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Detecting falls using a fall indicator defined by a linear combination of kinematic measures

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ABSTRACT

The objective of this study was to determine whether a novel fall detection model based on the statistical process control chart performed better when the fall indicator was defined by a linear combination of kinematic measures. To specify the fall indicator, an optimization procedure was performed in which the trial and error method was used to determine the relative weightings of the selected kinematic measures associated with the optimal fall detection performance. The highest sensitivity, highest specificity, and lowest sum of squared errors of the fall detection model obtained from this study were 97.3%, 99.2% and 0.00133 respectively. These findings suggested that using the fall indicator defined by a linear combination of kinematic measures can lead to improved fall detection performance compared to that defined by a single kinematic measure.

1. Introduction

Fall detection has been recognized as an effective approach for fall prevention (Bourke et al., 2007). It can minimize fall related injuries by initiating timely medical treatment (Rajendran et al., 2008). Besides, early detection of falls in the pre-impact phase can help activate on-demand protection device, such as the inflatable airbag, so that any injuries caused by fall impacts can be avoided (Tamura et al., 2009).

Kinematic measures have been widely used to define fall indicators in the existing fall detection models. Advantages of using kinematic measures to define fall indictors are twofold. First, kinematic measures can reflect changes of body dynamics due to falls in a real-time manner. For example, Liu and Lockhart (2014a) revealed that trunk angular kinematics during slip-induced backward falls is clearly distinguishable from those during activities of daily living. In an earlier study, we also found that kinematic measures such as trunk vertical velocity and shank frontal velocity can distinguish slip-induced falls from normal walking and slip recovery (Hu and Qu, 2013). Second, body kinematic measures can be monitored by wearable inertial sensors which make long-term tracking of fall risks technically feasible. In fact, many researchers have recently proposed fall detection approaches by using inertial sensors to monitor body kinematics (Liu and Lockhart, 2013, 2014b; Özdemir and Barshan, 2014).

Some fall detection models used a single kinematic measure as the fall indicator (Rougier et al., 2007; Wu and Xue, 2008). For example, in Wu and Xue (2008), a fall was considered to occur if the trunk vertical velocity exceeded a pre-determined threshold. A single kinematic measure may not sufficiently account for falling dynamics. Therefore, in order to increase fall detection performance, many researchers used multiple kinematic measures to detect falls. In Wu (2000), for instance, a fall was detected if both the vertical and horizontal trunk velocity exceeded 1 m/s. More recently, Jacob et al. (2011) have used the gravitational force, the angular velocity and the angular acceleration at lower back to detect the occurrence of falls. In their model, falls were considered to occur if the acceleration measures exceeded 2.73 g, angular velocity measures exceeded 2.74 rad/s, and angular acceleration measures were over 0.04 rad/s^2 at the same time. In these studies, 'AND' logic was commonly used to combine various kinematic measures when defining the 'fall' condition. In other words, a fall was considered to occur only when the selected kinematic measures all satisfied the pre-defined criteria simultaneously. As a result, miss detection has to be reported on a more frequent basis (i.e. decreased sensitivity).

We presented a novel fall detection model based on the statistical process control chart (Hu and Qu, 2014). This model was superior to previous fall detection models mainly in two aspects. First, the fall indicators in this fall detection model were selected

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based on experimental findings, which improved the validity of this model. Second, this fall detection model was individual-specific, which can account for the variability of human motion patterns. In Hu and Qu (2014), the performance of the proposed fall detection model was examined separately for each selected kinematic measure. As more kinematic measures contain more information regarding falling dynamics, we aimed to examine the performance of our proposed fall detection model using a fall indicator defined by a linear combination of kinematic measures in this study. An optimization procedure was performed to specify the combination of the selected kinematic measures associated with the optimal fall detection performance.

2. Methods

2.1. The fall detection model

Based on the findings from Hu and Qu (2013), five kinematic measures were selected as the fall indicator candidates for the fall detection model. The fall detection model was developed based on the statistical process control chart in three steps (Hu and Qu, 2014). Briefly, in step 1, the autocorrelation coefficient function (ACF) was used to assess the autocorrelation in the fall indicator time series. If the autocorrelation was not found, we directly went to step 3 to construct the control chart using the original time series of fall indicators. Otherwise, in step 2, an autoregressive integrated moving average (ARIMA) model was used to eliminate the autocorrelation by generating non-autocorrelated time series. In step 3, the non-autocorrelated time series were used to specify the control limits of a Shewhart individuals control chart which was used for detecting the abnormal changes of body dynamics due to falls. After the model construction, the model was used to monitor the fall indicator in real time. If the fall indicator went beyond either the upper or lower control limit, a fall was considered to be detected. Otherwise, the activity was classified to be a non-fall activity. Details of the proposed fall detection model were presented in Hu and Qu (2014).

2.2. Definition of the fall indicator

In Hu and Qu (2014), the highest sensitivity (i.e. 94.7%) and highest specificity (i.e. 99.2%) were obtained by using the fall indicators defined by trunk vertical velocity and shank frontal velocity, respectively. Therefore, in this study, the fall indicator was defined by a linear combination of the trunk vertical velocity and shank frontal velocity as follows:

$$Fall\ indicator = xTVV_t + (1-x)SFV_t \tag{1}$$

where TVV_t represented the trunk vertical velocity, SFV_t represented the shank frontal velocity, and x was a weighting factor and within the range of [0,1]. In order to specify the value of x that was associated with the optimal fall detection performance, an optimization procedure was performed whose objective function was to minimize the sum of squared errors of the fall detection model. The sum of squared errors was defined as follows:

$$\text{sum of squared errors} = (\text{type I error})^2 + (\text{type II error})^2 \tag{2}$$

where type I error = 1-specificity and type II error = 1-sensitivity. In the optimization procedure, the trial and error method was used. In particular, x was set at various values with an equal interval of 0.01 within its specified range (i.e. x = 0, 0.01, 0.02, 0.03,..., 0.98, 0.99, and 1). Using the fall detection model developed in Hu and Qu (2014), the sum of squared errors corresponding to each x value was calculated. The optimal x was identified as that associated with the minimum sum of squared errors.

2.3. Data selection

The data used for model development and evaluation were from our earlier experiment (Hu and Qu, 2014). Sixty young participants were involved in the experiment including 30 males and 30 females (Age: 24.2 ± 2.1 years; Height 169.1 ± 9.2 cm; Weight 58.5 ± 10.3 kg). In total, there were 233 slip trials and 240 normal walking trials obtained from the experiment. Among the slip trials, there were 120 successful balance recovery and 113 failed balance recovery (i.e. falls). The experimental trials from each participant were classified into two random subsets: training subset and testing subset. The training subset for each participant included one normal walking trial and one successful recovery trial and was used to specify the individual-specific fall detection model as described in Hu and Qu (2014). The rest experimental trials belonged to the testing subset which was used to examine the efficacy of the proposed fall detection model.

3. Results

Fig. 1 illustrated how the sensitivity, specificity and sum of squared errors changed with the weighting factor x. The smallest value of sum of squared errors = 0.00133 (sensitivity = 97.3% and specificity = 97.5%) was found when the weighting factor x was between 0.25 and 0.29. Besides, the highest sensitivity (97.3%) and highest specificity (99.2%) were achieved when x = 0.25–0.29 and x = 0.84–1, respectively.

4. Discussion

In the earlier investigation (Hu and Qu, 2014) that used a single kinematic measure to define the fall indicator, the highest sensitivity, highest specificity, and minimum value of sum of squared errors were 94.7%, 99.2% and 0.00390, respectively. In this study, the corresponding values we obtained were 97.3%, 99.2% and 0.00133 for sensitivity, specificity, and sum of squared errors, respectively. Therefore, the fall detection model based on the statistical process control chart performed better when the fall indicator was defined by a linear combination of kinematic measures. This finding is reasonable since more kinematic measures could better account for falling dynamics.

Some previous fall detection studies also used multiple kinematic measures to indicate the fall status (Nyan et al., 2008; Jacob et al., 2011; Wu, 2000). However, these studies mainly used 'AND' logic to combine kinematic measures which would result in decreased sensitivity. To overcome this problem, the fall indicator as a linear combination of kinematic measures was proposed in this study. The advantage of using the linear combination is that it is the simplest format of combination that makes the analysis and implementation easy. The improved fall detection performance have supported that linear combination is a wise choice to combine kinematic measures.

An optimization procedure was performed to specify the relative weightings of the selected kinematic measures. The trial and error method, which is a widely accepted heuristic method, was chosen in the optimization procedure because the optimization problem in the present study was a highly non-linear problem that can only be addressed by heuristic methods. In addition, the trial and error method was chosen because it is less computationally intensive compared to other heuristic methods such as genetic algorithms and simulated annealing.

The optimal weighting factor x was found to be within a range, not at a specific value. This is because of the limited amount of experimental data (i.e. 240 normal walking trials and 233 slip trials including 120 successful balance recovery and 113 falls) available