Identification of Postural Transitions Using a Waist-Located Inertial Sensor

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Abstract. Analysis of human movement is an important research area, specially for health applications. In order to assess the quality of life of people with mobility problems like Parkinson's disease (PD) or stroke patients, it is crucial to monitor their daily life activities. The main goal of this work is to characterize basic activities and their transitions using a single sensor located at the waist. This paper presents a novel postural detection algorithm which is able to detect and identify 6 different postural transitions, sit to stand, stand to sit, bending up/down and lying to sit and sit to lying transitions with a sensitivity of 86.5% and specificity of 95%. The algorithm has been tested on 31 healthy volunteers and 8 PD patients who performed a total of 545 and 176 transitions respectively. The proposed algorithm is suitable to be implemented in real-time systems for on-line monitoring applications.

Keywords: Postural transitions, Accelerometers, Inertial Systems.

1 Introduction

Motion tracking and identification of daily life activities by inertial systems are useful in the evaluation of the quality of life in the elderly or patients with mobility problems [1], for example stroke patients or those with Parkinson's disease (PD). Among daily life activities, postural transitions (PT), mainly sit-to-stand (SiSt) and stand-to-sit (StSi), are very important since they are the most mechanically demanding activities and are considered as a prerequisite of walking [2]. For dependency care area, analyzing these transitions could be crucial for fall prevention [3] [4].

There are different methods to study and analyze human movements such as electromyography [5], photography and video [6], stereograph [7] and electrogoniometry with a pressure platform [1]. However, these systems are cumbersome and uncomfortable. Therefore, these systems cannot be used in an ambulatory monitoring.

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Nowadays, Micro-Electro-Mechanical-Systems (MEMS) technology allows smaller and lighter sensors, such as miniaturized accelerometers and gyroscopes. The small size and low energy consumption enables the embedding of the sensors in devices that can be worn easily and can operate for a long time running on a small battery. MEMS have already been widely used to study human motion, and particularly in PT. For example, Bidargaggi et al. analyzed the waveform of a previously detected transition by reconstructing the accelerometer signals in the waist using wavelets in order to determine whether a SiSt or StSi transition occurred [8]. Najafi et al. used a gyroscope to obtain the chest tilt and consequently, detect postures [9]. By means of the frequency response of the gyroscope signal, they discovered a frequency band below 0.68Hz in which a significant peak appears when a PT has occurred. Najafi et al. combined this approach with other methods and constraints to generate a complete algorithm that recognizes basic activities in daily life [1]. Another interesting study used a mobile phone situated in a trouser pocket in a fixed position [10]. Through the correlation of the signal obtained with a signal template, a SiSt or StSi transition was identified. Static positions, like standing, sitting or lying can be identified by analyzing the accelerometer values in window sequences [11]. However, a sit position can be confused by a standing position depending on the tilt of the body. Thus, a dynamic and a change in the stationary movement analysis are proposed in this work.

This paper presents a novel postural transition detection algorithm using a unique triaxial accelerometer located at the waist, which is considered a comfortable location to carry an inertial sensor. The algorithm is suitable to be inserted in a microcontroller, since there are no complex calculations that require large memory usage or long time periods to calculate parameters for the algorithm. This algorithm presented has been tested in a database of 31 healthy patients and 8 PD patients. The final goal of this algorithm is to enable the evaluation of the quality of life in PD patients and enhance movement disorder detection algorithms for PD that are being developed under REMPARK project by means of the same inertial sensor located in the same place [12] [13].

2 Posture Transition Algorithm

A static position is characterized by the absence of movement and, then, only gravity (G) is measured by means of the module of the accelerometer axis (ax, ay, az), as shown in Eq. (1). Thus, when the sensor is located in the waist as shown in Figure 1, similar measurements may be obtained from different static positions, e.g. sitting and standing postures. Consequently, in order to discriminate between sit and stand postures it is needed to identify postural transitions. However, when a person is lying, the weight of the gravity may fall in the anterior axis (ax) or lateral axis (az).

$$\left.\sqrt{a_x^2 + a_y^2 + a_z^2}\right|_{static} = \mathrm{G} = 9.81\ \mathrm{m/s^2} \tag{1}$$

In dynamic postures, Eq. (1) is not valid, since accelerations applied to the inertial sensor makes vary value of Eq. (1), therefore, another features must be analyzed in order to study posture transitions, for example frequency response. According to Najafi et al., frequency response below 0.68Hz corresponds to postural transitions [9]. In this work, a Short Time Fourier Transform (STFT) is used to detect transitions. Formally:

$$X(f,t) = \int_{-\infty}^{\infty} w(t,\tau)x(t)e^{-i2\pi ft}dt \tag{2}$$

where x(t) is the accelerometer signal to be transformed, w(t, τ) is the window function to be analyzed. The power spectral density of the window analyzed is composed by the amplitude of the signal and its frequency. A harmonic in the band below 0.68Hz which overpasses a certain threshold (Th_1) is considered to lead to a postural transition event. This threshold will be set as the value that maximizes the minimum of sensitivity and specifity of a posture transition detection training dataset.

Once any postural transition is detected, it should be then identified. A simple approach which takes advantage of how gravity changes between axes in a PT is proposed. More concretely, the following condition differentiates the SiSt and bending down (BD) from StSi and bending up (BU) transitions:

$$\Delta(Wx - Wz) = \begin{cases} StSi, BU & < -Th_2 \\ SiSt, BD & > \ Th_2 \\ other & \end{cases} \tag{3}$$

$$W_x = \frac{\sum_{i=1}^{n} a_x(i)}{n} \tag{4}$$

$$W_z = \frac{\sum_{i=1}^{n} a_z(i)}{n} \tag{5}$$

where a_x and a_z in Eq. (4) and Eq. (5), are the anterior and lateral acceleration vectors of n samples, respectively. Th_2 value has been set by maximizing the minimum specifity and sensitivity on the identification of the StSi and SiSt.

Fig. 1. Inertial Sensor

Assuming that the sensor is located according to Figure 1, the explanation of Eq. (3) is based on the effect of gravity on the axes. Overcoming the negative threshold on Eq. (3) means that the person has made a StSi or BU transition since Z axis tends to point the superior direction, then Z axis value is increased due to gravity and makes left part of Eq. (3) more negative when sitting. On the other hand, Eq. (3) might not vary and remains close to zero when the subject realizes stationary movements, for example walking, running, standing, sitting or lying. Furthermore, a decreasing value in Z axis is obtained because of the bending forward movement when a SiSt transition begins. The X axis is directed against gravity and tends to become positive when standing up. Note that anatomy and belt mounting has a very strong effect on the data captured and, consequently, only one axis might change instead of both X and Z axis. In order to overcome this problem, a relation among X and Z axis is used in Eq. (3).

The state machine shown in Figure 2 has been developed in order to establish the complete PT classifier. In this state machine it is very important to know the initial conditions since the triggering of the indicator given by Eq. (3) results in 2 possible posture transitions, which are distinguished through the initial conditions.

Furthermore, a Lying postural transition is detected whether the Y axis changes, if Y is under 0.5G it is understood that the person is in a prone position.

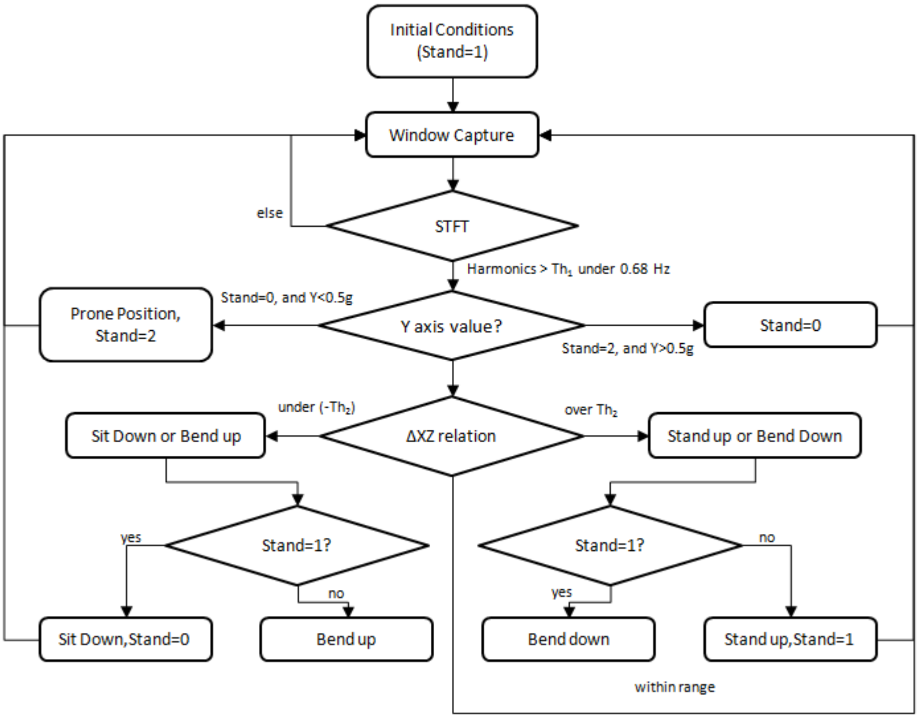

Fig. 2. Activity Recognition Algorithm

3 Experiments

The experiments have been performed using an inertial data-acquisition device developed at the Research Centre for Dependency Care and Autonomous Living of the Technical University of Catalonia (CETpD-UPC). This device has been already used in other research works [14]. With a size of 77x37x21 mm3, it is smaller than a mobile phone. The accelerometer used is LIS3LV02DQ, which is 3-axial and has a full scale of ± 6G (1G=9.81 m/s2) and has the data information conditioned and digitalized. The inertial data is stored in a μSD card.

Two test protocols have been performed. The first test protocol, which includes different daily life activities, was performed by 36 volunteers (22 men and 14 women, ages from 21 to 56 years old, mean age of 35.77 and standard deviation of ± 9.58). 5 randomly chosen volunteers have been used to set thresholds, and the rest have been used to test the classifier. Six transitions have been taken into account in this work: Bending up/down (BU/BD), Sitting from Lying (SL), Lying from Sitting (LS), Stand-to-Sit (StSi), Sit to Stand (SiSt). The participants wore an inertial sensor at the waist, fixed as shown in Figure 1. Every subject performed the test twice, removing his belt and relocating it again between tests. Each test lasted 3-4 minutes approximately.

Participants were video recorded in order to have a visual gold-standard. A total of 625 transitions have been analyzed, 80 of them were used to set thresholds Th_1 and Th_2, among which 40 transitions belong to Sit-to-Stand and Stand-to-Sit transitions, 20 belong to Lying transitions and the other 20 to Bending transitions. The other 545 transitions were used to test the classifier, among which 311 transitions belong to Sit-to-Stand and Stand-to-Sit transitions, 124 belong to Lying transitions and the other 110 to Bending transitions. The second test protocol was performed by 8 patients with PD, who formed part of MOMOPA project database [15]. The entire tests were also video-recorded, and the thresholds achieved with the 5 randomly healthy volunteers were not changed in order to validate the algorithm in both data bases. A total of 176 transitions have been analyzed, 88 of them were SiSt and 88 were StSi. The signal has been sampled at 40Hz in both tests, which is enough to measure human motion [16]. Signal was divided into 128 samples windows, which have a duration of 3.2 seconds. This window length is enough since, according to Kralj's et al., the maximum time of a transition is 3.3 seconds [1]. However Kerr et al. confirmed that transitions may last up to 2 seconds in elderly people [7]. Windows are 50% overlapped to prevent possible loss of information.

4 Results and Discussion

A total of 80 transitions belonging to 5 purely random chosen healthy volunteers have been used to set Th_1 and Th_2, which are the detector and identifier thresholds of SiSt, StSi BU and BD transitions. Th_1 has been set to *2* having maximized the minimum sensitivity and specifity of detecting a transition among the 80 training set transitions. Th_2 has been set to 1.5 through the same approach.

A total of 545 transitions have been evaluated (311 SiSt and StSi, 110 Bending and 124 Lying transitions). Results of sensitivity and specifity on healthy volunteers are shown in Table 1. Note that TN,TP,FN and FP mean True Negative cases, True Positive cases, False Negative cases and False Positive cases respectively, while Sensitivity= $\frac{TP}{TP+FN}$, and Specifity = $\frac{TN}{TN+FP}$.

Table 1. Sensitivity and Specifity from different postural transitions on healthy volunteers

Activity	Predictions		N. Transitions	Result	
SIT TO STAND	TN	359	156	Sensitivity	0,865
	TP	135			
	FN	21		Specifity	0,992
	FP	3			
STAND TO SIT	TN	359	155	Sensitivity	0,871
	TP	135			
	FN	20		Specifity	0,986
	FP	5			
BEND UP	TN	442	55	Sensitivity	0,946
	TP	52			
	FN	3		Specifity	0,996
	FP	2			
BEND DOWN	TN	446	55	Sensitivity	0,873
	TP	48			
	FN	7		Specifity	0,996
	FP	2			
LYING FROM SIT	TN	432	62	Sensitivity	1,000
	TP	62			
	FN	0		Specifity	1,000
	FP	0			
SIT FROM LYING	TN	432	62	Sensitivity	1,000
	TP	62			
	FN	0		Specifity	1,000
	FP	0			

Table 2 shows the results of the algorithm applied to 8 PD patients using the same parameters used with healthy people.

Table 2. Sensitivity and Specifity from different postural transitions on PD patients

Activity	Predictions		N. Transitions	Result	
SIT TO STAND	TN	214	88	Sensitivity	0,932
	TP	82			
	FN	6		Specifity	0,963
	FP	8			
STAND TO SIT	TN	214	88	Sensitivity	0,92
	TP	81			
	FN	7		Specifity	0,955
	FP	10			

The method detects SiSt, StSi, BU and BD transitions with a specificity over 0.98. However, sensitivity measurements decrease especially at Bend Down, StSi and SiSt transitions, which have sensitivity around 0.90. In these cases volunteers tend to Bend down more slowly than when they Bend up, consequently Th_1 is not enough to detect a transition so an adaptive threshold is proposed for future work in order to enhance these results. The StSi and SiSt transitions drawbacks come when volunteers sit at the bed. It has been found that some people have sat dropping, similarly to a fall, provoking deep rebounds in the signal. However, calculating the mean of the X axis and Z axis in a window of data neglects this effect by acting as a low-pass filter.

The postural transition algorithm described uses a single accelerometer located at the waist, and is based on the effect of gravity on the accelerometer axis. The sensor location is very important because it maximizes the difference between frontal acceleration or X axis and lateral or Z axis as considered in Eq. (2). For instance, if the sensor is located at a lateral side of the waist, then the lateral axis would be orthogonal to the rotations performed during postural transitions, thus gravity effect would be negligible and Eq. (2) would remain constant to postural changes. One of the main features of the system is the windowing-based analysis. On the one hand it allows reducing latency time, in other words, a result of the algorithm can be given in each window. On the other hand it permits the microcontroller to lighten the load of memory used to analyze the signal since it analyzes only a window instead of the whole signal.

As part of future work, it is proposed to enhance the correct identification of the PT by detecting some other activities, for example walking, running or activities that a person can only execute when she/he is stand. On the other hand this algorithm has to be validated in a larger database which is currently being performed with real PD patients which have to execute PT in their daily life in a home-environment situation.

5 Conclusions

Postural transitions are an important activity of daily life, and measuring them can be useful to evaluate quality of life. The postural transition detector presented in this work detects and identifies 6 different postures and uses a single accelerometer in a very comfortable position. The method has been shown to detect PT with specificity over 0.98 and sensitivity 0.865. It has also been tested in real PD patients, where the results achieved are 0.92 on sensitivity and 0.95 on specifity. The algorithm is suitable to be implemented in real-time for online monitoring as the algorithm as it is based in windowing analysis.

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