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Statistical Data Mining of Streaming Motion Data for Fall Detection in Assistive Environments

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Abstract— **The analysis of human motion data is interesting for the purpose of activity recognition or emergency event detection, especially in the case of elderly or disabled people living independently in their homes. Several techniques have been proposed for identifying such distress situations using either motion, audio or video sensors on the monitored subject (wearable sensors) or the surrounding environment. The output of such sensors is data streams that require real time recognition, especially in emergency situations, thus traditional classification approaches may not be applicable for immediate alarm triggering or fall prevention. This paper presents a statistical mining methodology that may be used for the specific problem of real time fall detection. Visual data captured from the user's environment, using overhead cameras along with motion data are collected from accelerometers on the subject's body and are fed to the fall detection system. The paper includes the details of the stream data mining methodology incorporated in the system along with an initial evaluation of the achieved accuracy in detecting falls.**

I. Introduction

In the case of elderly or disabled people living on their own, there is a particular need for monitoring their activity. Furthermore, approximately 33% of persons over the age of 65 and 50% of persons over the age of 85 experience a fall each year [1]–[3]. The injuries associated with falls can have serious consequences. For example, following hip fracture, 50% of older people are unable to live independently, 25% will die within six months, and 33% die within one year [1]–[3].

The goal of monitoring an individual behavior is the detection of major incidents such as a fall, or a long period of inactivity in the same place. Several techniques have been proposed for identifying emergency situations processing motion, audio or video streaming data produced by corresponding sensors. This paper presents a human body fall detection system based on a statistical data mining methodology that may be used on streaming data. The fall detection system uses visual data from overhead cameras in the user's environment, along with motion data captured by wearable accelerometers.

We can formulate the problem of fall detection as an instantiation of a general change detection task. Subsequently we can model this with the aid of parametric models in which the parameters are subject to abrupt changes at unknown time instants. An effective technique to solve such problems is the cumulative sum (CUSUM) algorithm, which we will employ in this work [4].

The overall architecture of the fall detection system is depicted in Figure 1. The rest of the paper is organized as follows. In Section II, we give background material and related approaches found in the literature. Next, in Section III we present the methodology of the CUSUM algorithm, while Section IV is devoted to the experimental set up and evaluation. The paper ends with concluding remarks and some future research directions.

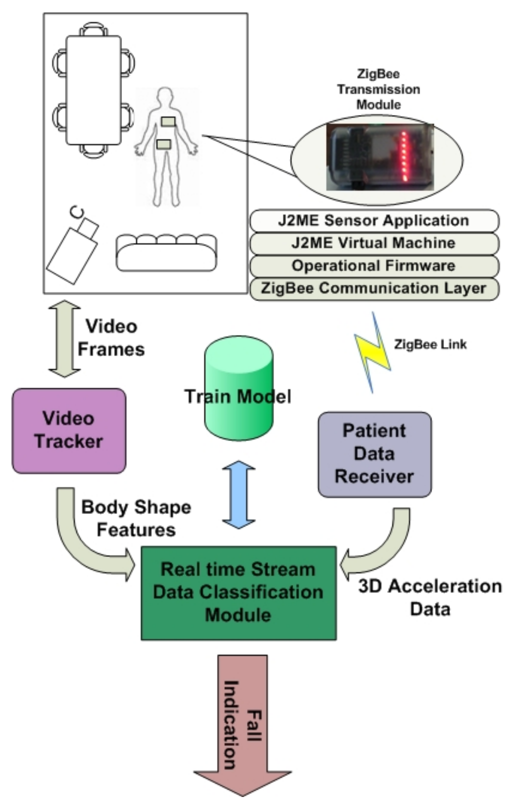

Fig. 1. System architecture

II. Related Work

Although the concept of activity recognition with focus on fall detection is relatively new, there already exists significant related research work in the field, which may be retrieved from the literature [5]–[10]. Information regarding the human

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movement and activity in assisted environments is frequently acquired through visual tracking of the subject's or patient's position. Overhead tracking through cameras provides the movement trajectory of the patient and gives information about user activity on predetermined monitored areas. Unusual inactivity (e.g. continuous tracking of the patient on the floor) is interpreted as a fall.

A different approach for collecting patient activity information is the use of sensors that integrate devices like accelerometers, gyroscopes and contact sensors. The latter approach depends less on issues like patient physiology (e.g. body type and height) and environmental information (e.g. topology of monitored site) and can be used for a variety of techniques enabling user activity recognition [5]. Regarding fall detection, developers use accelerometers, gyroscopes and tilt sensors for movement tracking. Collected data from the accelerometers (i.e. usually rotation angle or acceleration in the X, Y, and Z axis) are used to verify the placement of the patient and time occupation in rooms and detect abrupt movement that could be associated with a fall.

Detection is performed using predefined thresholds and association between current position, movement and acceleration. In previous works [9], [10], we have presented a patient fall detection system based on such body sensors that utilized advanced classification techniques and Kalman filtering for producing post fall detection.

Since, the collected sensory data are streaming data, in this work, we try to detect falls in real-time, classifying each sample of the data stream upon its acquisition. Therefore, we split and categorize time frame as walk or fall. To this end, a change detection algorithm is employed. The goal of this algorithm is to detect significant changes, while rejecting unimportant ones.

III. The Cumulative Sum Algorithm

The cumulative sum (CUSUM) algorithm was first proposed in [4]. CUSUM is a change detection algorithm that can be used both for on-line and off-line change detection. In this work, we will utilize the on-line version of the CUSUM algorithm. To this end, we will focus on a technique connected to a simple integration of signals with adaptive threshold [11].

To describe the change detection algorithm, we consider a sequence of independent random variables y_k, where y_k is a sensor signal at the current time instant k (discrete time), with a probability density $p_\theta(y)$ depending only upon one scalar parameter θ. Before the unknown change time t_0, the parameter θ is equal to θ_0, and after the change it is equal to $\theta_1 \neq \theta_0$. Then, the problem is to detect and estimate this parameter change. In this work, our goal is to detect the change assuming that the parameters θ_0 and θ_1 are known. In practice, parameters θ_0 and θ_1 can be estimated using test data.

Next, we introduce the basic idea used in quality control. Samples with fixed size N are taken and at the end of each sample a decision rule is computed to test between the two following hypotheses about parameter θ:

$$H_0 : \theta = \theta_0$$

$$H_1 : \theta = \theta_1.$$

As long as the decision is in favor of H_0, the sampling and test continue. Sampling is stopped after the first sample of observations for which the decision is in favor of H_1.This sample also determines the stopping time. We will use the following notation. Let

$$S_j^K = \sum_{i=j}^{k} s_i, \quad \text{where} \quad s_i = \ln \frac{p_{\theta_1}(y_i)}{p_{\theta_2}(y_i)}$$

is the log-likehood ratio for the observations from y_i to y_k. We refer to s_i as sufficient statistic. Let us now consider the particular case where the distribution is Gaussian with mean value μ and constant variance σ. In this case, the changing parameter θ is μ. The probability density is

$$p_\theta(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$$

and the sufficient statistic s_i is

$$s_i = \frac{\mu_1 - \mu_0}{\sigma^2}(y_i - \frac{\mu_0 + \mu_1}{2}).$$

The corresponding decision rule is then, at each time instant, to compare this difference to a threshold as follows:

$$g_k = S_k - m_k \geqslant h$$

where

$$m_k = \min_{1 \geqslant j \geqslant k} S_j.$$

The stopping time is

$$t_a = \min\{k : g_k \geqslant h\},$$

which can be rewritten as

$$t_a = \min\{k : S_k \geqslant m_k + h\}.$$

This decision rule is a comparison between the cumulative sum S_k and an adaptive threshold $m_k + h$. Because of m_k, this threshold not only is modified on-line, but also keeps complete memory of the entire information contained in the past observations. Moreover, in the case of change in the mean of a Gaussian sequence, S_k is a standard integration of the observations.

IV. Experimental Setup and Evaluation

Our main concern in the following experiments is to effectively detect on-line the exact time that a walking person starts falling. To achieve this we use the CUSUM algorithm described above on four independent sensor signals. In our experiments, three different datasets have been tested. Each dataset contains four synchronized data streams, taken from a person who is walking and then falls. More specifically, the person wears an accelerometer and the accelerations in the X, Y, and Z axis are recorded. Additionally, overhead cameras capture visual data and a rectangular blob is tracked around

TABLE I

THE NUMBER OF FALSE ALARMS AND THE DELAY FOR SEVERAL h VALUES

h	0.005	0.010	0.050	0.100	0.150	0.200	0.500	1.000	1.500	2.000
Accelerometer (x axis)										
False Alarms	11	9	1	0	0	0	0	0	0	0
Delay	2	2	2	2	2	2	10	20	28	36
Accelerometer (y axis)										
False Alarms	22	12	0	0	0	0	0	0	0	0
Delay	3	7	30	86	86	86	86	86	86	86
Accelerometer (z axis)										
False Alarms	2	0	0	0	0	0	0	0	0	0
Delay	5	4	16	20	24	30	86	86	86	86
Blob size										
False Alarms	8	8	5	3	1	1	0	0	0	0
Delay	0	0	2	4	5	6	12	55	65	73

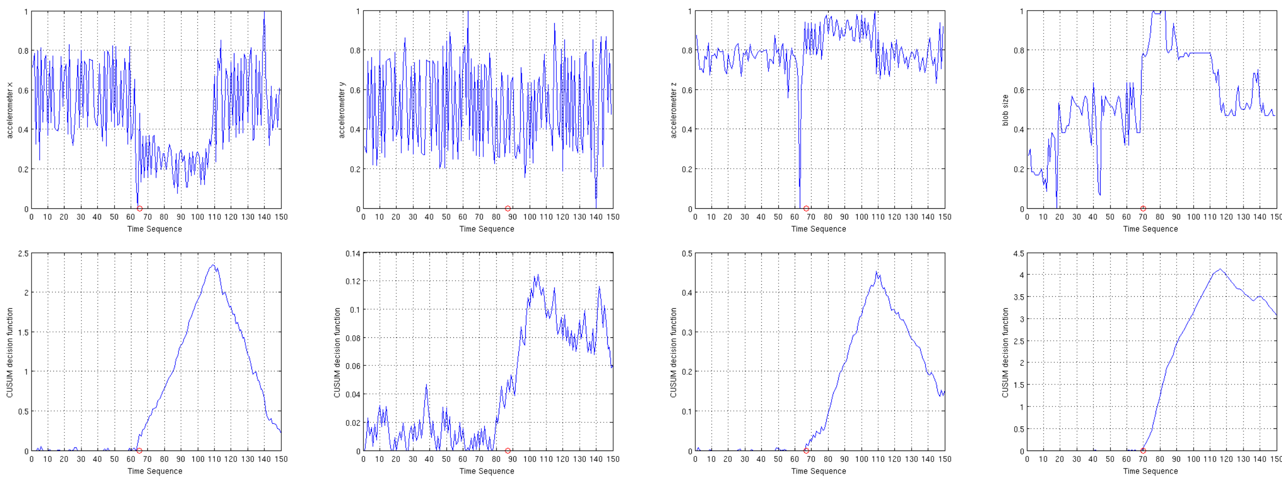

Fig. 2. The time sequence of each dimension of the dataset (top) and the corresponding CUSUM decision function (bottom). The red circle at each figure denotes the optimal change point found by the CUSUM algorithm

the moving body within the frames. The size of the blob is fourth signal.

To measure the efficiency of the adopted methodology, we use two metrics. The number of *false alarms* (i.e. the number of times that the algorithm detect a fall before the true fall has happened) and the *delay* (i.e. the number of signal frames that have passed between the actual start of the fall and the fall detection).

Table I illustrates the results of the CUSUM algorithm with respect to the number of false alarms and the delay of the true alarm for several values of the parameter h. As shown, in most cases, using a small value for h a significant number of false alarms exist; as h grows the number of false alarms drops rapidly. On the other hand, the delay of the true alarm grows for higher values of h.

It is important to note that there are cases where the false alarms are few or even none and still the delay value is very small. It can be noticed that for h values between 0.05 and 2, in most cases, the fall is accurately detected. The parameters of the algorithm, which are the mean values of each sensor output before and after the actual fall, are considered known.

Figure 2 depicts the time sequence of each signal of a dataset and their corresponding CUSUM decision function. The red circle in the figures denote the change point detected by the algorithm. As shown, based on that change point we can clearly detect when a person is walking and effectively detect falls in real-time. Tables II and III illustrate the results of the CUSUM algorithm for several values of the parameter h, for datasets two and three respectively.

Since our goal is to detect significant changes, normalizing the signals makes no difference; the actual minimum and maximum values are not needed. From the analysis of the experimental results, it is evident that the data streams from the wearable accelerometer (especially x and z axes) and the blob size give the most accurate fall detection.

Finally, we could use only the first data stream to compute the mean values of each sensor output before and after the actual fall, as well as to estimate suitable values for the parameter h. For example, Table I suggests that optimal values of h for the accelerometer x axis, the accelerometer z axis, and the blob size are $0.1, 0.01$, and 0.1, respectively. When the CUSUM algorithm is applied to the other two data streams, these values give very accurate results (see Tables II and III).

V. CONCLUSIONS

This paper presents a human body fall detection system that detects falls utilizing a statistical data mining method-

TABLE II

THE NUMBER OF FALSE ALARMS AND THE DELAY FOR SEVERAL h VALUES

h	0.005	0.010	0.050	0.100	0.150	0.200	0.500	1.000	1.500	2.000
Accelerometer (x axis)										
False Alarms	16	13	1	1	0	0	0	0	0	0
Delay	1	1	1	2	3	4	9	16	22	29
Accelerometer (y axis)										
False Alarms	30	29	6	1	0	0	0	0	0	0
Delay	1	1	1	2	1	2	12	40	63	79
Accelerometer (z axis)										
False Alarms	4	4	1	0	0	0	0	0	0	0
Delay	2	2	2	2	3	5	13	33	45	61
Blob size										
False Alarms	0	0	0	0	0	0	0	0	0	0
Delay	2	3	5	5	6	6	8	10	12	14

TABLE III

THE NUMBER OF FALSE ALARMS AND THE DELAY FOR SEVERAL h VALUES

h	0.005	0.010	0.050	0.100	0.150	0.200	0.500	1.000	1.500	2.000
Accelerometer (x axis)										
False Alarms	10	8	1	0	0	0	0	0	0	0
Delay	0	0	1	0	0	0	8	21	29	38
Accelerometer (y axis)										
False Alarms	23	20	0	0	0	0	0	0	0	0
Delay	1	3	22	34	84	84	84	84	84	84
Accelerometer (z axis)										
False Alarms	2	0	0	0	0	0	0	0	0	0
Delay	3	2	11	16	19	24	84	84	84	84
Blob size										
False Alarms	3	3	0	0	0	0	0	0	0	0
Delay	1	1	5	6	7	7	11	14	17	21

ology. The main advantages of the proposed methodology are that it is suitable for streaming data and that it reaches a prompt decision. The implemented fall detection system uses visual data captured from the users environment by overhead cameras along with motion data, which are collected from wearable accelerometers. Human falls are detected utilizing the cumulative sum (CUSUM) algorithm, which is one of the most effective techniques for change detection. As shown in our experiments, real-time prompt fall detection is possible. In a future work we intend to combine data of additional sensors (e.g. biosignals, audio, etc.) with data mining techniques and change detections algorithms to further improve the accuracy of the system and add additional functionalities, such as fall severity estimation.

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