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An individual-specific fall detection model based on the statistical process control chart

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ABSTRACT

Falls remain one of the leading causes of fatal and nonfatal injuries in many countries. Fall detection is an important method to protect fallers by minimizing injury severity. There are some common limitations in existing fall detection models. In particular, the fall indicators and detection thresholds were arbitrarily predetermined without any theoretical and/or experimental basis, and most fall detection models cannot address inter-individual differences. This study presents a novel pre-impact fall detection model based on the statistical process control chart that is able to address the existing limitations. The fall indicators in this model were selected based on experimental findings. The fall detection model is individual-specific, since it is constructed using individual historical movement data. The fall detection model demonstrates a high accuracy with up to 94.7% sensitivity and 99.2% specificity. In addition, this model can also provide sufficient time for triggering fall protection device in the pre-impact phase, thus efficient in preventing fall injuries.

1. Introduction

Falls were reported as one of the leading causes of fatal and nonfatal injuries in many countries (Antao et al., 2008; Bakhtiyari et al., 2012; Zytoon, 2012). In the year of 2010, approximately 26,006 adults in the US died as a result of falls, and 9,146,026 patients were treated in emergency departments for fall related injuries (The US Centers for Disease Control and Prevention, 2010). The consequences of falls are particularly devastating among older adults. In the US, 10,300 fatal and 2.6 million non-fatal fall related injuries were reported among older adults aged over 65 years in 2000 (Stevens et al., 2006). Seventy percent of all emergency department visits by people over the age of 75 years were related to falls and 40% of hospital admissions in this age group resulted from fall-related injuries (Sattin, 1992). In Singapore, falls or fall related incidents are the leading mechanism for elderly patients' (above 65 years old) sustaining trauma, and account for 85.3% of all injuries in hospital emergency department (Yeo et al., 2009).

Fall detection has been suggested to be able to protect fallers by minimizing injury severity after the occurrence of a fall (Bourke et al., 2007). Recent studies revealed that fall detection followed by immediate reporting to caregivers can improve health outcome by initiating faster and appropriate medical care or evaluation (Rajendran et al., 2008). Besides, early detection of falls in the pre-impact phase can possibly activate fall prevention devices (e.g. inflatable airbag) to avoid injuries caused by physical impacts with the ground (Tamura et al., 2009).

Existing fall detection methods are mainly threshold-based (Bourke et al., 2007; Noury et al., 2000; Rougier et al., 2007; Wu, 2000). For instance, in Wu (2000), a fall was detected if both the vertical and horizontal trunk velocity exceeded 1 m/s. Similarly, Noury et al. (2000) also used the trunk velocity as one of the fall indicators and a fall was considered to occur if the trunk vertical velocity exceeded a pre-determined threshold. More recently, Bourke et al. (2007) have simulated eight different types of falls and eight-different types of activities of daily living (ADLs) in a laboratory setting. Trunk and thigh kinematics were measured by three-axial accelerators attached to the trunk and thigh, respectively. The fall detection thresholds were defined by the smallest positive and negative peaks of the trunk and thigh resultant accelerations during simulated falls. They reported that falls could be distinguished from ADLs based on a data set including 480 movements.

Although, threshold-based fall detection methods have been widely investigated, there are some common limitations in the existing methods. Firstly, the fall indicators and detection thresholds were arbitrarily predetermined without any theoretical and/or experimental basis. The selection of fall indicators and detection thresholds directly affects the fall detection performance. Secondly, the existing fall detection methods cannot address inter-individual differences. However, it is well known that different

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individuals may have different motion patterns and characteristics. Further, only voluntary falls were simulated in the existing fall detection studies, while accidental falls in reality were mainly involuntary in nature. Thus, external validity of the existing fall detection studies is questionable.

In the present study, we aimed to develop a novel fall detection model that was able to address the existing limitations in fall detection. The statistical process control chart that has been widely used in the field of quality control (Woodall et al., 2004; Haridy and Wu, 2009; Mohammed et al., 2009) can effectively detect the abnormal changes in system performance by tracking the process performance over time. Fall detection shares some common features with quality control in terms of data collection and detection of abnormality. Thus, the novel fall detection model presented here was based on the statistical process control chart. Slips are one of the most common causes leading to accidental falls (Courtney et al., 2001), and nearly 70% of falls occur during walking (Berg et al., 1997). Thus, the proposed model was developed to detect slip-induced falls during locomotion. Besides addressing the limitations in the existing fall detection methods, the proposed model was also expected to be associated with high sensitivity and specificity.

This paper is organized as follows. In Section 2, an introduction to the statistical process control chart is given to help readers better understand the proposed fall detection model. Section 3 provides the steps to develop the fall detection model based on the statistical process control chart. Section 4 depicts the application of the proposed fall detection model in detecting slip-induced falls during locomotion. Sections 5 and 6 presents the results and discussion, respectively.

2. The statistical process control chart

2.1. Conventional statistical process control

The conventional statistical process control chart is based on the theoretical concept of Shewhart statistical process control (Shewhart, 1931) which indicates that if a process is under statistical process control, the future variation of such process can be predicted within the control limits (Shewhart, 1931) and the abnormal variation (also called special cause) is detected when the data are out of the control limits. These control limits define the natural range of variation. In general, there are an upper and a lower control limit which are obtained from historical data and represent the limits of the under-controlled state of certain activities. Any points falling outside of these control limits indicate the occurrence of abnormal activities. In a common practice of the Shewhart statistical process control chart, the “three sigma control limits” are always applied, where the control limits are defined by three times of the standard deviation (Shewhart, 1931). Previous industrial applications have demonstrated that the Shewhart statistical process control chart is a simple and powerful tool to detect the sudden and substantial abnormal changes in data without frequent false alarms (Montgomery et al., 2008; Woodall et al., 2004; Benneyan et al., 2003; Haridy and Wu, 2009).

2.2. Autocorrelation in the process data

A standard and important assumption when applying conventional statistical process control techniques is that the process data must be independently and identically distributed (Montgomery, 2009). This assumption is always violated in practice due to the existence of autocorrelation in the process data. Autocorrelation refers to the correlation of a variable with itself over successive time intervals. Autocorrelation may compromise the performance of the control chart especially leading to increased false alarms (Alwan and Roberts, 1988; Maragah and Woodall, 1992; Thaga, 2008). For example, Thaga (2008) suggested that positive autocorrelation of the process variables can result in severe negative bias in traditional estimators of the standard deviation. This bias produces much tighter control limits than desired and as a result more false alarms are generated. Lu and Reynolds (1999) also observed that autocorrelation in the monitored data can result in a higher false alarm rate than expected. Given the adverse effects of autocorrelation on the performance of the statistical process control chart, there is a need to take into consideration autocorrelation when designing the statistical process control chart.

2.3. Time series based control chart

Many practical solutions have been provided to eliminate the effects of autocorrelation and nonstationarity for the statistical process control chart (Box and Kramer, 1992; MacGregor, 1987, 1990; Montgomery, 2009). One commonly used solution is modeling the data through an appropriate time series model and estimating residuals from the model (Alwan and Roberts, 1988). The autoregressive-integrated-moving-average (ARIMA) model is one of the time series models that can be applied for modeling and forecasting the autocorrelated time series data (Alwan and Roberts, 1988; Haridy and Wu, 2009).

In time series analysis, the autoregressive model and moving average model are commonly used. The ARIMA model is an integration of both the autoregressive and moving average models. In the autoregressive model, one specific observation in a time series is dependent on previous observations. In other words, the observation at time $t(x_t)$ can be regressed on its past consecutive values plus an error (also known as random shock) (e_t) as in the following equation:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots + e_t \tag{1}$$

or equivalently as:

$$\left(1 - \sum_{j=1}^{\infty} \phi_j B^j\right) x_t = e_t \tag{2}$$

where ϕ_j is the autoregressive parameter and B^j is known as the backshift operator that is defined as:

$$B^j x_t = x_{t-j} \tag{3}$$

The moving average model, on the other hand, suggests that each observation in the time series can be affected by the past random shock (i.e. error) that cannot be accounted for by the autoregressive component. In the moving average model, each observation in the time series can be represented as a linear combination of errors and a constant (μ) as:

$$x_t = \mu + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots \tag{4}$$

or equivalently as:

$$x_t - \mu = \left(\sum_{j=1}^{\infty} \theta_j B^j\right) e_t \tag{5}$$

where θ_j is the moving average parameter.

The ARIMA model can be used to model the autocorrelation in original data set and generate the non-autocorrelated residuals in an output data set by applying an initial “differencing” step. The conventional statistical process control chart (e.g. Shewhart control chat) can then be developed based on these residuals.