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Walking behavior change detector for a "smart" walker

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Abstract

This study investigates the design of a novel real-time system to detect walking behavior changes using an accelerometer on a rollator. No sensor is required on the user. We propose a new non-invasive approach to detect walking behavior based on the motion transfer by the user on the walker. Our method has two main steps; the first is to extract a gait feature vector by analyzing the three-axis accelerometer data in terms of magnitude, gait cycle and frequency. The second is to classify gait with the use of a decision tree of multilayer perceptrons. To assess the performance of our technique, we evaluated different sampling window lengths of 1, 3 an 5 seconds and four different Neural Network architectures. The results revealed that the algorithm can distinguish walking behavior such as normal, slow and fast with an accuracy of about 86%. This research study is part of a project aiming at providing a simple and non-invasive walking behavior detector for elderly who use rollators.

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Keywords: HCI, Gait Analysis, Walking Behavior, Mobility, Accelerometer, Elderly care, Gerontechnology, Interpersonal variability

1. Introduction

The proportion of senior citizens is increasing in many countries. Around 23% of the population is already aged 60 years or over and that proportion is estimated to reach 32% in 2050[1]. Loosing complete or part of mobility, affects not only the ability to walk but also the ability to perform personal care. This is a major concern for life quality, which causes dependence on others in daily life. To help with their mobility, millions of people thus use rollators. However, in several situations these devices fail to help and even contribute to increase the likelihood of an accident producing falls. Approximately, 87% of elderly people falls are attributable to walkers use[2].

Falls occur as a result of a complex interaction of risk factors. The main risk factors are classified in three different categories: environmental, behavioral and biological. Environmental factors encapsulate the interplay of individuals physical condition and the surrounding environment. They include home hazards and hazardous features in public environment. Behavioral risk factors include those concerning human actions and affective states. Biological factors embrace characteristics of individuals that are pertaining to the human body like: age, gender and physical impediments.[3].

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In this context, the *Eyewalker* project targets the development of an independent accessory that can simply be clipped on a standard non-motorized walker. The goal of the *Eyewalker* device is to warn users of potentially risky situations; in a similar manner we have started working on environmental factors on Cloix[4] and Weiss[5]. In this paper, we focus on the behavioral factors and study the walking behavior to identify and analyze possible causes of rollators accidents. Movement analysis is a powerful and intuitive way of determining a subject's health, functional and emotional status[6]. Gait analysis provides relevant information about the affective state; the categories happy, sad and angry are distinctive in motion[7]. Crane and Gross[8] identify gait velocity, stride length and cadence as significant parameters which are affected by emotion.

Gait analysis is already used for clinical assessment, but it is often constrained to a laboratory environment. The systems are expensive, they must be installed in appropriate rooms and can only record movements in a small area. We propose a new non-invasive approach to detect walking behavior for rollator users. This work uses the acceleration data in order to extract gait parameters and detect a modification in the user walking behavior. Our approach is based on the motion transfer by the user on the rollator. We aim at determining whether is it possible to classify normal/fast/slow walk pace from acceleration samples. The fast and slow gait speeds are related to the highest risk of fall. Falls due to fast gait are more likely to happen outdour, while indoor falls are more likely to occur with individuals walking slowly. Furthermore, a decline in gait speed is an important predictor of future falls[9], since slow gait is related to affective disorders like depression and bipolar[10].

The paper is organized as follows: Section 2 discusses relevant work related to the state of the art in gait analysis; Section 3 presents the proposed methodology to detect walking behavior. Section 4 describes the experiment and the obtained results. Finally, conclusions and future work are given in Section 5.

2. Related Work

In the last few years more attention has been given to human behavior and the gait is a way to detect changes. Various psychological studies indicate that humans are not only capable to recognize the intended action, but also gender, identity and even emotions from body movements[11,12].

Gait analysis is the evaluation of the manner or style of walking usually done by observing the human as he/she walks in a straight line. This evaluation can be performed in two different ways. The first is by empirical analysis, while the second is based on sophisticated instrumentation measuring body movements, body mechanics and activity of the muscles. Various works were carried out using different hardware such as force platform, optical markers and 3D-cameras. But these motion capture systems are expensive and they must be installed in appropriate rooms and can only be operated by specially trained personnel. These systems can only record movements performed in a small area[13].

A simple way to analyse the motion is to use accelerometers. In motion analysis, the main interests are activity recognition[14] and detection of specific gait events (e.g. falls). Most research on fall detection uses the linear acceleration and gyroscopes. They typically detect falls by applying thresholds to accelerations, velocities and angles[15,16]. However, the performance of these systems depend strongly on the position of the sensors (e.g. the wrist, waist, ankle) and they can not help to prevent accidents.

A current research challenge is the authentication of users based on gait recognition. The research described in Rong et al[17] is focused on the identification of a person based on the way that he/she walks using dynamic time warping. However, during a natural walk, a person could change the way that he/she walks making it difficult the identification. Nickle et al[18], conducted a similar study of user authentication using Hidden Markov Models, however, their results are not sufficiently accurate and the performance of their algorithm is strongly related to the sensor. Specifically, they collected data from a standard mobile phone with low sampling rate.

Finally, many studies have been conducted to find the best position body on the where to carry the accelerometers; despite all these studies, the acceptance of the user has not been showed[19].

3. Methodology

The main purpose of this research is to implement an algorithm capable to detect a walking change in real time without any sensor on the user. Not having to put any sensor on the user is a key requeriment for user acceptance.

Fig. 1. (a) Hardware setup; (b) Accelerometer axis configuration.

We propose a detection method involving several specialized Artificial Neural Networks (ANN) combined in a simple decision procedure. Specifically, we use a decision tree of ANN.

The method developed in this research study comprises of three key stages. Firstly, accelerometer signals from the sensor are acquired and standardized. Secondly, we extract the gait feature of each segment. And finally, we apply a decision tree in order to detect the walking behavior of the user.

3.1. Data Acquisition and Preprocessing

We use a Shimmer[20] sensor in order to extract the acceleration data on the X,Y,Z axis. Shimmer is a small wireless sensor platform designed to integrate wireless body sensor technology into a wide range of application areas.

The sensor is equipped with an 8 MHz Texas Instruments MSP430 CPU. The RAM is of 10 KB, the Flash memory of 48 KB and 8 channels of 12 bits A/D are used. The wireless connection is established using the Class 2 Bluetooth radio and data is acquired using the 3-Axis Freescale accelerometer placed on the walker as shown in Fig. 1. Moreover, the device provides a MicroSD of about 2 Gbytes and an Integrated Li-Ion battery that provides wearability. For our experiments, data acquisition was performed using a sampling frequency of 51.2 Hz for each channel. Additionally, each axis reports the current magnitude of acceleration in terms of $[g]$, where 1 $[g]$ is equal to the force of Earth's gravity.

It is important to remark, that in movement like walking, the signal presents harmonics and the sensor can add some noise. It is imperative to apply a filter in order to obtain a clear signal. For this purpose, a wavelet denoising filter was applied[21]. It allows to remove the noise present in the signal while preserving the signal characteristics[22]. In this study, we applied symlets wavelet with decomposition level 3 and soft-thresholding to filter 3D acceleration noise. Additionally, the signal was normalized to a range -1 and 1 $[g]$. Then we used a sliding window that overlaps 50% of the window length.

3.2. Gait Feature Extraction

Feature extraction was performed to recognize the principal characteristics of gait. These characteristics are divided into three groups: 3-axis acceleration (see Sec.3.2.1), gait cycle (see Sec.3.2.2) and frequency domain features (see Sec.3.2.3).

The coordinates are shown at Fig.1(b): X corresponds to the vertical axis with respect to the ground, Y correspond to the horizontal axis which is perpendicular to the direction of walking, and Z corresponds to the horizontal axis along the walking direction. The signal is segmented with different window lengths. Afterwards, we extract the feature of segments to detect the walking behavior. A classic example of the signal in the $Z-axis$ sampling in 1, 3 and 5 seconds is shown in Fig. 2.

3.2.1. 3-Axis Acceleration

As previously mentioned, we use a three-axis coordinates system to extract the acceleration values. The global acceleration, A_{xyz}, is a representative parameter which includes gait acceleration ($Z-axis$), trunk's vertical acceleration ($X-axis$) and lateral acceleration of pelvis ($Y-azis$). The global acceleration is defined as:

$$A_{xyz} = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{1}$$

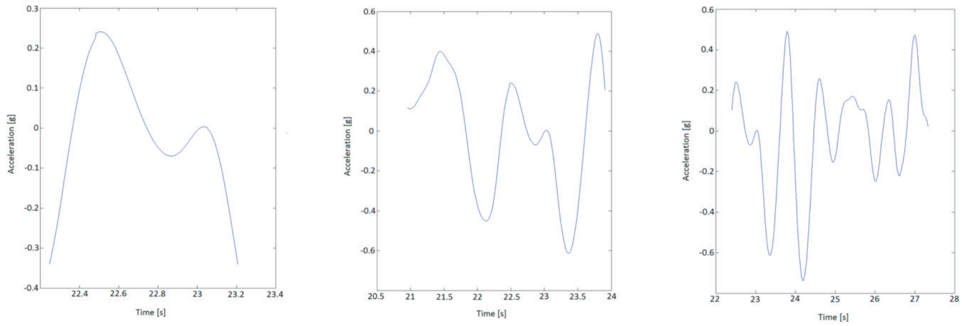

Fig. 2. Example of a gait in a sampling window of (a) 1 second ; (b) 3 seconds (c) 5 seconds.

where A_{xyz} is the resultant acceleration; and A_x, A_y, A_z are accelerations in the accelerometer's local coordinates system.

We implemented the cross correlation between $Z-axis$ and the signals in X and Y coordinates, in order to detect if there is a similarity between the axis where the users' walking are visible (*Z-axis*) and the others two axis. The cross correlation is defined as:

$$Corr_{x,z}(l) = \sum_{n=0}^{N} x(n)z(n-l) \text{ and } Corr_{y,z}(l) = \textstyle\sum_{n=0}^{N} y(n)z(n-l) \tag{2}$$

The feature extracted from the 3-axis signal from each segment were: variance of the resultant acceleration, $var(A_{xyz})$; mean acceleration on all three axes and the resultant acceleration, $\overline{A_{xyz}}$, $\overline{A_x}$, $\overline{A_y}$, $\overline{A_z}$; and correlation between X , Y and Z. The feature vector of the i^{th} segment for 3-axis signal is represented by:

$$F_{xyz}(i) = [var(A_{xyz}), \overline{A_{xyz}}, \overline{A_x}, \overline{A_y}, \overline{A_z}, Corr_{x,z}, Corr_{y,z}] \tag{3}$$

3.2.2. Gait cycle

Human walking is a periodic movement of the body parts and includes repetitive motions. To understand this periodic walking course better and more easily, we can divide it into gait cycles. The gait cycle can be seen as the period of time from one heel strike to the next heel strike of the same foot[23]. The gait can be divided into two phases: the stance and swing phase (Fig. 3).

A peak detection is applied in the $Z-axis$ to find the peaks associated with the gait cycle. Some small false peaks could be produced during walking. We set a peak filter to eliminate the false peaks between two maximum peaks. From Fig. 3(b), the peaks A,B and C have been detected and the time of each peak is computed respectively.

We know that the stance phase is longer than the swing phase, then if:

$$t_B - t_A > t_C - t_B \Rightarrow T_{Stance} = t_B - t_A \text{ and } T_{Swing} = t_C - t_B \tag{4}$$

Otherwise,

$$T_{Stance} = t_C - t_B \text{ and } T_{Swing} = t_B - t_A \tag{5}$$

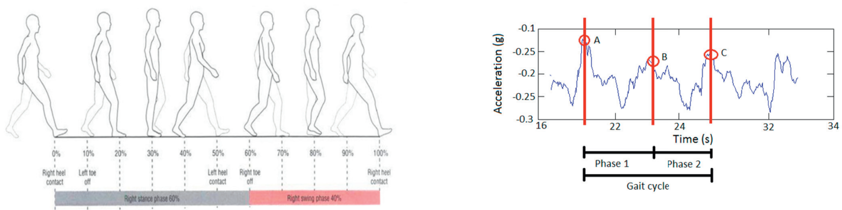

Fig. 3. (a)Gait Cycle[24] (b) Shimmer data collected along the Z-axis during a typical walk.

The duration of the gait cycle is given by:

$$GaitCycle_{time} = T_{Stance} + T_{Swing} \tag{6}$$

The Cadence value is defined as the number of steps per minute.

Finally, the feature extracted from the gait cycle from each segment is defined as:

$$F_{gait}(i) = [GaitCycle_{time}, T_{Stance}, T_{Swing}, Cadence] \tag{7}$$

3.2.3. Frequency domain feature

The periodicity of the cycle is easy to detect from the horizontal acceleration signal ($z - axis$). The Fast Fourier transform (FFT) can be applied to extract the frequency content of a segment. We used FFT to extract the fundamental frequency of the signal. The Entropy measures the distribution of frequency components and the Energy is the sum of square discrete FFT-component magnitudes of the signal.

The feature vector extracted in the frequency domain is given by:

$$F_{freq}(i) = [Z_{fundamentalfrequency}, Z_{Entropy}, Z_{Energy}] \tag{8}$$

Finally, all features extracted from the segment are organized in a vector:

$$F(i) = [F_{xyz}(i), F_{gait}(i), F_{freq}(i)] \tag{9}$$

3.3. Decision tree

The segment feature is used to detect the walking behavior. Specifically, our goal is identify five different classes: no movement, movement, slow, normal and fast. The decision procedure is decomposed into a decision tree containing three binary classifiers (see Fig. 4). For each binary classifier, we consider a ANN multilayer perceptrons with n neurons in the input layer ($F(i)$), l neurons in the hidden layer and m in the output layer. The size of the hidden layer is determined empirically (see Sec.4.3), whereas the output layer has two neurons. Each neuron representing a class; for instance, the *Normal vs Abnormal* classifier, one represents the detection of *Normal* walk pace and the other indicates *Abnormal* walk pace.

Firstly, we detect whether one is moving or not. If one is moving we detect if it is a normal or abnormal behavior. In case the behavior is abnormal, the walk pace can be classified as fast or slow.

4. Evaluation

A data set has been collected from a group of of 6 participants; 4 males and 2 females between 30 and 48 years old. Each participant was asked to walk a route of 18 meters. The route considered a different walk pace each 6 meters: starting with normal, followed by fast, and ending with slow (see Fig. 5). Each participant walked the same distance twice and changed her/his speed at markers installed on the path. The information about the ground truth associated with each experiment (when the walk has begun, changed and ended) has been obtained from the video sequences taken from a camera attached to the walker. The obtained gait data was used to create two data sets for each person. The training set of our detector corresponds to the first set, the second being used as an independent testing set.

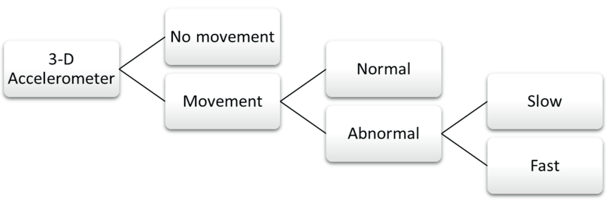

Fig. 4. Decision tree.

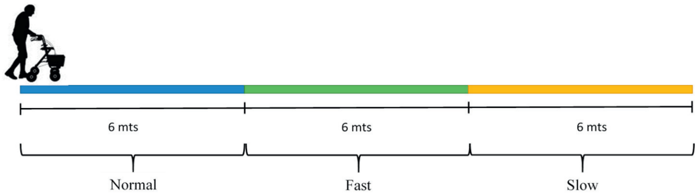

Fig. 5. Experiment setup.

Accuracy, Sensitivity and Precision were used as the standard measures for the evaluation of the classifiers. Accuracy is defined as a measure of performance to identify correct recognition rate. Sensitivity is the measure of positive results, a test with a good sensitivity has a low false negative rate. Precision is another important measure, it measures the rate of positive classifications; a classifier with a high precision has a low type I error (otherwise known as false positive) rate. The Accuracy, Sensitivity and Precision are given by:

$$Accuracy = \frac{\sum True_{positive} + \sum True_{negative}}{\sum Total_{population}}, \; Sensitivity = \frac{\sum True_{positive}}{\sum Condition_{positive}} \text{ and } Precision = \frac{\sum True_{positives}}{\sum Test_{outcomepositive}} \quad (10)$$

4.1. Evaluation of the Accelerations Obtained for the Different Walk Paces

The distribution of acceleration for each walk pace for one user is shown on Fig. 6. We observe that accelerations present a wider distribution as users are asked to increase the velocity. We notice that the difference between a normal and a slow gait is smaller that the one presented between a normal and a fast gait.

In our experiment, slow walk paces go from 0.69 [g] to 0.82 [g], and the most frequent acceleration is at 0.77 [g]. Normal walk paces go from 0.68 [g] to 0.84 [g], and the most frequent acceleration is at 0.77 [g]. Finally, fast walk paces go from 0.60 [g] to 0.98 [g], and the most frequent acceleration is at 0.76 [g]. We observe that the peak of all walk paces is situated around the same acceleration.

4.2. Evaluation of Different Window Lengths

First of all, we analyze the data using 1, 3 and 5 seconds as window lengths show in Table 1. The best classifier is the *Movement vs No movement* with an improvement with increasing window length in most of the cases of a 20% approximately. The window length that provides the best results for accuracy and precision is the one with length 5 seconds. In terms of sensitivity, window lengths of 3 and 5 seconds exhibit similar performance. Taking into account window lengths of 5 seconds we can state that the best accuracy and precision are obtained for *Slow vs Fast* classifier. Moreover, we can observe that the results between *Normal vs Slow* and *Normal vs Fast* are very similar. The worst accuracy and precision are obtained when dealing with walk paces that are classified as *Normal* or *Abnormal*. In addition to this, we observe that walk paces defined as *Normal* or *Slow* and *Normal* or *Fast* get similar sensitivities. It is remarkable to mention, that the classifiers *Normal vs Abnormal* and *Slow vs Fast* present an improvement of about 10% with respect to the other two classifiers mentioned. Furthermore, they offer almost identical results.

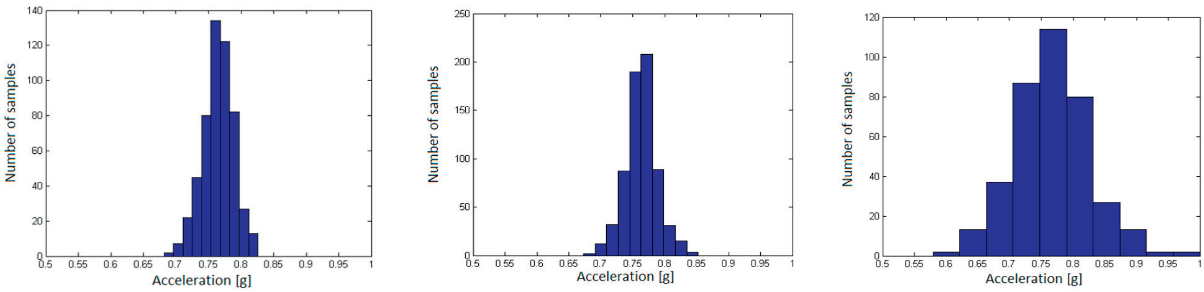

Fig. 6. Example of (a) Slow gait ; (b) Normal gait; (c) Fast gait.

Table 1. Evaluation of different sampling window lengths.

	Accuracy			Precision			Sensitivity		
Window length (s)	1	3	5	1	3	5	1	3	5
Movement vs No movement	96.2	95.0	94.7	96.9	95.8	96.8	98.3	96.5	96.8
Normal vs Abnormal	75.8	75.9	76.0	78.5	76.1	75.2	85.9	90.9	94.0
Slow vs Fast	75.9	77.0	96.0	78.1	76.2	94.7	86.9	86.2	94.7
Normal vs Slow	75.2	78.4	81.4	79.8	81.0	89.1	84.6	91.5	84.4
Normal vs Fast	74.7	78.4	81.4	80.1	81.0	89.1	84.3	91.5	84.4
Average	79.6	80.9	85.9	82.7	82.0	89.0	88.0	91.3	90.9

Table 2. Evaluation of different number of neurons in the hidden layer.

	Accuracy				Precision				Sensitivity			
Neurons (l)	5	8	10	15	5	8	10	15	5	8	10	15
Movement vs No movement	93.8	95.0	93.8	94.4	96.1	95.8	95.8	96.1	96.5	98.1	96.5	96.9
Normal vs Abnormal	76.7	75.9	80.9	73.5	78.1	76.1	88.2	74.6	88.5	90.9	81.2	89.1
Slow vs Fast	80.0	77.0	83.5	82.6	78.0	76.2	83.8	83.6	90.0	86.2	87.7	86.2
Normal vs Slow	79.5	76.7	77.6	79.8	85.0	77.8	78.6	82.6	86.5	94.3	94.3	90.9
Normal vs Fast	79.5	76.7	77.6	79.8	85.0	77.8	78.6	82.6	86.5	94.3	94.3	90.9
Average	81.9	80.3	82.7	82.0	84.4	80.7	85.0	83.9	89.6	92.8	90.8	90.8

4.3. Evaluation of Different ANN Arquitectures

In order to determine the best number of neurons in the hidden layer we analyzed the data sets taking into account all the walk paces proposed. As previously, the best results are obtained when dealing with walk paces defined as *Movement* or *No movement*. In general terms, the best results for accuracy and precision were obtained for ANN of 10 hidden neurons, while for sensitivity ANN of 8 neurons show an improvement of 2% compared to 10 neurons. Concerning classifiers, *Normal vs Abnormal* and *Slow vs Fast* present an improvement of about 5% in terms of accuracy and precision when compared with the *Normal vs Slow* and *Normal vs Fast*. However, in terms of sensitivity the last two classifiers mentioned offer an improved performance of about 10% compared to the other two classifiers.

5. Conclusion

Walking behavior is a vital skill that can show important medical, affective and cognitive information about the user. The developed algorithm allows in real time to detect if the walker is being used or not (*Movement vs No Movement*), and can also determine to some extent the different walk paces (slow, normal and fast). This research investigated the possibility to identify the walking behavior of rollator user, based on the motion transferred by the user to the walker. Our results confirm the possibility to detect walking behavior changes without any sensor on the user.

This detector was built using three binary ANN cascade classifiers, each classifier differentiating two classes. The proposed method proposed uses a gait feature vector using three-axis accelerometer data in terms of magnitude, gait cycle characteristics and frequency domain. The main results of our research show that the best classifier is (*Movement vs No Movement*) and the most difficult classes to distinguish are *Normal and Abnormal*. The experiments demonstrate that the use of a window length of 5 seconds gives improvement in the accuracy about 5% compared to window lengths of 1 and 3 seconds. Our studies show that the ANN with 10 neurons in the hidden layer achieved the best performance in terms of accuracy and precision, but the ANN with 8 hidden neurons gave the best performance in terms of sensitivity of the system. The experiments show promising results which reflect that our walking behavior detector can be used in real situations and in real-time.

Future work will be carried out in order to reduce the false positive rate by filtering on the temporal dimension and ignoring initial and trailing oscillations (outside the walking section of the trace). In parallel to doing evaluations with more participants, we plan to extend our detector to the cases when the user is not walking on a straight line. In addition, we will envisage some data reduction to focus on relevant parameters and eliminate those that might disturb the recognition process. Finally, we intend to investigate how walking behavior can inform about the changes of affective states that can potentially lead to harmful situations.

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