Eurographics/ ACM SIGGRAPH Symposium on Computer Animation (2008)
R. McDonnell (Editor)

Posters and Demos

Interactive Character Posing from Large Motion Database

Xiaomao Wu Lionel Reveret Maxime Tournier

INRIA, University of Grenoble, France

Abstract

We present an interactive character posing scheme based on a learned prior model from large motion database. The proposed scheme aims at generating poses that look as natural as possible while satisfying user constraints. We use an adaptive cluster algorithm to select a representative frame-set from the database, and a sparse approximation algorithm to accelerate the training and posing processes.

1. Introduction

Traditional optimization-based IK techniques are widely adopted for real-time character posing. However, it may produce unnatural poses due to the high redundancy of the IK chains. Using joint limits and energy terms can partially solve this problem, but are not sufficient to guarantee the naturalness of a pose.

Style-based IK (Style IK) [GMHP04] is a robust and powerful technique for character posing from small datasets. It does not guarantee that poses still looks natural when desired poses are far away from that of the training data.

We present a scheme for interactive character posing from large motion database. Our scheme makes it possible to process a database containing 1330718 frames in 10 hours, and edit a pose interactively after the training process. The training process only needs to be performed once. The training results can be saved and reused for later pose editing. The proposed scheme can replace traditional IK algorithms and is easy to be integrated into existing animation packages.

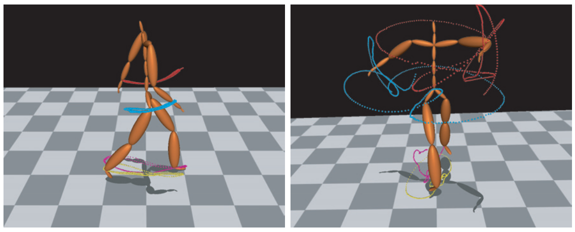

Figure 1: *Local joint positions of four handles of two motions. Left: A walking motion containing 316 frames. Right: A dancing motion containing 500 frames. As style IK is based on training poses that only span a narrow space, it may produce unnatural poses if the target pose is far away from those in the training data set.*

2. Method

The process of our scheme can be stated as follows: a user provides a motion database containing various kinds of motion types. Our system then learns a prior model from the database. Once the model is obtained, user can interactively pose the character by dragging user-defined IK handles. Our system automatically generates natural looking poses while satisfying user constraints.

There are two main challenges: how to learn a prior model from a very large database containing millions of frames, and how to maintain interactive speed for pose generation. We tackle the first challenge with representative frame-set selection. As the poses in the database are highly redundant, we utilize a adaptive clustering algorithm to reduce the number of poses. The second challenge is resolved with approximate learning of the GPLVM model with Fully Independent Training Conditional (FITC) Approximation [SG06].

There are three stages in our system. First, select a representative frame-set from the motion database. Second, learn a model from the selected frames. Finally, solve an optimization problem by combining prior and constraints. The first two steps only need to be done once. These three stages are stated in the following subsections.

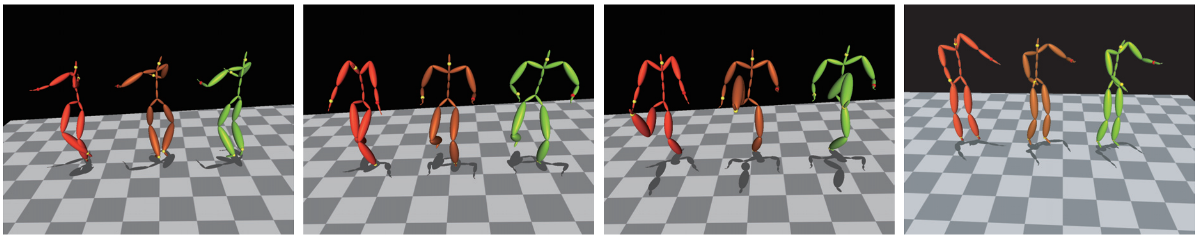

Figure 2: *Compare our method with traditional IK. The left, middle and right figures represent the results of traditional IK, the ground truth and our method.*

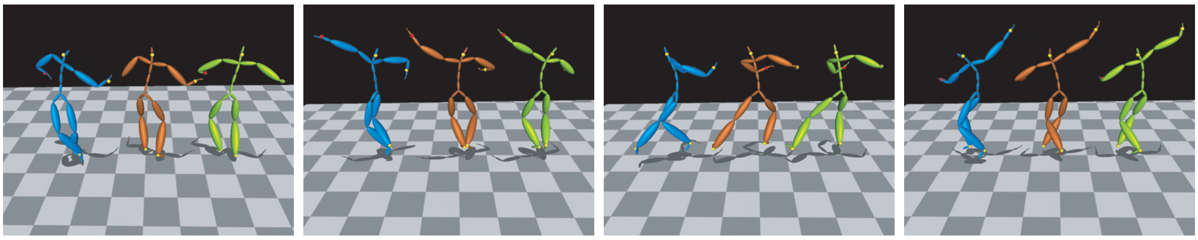

Figure 3: *Compare our method with style IK. The left, middle and right figures represent the results of style IK, the ground truth and our method. These poses are selected to be different from the training poses of styleIK.*

2.1. Selecting representative frames from database

A motion database may contain millions of frames. Current desktop PCs can only train a full GPs model for about 2000 frames. Sparse approximation can improve the training capacity, but is impossible to deal with more than 10000 frames. Fortunately, there are a lot of similar poses in the database. It is not necessary to include all the poses to train the model. We use a clustering algorithm called filtering algorithm to decrease the computational complexity. The filtering algorithm is an efficient implementation of k-means algorithm. It uses kd-tree to maintain a subset of candidate centers. Since update is not needed for each clustering stage, the filtering algorithm runs much faster than popular k-means algorithms while maintain satisfactory errors.

2.2. Learning a model from representative frames

We use Gaussian Process Latent Variable Models (GPLVM) which is derived from Gaussian Processes (GPs). Unlike Style IK, we use a sparse approximation called Fully Independent Training Conditional Approximations (FITC) to enable fast training speed and deal with large training data set.

3. Results

We evaluate our method for interactive character posing. All of our evaluations are performed on motion capture data of the CMU database. The experiments were performed on a Dell precision 390 computer with 2.13 GHz dural CPU and 3.5 GB RAM. It takes 8 minutes and 12 seconds to learn the model from the selected representative frame-set with Matlab code, but 24 hours for SGPLVM (Scaled GPLVM) to train the same dataset. The number of iterations we use for sparse IK and SGPLVM is 100, the latent dimension is 12, and the number of inducing variables is 200.

After the model is learned from the representative frame-set, we use an IK solver which utilizes LBFGS optimization to synthesize poses according to user constraints. The average time for synthesizing a pose is 1 second for our system, and 8 seconds for style IK.

We compare our method with traditional IK (Figure 2)and style IK(Figure 3). The results demonstrate the effectiveness of our method.

4. Conclusion

We propose a useful scheme for posing a character in a large reachable space. The proposed scheme is able to generate as-natural-as-possible poses in a large reachable space while satisfying user constraints.

References

[GMHP04] GROCHOW K., MARTIN S. L., HERTZMANN A., POPOVIC Z.: Style-based inverse kinematics. *ACM Trans. Graph 23*, 3 (2004), 522–531.

[SG06] SNELSON E., GHAHRAMANI Z.: Sparse gaussian processes using pseudo-inputs. In *Advances in Neural Information Processing Systems 18* (2006), The MIT Press.