

# Probabilistic Motion Sequence Generation

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## Abstract

*Creating long animation sequences with non-trivial repetitions is a time consuming and often difficult task. This is true for 2D images and even more true for 3D sequences. Based upon the idea of video textures we propose a simple algorithm to create new user controlled animation sequences based only on a few key frames by the analysis of velocity and position coherence. The simplicity of the method is achieved by carrying out the calculations on the main principal components of the reference animation, hence reducing the dimensionality of the input data. This also leads to significant compression. Smooth animations are ensured, using one of the proposed blending schemes.*

## 1 Introduction

The usage of computer generated images (CGI) and especially animations of humans or creatures in feature films [9, 8, 4] and computer games is steadily increasing. Animating sequences per hand is a difficult and time consuming process. Often only short basis sequences exist and have to be extended to longer sequences (e.g. walk of an avatar) with non trivial repetitions and can not be solved by simple copy and paste. In this paper we extend the idea of video textures as introduced by Schödl et al.[21] to geometry and generalized attributes like vertex normals, velocities or reflection properties. Similar to Lee et al.[17] control of the avatar can be achieved, but in contrast to the latter we are not restricted to motion capture data. The analysis of a given short basis animations leads to the creation of transition probability matrices, which store frame-to-frame coherence information. Because the amount of data of the basis sequence might be impractical to store, we achieve compression and computation of the transition matrices by reducing the dimensionality of the input data, using principal component analysis. To ensure the preservation of the motion dynamics we also split geometry related data (vertex positions) and animation related data (vertex velocities) and analyze them independently. During runtime the algorithm creates endless or fixed length sequences. Depending on the quality of the input data we propose two blending schemes

to ensure smooth animations.

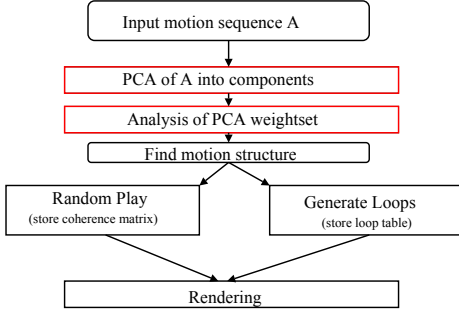
### 1.1 Related Work

The basic idea to search for coherence in frames of image sequences was introduced by Schödl et al.[21] with the term video textures. The goal of this work was to create endless or fixed length image sequences with non-trivial repetitions. Modelling the textures as Markov processes simple frame-to-frame distances are computed and mapped to transition probabilities. Simple filtering is used to preserve dynamics. This work focuses only on image based animations, not on geometry. Geometry animation in this field naturally focuses on human motion. The sequences are driven by key frames, rule-based systems [6, 18, 5, 19, 7], control systems and dynamics [22, 16, 11, 10] and motion capture data [12, 17]. Knowledge from biomechanics and motion studies is often involved to insure natural looking output. A lot of recent work is restricted to special animation cases, e.g. diving. Lee et al.[17] uses the method described with video textures to compute coherence between motion capture data to generate new data based on several input methods. They rely on a precomputed database and focus also on different control mechanisms for the avatar. To reduce the dimensionality of the input data, Alexa et al.[2] use principal component analysis of the animation to compress the needed data, but are restricted to a whole given sequence. Bowden[3] uses also PCA to simplify the motion based on feature points of the objects. While Lee et al.[17] is based on motion capture data and Bowden [3] introduces the idea to use dimensionality reduction for the data, we want to combine video textures and PCA to allow the handling of arbitrary geometry animations, including geometry attributes like normals or local reflection properties.

### 1.2 Algorithm Overview

Motion or animation data is often given in the form of key frames containing all necessary information like vertex positions, normals, connectivity information etc. Our algorithm first does an analysis of the already finished animation  $A$  of the length  $l$ , which can be modelled by an artist, based on motion capture data, procedural created or obtained using any other form of data generation. In our examples we use animations of short or medium length ( $l = 115, 190$ ).

To have a diversity in the animation, the length and hence the data amount is often much higher. But also using only a small  $l$  can involve huge data amounts. Therefore we first compress the animation  $A$  using a principal component analysis (PCA) [13, 15, 20]. The motion structure is com-



**Figure 1. Algorithm Overview.**

puted, using only the weights of the eigenvectors, hence can be computed efficiently depending only on the number of PCA components used. The main idea is, that similarities between frames are transferred into the PCA weights. As in Schödl et al.[21] we compute a coherence and transition matrix, which can be used to create either infinite random or length controlled loops during rendering, as shown in figure 1. The rest of the paper is organized as follows. In section 2 we describe the data analysis in detail, followed by the results section 3 in which we demonstrate our method with examples and discuss blending between transitions.

## 2 Data Analysis

Given an animation  $A$  of  $l$  frames length and constant connectivity, we define the vector  $A_i$  to contain all vertex positions of the geometry for frame  $i \in [0, \dots, l] \subset \mathbb{N}$ . We perform a PCA of these vectors, resulting in a series of  $c$  eigenvalues  $\lambda_{ik}$  and eigenvectors  $F_k$ ,  $k \in [1, \dots, c] \subset \mathbb{N}$ , latter we will call *eigenframes*. We use  $\lambda_{i0} = 1$  and the mean of  $A$  as  $F_0$ . The first  $c < l$  eigenframes approximate any of the original frame  $A_i$  in such a way that the sum of the squares of the projection errors onto the affine subspace spanned by  $\{F_0, \dots, F_c\}$  is minimized

$$A_i \approx \sum_{k=0}^c w_{ik} F_k, \quad i = 0 \dots l. \quad (1)$$

The coefficients  $w_{ik} = \langle A_i, F_k \rangle$  are weights, were  $\langle \cdot, \cdot \rangle$  denotes the standard scalar product in  $\mathbb{R}^{3 \times N}$ , where  $N$  is the number of vertices of the geometry. Following the work of Schödl et al. [21] and Lee et al. [17] we also model the data as a first-order Markov process, hence the transition between states depends only on the current state, which in our case are the given key frames in  $A$ . The Markov process is represented as a matrix  $P_{ij}$  storing the probability of a transition from frame  $i$  to frame  $j$ . This matrix is com-

puted, by first computing the frame-to-frame distances  $D_{ij}$ , which we define by the differences of the PCA weights  $w_{ik}$ :

$$D_{ij} = \sum_{k=0}^c |w_{ik} - w_{jk}| \quad (2)$$

As in Schödl et al., the transition probabilities from frame  $i$  to frame  $j$  are computed using an exponential function  $P_{ij}$ , as follows:

$$P_{ij} \approx \exp(-D_{i+1,j}/\sigma) \quad (3)$$

where  $\sigma$  controls the mapping between the distance measure and the probability of the transition. Higher values for  $\sigma$  allow for a greater variety at the cost of poorer transitions. Transitions with high probabilities are the ones, where the successor of  $i$  is similar to  $j$ , hence  $D_{i+1,j}$  is small. To propagate the forward motion, the probability for frame  $i+1$  should be higher than for  $i$  itself. All probabilities are normalized per row, hence  $\sum_j P_{ij} = 1$ .

### 2.1 Motion Dynamics

To preserve the dynamics of the motion, we also compute all central velocities  $V_i$  for all vertices per frame  $i$ ,  $i \in [1, \dots, l]$ . Using the vertex positions  $p_{in}$  stored in  $A_i$  we compute the velocity  $v_{in}$  for vertex  $n$  and frame  $i$ :

$$v_{in} = ((p_{in} - p_{i-1,n}) + (p_{i+1,n} - p_{in}))/2 \quad (4)$$

where we define  $v_{0n} = v_{ln} = 0$  for all  $n$ . Computing a separate PCA on  $V_i$  and denoting the weights as  $w_{ik}^*$ , were  $i \in [0, \dots, l]$  is the number of the frame the velocities are to be reconstructed for and  $k \in [0, \dots, c^*]$  with  $c^*$  the number of components we get similar to equation 2:

$$D_{ij}^* = \sum_{k=0}^{c^*} |w_{ik}^* - w_{jk}^*| \quad (5)$$

and finally  $P_{ij}^* \approx \exp(-D_{i+1,j}^*/\sigma^*)$  (6)

where  $\sigma^*$  is the mapping parameter respectively. We also propose another simple method to propagate the *forward* motion, that is to keep a simple list of the last  $m$  visited frames.  $m$  should be a fairly small number ( $m < 5$ ), to prevent certain motions, e.g. waving arms up and down or other jittering. While on the one hand according to the system itself this is a valid motion, it might be desired to prevent this for more natural animations.

### 2.2 Generate Jump map

To create the final probability map  $\hat{P}_{ij}$ , which we call jump map we use position and velocity coherence as follows:

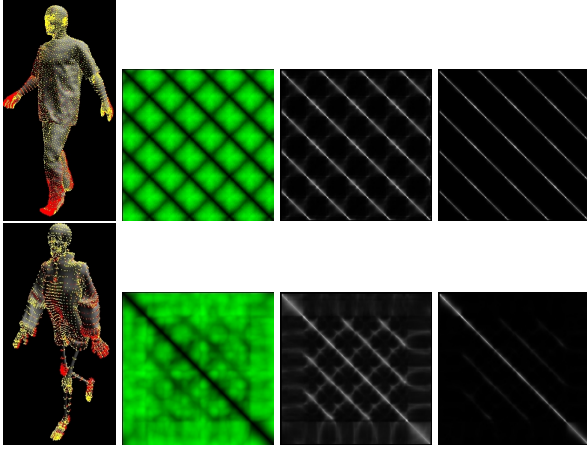
$$\hat{P}_{ij} = P_{ij} P_{ij}^* \quad (7)$$

To allow different emphasis on either the position coherence

( $w$ ), the velocity coherence ( $w^*$ ) or both, we propose the following extension to equation 7:

$$\hat{P}_{ij} = [q + (1 - q)P_{ij}][q^* + (1 - q^*)P_{ij}^*] \quad (8)$$

where  $q, q^* \in [0, 1]$  control the emphasis. Note that values between 0, 1 create a base probability for either  $q$  and/or  $q^*$  to ensure that  $\hat{P}_{ij} \in [0, 1]$ . The resulting map now can be used either to generate infinite random or fixed length looped sequences. Besides the vertex positions we also include the vertex normals in the vectors  $A_i$ . The reconstructed normals later can be used in the rendering step for proper shading. Figure 2 shows examples for  $D_{ij}, P_{ij}, D_{ij}^*, P_{ij}^*$  and  $\hat{P}_{ij}$ .



**Figure 2. Difference matrices and jump maps for the AVATAR (top) and SKELETON (bottom) sequence. Left to right:  $D_{ij}, P_{ij}^*$  and  $\hat{P}_{ij}$ .**

### 2.3 Blending Transitions

Because we allow also transitions from  $i$  to  $j$  which have larger differences, slight discontinuities can occur. Instead of jumping directly from frame  $i$  to  $j$  we blend with a chosen amount  $b$  of blending frames  $i^\diamond$ :

$$i \rightarrow i_1^\diamond \rightarrow i_2^\diamond \rightarrow \dots \rightarrow i_b^\diamond \rightarrow j \quad (9)$$

For our examples we found  $b = 3$  to yield smooth animations. The blending itself is done on the PCA weight set. Let  $w_{ik}$  be the weights for the  $c$  PCA components for frame  $i$  and  $w_{jk}$  for frame  $j$ , respectively. The blending weights  $w_{i_t^\diamond k}$  for frame  $i_t^\diamond, t \in [1 \dots b]$  are linear interpolated between the weights for  $i$  and  $j$ :

$$w_{i_t^\diamond k} = w_{ik} + \frac{w_{jk} - w_{ik}}{b(b - t + 1)} \quad (10)$$

$\forall k, k \in [0 \dots c]$ .

**2.3.1 Variable Length Transitions** In contrast to transitions with constant length we also propose transitions with

dynamic length, depending on the Euclidean distance between the frames  $i$  and  $j$ . This is done by introducing a smoothness parameter  $s$ , which defines the minimal distance which should be covered by a single transition step. A good starting point for  $s$  is the mean distance  $s = \bar{d}$  between the frames in the animation sequence  $A$ . From this it follows that the parameter  $b$  in equation 9 is computed for each transition as follows:

$$b = \frac{\|\tilde{A}_i - \tilde{A}_j\|_2}{s} \quad (11)$$

where  $\tilde{A}_i$  is the reconstructed geometry for frame  $i$ .

## 3 Results

We implemented our method under Windows 2000 on a 1.5GHz Athlon with a state-of-the art graphics accelerator. All computations besides the rendering are done by the CPU. The accompanying video clips [1] show two examples of initial animations  $A$  and two new long sequences generated out of it. The rendering is done with OpenGL and Phong shading, using the reconstructed vertex normals.

### 3.1 PCA Reconstruction Error Analysis

The error of a reconstructed geometry depends on the number of PCA components used. Because the usable number might be limited through speed and/or memory restrictions we introduce two errors  $E$  and  $E^*$ , corresponding to the position and to the velocity with a given number of components  $c$  and  $c^*$ , respectively. They are defined as follows using  $N$  as the number of vertices in the geometry:

$$E(c) = \sum_{i=1}^{l-1} \frac{\sum_{n=0}^N \|p_{in} - \tilde{p}_{in}\|_2}{\sum_{n=0}^N \|p_{in}\|_2} \quad (12)$$

$$E^*(c) = \sum_{i=1}^{l-1} \frac{1}{N} \sum_{n=0}^N \frac{\|v_{in} - \tilde{v}_{in}\|_2}{\|v_{in}\|_2} \quad (13)$$

where  $E$  is a relative error for the geometry of the object and  $E^*$  is expressed as a relative velocity error per vertex.  $p_{in}$  is the position in world coordinates and  $v_{in}$  the central velocity of the vertex  $n$ , respectively.  $\tilde{p}_{in}$  and  $\tilde{v}_{in}$  are the reconstructed vertices and velocities. Note, that this reconstruction error makes only sense to have a quality indicator for the newly generated sequence, therefore, in which amount the PCA reconstruction error determines the similarity between the original and the new sequence. These errors are discussed in section 3.3. Evaluation showed that  $c = 10$  for the geometry and  $c = 5$  for velocity result in appropriate reconstruction.

### 3.2 PCA Compression Ratio

The number of used eigenvectors for the reconstruction effects the compression ratio of the input basis sequence. With  $c = 10$  components compression ratios from 1:15

(9.2MB) for the avatar and 1:13 (5.6 MB) for the skeleton are achievable. See table 1 for the error dependence.

### 3.3 Generated Sequences

We have tested the algorithm with two animation sequences, namely AVATAR (115 frames, 20948 vertices) and SKELETON (190, 12427) (see figure 2) with velocities shown in red. A generated sequence is shown 3. The accompanying video for the animations can be found at [1]. If  $\sigma$  is too low or too high, instability occurs and only a spe-

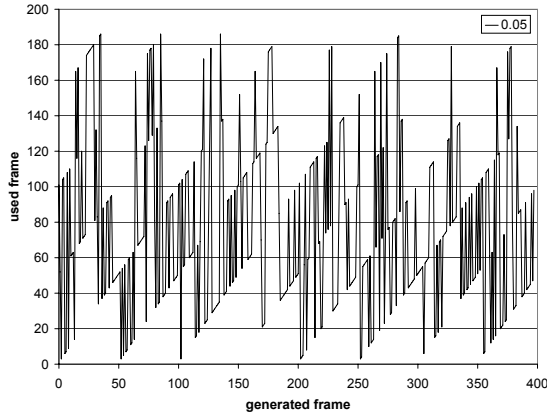


Figure 3. New avatar sequence ( $\sigma = 0.05$ ).

cific range results in proper new animations. For the avatar sequence we found  $\sigma \approx 0.05$  to generate natural animations and for the skeleton  $\sigma \approx 0.30$ , respectively. The influence of the parameters  $q$  and  $q^*$  was also evaluated. If only one criterium is considered, either velocity  $q = 0.0, q^* = 1.0$  or position  $q = 1.0, q^* = 0.0$ , the first 100 or 140 frames are sufficient to find good transitions for constant  $\sigma$ . If both criteria are considered, valid transitions are restricted to an extend, that the algorithm needs all frames of the input sequence or even more. Table 1 shows the reconstruction errors  $E$  and  $E^*$  for the animations depending on the number of PCA components ( $c$ ) used. To control the animations a basis of basic animations sequences is generated and based on user choice, the appropriate subbasis is chosen. Other control interfaces based on choice, sketching or vision as described in Lee et al.[17] could also be applied.

$c$	avatar( $E$ )	avatar( $E^*$ )	skeleton( $E$ )	skeleton( $E^*$ )
0	25.06	188.55	31.79	172.14
2	4.96	121.25	16.19	151.95
6	1.63	48.49	8.042	92.76
10	0.99	26.09	5.09	73.82

Table 1.  $E$  and  $E^*$  errors.

## 4 Conclusions

Our method handles arbitrary animated geometry to generate new endless or fixed length sequences with non-trivial

repetitions. It needs only a small basis animation and uses frame-to-frame position and velocity coherence of principal component reconstruction weights, including data compression. Depending on the number of components used and the error allowed, the complete reconstruction and evaluation can be done at interactive to real-time frame rates on consumer hardware. This allows the easy usage of this technique in the entertainment field, e.g. for computer games.

### 4.1 Future Work

PCA reconstruction and random sequence generation directly on the GPU using texture lookups and avoiding bus load, while storing the coherence matrices as textures and better compression and reduction of the number of components by using local principal component analysis [14].

### 4.2 Acknowledgements

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