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Ranking risk exposures for situational surveillance of falls with sensors

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ABSTRACT

Falls pose a significant public health problem. The usefulness of wearable sensors for detection of falls is well-known. We propose a novel optimization-based approach that was formulated for ranking exposures to falls using information streamed from multiple sensors. Our method incorporates statistical estimation. We illustrate our technique on synthetic data. Future research is aimed at assessing the validity of this new method.

1. Introduction

In this paper we develop and describe a novel optimization method for sensor-based surveillance and monitoring of hazardous situations that may result in falling. In this approach, the focus is shifted from traditional falls detection to situational assessment related to falls. Falls can arise in variety of situations when a person looses balance and fails to regain it. For instance, either trips or slips may lead to a loss of balance that could possibly result in a fall. The ability to distinguish various kinds of exposures to falls could potentially be used for acquiring the personalized data on situational risk of falls. Furthermore, the capacity for differentiating among exposures to falls can be utilized in new technologies for mobility assistance and falls prevention. Accordingly, the long-term objective of this research is to enable smart sensor-based technologies for recognizing and differentiating among various types of exposures to falls.

The presented new approach for ranking situational exposures to falls is general, and not specific to age-related falls. However, falls in older adults serve as a long-term motivation behind this research, since older population is disproportionably affected by falls. Falls in elderly is a globally recognized public health problem that is projected to worsen due to the worldwide population aging [1]. In the United States, one third of adults of 65 years and older falls each year [2]. Falls in older adults result in reduced mobility, loss of functional independence, depression, trauma, and death. In healthy, active older adults situational and environmental factors may be predominant sources of falls risk [3].

A fall is commonly defined as an unintentional event that results in a person coming to rest on a ground, floor, or lower level and that excludes a seizure, heart attack, stroke or a major displacing force (e.g., an earthquake) [4]. A fall is said to happen in the following three phases [3]. The first phase is the initiating event or a perturbation that creates a loss of balance, i.e., displaces the center of mass beyond its base of support. The second phase is a failure to detect and correct this displacement in time to regain balance and avoid a fall. The third phase is the contact with the resting surface (e.g., ground or floor) causing the transmission of forces to organs and body tissue.

A near fall is traditionally defined as a loss of balance or stumble event that would result in a fall if sufficient recovery mechanisms were not activated [5]. This definition has been recently extended in [5] to include the activation of at least two of the fall-specific compensatory mechanisms. These may involve unplanned movement of arms or/and legs, unplanned change in stride length, lowering of the center of mass, unplanned change in stride velocity, and trunk tilt. The new definition of near falls helps improve differentiation of these events from obstacle negotiation [5]. Near falls are related to fall risk, occur more frequently than falls and may precede falls [6]. The frequency of near falls may provide a broader, more robust estimate of falls risk [5].

The first phase is common to falls and near falls. This phase begins with a perturbation or initiating event that involves external factors such as environmental hazards as well as physical

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activities in progress at the time of the event. For instance, different environmental hazards cause trips versus those that cause slips. Trips and slips are two commonly distinguished types of exposures to falls or near falls. While the absence of falls risk exposure includes both the usual physical activities (such as walking) and the activities with obstacle avoidance. The ability to rank these in terms of their likelihood can be useful for gaining insights into situational and environmental risk factors of falls. Furthermore, a different fall prevention mechanism would be more suitable for trips versus slips. When combined with fall detection, the ranking of exposures could potentially enable more effective prevention.

Falls detection received and continues to attract a lot of attention from both researchers and practitioners [7,8]. The usefulness of wearable sensors for detection of falls is well-known. As reviewed in [8], many studies confirm usefulness of wearable sensors and sensor systems for detection of falls with the analytical methods ranging from simple thresholds [9] to advanced neural networks [10]. In practice, simple sensors are often used to monitor the activity of daily living (or ADL) and generate the alarms if no activity is detected at certain periods of time. Recent research indicates that an improved detection of falls is possible using the complementary information from sensors placed at different locations on a body [11].

The main contribution of this paper is a new analytical approach for sensor-based surveillance and risk assessment of falls. Most research work to-date deals with either sensor-based falls detection [7–9,12–16] or sensor-based assessment of overall falls risk [17–20]. In contrast, here we present a new mathematical framework for dealing with the situational assessment of falls risk exposures using multiple sensors. Wearable sensors (specifically, accelerometers) allow to record the information about motion of a human body that may be useful for understanding loss of balance [8,21]. Multiple sensors can be positioned on various locations of a body to potentially provide complimentary information [11]. The presented approach combines mathematical techniques to analyze the signals from motion sensors and rank distinct types of falls exposures.

We propose a distinctly new modeling framework for sensor-based monitoring of falls. Our framework combines statistical estimation with combinatorial optimization. We show how our approach can be applied on the simple example with two basic exposures and simplified synthetic data for two sensors. The presented example is not meant to demonstrate the validity of our approach. Additional research is needed to validate the proposed analytical approach on real data. Currently, we are collecting the data with a system of wearable sensors in human subject experiments. The acquired dataset will be used in future studies to assess the validity of the new optimization-based method.

The paper is organized as follows. In Section 2 we describe the proposed novel methodology for monitoring and risk assessment of falls. This section is split into two parts because the approach combines combinatorial optimization and statistical estimation to rank risk exposures from streams of sensor data. First, we formulate the task of ranking distinct types of risk exposures to falls as the problem of maximizing the likelihood of observed data. Second, we derive the formulas for the coefficients of the maximization problem and reduce the task of finding the coefficients to statistical estimation of certain density functions. The formulation of the maximization problem is presented in Section 2.1, followed by the methods for estimating the coefficients that are described in Section 2.2. In Section 3, a detailed example is provided to show how to use the approach. The example is not intended to demonstrate the validity. The validity will be addressed in future studies. For transparency and simplicity, we use artificial data as a very rough approximation of two sensor signals. The synthetic data are defined analytically, split into the past data (for training) and the future data (for testing), and used to rank likelihood of falls versus no-falls for future observations. Some clarifications on the new approach and the example, along with the limitations of this study and the future research directions are discussed in Section 4. Finally, in Section 5 we present the conclusions and discuss the advantage of our approach compared to other methods.

2. Optimization and estimation-based methodology for ranking risks of falls from multiple sensors

In this section we describe a new methodology for ranking distinct types of potential exposures to falls and near falls based on the past data. The methodology uses a combination of optimization and statistical approaches. Together, the approaches allow tracking these risk rankings in time and can potentially lead to the development of new devices for falls prevention.

2.1. Formulation of the optimization problem

Information technology plays an increasing role in personalized health monitoring. Simple wearable devices equipped with sensors such as pedometers and activity trackers are used to monitor various characteristics, such as a number of steps taken, calorie expenditure, distance traveled, etc. These devices allow their users monitor their physical activity, and improve health and fitness. Exposure of adults to risks of falling can be monitored with sensor-based wearable devices.

In monitoring exposure to falls, a key surveillance challenge is to estimate the types of fall risk exposure (e.g., slip, trip, absence of exposure, etc.) present in the past, current, or future state of a person based on a sequence of data from one or more sensors. The focus of the present work is on the basic types of exposures, which can be identified with the sensors that generally provide kinematic information such as acceleration and balance.

Suppose that one or more sensors, either wireless or wired, are placed at various locations on the subject's body. This sensor or system of sensors produces a stream of data (or measurements), each with distinct time label. These data can be arranged into sequences of observations called time series, each corresponding to the specific sensor and ordered according to time labels. Formally, let $t_k \geq 0, k = 1, 2, \ldots$ be a sequence of times. Let S denote the total number of sensors used, and let the index $s, s = 1, 2, \ldots, S$ represent the sensor number. At time t_k each sensor s has an N-dimensional noisy measurement vector $(x_1^s(t_k), x_2^s(t_k), \ldots, x_N^s(t_k)) \; =: \; \overline{X^s}(t_k)$ associated with it. Let D denote the dimensionality of a combined vector of measurements from all S sensors, then $D = N \times S$. In general, $D = \sum_{s=1}^{S} N_s$, where N_s is the dimensionality of sth sensor (e.g., a 3-D accelerometer has dimensionality 3).

In the human subject, we define the exposure to the risk of falling as the quantified *potential* for a sudden loss of balance that might occur as a result of some activity or event. We are interested in assessing the exposure to the risk of falling in the current state, where the exposure is determined or quantified based on potential for a sudden loss of balance to happen within some specified period of time in the future. We assume that this period starts from the current moment of time and call it the prediction period.

Suppose the prediction period is represented by time τ.

Exposure to falls risk can be categorized in a variety of way depending on the goals of risk monitoring. For instance, preventive monitoring of falls risk situations may lead to the exposure to risks of fall be categorized based on the initiation of the fall exposure (e.g., right leg-initiated potential loss of balance or balance loss originating with left leg, etc.), or alternatively on the type of balance loss (e.g., potential slip vs. potential trip, etc.). For a sake of brevity we will use risk exposure and risk interchangeably.