More Comparisons

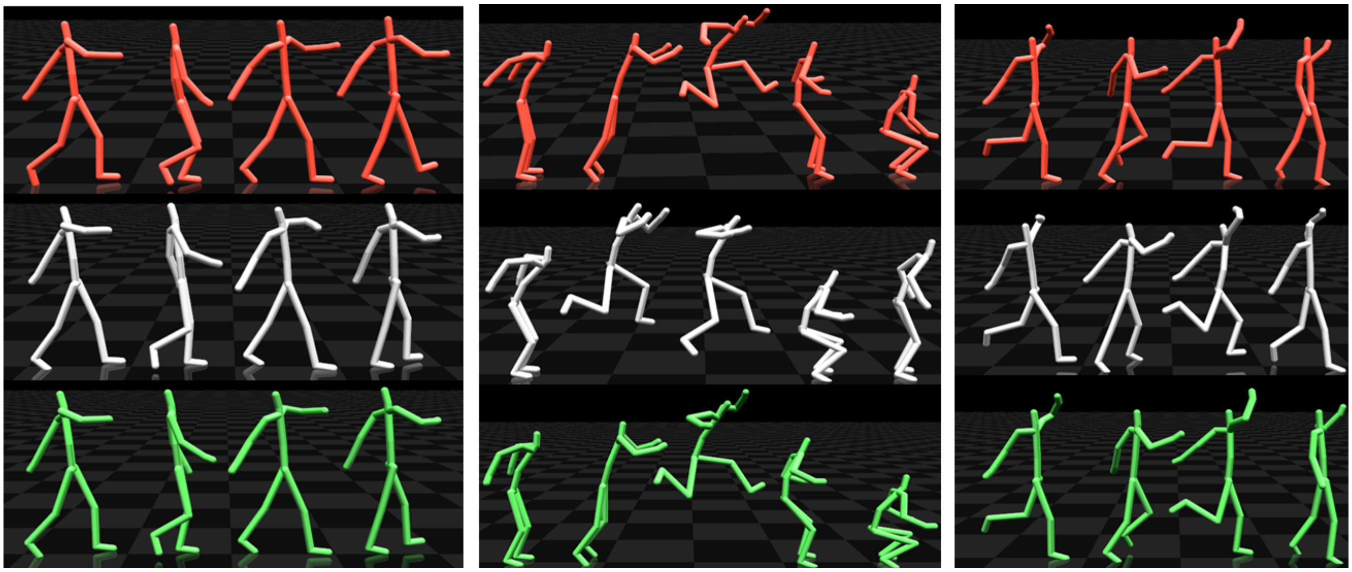

Figure 1: *Leave-out-one evaluation: (top) ground truth motion data; (middle) output animation by Wang et al. [2007]; (bottom) output animation by our method. Note that the left, middle, and right figures show the results from our walking data sets, jumping data sets, and our heterogeneous data sets, respectively.*

1 Comparison Against Wang and Colleagues [2007]

We compared our method against the method described in [Wang et al. 2007]. They introduced a Gaussian Process latent model with multifactor kernel to model stylistic variations of human motion. While their original paper is focused on constructing multilinear models using Gaussian process latent variable model (GPLVM) and applying the learned model for motion prediction and synthesis, we apply them for style transfer. To translate styles for the input motion, we first use a MAP framework to solve for all the parameters including both latent content and style parameters. We then keep the content factor fixed and change the style factor to generate a stylistic motion.

There are two models: Multifactor Balanced Gaussian Process Dynamic Model (Multifactor B-GPDM) and Circular Dynamic Model (CDM). We compared our method against both methods but found that CDM yields more satisfactory results than Multifactor B-GPDM. Therefore, we focus our comparison on CDM only. The accompanying evaluation video shows a comparison between two methods. CDM constrains dynamic variables of a multifactor GP latent model along a 2D unit circle. In particular, they are assumed to be uniformly spaced on the circle, described by the initial position and step length. Other factors in the kernel function are assumed to be invariant for a specific motion sequence. To translate styles for the input motion, we first use a MAP framework to solve for all the parameters. We then keep the content factor fixed and change the style factor to generate a stylistic motion. Specifically, we sample the dynamic variables on the circle, with the step length estimated by fitting a linear or bilinear model between factors and their step lengths, as described previously [Wang et al. 2007]. All of the latent variables and hyper-parameters are trained based on source code from the authors [Wang 2015].

We perform leave-one-out cross-validation on both homogenous and heterogeneous data sets. Both data sets contain motions with two styles, namely, "proud" and "neutral". We use the same metric described in Section 7.2.1 to measure the spatial and temporal errors. Note that the temporal errors in CDM are not available because CDM generates output stylistic animation directly in the physical timeline rather than in the canonical timeline.

We first tested our method and CDM on cyclic motions (walking). The results obtained from both methods are of high quality perceptually, but our method produces more accurate results. We then tested on acyclic motions (jumping). We have found that CDM fails to achieve satisfactory results, while our method still obtains good results. One possible reason why CDM fails to obtain good results on jumping is that it assumes the input motion is cyclic. We further tested the two methods on the heterogeneous data sets, including walking, running and jumping. As shown in Table 1, our method achieves more accurate results than Wang et al. [2007]. The evaluation results are shown in the accompanying video though we show some sample frames in Figure 1.

Data sets	Wang et al. [2007]	Our method
walking	5.67 ± 2.12	4.43 ± 0.25
jumping	16.41 ± 6.46	7.39 ± 1.00
walking+running+jumping	17.75 ± 6.35	4.76 ± 0.85

Table 1: *Leave-one-out cross validation on our method and Wang et al. [2007]: comparisons of means and standard deviations for pose synthesis errors (cm).*

References

WANG, J. M., FLEET, D. J., AND HERTZMANN, A. 2007. Multifactor gaussian process models for style-content separation. In *Proceedings of the 24th International Conference on Machine Learning*, ACM, New York, NY, USA, ICML '07, 975–982.

WANG, J., 2015. Gaussian process models for style-content separation. http://www.dgp.toronto.edu/˜jmwang/gpsc/.