Journal of Biomechanics 42 (2009) 436–442

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Motion segmentation method for hybrid characteristic on human motion

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ARTICLE INFO

Article history:
Accepted 29 November 2008

Keywords:
Motion segmentation
Repetitive motion
Period identification
Ergonomic evaluation

ABSTRACT

Motion segmentation and analysis are used to improve the process of classification of motion and information gathered on repetitive or periodic characteristic. The classification result is useful for ergonomic and postural safety analysis, since repetitive motion is known to be related to certain musculoskeletal disorders. Past studies mainly focused on motion segmentation on particular motion characteristic with certain prior knowledge on static or periodic property of motion, which narrowed method's applicability. This paper attempts to introduce a method to tackle human joint motion without having prior knowledge. The motion is segmented by a two-pass algorithm. Recursive least square (RLS) is firstly used to estimate possible segments on the input human-motion set. Further, period identification and extra segmentation process are applied to produce meaningful segments. Each of the result segments is modeled by a damped harmonic model, with frequency, amplitude and duration produced as parameters for ergonomic evaluation and other human factor studies such as task safety evaluation and sport analysis. Experiments show that the method can handle periodic, random and mixed characteristics on human motion, which can also be extended to the usage in repetitive motion in workflow and irregular periodic motion like sport movement.

1. Introduction

The main purpose on ergonomic analysis is focused on quantified measurement on working posture, and how it relates to the occupational injuries or musculoskeletal disorder. Previous approaches required trained observers to give posture score based on some formulated methods (Latko et al., 1997, 1999; McAtamney and Corlett, 1993), which might induce large error and the result became subjective. To increase the accuracy and the quantity of measurement, automation process like video-based analysis was proposed to recognize and retrieve human-motion data (Albu et al., 2008; Blake et al., 1995; Gavrila and Davis, 1995; Lu et al., 2000; Min et al., 2008; Niyogi and Adelson, 1994; Yacoob and Black, 1998). Newer method like optical motion-tracking system was adopted by more researchers, especially in animation, movie industry and ergonomic analysis due to its simplicity and efficiency in retrieving detailed and realistic human joint information. Though it had the shortcoming of occasional loss of data, solution was suggested by the previous study (Ormoneit et al., 2005).

Ergonomic study requires analyzing on a specified joint or limb (a group of joints) given a figure on how injury is related to a particular motion or task. Some scoring methods were commonly used where the repetitiveness and static load could only be added on the overall score by the user subjectively (Hignett and McAtamney, 2000; McAtamney and Corlett, 1993). Those methods may not match with the modern needs of analyzing repetitive and static motion in quantitative and efficient way. Motion segmentation method was then proposed to represent motions as a sequence of movements or "sub-motions", which were often modeled by dynamic systems. The method was discussed in numerous studies for not only repetitive motion analysis but also in dynamic manipulation, motion synthesis and robotic learning (Kimura et al., 2006; Troje, 2002). Different approaches were proposed like the statistical approach of principal component analysis (PCA) which represented the motion in a low-dimensional linear model (Jolliffe, 2002; Troje, 2002; Yacoob and Black, 1998; Zhang and Troje, 2007). Other researches also suggested modeling the data with dynamic non-linear systems (Kimura et al., 2006; Seitz and Dyer, 1997) or linear systems (Aström, 1970; Aström and Wittenmark, 1997; Blake et al., 1995; Lu et al., 2000; Lu and Ferrier, 2004). Event classification and motion-recognition techniques were also developed for switching and grouping the dynamic models for segmentation and further analysis (Blake et al., 1995; Campbell and Bobick, 1995; Gavrila and Davis, 1995; Lu and Ferrier, 2004; Min et al., 2008; Niyogi and Adelson, 1994; Yacoob and Black, 1998).

The previous studies often assumed input motion as periodic, followed their focus on analyzing repetitive motion. However, in some cases, there are difficulties in defining the composition of

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doi:10.1016/j.jbiomech.2008.11.038

motion nature. We may not always have enough information to provide an accurate prediction on some joints movement like wrist twisting. Moreover, classifying a whole motion into either non-periodic or periodic is not reasonable, as the task may produce both repetitive and random complex motion by user variation and task nature. To prevent the analysis affected by subjective perception on specific motion and increase the generality of analysis, we should give no assumption on motion nature.

This paper presented a two-pass method for gathering essential ergonomic data, which segmented and modeled human joint motion without the needs of any prior knowledge. The motion is preliminarily segmented into divisions and the loss of value of particular precision is guaranteed to be minimized (the first-pass segmentation). The first-passed divisions are then further segmented by motion nature (the second-pass). The final segments are either representing a random motion or a cycle of periodic motion, which are modeled by damped harmonic model. This method can be applied to most of the motions, including periodic, random, or mixed motions. Many important motion parameters like motion range, frequency and duration can also be estimated. Experimental results demonstrated that different kinds of complex human motions could be handled by this method without stating any assumption. Discussion on the method's shortcomings, limitations and further improvements and developments were also presented at the later part of this paper.

2. Method

2.1. First-pass segmentation algorithm

Joint angle is often adopted as a measure when researchers are dealing with ergonomic issues. Some papers divided joint angle into two- or three-dimensional space, especially for those video-based methods (Albu et al., 2008; Lu et al., 2000; Lu and Ferrier, 2004; Min et al., 2008; Niyogi and Adelson, 1994; Ormoneit et al., 2005; Polana and Nelson, 1997; Zhang and Troje, 2007). A hierarchical digital human model (DHM) was defined and the joint angle estimation was adopted according to the algorithm of hierarchical rotational matrix calculation mentioned in the previous study (Lau and Wong, 2007).

Some researchers described human joint motion in multidimensional form in time series. For instance, "upper arm", "elbow" and "wrist" are grouped as "arm" motion. In this paper, we would like to present the segmentation algorithm for analyzing localized risk factor on specific joint. Therefore, the motion is described as one-dimensional way to give detailed analysis on each joint motion. We treat the joint motion data (joint angle) as a sequence of signal without any prior knowledge of the characteristic. The sequence is then divided into meaningful segments.

Let $x_t \in R$ denotes the state vector of a joint (in this paper, the only state is the joint angle) at time t where $t = 1, 2, \ldots, N$. The auto-regression (AR) model is chosen to describe human motion since motion tracking requires prediction and measurement processes, in which a statistical framework of deterministic and stochastic model is adopted. And AR model, which relates previous data to new data, is similar to human-motion nature whose current state is related to future state (Ljung and Söderström, 1983):

$$x_t = \theta^T \varphi(t) + \nu(t) \tag{1}$$

where $\theta^T = (A_1, A_2, \ldots, A_N)$ are the parameters for describing the dynamic relationship between the signal with its previous value. $\varphi^T(t) = (x_{t-1}, x_{t-2}, \ldots, x_{t-N})$ represents the lagged output data, $\nu(t)$ states for the disturbance, which is set as a zero mean white noise.

In this paper, second-order auto-regression model is used to represent the motion data, which can describe complicated human-motion dynamics (Lu et al., 2000):

$$x_t = A_1 x_{t-1} + A_2 x_{t-2} + \nu(t) \tag{2}$$

where A_1 and A_2 are dynamic parameters representing the motion. Eq. (2) can be written in a more compact form by using a state vector $\chi(t) = (x_{t-1} - \bar{x}, x_{t-2} - \bar{x})^T$ where $\bar{x}$ is the mean of input data, and converting $\nu(t)$ into the following form (Lu et al., 2000):

$$\chi(t) = A\chi(t-1) + Be_t \tag{3}$$

where

$$A = \begin{pmatrix} 0 & I \\ A_2 & A_1 \end{pmatrix} \quad \text{and} \quad B = \begin{pmatrix} 0 \\ B_0 \end{pmatrix}$$

Eq. (3) shows a first-order auto-regression process in that A describes the deterministic part and B describes the stochastic part of the system. The segmentation problem is to find where the dynamic fitting parameters change significantly. Parameter estimation of $\hat{A}(t)$ can be predicted by the recursive least square (RLS) model for time-varying system (Aström, 1970; Ljung and Söderström, 1983)

$$\begin{aligned} \hat{A}(t) &= \hat{A}(t-1) + L(t)[\chi(t) - \chi(t-1)\hat{A}(t-1)] \\ L(t) &= \frac{P(t-1)\chi(t-1)}{\lambda(t) + \chi^T(t-1)P(t-1)\chi(t-1)} \\ P(t) &= \frac{1}{\lambda(t)}\left\{P(t-1) - \frac{P(t-1)\chi(t-1)\chi^T(t-1)P(t-1)}{\lambda(t) + \chi^T(t-1)P(t-1)\chi(t-1)}\right\} \end{aligned} \tag{4}$$

Here, we present an enhanced segmentation process based on the previous study as the first-pass algorithm (Lu and Ferrier, 2004):

1. Run a moving averaging on the input data to remove the noise of original motion-captured data.
2. Subtract the data by the mean to compact the data.
3. Apply recursive least square with discounted measurements to find A_1 and A_2 at time t.
4. Compute the Frobenius norm of the difference matrix of A between current and previous time.
5. Find the turning points in the Frobenius norm graph. Mark the points as "peak points" if their value exceed a particular percentile value of the whole graph.
6. For each set of peak points found by particular percentile, set the value of all points to one and merge the nearby peak points by running a moving average. The moving-range should be sufficient to merge all scattered stems (peak points) into groups with single peak. In trial, the range is about 1–5% of the input motion length, according to complexity of motion. Smaller moving-range will produce segmentation points with higher precision. However, too short segment may not provide enough information for the model fitting mentioned in the next section.
7. Set the highest points of each merged group as the possible segmentation points.
8. For each set of segmentation points, set A_1 and A_2 of each segment as constants by using the value of the starting time of that segment, which is estimated in Step 3.
9. A particular percentile value will produce a set of segmentation points. The optimized set of segmentation points is found by minimizing the sum of criterion (loss) function of each segment for all tested percentiles. If there are totally s segments, the loss function of each segment $i = 1, 2, \ldots, s$, each with starting time t_i and length of N_i can be estimated by

$$V_i(A) = \sum_{k=t_i}^{t_i+N_i} \overline{\beta}(N_i, k)[x_k - (A_1^i x_{k-1} + A_2^i x_{k-2})]^2 \tag{5}$$

where A_1^i and A_2^i are the values of A_1 and A_2 of segment i, $\overline{\beta}(t,k) = \lambda^{t-k}$ by supposing the forgetting factor $\lambda(k) = \lambda$ for all ks and we use $\lambda = 0.98$ in the experiments.

The Frobenius norm of difference matrix of A actually shows the change of fitting parameters (A_1 and A_2) in the motion. Turning point means a possible change of fitting model in the dynamic system, thus possible segmentation point. The accuracy of the algorithm depends on how precise is it in choosing the percentile level. In the experiment, the percentile level was tested from 99 down to 50 with one decrement.

The only parameter for this process is the moving-range in Step 6 (suppose enough large percentile range and suitable precision are used). Smaller values produce more segmentation points, with smaller loss, suitable for random motion, and larger values produce fewer segmentation points, dividing motion into groups of periodic motion with multiple cycles, suitable for low-varying or periodic data. A general example of the lower arm joint angle of a hand-waving motion with 20 frame per second (FPS) is shown in Fig. 1 with higher precision and Fig. 2 with lower precision. The segmentation with larger moving-range included a group of periodic data, while that in smaller moving-range segmented motion into nearly half cycle for a segment. In practice, control for the output using smaller moving-range is difficult. Especially in low-varying or periodic motion, small moving-range may segment motion into either single cycles or half cycles.

In this paper, state vector in RLS is one-dimensional only. If the dimension is increased by including multiple joint angles inside the state vector x_k. The above algorithm would still applicable by changing the matrix dimension of fitting parameters and the first-passed Frobenius norm should act as a new motion data and repeat Steps 1–4 before going into Step 5 if this one-pass algorithm does not give satisfactory result.