KEY-POSTURE EXTRACTION OUT OF HUMAN MOTION DATA BY CURVE SIMPLIFICATION

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Abstract— **Recent progress in 3-D capture technology has made it possible to obtain much of realistic motion data of human subjects. Being captured in high frame rates, compression or extraction of key postures out of the motion data is useful for storage, transfer and browsing among them: this can serve as an important pre-processing for applications such as rehabilitation, ergonomics and sports physiology. This paper addresses these problems by treating the motion data as trajectory curves in a high-dimensional space and doing a novel application of a curve simplification algorithm, typically used for planar curves, to human motion data.**

Keywords—**Keywords - Human motion data, compression, key posture, curve simplification**

I. Introduction

Recent development of capture technology for human motion data has resulted in much use of it in motion analysis and synthesis [1][2][5][10]. While video sequences provide those projected onto 2D image planes, the capture technology based on magnetic or optical devices makes it easier to get 3D motion data such as positions or orientations. Analysis or synthesis based on the captured data benefits rehabilitation, ergonomics, sports physiology and many other applications. Being captured in high frame rates, efficient storage and browsing of the data are, hence, important analogously to those of other multidimensional data such as images and video sequences. This paper addresses the problems by treating the motion data as high-dimensional curves and running a curve simplification algorithm to them. We applied this technique to compression of the motion data and automatic extraction of key postures summarizing the motion content.

Section II describes a curve simplification algorithm typically applied to planar curves in 2 dimension. Treating the human motion data as trajectory curves of high dimensions, the simplification algorithm is shown applicable to the motion data and experimental results for the compression and the summarization are presented in section III. Discussion and conclusion follow it.

II. Curve Simplification Algorithm

Curve simplification has been used in cartography, computer graphics, pattern recognition, image processing, computer vision and computational geometry. Given a curve as a chain of line segments, a simplification algorithm generates an approximation of it with a smaller number of vertices.

For our application, we chose Lowe's algorithm [6] which outperforms other algorithms for curve simplification according to an assessment [8]. The algorithm approximates the polygonal chain by selecting a subset of vertices from the original chain.

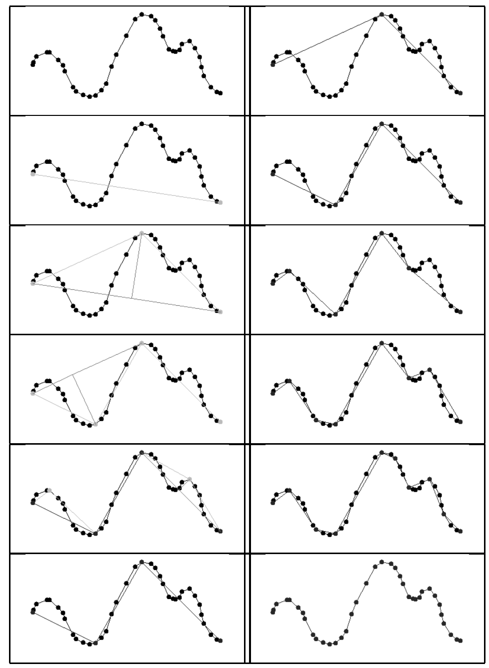

Fig. 1. Curve simplification. (Left column) step-by-step visualization of the simplification with a given error tolerance. (Right column) Results of the simplification to the same curve but with different error tolerances.

The line segments defined by the selected vertices form a candidate for the final approximation chain. In the beginning, the algorithm approximates the polygonal chain by one straight line segment that connects its two endpoints. This approximation is tested using a distance criterion: the maximum deviation of any point from the line divided by the length of the line segment. If the criterion is not satisfied, the line segment is sub-divided into two segments at the curve point most distant from the straight line segment. This procedure is recursively repeated until the resulting approximation satisfies the error tolerance specified for the given distance criterion (see Figure 1.)

Notice that, though typically used for planar curves in 2 dimension, the simplification algorithm does not depend on the dimension of the curve to be simplified: it only needs the distance from a point to a line. Hence, we are able to run the algorithm to curves in higher dimensions to simplify them.

III. Results

We used motion data of a human subject tracked by magnetic devices: position of the subject and orientations of its joints over time. A model based on specification for a standard hu-

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l_elbow	r_elbow
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l_knee	r_knee
l_ankle	r_ankle
vc2	vt10
sacroiliac	vl5

TABLE I
THE 15 JOINTS DRIVEN BY THE CAPTURED MOTION DATA.

manoid[4] was used to visualize the captured motion data (Figure 3.) Among 57 joints in the body, 15 joints were driven by the captured data (Table I.)

Orientation of each joint, *i.e.*, an rotation axis and an angle around it, can be casted as a 4 dimensional point. Since the values of orientations change over time, motion in orientation can be considered as trajectory curves in a 4+1 dimensional space: the extra dimension by time. By running the curve algorithm to each of the motion curves, we are able to simplify them and reduce the size of the motion data (Figure 2.) Though the size of the simplified motion reduces with increasing error tolerance (Figure 2), its visual quality does not degrade until the size reaches about 20% of the original one: the simplified one is hardly distinguishable from the original one (Figure 3.)

Instead of a *set* of trajectory curves for the joint orientations, the motion data can also be considered as a *single* curve in a higher $N+1$ dimensional space. The whole posture of the body at a time can be represented by the values of orientations of each joint and therefore a point in a N dimensional space: for our case, $N = 15 \times 4$. The simplification algorithm on this higher dimensional curve results in a set of key postures which can be used for visual summarization of the motion data. As shown in Figure 4 (a), the proposed method adaptively samples the key postures depending on the motion content: most of the key postures belong to the first half of the time interval where much of change in postures occur. Contrary to this adaptive sampling, an uniform sampling includes many of redundant postures from the second half of the time interval while missing some of the important postures as in Figure 4 (b): for example, it cannot tell whether the body turns left or right before showing the back.

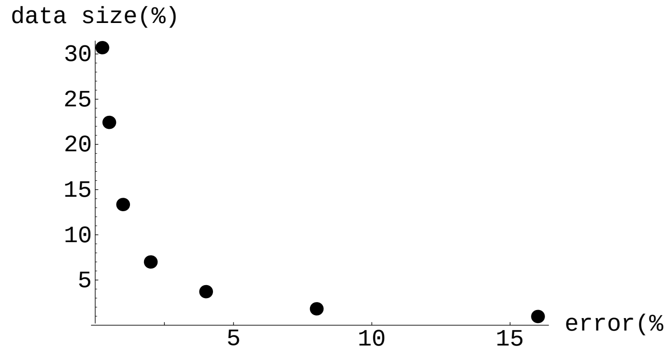
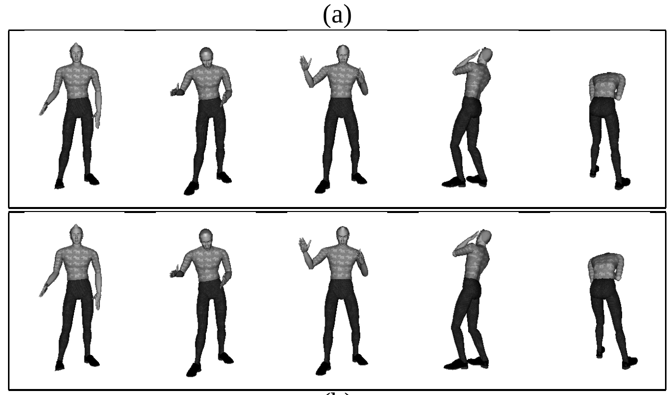


Fig. 2. Data size of the simplified motions over the error tolerance.

(a)



(b)

Fig. 3. **(a)** Original motion, **(b)** Simplified one with 0.5% error tolerance and 22.4% size of the original one. Notice that the last postures show a slight difference between them otherwise visually indistinguishable.

IV. DISCUSSION AND CONCLUSION

Curve *fitting* is a standard approach for the compression of captured motion data [9][10]. For example, a set of non-uniform B-splines curves are fitted to the motion data [9]: a B-spline curve is a piecewise polynomial with a set of *coefficients*. This fitting technique determines and keeps the coefficients which do not serve as a visual summary of the motion data. Our approach of curve *simplification*, on the other hand, can determine and keep a subset of *postures* comprising the given motion data. Therefore, it is useful either for the compression or the visual summary, the latter of which should be applicable in browsing a set of captured motion data.

A similar technique of curve simplification [7] has been applied to summarization of video sequences [3]. For biomedical application, however, it has limited potential since a video sequence is not an inherent representation of human motion: not only the motion content but also camera view angle, lighting and many others affect the video content. A feature vector for a video sequence, therefore, has to be carefully crafted [3]. This contrasts with our application to 3D human motion data which are both view and lighting independent.

A novel application of a curves simplification algorithm to human motion data was presented. It treated the motion data as trajectory curves in high dimensions and ran the simplification algorithm to the curves. The experimental results showed its usefulness in either compression or visual summary of the data, which can serve as a useful pre-processing of human motion data for rehabilitation, ergonomics and sports physiology.

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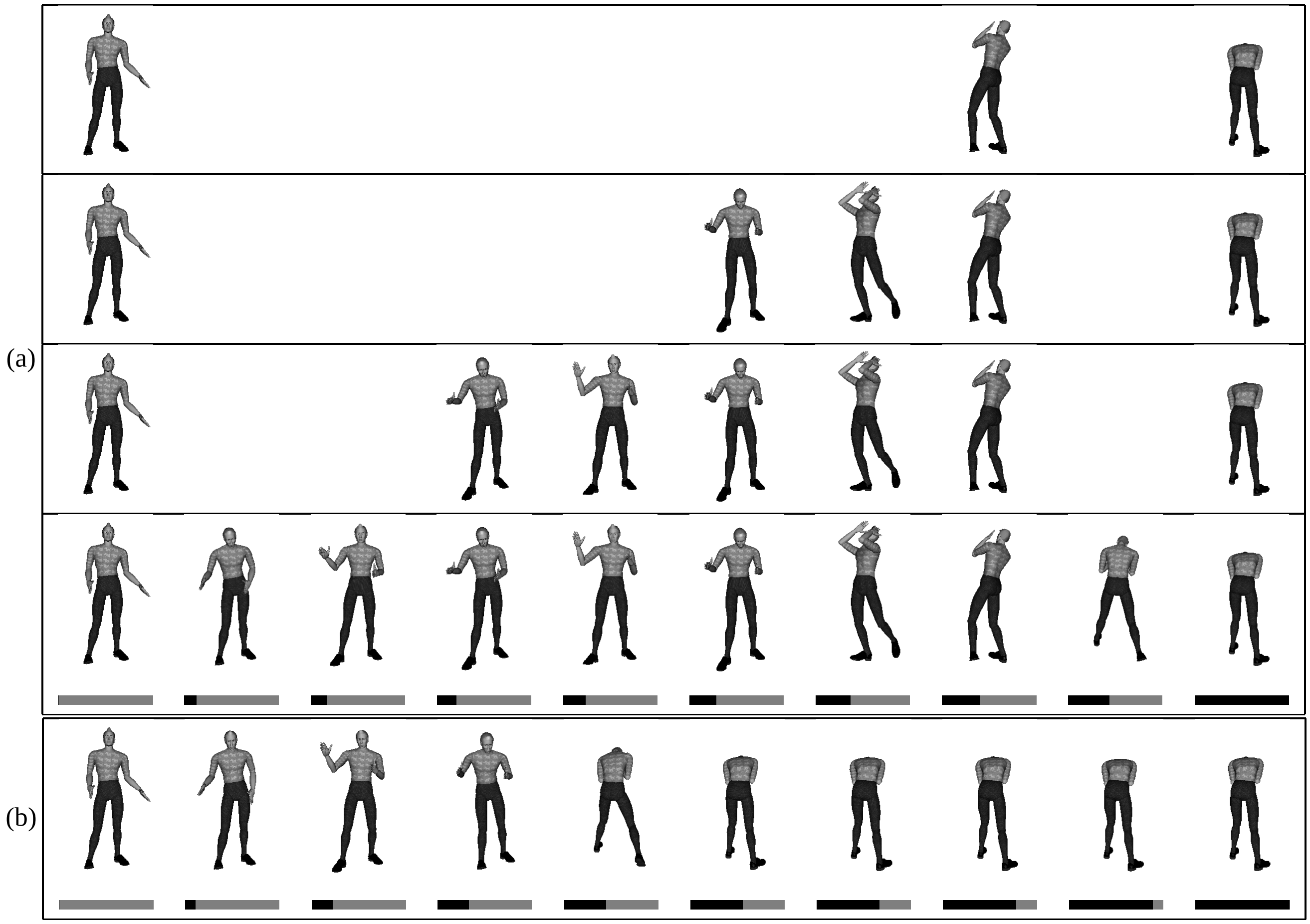

Fig. 4. Automatic extraction of key postures, adaptive vs. uniform. Each of the horizontal bars indicates the time when its posture is shown during the playback of the animation. **(a)** A hierarchy of key postures *adaptively* sampled by the curve simplification method. Four sets or rows of the key postures with different error tolerances: the smaller error tolerance, the more numbers of key postures. **(b)** A naive extraction of key postures by sampling *uniformly* in time.

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