Expressive Features for Movement Exaggeration*

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1 Introduction

Given a single motion-capture sequence of a person performing a dynamic activity at a particular *intensity* (or effort), our goal is to automatically warp that movement into a natural-looking exaggerated version of that action. Consider warping a movement of a person lifting a lightweight box to make the movement appear as if the box were actually very heavy. We describe an efficient data-driven approach applicable to animation re-use that learns the underlying regularity in an action to select the most "expressive" features to exaggerate. Other "style-based" approaches are presented in [Gleicher 1998; Brand and Hertzmann 2000; Vasilescu 2001].

We first collect motion-capture examples of a person performing an action at different intensities (See carrying example in Fig. 1). The data are placed into a matrix A with each column corresponding to a specific DOF trajectory, with each intensity set following the other. Singular Value Decomposition, $A = U\Sigma V^T$, is used to generate a representative trajectory basis U from which we perform efficient computations to rank trajectory expressibility.

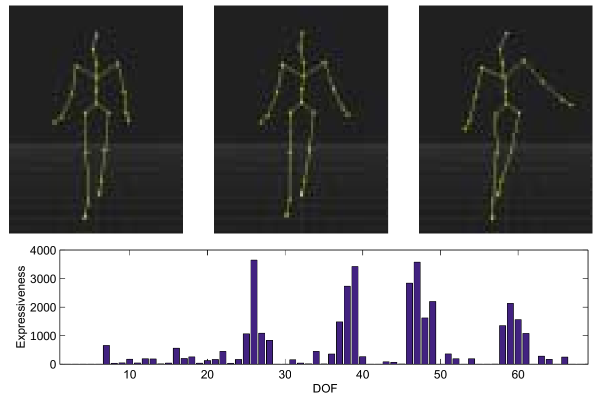

Figure 1: Top: Motion-capture sequences of a person carrying a bag (not shown) with weight 0, 25, and 50 lbs (shown left to right). Bottom: Modal expressiveness plot for the carrying examples.

2 Identification of Expressive Trajectories

The "expressiveness" of a joint-angle trajectory across different intensities is based on how large and how predictable the changes appear. *Observability* measures the magnitude of change across intensity, and is calculated as the Euclidean distance of trajectory projections on U between the first and last intensities. We additionally weight the influence of this change with the sum of bone lengths of the joint's children. To determine if those changes have *predictability* (to enable correct exaggeration), we compute an eigenvalue-weighted sum of projection correlations across intensity on each basis vector.

The expressiveness E for a joint-angle trajectory across intensity is computed as $E = O \cdot P^2$, which effectively attenuates the observability values when the predictability is low. The expressibility plot for the carrying examples is presented in Fig. 1. The resulting expressibility values for all the joints are normalized, sorted in descending order, and accumulated until reaching a desired percentage of expressiveness. This results in a smaller set of key features.

3 Exaggeration Models

We model the selected trajectory projections across intensity with intensity-to-coefficient mappings. Given a new motion-capture sequence, the selected expressive trajectories are extracted and projected onto U. Assuming an arbitrary starting intensity index for this motion, we use the intensity-to-coefficient mappings to produce new projection coefficients that either consistently exaggerate or diminish the current intensity of the motion. The approach is easily extended to include multiple people in the training set. We union the top expressive features for each person and average the intensity-to-coefficient mappings to create a generalized model.

4 Experiments

Using a Vicon-8 motion-capture system, we collected light, medium, and heavy carrying sequences for two people of different height, weight, and gender. A single walk cycle was automatically extracted and time-normalized to 50 samples. The expressive feature set and intensity-to-coefficient mappings were computed.

To validate the selected expressive features, we swapped those key trajectories between the lightest and heaviest examples for one person. The results were nearly identical to the actual motions. To examine the capability of the averaged model, we warped person-1: light-to-heavy and person-2: heavy-to-light. The resulting motions appeared natural. We additionally generated novel exaggerations for a person not used in training. Within limitations, the model exaggerated the intensity to produce believable movements.

5 Conclusion

We presented a fast and efficient method to exaggerate motion-capture with naturalistic results. The approach identifies the most expressive motion features within a low-dimensional sub-space and models the regularity across performance intensity. The resulting system can exaggerate new motion sequences without the need for additional supportive input.

References

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