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Reduction of mixed noise from wearable sensors in human-motion estimation☆

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ABSTRACT

This paper proposes a method whereby output from wearable devices is processed to estimate user motion. Output data contains mixed noise, which can accumulate when calculating distance errors. In the present experimentation, when data increased per time interval, increased error was incurred. To counter this effect, noise was reduced by means of a Wavelet Shrinkage/Kalman Filter fusion method. The input methods, input speed, sampling rate and other parameters were varied for 28 motions with 10 trials, and their effects on noise reduction were observed. The results showed a 2–15 dB improvement in noise reduction relative to the Gaussian White Noise Reduction method. This effect was especially noticeable when there was an increased level of data. When the sampling rate was high and the motion speed slow, both noise reduction and the motion-recognition run time were high. The motion-recognition rate averaged over all 28 motions was determined to be 23%.

1. Introduction

The data output from sensors attached to various wearable devices contains amalgams of irregular noises. Noise can arise from various factors such as white noise, quantization error, and others. Inaccurate data caused by human motion is a contributing factor to noise. Numerous methods and models exist that attempt to eliminate error stemming from noise [1–10]. Past studies have found that only 49% of the total data received from various measured data were useful [11], and in the case of extended-time measurements, 3–60% of error was observed for each interval [12].

Various methods have been proposed for determination of data noise values and reduction of noise. The rule-based method, linear regression, time-series analysis, and learning method are among the currently employed reduction techniques [13]. The rule-based method takes time-series data and analyzes trends while simultaneously determining an ideal value that is dependent on the type of error. It divides the data equally into N sets and computes their standard deviation, considering values lying outside the threshold as Noise. However, it is common that certain devices produce spatial data that correlates with instrumentation data lying outside the boundaries of the spatial data area; therefore, simultaneous analysis of data collected from multiple devices is a more effective method of noise reduction.

The noise reduction process must minimize the effect of noise on data in order to raise confidence. In the present study, a two-filter fusion method was utilized to reduce noise from the data output of an accelerometer, and according to the

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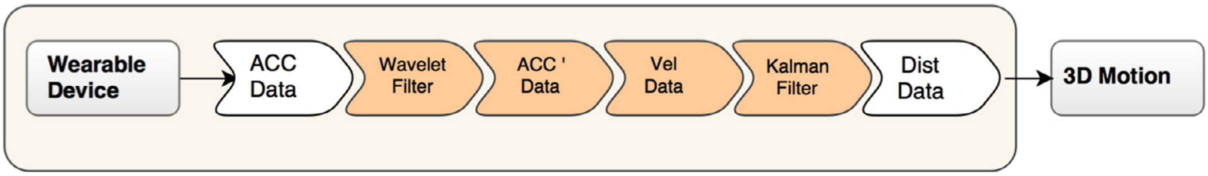

Fig. 1. System diagram.

results, post-filtering motion estimation was performed. The noise was reduced by wavelet signal analysis of the initially measured acceleration, and the impact on the original motion data was minimized. Kalman filtering was then applied to the accumulated acceleration values to reduce the error. The Kalman filtering was applied specifically to the acceleration domain in order to minimize incurred data changes.

Wavelet diversification was introduced in the early 1980s for analysis of seismic response [14]. A high-speed wavelet diversification algorithm was suggested based on multi-resolution analysis and a signal/video wavelet construction method [15]. In 1988, Daubechies, using Mallat's multi-resolution analysis, proved the existence of, and developed a means of detecting, orthogonal wavlets having compact support and a smooth shape [16].

Wavelet noise reduction is based on multi-resolution analysis. It is essential to utilize a determined threshold value to discriminate wavelets having noise elements from those without noise. Donoho and Johnstone proposed a threshold-based wavelet shrinkage method for efficient seperation of noise from original signals [17]. It establishes a proportional threshold value by estimating the magnitude of the signal with noise. In Section 2 of this paper, different noise reduction method is described, and mixed noise reduction system is presented and evaluated. Section 3 describes some experimental results of this system. Finally, the conclusions of this paper are presented in Section 4.

2. Method

Motion data input through wearable devices contains different types of noise. The most common sources of noise are binary error, gravitational acceleration error, vibration and mechanical movement error, and white noise. Acceleration and angular velocity data obtained from human motion, if such information is to be useful, cannot contain large changes in magnitude. Therefore, in the present study, Wavelet Shrinkage was utilized to eliminate system noise, including white noise, from an accelerometer. Error due to vibration and mechanical movement subsequently was eliminated from the angular velocity domain through Kalman filtering. Finally, the noise-reduced data were compared with the original movement for motion estimation. This procedure, as outlined immediately below, is illustrated in the following Fig. 1.

1. Output signal measurement
2. 1st round noise reduction in acceleration domain using wavelets
3. 2nd round noise reduction in angular velocity domain using Kalman Filtering
4. Calculation of 3D distance using noise-reduced data
5. Comparison of noise-reduced data to original movement for motion estimation

The measured noise was modeled by the equation

$$x(t) = s(t) + w(t) \tag{1}$$

where w*(t)* is the value of Gaussian white noise (including vibrational error, quantization error, etc., from the data collection process); *s(t)* is the ideal data value, and *x(t)* is the noise-damaged data value. The noise reduction process can be characterized as taking a measured value of *x(t)* and approximating *s(t)*. The optimal estimation is achieved by maximizing the signal-to-noise ratio (SNR). In this study, noise was reduced by using wavelet shrinkage as a basis for determining a threshold value and then using *x(t)* and the estimated values of *s(t)* [17]. This method is a simplified and efficient means of noise reduction. Data with noise is wavelet transformed, after which threshold values are applied to the transformed wavelets. Results with reduced noise can be obtained by reverse wavelet transform. The threshold process takes each substitution's absolute value and compares it with the threshold value; it then categorizes it as hard thresholding (T-hard) or soft thresholding (T-soft). A T-hard value is obtained when the absolute value of each substitution value is less than the threshold value; it is then determined as noise and replaced with a '0' value. A T-soft value is obtained when all of the coefficients are decreased by the threshold value (see Fig. 2).

$$\begin{aligned} \eta_H(\omega, \lambda) &= \omega 1\{|w| > \lambda\}, \\ \eta_S(\omega, \lambda) &= \mathrm{sgn}(\omega)\{|w| - \lambda\}_+ \end{aligned} \tag{2}$$

The threshold-treated coefficients are then inversed. The selection of $\lambda = \lambda^u$is based on statistical data and determined by the following equation, which is dependent on the noise standard deviation as well as the collected *x(t)* values, both of which determine the magnitude of N:

$$\lambda = \lambda^U := \sqrt{2 \ln N} \sigma \tag{3}$$

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