such as heelstrike and toe-touch are interpreted and processed by the human locomotor system in order to trigger actions that will control the basic aspects of a human gait. Moreover, there is a weak dependence between the joints of the arms and legs. This happens due to the necessity of a balance control that is achieved by a cross synchronization of arms and legs motions.

Our approach uses the autocorrelation method described in the previous section in order to detect the predominant cycle associated to a group of joints. For each group of joints, the autocorrelation method is applied to all motion curves, resulting in a set of fundamental cycles. We take the greater of these cycles as the representative of the group. This representative cycle is then used as the window size that will be applied to all motion curves of the joints within the group. With this choice, we guarantee that all other fundamental cycles (which in periodic or near–periodic motions are multiples of a predominant fundamental cycle), will be correctly replicated during the time warping.

We have applied this method in several near–periodic motions, with promising results. Figure 19 shows some frames from a walk motion. As discussed before, in this case there is a strong dependence within the group of joints that represent the arms and legs. Also, there is a weak dependence (cross synchronization) between these groups due to balance control.

In Figure 20 we present selected frames from a backflip kick motion. Note that in this case there is still a strong dependence within the group of joints that represent the arms and legs, but the weak dependence now is represented by a coupled synchronization of arms and legs. The right arm of the figure is responsible for the initial impulsion of the body before the flip. The right leg follows the rotational movement of the arm, generating the necessary propulsion to complete the flip. Also, note that the left arm and leg basically have the same rotational behavior, rotating through the vertical torso axis in order to complete the movement.

7 Conclusions and Future Work

We have presented a technique for cyclification of motion curves. The method is based on a time warping algorithm that works on the time $\times$ frequency domain of the motion curves, thus preserving the characteristics of its frequency components. We have successfully applied our algorithm to several periodic and near–periodic motion curves. Also, we have proposed a method for cyclification of articulated figure motion, based on an analysis of strong and weak dependencies between the segments of the body. In this case, the first results were promising, but we are still investigating the different aspects of this problem.

As future research, we plan to extend and improve the method to work with complex human figure motion, as well as with facial animation. In this case, there is a strong relationship between the facial parameters and audio signals. Non–linear editing of audio and video sequences, and film dubbing (lip–sync) are important applications that could benefit from the usage of our method. Our future objective is to implement the time warping algorithm in a full animation system, in order to transform simultaneously human motion, facial animation and sound.

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Figure 19: Selected frames from a walk sequence.

Figure 20: Selected frames from a backflip kick sequence.

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