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Automatic spline smoothing of non-stationary kinematic signals using bilayered partitioning and blending with correlation analysis

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ABSTRACT

Measurement errors of kinematic signals introduced by motion capture systems are unacceptably amplified when differentiating the signal to derive acceleration. Existing fully automatic methods for solving this problem have a weakness on non-stationary signals involving impacts, while semi-automatic methods each require that users carefully determine the values of configurable parameters. We propose an automatic method that estimates acceleration from non-stationary kinematic signals using bilayered partitioning and blending (BPB) with correlation analysis. The method has a configurable parameter, the partition length, and the recommended value of the partition length that is empirically derived can be used without prior knowledge of kinematic signals. Having applied this algorithm to synthetic sinusoidal data, benchmarking data in the biomechanics community, and our own measurement data, we compared the results with those of existing automatic methods. The evaluation confirms that the proposed method estimates acceleration more accurately from non-stationary signals than existing fully automatic methods and is more robust than existing semi-automatic methods.

1. Introduction

Biomechanical motion analysis is usually performed using kinematic signals measured by motion capture systems because these can measure the position and orientation of multi-joint movements simultaneously [1,2]. However, systematic measurement errors of the motion capture systems appearing in the form of noise in the recorded displacement signals are unacceptably amplified when differentiating displacements to obtain velocity and acceleration. Although noise removal algorithms have been widely adopted to address this issue, mis-specified parameter values for these algorithms lead to inaccurate acceleration estimation. Thus, attempts have been made to automate the process of estimating acceleration from displacement signals.

The first attempts at fully-automatic acceleration estimation utilized the characteristic of white noise. Woltring [3] proposed generalized cross-validation spline smoothing (GCVSPL), which used generalized cross-validation [4] for choosing a smoothing parameter. D'Amico and Ferrigno [5] proposed the linear-phase autoregressive model-based derivative assessment algorithm (LAMBDA), which identified an optimal cut-off frequency by modeling the original noisy input measurements based on an autoregressive model. Cappello et al. [6] and Challis [7] estimated an optimal cut-off frequency using the fact that the autocorrelation coefficient of white noise is zero. Liu et al. [8] presented a fully automatic motion capture data denoising approach based on filtered subspace clustering and low rank matrix approximation, but did not consider the estimation of both velocity and acceleration. The limitation of these fully automatic methods is that they are aimed at stationary signals and are not suited to non-stationary signals involving impacts. More specifically, they attenuate peak acceleration at an impact while leaving considerable noise in the rest of the signal.

Thus, various other approaches have been proposed to handle non-stationary signals correctly. Ismail and Asfour [9] showed that the discrete wavelet transform could be used as an alternative to traditional noise removal algorithms. Wachowiak et al. [10] also used a discrete wavelet transform and proposed a new strategy for thresholding. However, the issue of choosing a mother wavelet remains, and there is no general thresholding rule that is suitable for estimating acceleration.

Giakas et al. [11] used the Wigner distribution [12] to remove noise by way of a time-frequency domain to deal with non-stationary kinematic signals, and Georgakis et al. [13] improved the

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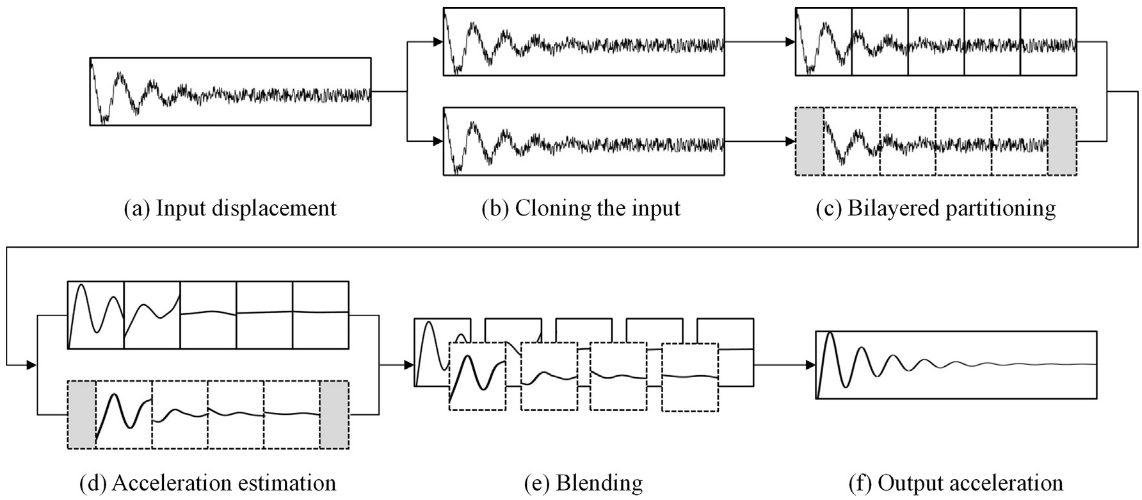

Fig. 1. Overview of the BPB method: (a) input displacement data; (b) cloning the input data; (c) bilayered partitioning; (d) acceleration estimation of each section; (e) blending the estimated acceleration values of overlapped sections; and (f) blended acceleration.

Wigner-distribution-based method using a smooth roll-off boundary. However, Alonso et al. [14,15] indicated that this method is difficult to automate and, thus, proposed a new automatic method using singular spectrum analysis (SSA), which needs only a single user-specified parameter: the window length. Alonso et al. [16] also presented a technique using the Newmark method, but it requires three user-specified parameters.

Erer [17] proposed an adaptive Butterworth filter, which improved the performance compared with that of SSA, while Georgakis and Subramaniam [18] proposed a method based on the fractional Fourier transform, which, in turn, showed better performance than Erer's method. However, each of these methods requires two or more parameters to be determined by the user, and their resulting acceleration is sensitive to these parameters. This means that users must specify the parameters carefully to obtain accurate acceleration.

The aim of this paper is to estimate acceleration from non-stationary kinematic signals in a more automatic way, while matching the accuracy of recent semi-automatic methods. Thus, we propose a bilayered partitioning and blending (BPB) method to handle non-stationary signals, and then apply correlation analysis to the automatic smoothing of each partitioned section of the input signal. Since the proposed method needs only a single configurable parameter, the partition length, to which the resulting acceleration is shown to be robust through experiments, the proposed method can be automated with the recommended partition length. We evaluated the performance of the proposed method by applying it to three signals: a synthetic sinusoidal signal, a benchmarking signal, and a jumping signal acquired with our own motion capture system.

The proposed method is briefly introduced in Section 2, and each step of the proposed method is explained in detail in Section 3. Then, the experimental data sets are introduced in Section 4, and we discuss the experimental results in Section 5. Finally, the paper is summarized and concluded in Section 6.

2. Overview of BPB

If a non-stationary signal is partitioned into several subsections, the non-stationary feature of the signal is weakened at each partitioned section. Thus, the accuracy of acceleration can be improved by individually estimating acceleration for each section. However, discontinuities occur at the boundaries of the sections because of the edge effects [19] of the smoothing methods. Therefore, we propose the BPB method as depicted in Fig. 1, which makes a clone signal (a copied layer in Fig. 1(b)) and uniformly divides the two layers so that each section of the original layer overlaps with half of the adjacent section of the copied layer (Fig. 1(c)), separately estimates the acceleration for each section (Fig. 1(d)), and, finally, blends each overlapped acceleration pair of the half sections (Fig. 1(e)). The final blending step is for the weighted average of the double estimates of the same section of a signal in order to ensure that the weight at the end of each section is zero to overcome the edge effects. In the next section, we explain each step in greater detail: the partition length in Section 3.1, the automatic estimation of acceleration in Section 3.2, and the blending in Section 3.3.

3. Methods

3.1. Partition length

The partition length is the only configurable parameter of our method. The estimated acceleration is more accurate with a smaller partition length because this is better for dealing with non-stationary signals. However, the length of data points, at which the edge effect occurs, is invariant, and the estimated acceleration of each partitioned section is more influenced by the edge effect as the partition length decreases. From the work of Woltring [3], it is known that the shortest signal length in number of data points, from which acceleration can be automatically estimated, is generally about 40. Empirically, we found that the minimum partition length is about 30, and we recommend 50 for general cases in the proposed method by our experiments including the results explained in Section 5 with Fig. 8(d), Fig. 9(d), Fig. 11(d), and Fig. 12(d).

3.2. Automatic estimation of acceleration

In this section, the method that automatically estimates acceleration for each individual partition is presented. The correlation analysis in Section 3.2.2 is performed to derive a correlation equation used in the proposed method; the derived correlation is used in the iterative estimation process in Section 3.2.3, which is performed separately for each given input signal.

3.2.1. Spline smoothing

Existing fully automatic methods for estimating acceleration from displacement measurements are based on statistical signal