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Detecting Stumbles with a Single Accelerometer*

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Abstract— **Falls are a common problem in the elderly population, and their prediction has been a major interest for the medical field. The relationship between stumbles and falls has not been very well understood yet. A critical requirement in advancing the study of this relationship is the realization of a realistic and effective stumble detection system. In this paper, we present a system for the detection of stumbles during walking. Our system consists of a single low cost triaxial accelerometer that may be worn by patients and is convenient for a wide range of subjects. We formulate the problem as an anomaly detection and we validate our system with a large data set collected from 9 subjects. The data set contains a total of 100 stumbles and 45 minutes of walking. We compare 7 different placements for the accelerometer, and show that our system achieves a 99% detection rate, with a 0.2% false alarm rate using an accelerometer worn on the chest.**

I. INTRODUCTION

Falls pose a major health problem in the elderly population, and they account for a significant portion of their injury and death. Injuries resulting from falls can be not only physically, but mentally detrimental [14], resulting in the reduction or loss of one's independence [8]. A recent study by the center for disease control and prevention (CDC) shows that one in every three adults (age 65 and older) falls each year. For example, in 2008 more than 19,700 adults (65 or older) died from unintentional fall injuries. In 2009, 2.2 million injuries were treated in emergency departments, and more than 581,000 were hospitalized. The injuries included: hip fractures, spine fractures, leg fractures, and head traumas. In the same year more than $19 billion were spent on fall related injuries [7].

Due to these reasons, understanding falls and their precursors became a major topic in medicine and public health. For example, in 2009 the institute of medicine (IOM) listed research on falls and their prevention among older adults, in their first quartile of priorities [15]. The current methods of fall prevention and predictions consist of exercise and balance training. This might be supplemented in the future by a system of a body sensor network, monitoring individuals, assessing the risk of falls, and predicting the likelihood of a future fall. This system would alert the user in case of a high risk of falling, and suggest what precaution they should take (e.g. resting, minimal activities, checking with a doctor, etc.). Statistically, the two leading causes of unintentional falls are loss of balance and stumbling [13].

Much of the effort in the research community focused on monitoring gait and loss of balance to assess the risk of falls [13]. The relationship between stumbles and falls is still not well understood, in other words, the following question is not yet answered:

Are frequent stumbles an indicator of high risk of falling?

The study of stumbles has been mostly about understanding stumbles, the recovery strategies, and the muscle and nervous system behavior when a stumble occurs. For example, it was established that there are two general strategies of recovery from stumbling: elevating and lowering. The elevating strategy occurs as a response to a perturbation during the early swing phase of gait, whereas the lowering strategy occurs during the late swing phase of gait [17] [4]. It was established that one's ability to perform such recovery methods after a stumble could be determined by one's ability to perform quick steps [4]. Weakening of the nervous system in the elderly may seriously restrict their ability to perform these quick steps during recovery, which may lead to a fall.

To date, the most common form of stumble reporting continues to be self-report. This method is obviously flawed and not reliable since it relies entirely on the ability to remember and report stumble events. However, the advancements in low cost and low power sensing technology, low cost storage systems, processing systems, and mathematical tools are now enabling us to continuously and remotely monitor the activities of people [1], [6], [16], [20]. In this work, we design a system that monitors the walking of people, and detects stumbles using a single low cost and low power accelerometer. This system does not directly answer the question above, but shows that we can detect stumbles using a single accelerometer worn on the body, and that the technology we are using will enable the study of the relationship between stumbles and falls.

The paper is organized as follows. In Section II we review the literature on stumble detection. In Section III we formulate the problem as anomaly detection, and show how the stumble data look. Section IV describes our system, and our data collection procedure. In Section V, we present and discuss the performance of our system. Finally, Section VI concludes the paper, and presents the future work.

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II. Related Work

Most of the related work in the engineering literature focuses on fall detection and fast reporting to doctors [2], [12], [14], [19]. Other related work focused on gait analysis and monitoring, such as balance, gait symmetry, and gait speed [13], [20]. Very few papers considered the problem of stumble detection, and no work was found on relating stumbles and falls. Related work in the medical literature focused on studying the biomechanics and muscle behavior when a stumble occurs. It was established that a fall occurs when the person is not quick enough to recover from a stumble and prevent the fall [18] [4]. The related aspect to our research is in the simulation of stumbles. There are two major categories in simulating stumbles: treadmill-based, and terrain-based. In [18], an experiment was designed based on a treadmill; subjects were asked to walk on a treadmill, and obstacles were dropped during early swing. It was found that the knee is bent more in order to lift the foot over the obstacle during stumbling. In [4], a treadmill-based experiment was also performed and the authors found that not only the lower limb motions, but also the control of the trunk is necessary to understand the recovery process. In this type of work, there was not any stumble detection. Stumbles were simulated, and studied without any evaluation of the detection.

There has been little research on systems for stumble detection. Two interesting papers that considered a version of the stumble detection problem. Both papers were motivated by the design of an intelligent and active lower limb prothesis. The objective is to build an intelligent prothesis that can detect a stumble when it occurs and have an active recovery response to prevent the subject from falling. In [10], the stumble detection and active recovery are based on accelerometers mounted on the prothetic limb. To simulate stumbles, a walkway is constructed with hidden obstacles that appear as subjects walk through it. They collected their data from 10 healthy subjects who were instrumented with three accelerometers on the left leg (foot, shank, and thigh). They collected 19 stumbles and 34 normal walk strides from 10 subjects. They report 100% detection accuracy, but do not report any false alarm rate or precision-recall results. This data set is unfortunately too small and not representative. In [21], the detection is based on accelerometers and EMG sensors that measure the muscle activity of the hip. They collected two sets of data. The first set is from 7 subjects with transfemoral amputations. Five of these subjects were asked to walk on a treadmill where sudden accelerations or decelerations of the treadmill were used to simulate stumbles; for each subject ten trials with sudden treadmill acceleration and then trials with sudden treadmill deceleration were tested. The speed, accelerations and decelerations were fixed and were the same for all 5 subjects. The other two were asked to walk on an obstacle course. A total of 15 trials were tested for each subject, and each trial was for 5 minutes. The total number of stumbles is not reported, but they report 100% stumble detection, and between 0% and 0.0009% false alarm rate (depending on the subject). They also report that the EMG sensors were necessary to achieve this very small false alarm rate. A main limitation of the treadmill data is that the acceleration is controlled and the speed of the walking is fixed.

In our work, we collect a bigger and more realistic data set. We use a single accelerometer, and we evaluate 7 different placements on the body not limited to the legs. We achieve very good results using only one accelerometer. Furthermore, our data set is collected on an outdoor terrain (as described below) where the speed of walking is natural and not controlled. It contains a total of 100 stumbles, and over 45 minutes of normal walk for 9 subjects.

III. Stumble Detection Methodology

A. Background and Notation

Before we formulate the the problem, we introduce and define the mathematical terms we are going to use. We borrow some of the definitions from [11], and extend them to our problem.

Definition 1: A 3-D Time Series is a sequence $D = \{d_{t_1}, d_{t_1+1}, \cdots, d_{t_m}\}$ of an ordered set of m real valued column vectors d_{t_i}, with time indices $t_i, i = 1, \cdots, m$.

Definition 2: A 3-D subsequence of length T of a 3-D time series D, is a 3-D time series $D_{t_i:t_i+T} = \{d_{t_i}, d_{t_i+1}, \cdots, d_{t_i+T}\}$.

We represent the 3-D Time Series D by a (4xm) matrix where the first row is the time indices t_i, and the second to fourth rows correspond to the column vectors d_{t_i}. We see now that the matrix corresponding to a 3-D subsequence of a time series D, is a sub-matrix of the matrix corresponding to D.

B. Problem Formulation

We consider the problem of human stumble detection using one acceleration sensor worn on the body, and we would like to test the effectiveness of different body locations. The accelerometer measures the [X, Y, Z]-components of the acceleration at the body location where it is mounted. The sensor could be worn on L different parts of the body. We would like to instrument the user for a long period of time (e.g. a day, a week, a month), and detect how many stumbles they had during that time. We model the acceleration data of each sensor as a 3-D time series of length m (m corresponds to the time period of interest, e.g. day, week, month, etc.), $D_l = \{d_{l,t_i}, d_{l,t_i+1}, \cdots, d_{l,t_m}\}$, where D_l is the acceleration data indexed by the body location $l \in \{1, \ldots L\}$ between the times t_1 and t_m, and d_{l,t_i} is the three dimensional vector of acceleration at location l and time t_i. To detect and count the number of stumbles in a 3-D time series D_l, we detect the occurrence of a stumble in every 3-D subsequence $D_{l,t_i:t_i+T}$. We associate a variable $S_{t_i:t_i+T} \in \{0, 1\}$ with every subsequence $D_{l,t_i:t_i+T}$ to represent the stumble, where $S_{t_i:t_i+T} = 1$ if a stumble occurs, and $S_{t_i:t_i+T} = 0$ otherwise. We assume that a single stumble could happen between t_i and $t_i + T$. We use a probabilistic approach, and define the following probabilities:

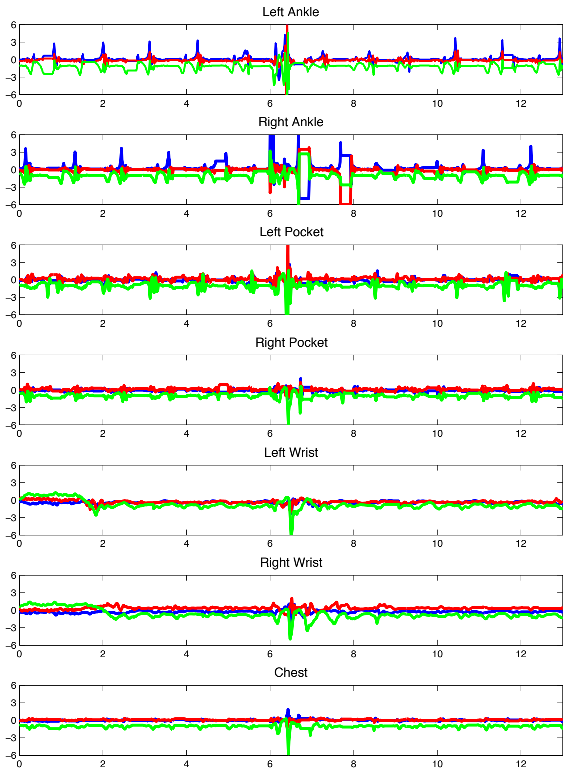

Fig. 1. A 13 seconds window of walking containing a stumble at 6.5, seen from different locations on the body. The x-axis is in seconds, and the y-axis is in g.

$P(D_{l,t_i:t_i+T}|S_{t_i:t_i+T}=0)$ = Probability that $D_{l,t_i:t_i+T}$ is a normal walk pattern,

$P(D_{l,t_i:t_i+T}|S_{t_i:t_i+T}=1)$ = Probability that $D_{l,t_i:t_i+T}$ is a stumble walk pattern.

The stumble detection problem now becomes a likelihood test comparing $P(D_{l,t_i:t_i+T}|S_{t_i:t_i+T}=0)$, and $P(D_{l,t_i:t_i+T}|S_{t_i:t_i+T}=1)$:

$$\frac{P(D_{l,t_i:t_i+T}|S_{t_i:t_i+T}=1)}{P(D_{l,t_i:t_i+T}|S_{t_i:t_i+T}=0)} \geq \tau, \tag{1}$$

i.e. a stumble is detected in $D_{l,t_i:t_i+T}$ when the likelihood ratio exceeds a threshold τ. We move to the feature space and we compute features from the raw acceleration $D_{l,t_i:t_i+T}$, and compute the likelihood test in the feature space. We compute a feature vector $f_{l,t_i:t_i+T}$, and get the following likelihood test:

$$\frac{P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T}=1)}{P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T}=0)} \geq \tau. \tag{2}$$

The first challenge is that the accelerometer measurements depend on the orientation of the accelerometers. Moreover, the accelerometers pick the gravity acceleration on the vertical axis which changes depending on the orientation of the sensor. Therefore, we first remove the gravity component

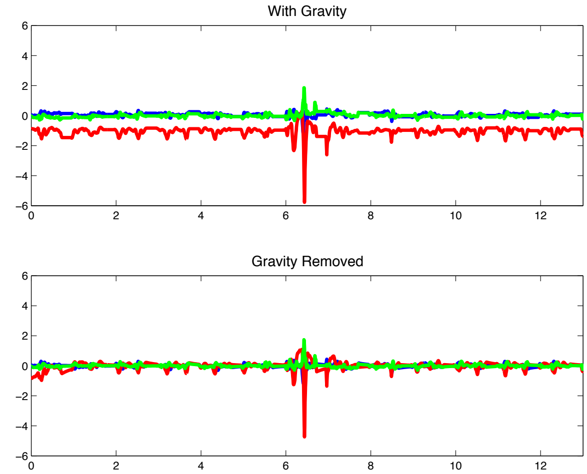

Fig. 2. A 13 seconds acceleration time series. The upper figure shows the raw acceleration, the red axis is at $-1g$ picking up the gravity acceleration. The lower figure show the acceleration after removing gravity by subtracting the decaying average. The x-axis is in seconds, and the y-axis is in g.

Features
Maximum value of m
Non Linear Energy Operator of m
FFT of m

TABLE I

FEATURES USED.

by subtracting the decaying average from each dimension of the raw accelerometer data [5], and then compute orientation invariant features. The decaying average is given by

$$\overline{D_{l,t_i}} = \frac{D_{l,t_i}}{L} + \frac{L-1}{L}\overline{D_{l,t_i-1}}, \tag{3}$$

where L is the decay factor. The important characteristic of the decaying average is that it adapts quickly to the orientation of the accelerometer, and removes the gravity component from all of the axes. Figure 2 shows a 13 seconds 3-D time series, the upper figure shows the raw data where gravity is picked up by the red axis. The lower figure shows the acceleration data after subtracting out the decaying average, the gravity component is gone. Note that the decaying average was subtracted from all three axes. After removing gravity, we extracted orientation-invariant features. In fact, we extracted features from the magnitude (the euclidean norm) of the [X, Y, Z] acceleration vector, $m = \left\|X^2+Y^2+Z^2\right\|$, which is orientation-invariant. For the detection of stumbles in a 3-D time series D_l, we compute the features for the 3-D subsequences, $D_{l,t_i:t_i+T}$. The features we used in this work are listed in Table I. Figure 1 shows a 13 seconds window of walking containing a stumble around the 6.5 seconds mark.

C. Stumbles as Anomalies

Anomaly detection refers to the problem of finding patterns in the data that do not follow a normal or expected behavior. These abnormal patterns are called anomalies or outliers. In our problem, a normal walk pattern represents the normal behavior in the data, and a stumble pattern corresponds to the anomaly. The key idea to our approach is that since the stumbles are rare events, it is hard to collect training data to model them. Therefore we use a semi-supervised anomaly detection approach where we only train a model for the normal walk patterns, and we detect stumble patterns as deviations from this model [3]. Mathematically, we need to estimate the density $P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0)$ from training data, and detect stumbles if $P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0)$ is low when $S_{t_i:t_i+T} = 1$. The stumble detection will be based on $P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0)$ as follows:

$$P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0) \leq \tau_l, \tag{4}$$

for some sensor specific threshold τ_l.

D. Estimating $P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0)$

In this work, we use a parametric approach and we estimate $P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0)$ by a Gaussian distribution:

$$P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0) = (2\pi)^{-\frac{k}{2}} |\Sigma|^{-\frac{1}{2}} e^{-\frac{1}{2}(f-\mu)' \Sigma^{-1} (f-\mu)} \tag{5}$$

where the parameters are the mean μ and the covariance matrix Σ. k is the dimension of the feature vector f, i.e. the number of features used. We estimate μ and Σ from training data. We used a Gaussian distribution since the different steps of a normal walk, represented by $P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0)$, are similar with small variations from one step to the other. Furthermore, we build a user-specific system where we estimate $P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0)$ for each user from their training data.

E. Setting the threshold τ_l and choosing T

After estimating $P(f_{l,t_i:t_i+T}|S_{t_i:t_i+T} = 0)$, we need to set the threshold τ_l. Again, τ_l is the threshold that corresponds to each location $l \in \{1, \ldots L\}$. We choose τ_l in order to control the false alarm rate of the stumble detector. Since the stumbles are rare events, there is a high probability that a lot of the detected stumbles are actually normal walk patterns. Thus, we would like to control the false alarm rate, and we choose to set τ_l in order to achieve a desired false alarm rate FAR_l. Note that FAR_l also depends on the sensor location on the body.

T is the time length used in parsing the 3-D time series D_l, or in other words T is the time length of the 3-D subsequences $D_{l,t_i:ti+T}$. The choice of T depends on the application of the stumble detection. For example, in [10] and [21] a stumble detection system was built for people with prosthetic legs. The goal was to detect stumbles in real time and right when they happen to actively move the leg accordingly, and prevent the fall from happening. In their application, T needed to be in the order of milliseconds, since the leg had to be moved quickly to help with the recovery from the stumble and prevent the fall. T was chosen to be 100ms in [10], and as low as 10ms in [21]. In other applications, doctors could be interested in monitoring their patients not in real time, and statistics of stumbles calculated

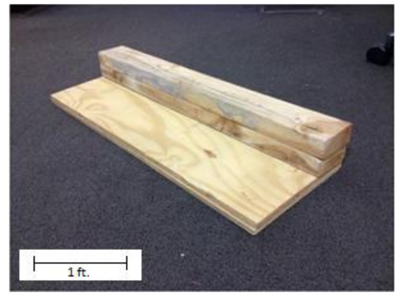

Fig. 3. Obstacle used

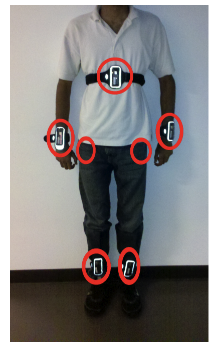

Fig. 4. Sensor positions

at the end of the day, or the week. In these applications, the stumble detection is done in post processing of the data, and a larger T could be used (now in the order of seconds). In our work, we chose $T = 4$ seconds. Another parameter that is associated with T is the step size used in parsing D_l, to get the corresponding subsequences $D_{l,t_i:ti+T}$. We choose non-overlapping subsequences, and choose the step size to be 4 seconds.

IV. Experiments

A. Data Collection

Our system consists of Gulf Coast Data Concept X6-2 mini tri-axial accelerometer sensors [9]. A total of 7 accelerometers were placed on various parts of the subjects' bodies; they were placed on the left and right wrist, the middle of the chest, left and right pocket, and left and right ankle (figure 4). The sensors were set to collect data at a rate of 160 Hz with a 16-bit data resolution and $\pm 6g$ acceleration range.

In order to simulate stumbles, we used a simple platform consisting of a 1 x 8 x 30 inch wooden base plank attached to two stacked 2 x 4 x 30 inch wooden studs (Figure 3), which created a low vertical barrier for test subjects during gait. Test subjects were blindfolded and listened to music through headphones so that they do not see or hear the person setting the obstacle in front of them, and to provide distraction. The volunteers were then told to walk in a straight line. The obstacle was placed in front of them at random times but no less than ten seconds after the start of a walk interval, whereupon the subject would come into the vicinity of the obstacle and either stumble and recover or walk over the

Subject	Number of Stumbles
1	7
2	10
3	12
4	11
5	11
6	12
7	14
8	10
9	13
Total	100

TABLE II

NUMBER OF STUMBLES FOR EACH SUBJECT.

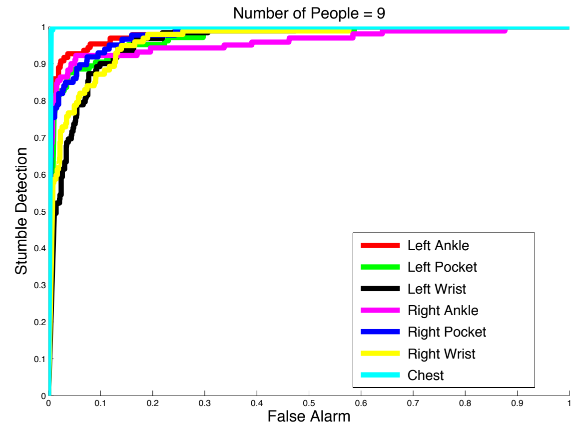

Fig. 5. ROC curve. The chest achieves a detection of 99% with a false alarm of 0.2%.

obstacle and continue walking. After the stumble, subjects would continue walking for one minute or more. The process was repeated about twenty times per test subject. Stumbling was followed by about 5 minutes of normal walk. Two individuals walked with the test subject to secure their safety, and prevent them from falling. The experiments took place on an open grassy court, and a video was recorded for ground truth. The data was collected from 9 test subjects (7 Males and 2 Females). We got a total of 100 stumbles, and table II shows the number of stumbles for each subject.

B. Limitations of the experiments

A main obstacle in designing activity monitoring systems is the validation process of the system. The system needs to be validated on people in realistic situations, as close as possible to everyday life. A data set should be collected and labeled for the real stumbles, and this procedure should be done for many people. This is very challenging, and we thought that a reasonable first step towards this goal is to collect data in a controlled environment and simulate stumbles that are easy to be labeled. Our experiments and data sets suffer from the following limitation:

1) One type of stumbles: We only simulate one type of stumble; stumbling on a fixed obstacle. Other stumbling types we did not consider include: stumbling on a cord, stumbling on a moving object, and slipping.
2) Controlled environment: The data sets are collected in a controlled environment.

Despite these limitations, the data are more representative than other experiments used in the literature. For example, [10] and [21], also use a controlled environment, but use a treadmill where they can control the speed to produce stumbles. The subjects were asked to walk on the treadmill, and stumbles were created with unexpected sudden changes in the treadmill's speed.

V. RESULTS

In this section, we present the stumbling detection results for our system, on the data described in Section IV. We used half of the data for training the stumbling detector, and half of it to test it. In rare event detection, it is not enough to look at accuracy and probability of misdetection since the events we are trying to detect are rare, and therefore the accuracy and probability of misdetection would be dominated by the non-rare events. These issues arise in classification problems when one class has far fewer points than the other classes. To resolve these issues we use the following quantities:

$$\text{FAR} = \frac{\text{Number of normal subsequences detected as stumbles}}{\text{Total number of stumbles}} \quad (6)$$

$$\text{Precision} = \frac{\text{Number of stumble subsequences detected as stumbles}}{\text{Number of all subsequences detected as stumbles}} \quad (7)$$

$$\text{Recall} = \frac{\text{Number of stumble subsequences detected as stumbles}}{\text{Number of stumble subsequences}} \quad (8)$$

In Figure 5, we present the performance of our system as a ROC curve, which is probability of detection versus false alarm rate. We evaluate each of the 7 locations, and show each as a curve. We see that the chest performs better than all the other locations; its ROC curve is higher and to the left of all other locations. With one chest sensor we could achieve a stumble detection of 99%, with a false alarm rate of 0.2%. In Figure 6, we show the precision-recall plots for our stumble detection system. We also see that the chest outperforms the other locations for the accelerometer.

There are two main reasons why the chest performs better than all the other locations. The first one is that the chest is the highest location from the ground, thus the shocks produced by walking get absorbed by the body and are diluted by the time they reach the chest. We can see this phenomenon in Figure 1. The walk peaks are smaller in the acceleration measured at the chest and the stumble pattern stands out more. The second reason is that the chest sensor is placed in the middle of the body, whereas all the other locations is either on the left or on the right of the body. We noticed that if a stumble happens to the left leg, the right side of the body might not pick up the stumble acceleration pattern, and vice versa. The only limitation of placing the accelerometer on the chest is that it could be hard to mount it on the chest, it is more feasible to place it in one of

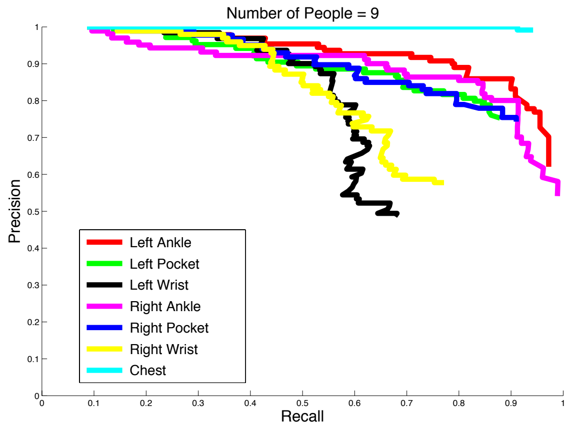

Fig. 6. Precision Recall Curve. The chest achieves a precision of 99% precision with a recall 94% (The end point of the chest curve).

the pockets or clip it to the belt at the waist. With the method used, the pockets were not good locations to detect the stumbles, but we plan to extend this work and use more powerful methods to be able to detect the stumbles more reliably at the pockets and the waist.

VI. Conclusion

In this paper we studied the problem of detecting stumbles using a $single$ accelerometer worn on the body. We evaluated seven locations and found that the chest is the best location to detect stumbles. Our approach learns a statistical model to characterize normal walking, and detects stumbles as anomalies or deviations from this model. We show that stumbles could be detected with a 99% accuracy and 0.2% false alarm rate with one sensor worn on the chest. Our system is personalized where we build a detector for each user tailored to their normal and stumble walking patterns. We described our system, and how we simulated the stumbles on an outdoor terrain. We also provided a big data set for 9 people, containing a total of 100 stumbles and more than 45 minutes of normal walking. For future work, we plan to take this study in three directions. The first direction is to collect more realistic data, containing more types of stumbles. The second direction is to collect data for elderly patients who have a high risk of falling. We plan to monitor them over a long period of time and use our current detector, based on controlled experiments, to help with the labeling of the real life data set. We believe that running our current detector on a real life data set would detect potential stumbles that could be combined with the information from the subject to reliably label the real stumbles. The third direction is more technical, and consists of developing more powerful detection techniques that could be used to detect stumbles from more plausible placements of the accelerometers, such as pockets. We hope that this work takes the research on stumble detection a step further towards the goal of realistic stumble detection systems, and towards understanding the relationship between stumbles and falls.

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