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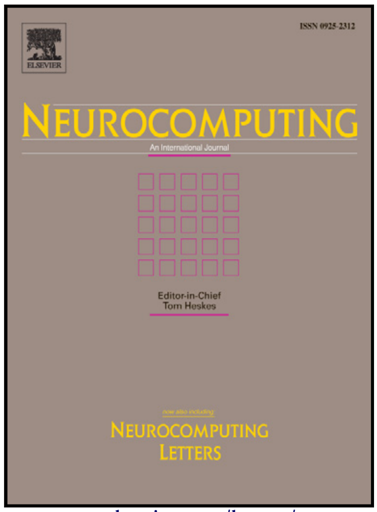

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Posture Transition Identification on PD patients through a SVM-based technique and a single waist-worn accelerometer

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ABSTRACT.

Identification of activities of daily living is essential in order to evaluate the quality of life both in the elderly and patients with mobility problems. Posture transitions (PT) are one of the most mechanically demanding activities in daily life and, thus, they can lead to falls in patients with mobility problems. This paper deals with PT recognition in Parkinson's Disease (PD) patients by means of a triaxial accelerometer situated between the anterior and the left lateral part of the waist. Since sensor's orientation is susceptible to change during long monitoring periods, a hierarchical structure of classifiers is proposed in order to identify PT while allowing such orientation changes. Results are presented based on signals obtained from 20 PD patients and 67 healthy people who wore an inertial sensor on different positions among the anterior and the left lateral part of the waist. The algorithm has been compared to a previous approach in which only the anterior-lateral location was analyzed improving the sensitivity while preserving specificity. Moreover, different supervised machine learning techniques have been evaluated in distinguishing PT. Results show that the location of the sensor slightly affects method's performance and, furthermore, PD motor state does not alter its accuracy.

Keywords: Accelerometer, Posture Transitions, Parkinson's Disease, Support Vector Machines

1. Introduction

Identification of activities of daily living (ADL) is crucial in order to evaluate the quality of life in the elderly and patients with mobility problems such as Parkinson's disease (PD) patients [1]. Among the different ADL, posture transitions (PT), mainly sit-to-stand (SiSt) and stand-to-sit (StSi), are specially relevant since they are the most mechanically demanding activities and are considered to be a prerequisite of walking [2,3]. In the dependency care area, analyzing these transitions could be essential to enhance fall prevention [4,5]. In the case of PD, which is the second most common neurodegenerative disease after Alzheimer's disease, PT are affected by motor symptoms suffered by patients, such as bradykinesia (slowness of movement) [6], dyskinesia (involuntary movements) [7] and freezing of gait [8], among others.

Several methods have been used in order to study PT, such as electromyography [9-11], goniometry [3,12], video [13], photography [14] and pressure platforms [15]. Since these systems rely on cumbersome, heavy or not wearable instruments, they cannot be used in ambulatory monitoring. Nowadays, Micro-Electro-Mechanical-Systems (MEMS) technology has opened up the possibility to use smaller and lighter sensors, such as miniaturized accelerometers and gyroscopes (inertial sensors). MEMS sensors are commonly embedded within wearable devices given their small size and low energy consumption [9,10]. This way, inertial sensors based on MEMS are widely used to study human movement and PT in particular. Moreover, since they provide a low consumption, several hours of monitoring is possible and, consequently, daily life and ambulatory monitoring is currently being researched [10,11].

In PT identification and monitoring, location of the inertial system is one of the most important factors involved in obtaining usable results from daily monitoring. In this sense, it should be considered that most of current algorithms are affected by the location in which the inertial sensor is worn. Given a change in the sensor position or orientation, human movement measurements will be affected and, in consequence, algorithm results will be altered. One example of this issue was reported by Bachlin et al; they reported in [12] that locating an inertial system at the leg improves the sensitivity of detecting a PD symptom called Freezing of Gait, contrasting the results obtained when the sensor is at the hip. On the other hand, comfort is another relevant factor since quality of life assessment involves wearing an inertial system during several hours [13]. In this sense, numerous works have analyzed PT locating the sensor in different parts of the body. Bidargaggi located an inertial sensor at the waist in order to analyze Sit-to-Stand (SiSt) and Stand-to-Sit (StSi) transitions [14] while Najafi placed the inertial system at the chest [15]. A headband with an inertial system was used by Aloqlah et al. for classifying human postures [16] and Bieber et al. performed a SiSt and StSi classifier using a mobile phone within a trouser pocket [17]. Among these different positions on which an inertial sensor can be worn, waist is the most comfortable one as concluded in a research work in which a questionnaire was responded by elderly people [18]. Moreover, waist position enables movement monitoring since waist is close to the center of mass of human body and, thus, the most representative part of human movement is monitored [19,20].

This paper aims to identify PT in PD patients by means of a unique accelerometer located at the waist. To this end, movement signals were collected from 20 PD patients and 67 users. More specifically, inertial signals from PD patients were collected at patients' home during periods of several hours based on an inertial sensor attached to the waist in a lateral position. However, given the duration of the monitoring and the anatomic differences among patients, its orientation and location were altered during data collection and they were, at least, slightly different among patients. Thus, this paper addresses PT detection assuming changes on the sensor placement. More specifically, an algorithmic approach is proposed to deal with two different sensor positions: on the one hand, anterior-lateral waist location, as shown in the left part of Figure 1.1, and, on the other hand, lateral waist, as shown in the right part of Figure 1.1. Signals employed in this paper belongs to, in the case of PD patients, *Personal Health Device for the Remote and Autonomous Management of Parkinson's* project (REMPARK) [21]. Signals from healthy users were gathered while users performed a specific set of activities and with the inertial sensor located at the two positions shown at Figure 1.1.

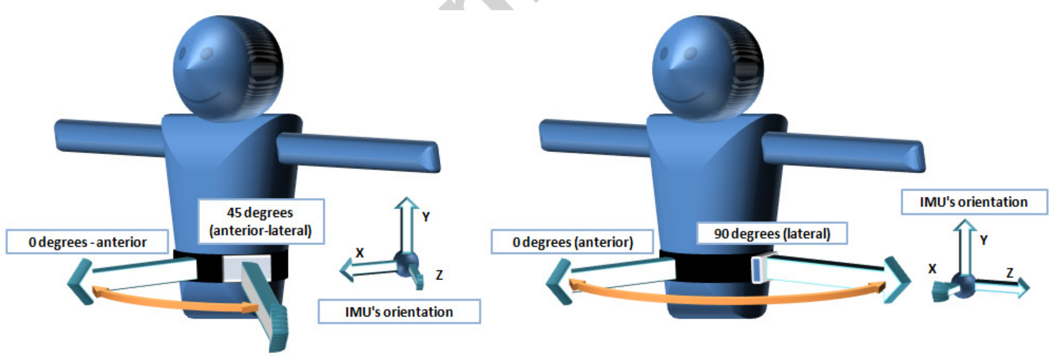

Figure 1.1: Orientation of the inertial system

The main goal of this paper is to present a robust algorithm capable to detect and identify posture transitions through a sensor placed at any location between the anterior and lateral left side of the waist. Therefore, 2 algorithms are compared, the first one, which was presented in prior works, was designed for signals obtained from the anterior-lateral waist location. This algorithm was tested in 8 PD patients achieving high performance results [22]. In this paper, results obtained by this algorithm on the set of signals from 20 PD patients and 67 healthy users are compared against those obtained by the proposed algorithm. This new algorithm introduces new features and a machine learning approach in order to enhance posture transition identification with different sensor orientations. Results show that the new algorithm improves sensitivity more than 7.5% in respect of the previous work and, moreover, it also provides sensitivities and specificities over 88% in both PD patients and healthy users.

The rest of this paper is organized as follows. First, related work on PT with MEMS based inertial systems is reported. Then, new algorithm proposed for PT identification is described. In the fourth section, experiments performed are detailed. Finally, obtained results are reported along with discussions and, in the last section, conclusions of the work are presented.

2. Related work

Posture transitions have been studied with many different systems, as previously shown. However, inertial systems based on MEMS have been the most spread approach to study and analyze these movements [23]. In this section, related work in the field of posture transitions and human movement activity recognition based on MEMS-based inertial systems is described [24].

In this literature review, two kinds of movements are distinguished. On the one hand, it is distinguished static activities or static postures, which are those postures during which human movement barely occurs and consist on sitting, lying and standing. On the other hand, dynamic postures or activities are those activities in which movement occurs, as during walking or posture transitions. Given this two-fold classification of human movement, signal analysis performed from inertial sensors is also distinguished in this sense. Static signal analysis consists in the analysis of inertial signals assuming that the subject measured is in a static posture, so that only gravity would be measured by an accelerometer, i.e. $\sqrt{\left(a_x^2+a_y^2+a_z^2\right)_{static}}=9,81m/s^2$, where a_x, a_y, a_z are accelerations measured in the three axis of the triaxial accelerometer. On the other hand, dynamic signal analysis assumes that a dynamic posture is being performed and, then, not only gravity is measured by the accelerometer since accelerations due to human movement are also sensed.

Many studies have examined physical activity recognition by means of static analysis. Veltink et al. analyzed static activities with 3 uniaxial accelerometers, 2 of them located at the chest and the other one at the leg [25]. Veltink et al. determined that it is possible to distinguish different activities evaluating the first-order statistics of accelerometer signals. Specifically, it was shown that standard deviation of these values enables distinguishing dynamic activities from static activities. Baek et al. recognized static activities with an accuracy of 100 % by means of a biaxial accelerometer and measuring the relative inclination against gravity placing the accelerometer at the waist [26]. On the other hand, Karantonis et al. developed a real-time classifier with the ability to distinguish various static and dynamic activities. Static activities were determined by a reduction of the activity provided by the Signal Magnitude Area (SMA) and then the inclination relative to gravity was analyzed.

Within the static activities, Karantonis et al. obtained 94.1% accuracy [27]. However, distinguishing positions just by measuring the tilt of the accelerometer respect gravity were shown to be troublesome since they might be easily confused. For example, Figure 2.1 shows how the inertial system remains at the same orientation in 2 different static postures. The same situation would happen in case that the inertial system was located at the thigh and the algorithm tried to recognize a Lying posture from a Sit posture. In consequence, the most common method employed to differentiate among static postures consists in including more inertial systems. For instance, Gjoreski et al. reported an accuracy improvement by including more than one sensor: 66% of accuracy on detecting 'Sit' was obtained, initially, with just an inertial system, which was enhanced up to a 99% of accuracy with 4 accelerometers.

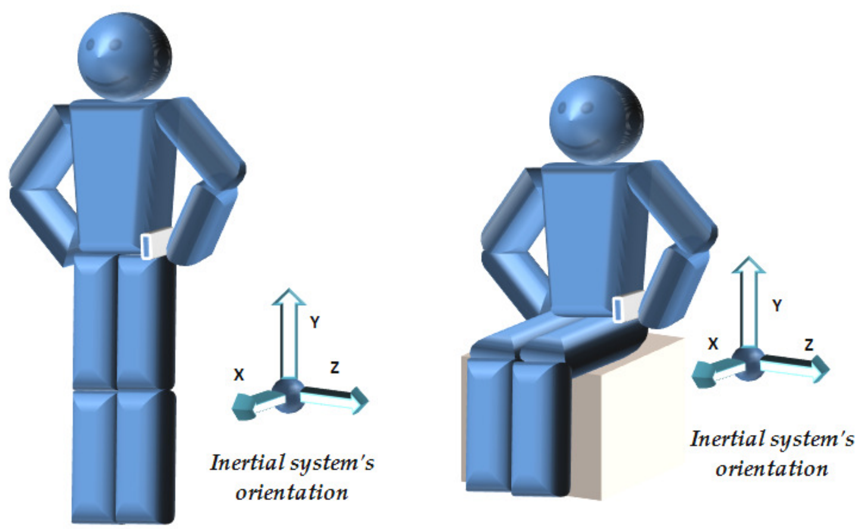

Figure 2.1: Posture recognition conflictive cases

Some authors, however, suggest the usage of dynamic analysis in order to detect posture transitions and, thus, determine the final posture achieved by the person. This approach enables the usage of a single sensor. For instance, Najafi et al. used a gyroscope in the chest and, based on discrete wavelets transform (DWT), a PT was determined [15]. Bao and Intille studied ADL with 5 accelerometers and using Short Time Fourier Transform (STFT) [28]. Dynamic Time Warping (DTW) was used by Ganea et al. by measuring similarities between some patterns and the obtained inertial signals from a triaxial accelerometer located at the trunk [29].

3. Posture Transition Identification Algorithm

In this section, the proposed PT algorithm is described and its different parts are detailed in different subsections.

The proposed PT identification algorithm's main goal is to ameliorate a prior algorithm which employed an inertial system located at the *anterior – lateral* position (AL) [22]. The enhancement consists in enabling the sensor to be additionally located at the lateral position since, during long monitoring periods, the movement sensor position may vary.

Signals provided by the accelerometer during a PT in both positions, anterior-lateral and lateral (AL-L) positions, differ as shown in Figure 3.1. If the inertial system is located in a lateral position, sensor's orientation before and after a PT might remain without change, as shown in Figure 2.1, and, in consequence, the acceleration values would measure gravity in the same way (right subfigure in Figure 3.1). On the other hand, when the inertial system is located in the anterior-lateral (AL) position, after a PT the sensor lies on the abdomen and, thus, its contraction slightly changes the orientation of the inertial system in respect of the one it had before the PT.

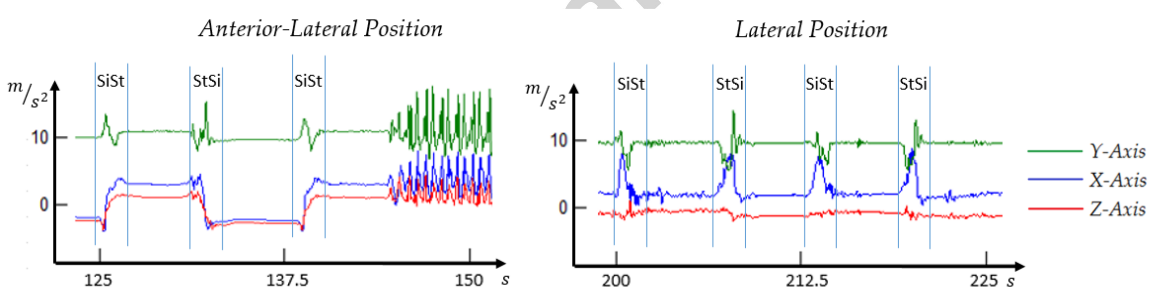

Figure 3.1: Posture transitions with different inertial system orientation from a PD patient

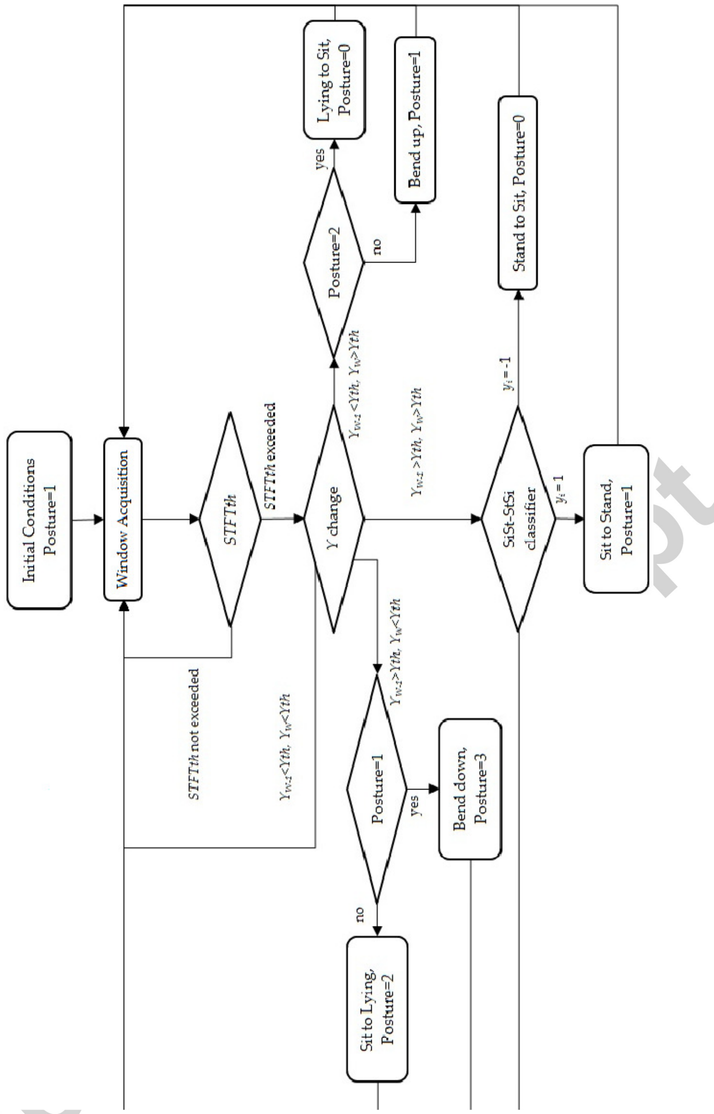

Figure 3.2: Posture Transition Algorithm

The proposed approach to identify PT transitions from AL-L positions is shown in Figure 3.2. It consists of a hierarchical structure of classifiers comprising:

- "STFT classifier", which is in charge of indicating whether a PT has occurred or not.
- "Y classifier", which indicates whether a person has its trunk in a vertical direction (Sit or Stand Posture) or, otherwise, the person is in a prone position (Bent, or Lying). In the schema, 'Posture' variable corresponds to this position, so that it has a value of '0' in case the person is sitting, a value of '1' when the person is stand, '2' when the person is lying and '3' when the person is bent.
- SiSt-StSi classifier is a SVM-based classifier which determines whether a StSi or SiSt PT has occurred. Given the differences between both PT, the input of this SVM is set to represent the signal's shape in the most relevant axis.

Following the hierarchy of classifiers, when a window acquisition is completed, a STFT is firstly performed in order to consider whether a PT has occurred or not. Then, Y_W (window average value of Y axis) is analyzed.

The rest of schema's decisions are based on previous states determined by 'Posture' variable, which must be initialized to a given value since the accelerometer signals might be similar if the person is either standing or sitting. This variable designates the 'static' posture and only a change on Y axis or a STFT may modify this value. If the user was previously in a 'Stand' position, and a 'Bent' condition is satisfied, it means that a 'Bend Down' PT has been performed. However, if the person was in a 'Sit' posture, the PT has been, then, 'Lying'. In the same way, if the person was Lying and Y_W indicates that the person has recovered the verticality of the trunk, the PT has been, in this case, 'Lying to Sit'. On the other hand, if the person was 'Bent', the person is now 'Stand'. However, if Y_W does not vary and indicates the person's trunk is vertical, a 'SiSt' or 'StSi' PT has occurred and the SiSt-StSi classifier is executed. Though, if the person remains in a prone position, there may have been a change of orientation while sleeping. In this case, no action is carried out.

Bending and lying postures, determined by vertical tilt, affect the Y axis independently of the sensor waist location. Thus, in respect of the previous AL algorithm, the identification of these two postures assuming AL-L positions remains unaffected. However, 'Stand' and 'Sit' postures detection is different since their transitions, as shown in Figure 3.1, are altered. To this end, a machine learning technique has been introduced in the AL-L approach. Another relevant difference of the new approach consists in the data employed. In prior works, experiments were performed under controlled conditions and the training data employed were gathered from healthy volunteers. On the contrary, the presented algorithm has been trained only with PD inertial data and with real life conditions, that is to say, in their homes.

Next subsection describes more concretely the different parts in which the approach is divided.

3.1 STFT classifier

The STFT classifier determines whether a person has performed a PT. A posture transition is considered as the movement during which a person's posture changes. This movement is detectable based on a STFT in which provides the repeatability of a signal during time [22]. The STFT, in contrast to the Fast Fourier Transform, is characterized by the analysis of the signal in a finite window of time. The discrete STFT is defined as:

$$X(m,w,k) = \sum_{n=-\infty}^{\infty} w[n-m]\,x[n]\,e^{-i2\pi k\frac{n}{m}} \tag{1}$$

where k is the harmonic for which the STFT is computed, m is window length being $x[n]$ the discrete signal to be transformed (x, y and z) and $w[n-m]$ is the window function in which the accelerometer samples belonging to this window are evaluated.

Let $XZ(m,w)$ be the sum of the amplitudes of the harmonics under 0.68Hz without considering the DC component (k=0) for x and z axis of the accelerometer:

$$XZ(m,w) = X(m,w,k_1) + Z(m,w,k_1) + \ldots + X(m,w,k_2) + Z(m,w,k_2) \tag{2}$$

where $k_1 = 1$, and $k_2 = \frac{F_s k}{m}$ F_s is the sampling frequency and $\cdot$ is the integer part of a real number.

Then, a PT event is determined based on:

$$PT\ event = \begin{cases} 1, & if\ XZ(m,w) > STFTth \\ 0, & if\ XZ(m,w) \le STFTth \end{cases} \tag{3}$$

where $STFTth$ is a threshold for the value computed from which a PT is considered to occur. Hence, and according to Najafi et al., a relevant frequency response below 0.68 Hz indicates that a PT has occurred [15].

3.2 *Y classifier*

On the other hand, the Y classifier determines the verticality of the trunk and is based on the average analysis of the accelerometer vertical axis at window-level $\left(Y_W = \frac{\sum_{i=1}^{n} a_i^y}{n} \right)$, where n is the number of window samples. This value (Y_W) is compared to a previously set threshold (Yth) and to Y_{W-1} in order to assess the evolution and, in consequence, determine, if necessary, the performed PT. Equation (4) shows the different results for the analysis of Y_W.

$$Posture = \begin{cases} Stand, Sit, SiSt, StSi, & if \quad (Y_W \wedge Y_{W-1}) > Yth \\ Bent\ or\ Lying, & if \quad (Y_W \wedge Y_{W-1}) < Yth \\ Bend\ up, Lying\ to\ Sit, & if \quad Y_W > Yth \wedge Y_{W-1} < Yth \\ Bend\ down, Sit\ to\ Lying, & if \quad Y_W < Yth \wedge Y_{W-1} > Yth \end{cases} \tag{4}$$

The final posture depends on the variable 'Posture' but, in the case of satisfying conditions $(Y_W \wedge Y_{W-1}) > Yth$ and $XZ(m,w) > STFTth$, the SiSt-StSi classifier must be executed.

3.3 SiSt-StSi classifier

The SiSt-StSi classifier determines which PT has occurred, either a StSi or a StSi PT. As Figure 3.1, signals obtained in the lateral position are very similar for both PT. In order to distinguish among them, a machine learning technique is employed. The input of this machine learning technique consists of the following input vector:

$$\boldsymbol{x}_i = \left[a_T^x, a_T^y, XZ_W \right] \tag{5}$$

where a_T^x and a_T^y are vectors composed of accelerations measurements from X and Y axis and *T* is the period during which signal samples must be used. XZ_W is defined as �$(X_W - Z_W)$ where $X_W = \frac{\sum_{i=1}^{n} a_i^x}{n}$ and $Z_W = \frac{\sum_{i=1}^{n} a_i^z}{n}$. a_i^X and a_i^Z are the anterior and lateral accelerometer sample values, respectively, at sample *i*, while *W* is the current analyzed window.

The period to analyze is determined as $t_r,\ldots,t_s$ such that (I) $r, s \in \mathbb{N}$, (II) $r = s - 1.5 \cdot windowlength$, (III) s is the ending sample of the window currently being analyzed and (IV) r is the sample belonging to the first sample of the prior window. Since window length is set to 128 samples, $t_r,\ldots,t_s$ comprise 192 samples, which cause a large number of inputs to the machine learning classifier. Once a method is chosen to classify SiSt and StSi, the model should be optimized. To lighten the computational burden, vector $\boldsymbol{x}_i$ with $1 + 2\cdot(s + r - 1)$ samples has been resampled to have length $1 + 2\cdot P$ where *P* is the number of samples after resampling a_i^x and a_i^y. The effect of altering the value *P* in terms of accuracy is shown in section 5.

3.4 Anterior-Lateral Algorithm

The prior work, had as a main goal the detection and identification of different PT with the sensor located at the *anterior-lateral* waist position shown in Figure 1.1 [22]. The algorithm was named as anterior-lateral algorithm (AL). This algorithm is the same shown in Figure 3.2 but, however, the SiSt-StSi classifier based on machine learning techniques is substituted by the following condition:

$$Posture = \begin{cases} StSi & if \quad (X_W - Z_W) < -XZth \\ SiSt & if \quad (X_W - Z_W) > XZth \\ & \quad other \end{cases} \tag{6}$$

where *XZth* threshold was set at 1.5. This condition relies on the variation of signal between the X axis and the Z axis when a StSi or SiSt PT is executed as shown in Figure 3.1. Parameters which took part in this algorithm were trained with a dataset achieved from healthy users. However, evaluation was performed over PD patients, achieving high accuracy results.

The AL algorithm is compared in this paper against the proposed AL-L algorithm using a given set of signals. This way, optimal parameters obtained with a fixed location inertial system will be compared to results achieved from an algorithm which works in optimal conditions in the left side of the waist.

4. **Experiments**

In this section, experiments performed to select the different classifiers that comprise the hierarchical structure of classifiers belonging to the AL-L and AL algorithms are reported. First, the data capture process is presented and, then, the training process is described.

4.1 Dataset description

Two signal databases have been used to evaluate both AL and AL-L algorithms. The first one was gathered from healthy volunteers (from now on D1) while the second one (from now on D2) was collected from PD patients.

In this paper, it is considered that a Lying state or a Bending state is not dependent on the PD motor state and only depends on trunk's tilt relative to gravity. In consequence, sensor's orientation is not important in the *anterior – lateral* plane. Thus, and since some posture transitions were not obtained at D2 database performed by PD patients, i.e. Bending Down, Bending Up, Sit to Lying and Lying to Sit , these PT are evaluated with D1 database. This way, signals obtained from D1 users were used to set *Yth* and signals gathered from PD patients (D2) were employed to set *STFTth* and to train the SiSt-StSi classifier.

D2 database is a subset of the signals collected within REMPARK project (http://www.rempark.eu) and has been built with the collaboration of 4 different hospitals: Maccabi Healthcare Centre (Israel), Fundazione Santa Lucia (Italy), National University of Galway (Ireland) and Centro Médico Teknon (Spain). Signals were collected from patients diagnosed with PD and with at least 2 points of Hoehn & Yahr Scale in a scale from 0 to 5 [30]. For this experiment, 20 patients (14 men, 6 women) have been selected with an average Hoehn & Yahr scale of 2.93 and a standard deviation of 0.37 points. Mean age of patients is 72.7 years old with a standard deviation of 5.1 years old. All patients performed the test protocol twice, being under the effects of the PD medication and without. All patients were in their homes wearing an inertial system called 9x2 [31]. PD patients have performed a total of 235 StSi PT and a total of 221 SiSt PT.

Regarding the location of the sensor at the D2 database, from the 38 sets of inertial signals obtained from 20 PD patients (2 patients did not perform the second test), 17 inertial signals were captured with the inertial system located at a lateral location and 19 inertial signals were taken with the inertial system at the anterior-lateral location, and, finally, 2 inertial signals were taken from an anterior location.

The inertial system employed to acquire inertial data contains an accelerometer (LIS3LV02DQ) and a dsPIC33F. Acquired data are stored in a μSD card at 200Hz. The inertial system's size is 77x37x21 mm^3 and it weights 78g [31]. All test protocols were video recorded in order to have a visual gold-standard.

D1 is composed of two groups of data collected. The first group of signals (from now on D11) was collected from users who wore the inertial system at the *anterior – lateral* position, and the second group (D12) from users who wore the system at the *lateral* position. The first group is composed of 36 healthy volunteers (22 men and 14 women, ages from 21 to 56 years old, mean age of 35.77 and standard deviation of ± 9.58). The second group is composed of 31 healthy volunteers (15 men, 16 women, ages from 23 to 53 years old, mean age of 35.32 and standard deviation of ±7.668). The protocol test on both groups consists in performing different activities, in which Bending and Lying PT are the analyzed PT. Table 1 shows the number of PT performed in this second database.

Table 1. Second dataset's number of events

Posture Transition	Number of events D11 (anterior-lateral location)	Number of events D12 (lateral location)
Sit to Lying	72	63
Lying to Sit	72	63
Bending Up	65	62
Bending down	65	62

This dataset has also been video-recorded having a visual gold-standard to correctly label data.

4.2 *Training and evaluation methodology*

In this section, the preprocessing methodology and classifier trainings and evaluations are detailed. Before treating inertial signals, they are pre-processed by, first, resampling at 40 Hz, since this frequency has been shown enough to analyze human movement [32]. Then, inertial signals are filtered in order to remove noise and communication data errors. The employed filter is a 2nd order Butterworth low-pass filter. Moreover, the inertial signal is windowed in 128-sample windows and overlapped at 50%, in order to any loss of events information between consecutive windows. With a 128-sample window length and a sample frequency of 40 Hz, a window of 3.2 seconds is suitable to analyze PT, since SiSt and StSi PT last about 3 seconds according to Kralj et al. and Kerr et al. [3,33].

4.2.1 SiSt-StSi detection

In this paper, 6 different classifiers have been tested to distinguish SiSt from StSi PT. In order to evaluate these classifiers, a 10 fold cross validation has been performed and the accuracy achieved by each classifier has been obtained in order to establish the selected one.

First, Artifical Neural Networks (ANN) have been used [34]. ANN establishes a mathematical relation between the outputs and the inputs and one of the most used methods in activity and posture recognition is the Multilayer Layer Perceptron [35], which is the employed method in the present work and it is trained by means of the backpropagation algorithm with three different learning rates. Second, K-Nearest Neighbor has been used [36], which employs the geometrical distance between the different patterns with respect of the different class centroids to assign a class to a pattern. Several values for the number of centroids (*K*) have been tested in order to obtain the best one. Values *K=3,10,20,…,50* have been used. The third method used is Naïve-Bayes, a probabilistic classifier based on the estimated conditional probability obtained through Bayes rule. This method has been shown to be a good classifier in activity recognition problems [28]. Logistic Regression and Random Forest have also been tested due to its effective functioning in some works [37,38]. Finally, SVM's with 4 kernels (Linear, Radial Basis Function, 2nd-order and 3rd order Polynomial) have been employed.

SVM's are a kind of machine learning techniques that map input vectors ($x_i \in \Re^N,\ 1 \le i \le l$) to a higher dimensional feature space by $\varphi(x_i)$. A hyperplane is built in order to separate the 2 classes, represented by $y_i \in \{1,-1\}$. The constructed hyperplane maximizes the classification margin, which, at the same time, maximizes the Vapnik-Chervonenkis dimension [39]. The optimal hyperplane is defined according to the following optimization problem:

$$\begin{gathered} maximize \quad W(\alpha) = \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{l}\left(\alpha_i\alpha_j y_i y_j \cdot K\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right)\right) \\ Subject\,to \quad 0 \le \alpha_i \le C,\ i = 1,\ldots,l \end{gathered} \tag{8}$$

in which *C* is the trade-off between balance and misclassification error and the kernel function $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ replaces the dot product $\varphi(x_i)\cdot\ \varphi(x_j)$.

Given that *C* and the kernel-dependent parameter values must be tuned, a sweep of values are tested through a 10-fold cross-validation method in order to obtain the final

SVM model. Moreover, given that SVM are easily implementable within a microcontroller as shown Boni et al. [40] and the amount of memory and the prediction time needed by SVM depend on the number of support vectors, in this paper, support vectors have been minimized in order to lighten computational burden. Each combination of parameters provides an average accuracy and number of support vectors. The selected parameters are those which provide an accuracy higher than *max(SVM model accuracy)-5%* and, among them, the minimum number of SVs.

All classifier models are compared based on their accuracy and, then, the best model is evaluated within the AL-L algorithm. A total of 20 iterations are performed to train and evaluate SiSt-StSi classifier with different datasets in order to evaluate its capabilities on identifying PT. In each iteration, from the 20 PD patients, signals from 10 of them will be randomly chosen to train the classifier, and the remaining signals will be used to evaluate the obtained model. Within the AL-L algorithm, this classifier is also evaluated along the *STFTth* as explained in the next section.

4.2.2 *Yth and STFTth threshold tuning*

Thresholds described in Section 3 that allow determining some postures are set through SVM's using a linear kernel $K(x_i, x_j) = x_i \cdot x_j$, in which the margin found that separates classes 1 and -1 is the chosen threshold, since x_i are actually scalar values.
The training set to determine *Yth* threshold is formed by 80 PT (40 PT from D11 and 40 PT from D12). On the one hand, output SVM labels $y_i = 1$ will be all those windows where the label indicates bending state or lying state. On the other hand, output labels $y_i = -1$ will be those windows indicating sit or standing postures. Results of training 40 PT from D11 and 40 PT from D12 will be evaluated at its respective datasets. The expected trained value for both datasets should be similar, since bending postures and lying postures are only dependent on the Y axis.

The second threshold (*STFTth*) is trained and evaluated only with PD patients according to the same methodology followed by the AL-L algorithm, setting and evaluating it 20 times. This threshold, along with the established rules at the hierarchical structure of classifiers, works as a filter to the SiSt-StSi classifier since only those windows that meet the condition of this threshold are evaluated by the SiSt-StSi classifier.

5. **Results and Discussion**

In this section, results obtained are reported. First, the SiSt-StSi classifier results are reported with different machine learning techniques. Second, the 10 fold cross-validation results are described and discussed comparing PD patients in ON and OFF state and the localization of the inertial system. Then, the classifier model is explained regarding the number of support vectors and input vectors. Afterwards, results of *Yth* are analyzed and evaluated with a random set of healthy volunteers. Finally, results of SiSt and StSi employing the AL and AL-L algorithm are shown and discussed.

5.1 Machine learning techniques results in SiSt-StSi classifier

Table 2 shows the results achieved after applying the previously described methods to the inertial signals obtained from 10 randomly chosen PD patients.

Table 2. Different machine learning techniques applied to SiSt-StSi classifier

Machine learning technique	*Main parameters*	*Accuracy obtained (%)*
K-NN	K=3	95
	K=10	93.125
	K=20	94.375
	K=30	93.125
	K=40	91.875
	K=50	91.25
Random Forest		93.75
Logistic Regression		93.125
Naive-Bayes		95.125
Neural Networks	Learning rate: 0.3	95.625
	Learning rate: 0.5	96.25
	Learning rate: 1	96.25
SVM with linear kernel	C: 100	96.25
SVM with 2nd-degree polynomial kernel	C: 10	97.5
SVM with 3rd-degree polynomial kernel	C: 10	73.125
SVM with RBF kernel	C: 10 σ: 0.001	98.75

Results show that the best classifier is the SVM with RBF kernel with almost a 99% of accuracy. SVM classifiers maximize the margin between classes, and, with the RBF kernel, they allow a higher generalization which fits better to the dataset used. The rest of machine learning techniques only minimize the empirical risk, this is to say that, in the evaluation of new data, the probability to decrease accuracy results is higher than SVM. SVM model with 2nd-degree polynomial kernel provides the closest result (97.5%). The K-NN algorithm, provides a descendant accuracy as *K* increases. This can be justified as the effect of overtraining. Logistic Regression, Random Forest and Naïve-Bayes provide a reduced accuracy compared to SVM with RBF kernel (~5% less). On the other hand, ANN accuracy results are slightly lower by reaching 96% of accuracy at a learning rate of 0.5. Due to the results obtained, SVM with RBF kernel is selected to be the machine learning technique that performs the SiSt-StSi detection.

5.2 *Motor state and location analysis*

In this section, the influence of the motor state of PD patients and the location of the inertial system when a PT is detected has been measured. Table 3 shows the results obtained in this section.

In order to observe the influence of the motor state on PD patients, a 10 fold cross-validation has been applied, firstly with PD patients who are in ON state (under the effect of PD medication and with a good motor control) and in OFF state (with a lack of medication effect and an altered motor control). The machine learning technique applied has been the one that better classifies SiSt from StSi PT's. This evaluation shows an accuracy of 97.6% for OFF states and 98.5% for ON states. This way, the SiSt-StSi classifier provides similar results in spite of the PD motor states in which patients were. A similar conclusion was obtained in a previous work in which a single location was evaluated [41], where a PT identification algorithm was trained with data from healthy users and was evaluated with signals acquired from PD patients, achieving results of sensitivity and specificity above 97% and 84% respectively.

Another parameter evaluated has been the location of the inertial system. Among the different tests performed by the 20 PD patients in ON and OFF states, a total of 15 tests were done with the inertial system worn at a lateral position, 12 tests were executed with the system located at an anterior-lateral position and, finally, 13 tests were carried out with system between both placements. The impact of the sensor location on detecting PT has been evaluated based on a 10 fold cross-validation with the selected SVM (RBF kernel). The SiSt-StSi classifier achieves an accuracy of 99.05% to those tests in which the system was worn in an anterior-lateral position, a 95.5% of accuracy is attained in those tests where PD patients wore the system in a lateral location, and an accuracy of 96.86% is obtained at the rest of the tests. The descend of accuracy achieved in a lateral position reflects the complexity of classifying SiSt from StSi with the inertial system located in a lateral position, as shown Figure 3.1.

Table 3. Motor state and location analysis results

	Motor State		Location analysis		
	ON state	OFF state	45 degrees	60 degrees	90 degrees
Accuracy obtained (%)	97.6	98.5	99.05	96.86	95.5

5.3 *Classifier optimization*

Once the classifier model is selected, it might be optimized in order to lighten the computational burden. In this case, SVM with RBF kernel is chosen and, thus, the number of support vectors and number of elements of the input vector should be reduced.

After selecting the SVM model parameters, the obtained model is trained again for values *P*=2, 4,…, 30. Hence, 15 new SVM models are obtained and the finally chosen model is the one which minimizes $SV_P \cdot (1+2P)$ having an accuracy higher than *max(SVM_model_accuracy)-2%*, where SV_P is the number of support vectors of the SVM model obtained.

Figure 5.1 shows the accuracy and the number of SV obtained for a given training data. As it is shown, in this case, the final SVM model chosen has an accuracy of 95.2%, and, 23 support vectors being *P*=6, meaning that the input vector length $\boldsymbol{x}_i$ is 13. As shown in Figure 5.1, the number of support vectors needed to keep a high accuracy is rather high having few elements for the input vector, however, when the input vector contains a significant number of elements, the number of support vectors increases due to the burden computation provoked without achieving higher accuracies. Therefore, the chosen model (highlighted zone) minimizes the number of inputs and support vectors while maximizes the accuracy. Note that previous machine learning techniques, including the SVM analysis, have been performed with *P*=385, which is difficult to implement within a microcontroller due to a high computational burden.

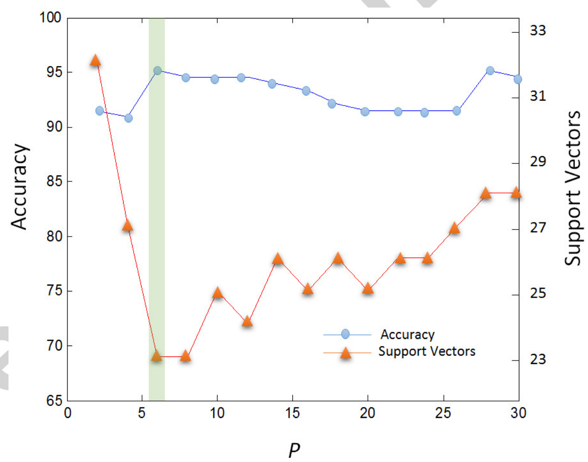

Figure 5.1: Example of SVM model selection according to parameter *P*, number of Support Vector and accuracy

5.4 Yth evaluation

Parameters employed to evaluate *Yth* are Sensitivity = $\frac{TP}{TP+FN}$ and Specificity = $\frac{TN}{TN+FP}$, in which TN, TP, FN and FP are, respectively, True Negative cases, True Positive cases, False Negative cases and False Positive cases. A TP is considered as *Y change* correctly detected. A TN is a period of more than 10 seconds correctly rejected. A FP is a *Y change* event incorrectly detected, and a FN a PT incorrectly rejected.

Table 4 presents the results achieved after training *Yth*. *Yth* obtained for D11 is 5.35m/s^2 and for D12 is 5.15m/s^2, which and has been evaluated with 31 patients from D11 dataset and with 26 patients from D12 dataset. In this table, 'BD' denotes Bend Down, 'BU' indicates Bend Up, 'SL' is Sit-to-Lying, and 'LS' signifies Lying-to-Sit.

Table 4. Yth evaluation results

	BD(D11)	BU(D11)	BD(D12)	BU(D12)	SL(D11)	LS(D11)	SL(D12)	LS(D12)
Sensitivity	0.88	0.95	1	0.99	1	1	1	0.99
Specificity	0.99	0.99	0.96	0.92	1	0.99	1	0.98

5.5 AL and AL-L algorithm evaluation

After setting *Yth* threshold at 5.25m/s^2, 20 iterations are performed where the *STFTth* threshold and the SiSt-StSi classifier are trained with 10 randomly chosen PD patients. The AL-L and the AL algorithms are, then, executed with the new parameters along the remaining 10 patients, randomly chosen for evaluation purposes. *STFTth* can be averaged to 3.5.

Results obtained with both algorithms are shown in Table 5 and 6. The training set and the evaluation set has been performed exclusively with PD patients wearing an inertial system at the left side of the waist. It is observed that, although AL presents specificities slightly higher than those provided by AL-L, AL-L sensitivities are clearly higher than the obtained by the AL algorithm approach.

Table 5. AL algorithm results

	Stand to Sit	Sit to Stand
Sensitivity (%)	83.88±3.11	81.48±2.93
Specificity (%)	96.2±0.84	93.45±0.87

Table 6. AL-L algorithm results

	Stand to Sit	Sit to Stand
Sensitivity (%)	88.48±3.61	92.26±2.18
Specificity (%)	95.51±2.02	88.21±1.79

The AL algorithm SiSt-StSi classifier relies on a relation between 2 axes (X and Z), thus, the PT is easier to detect if the relation $|\Delta(X_W - Z_W)|$ is high. However, this algorithm is tested in PD patients who wear the sensor in any place at the left side of the waist, between the anterior and lateral location. In consequence, this relation is not relevant when the inertial system is worn at the lateral of the waist as shown in Figure 3.1. Therefore, sensitivity values are lower than specificities, since many FN are obtained. In the case of AL-L, sensitivity values are improved more than a 7.5% in average, since not only the $\Delta(X_W - Z_W)$ relation is analyzed but also the signal shape, since X and Y axes are also part of the classifier input vectors and, therefore, a more complete analysis is performed on the PT.

Specificity values obtained by AL-L algorithm are also relevant since they are above 88% although it is lower than the obtained by the AL algorithm. This could be explained by the rebounds in the signal obtained when this PT is executed. Often, a PD patient does not stand up in a single movement and some attempts are performed before eventually standing up. Equation (6) may reject these attempts since rebounds do not provide a high value at $\Delta(X_W - Z_W)$. However, the waveform can be similar to a SiSt PT and, thus, some FP are produced in the case of the AL-L algorithm.

6. Conclusions

Posture transitions are an important activities of daily living and monitoring them is potentially useful to evaluate the quality of life of people with dependency. In this paper, a real-case scenario in which PD patients are monitored with an inertial sensor for several hours is considered. In this long monitoring periods, the inertial system, which incorporated a triaxial accelerometer and a μSD card in which signals were stored, was worn in the waist at different positions, from the left lateral side until the left anterior-lateral location. An algorithm called AL-L has been purposed to deal with the identification of posture transitions with a sensor located on these different positions.

AL-L algorithm enhances a previous algorithm (AL), given the changes observed in Stand-to-Sit and Sit-to-Stand transitions in the different locations described. In this paper, the AL-L and the AL algorithms have been tested on signals obtained from a total of 20 PD patients at their homes twice. The first time the patients were under the effect of PD medication (ON state) and the second one without the effect (OFF state). To complement the evaluation of both posture transition algorithms, signals from 67 healthy users have been evaluated in order to analyze bending and lying.

In order to select an optimal classifier for the AL-L algorithm, different machine learning techniques have been tested and their performances compared. Moreover, different groups of PD patients have been evaluated according to the motor state and the location of the inertial system. It has been observed that location of the system slightly affects the accuracy of the classifier, being the lateral position the most difficult one. However, the motor state does not affect to the classifier performance.

AL-L and AL algorithms have been tested with the same parameter values, being the main difference the inclusion of a SiSt-StSi classifier. Both algorithms have been evaluated 20 times with different evaluation sets. Results provided by the AL-L algorithm showed a significant increase in sensitivities (7.5% in average) against a slightly descent at specificity (3% in average) compared to the AL algorithm results. However, results at AL-L algorithm keeps values over 88% at both sensitivities and specificities identifying SiSt and StSi PT. On the other hand, the AL algorithm has sensitivities of 81.5% and 83.9%.

Further work consists in the real-time implementation of the AL-L algorithm, since it has been optimized to identify PT by minimizing the number of support vectors. A real-time validation of the algorithm is also necessary in order to confirm the well performance of the algorithm.

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7. References

[1] K.M. Culhane, M. O'Connor, D. Lyons, G.M. Lyons, Accelerometers in rehabilitation medicine for older adults., Age Ageing. 34 (2005) 556–560. doi:10.1093/ageing/afi192.

[2] H. Varol, Atakan, Supervisory Control and Intent Recognition of a Powered Knee and Ankle Prosthesis, 2009.

[3] K.M. Kerr, J.A. White, D.A. Barr, R.A.B. Mollan, Analysis of the sit-stand-sit cycle in normal subjects movement, Clin. Biomech. 12 (1997) 236–245.

[4] L. Nyberg, Y. Gustafson, Patient Falls in Stroke Rehabilitation□: A Challenge to Rehabilitation Strategies, Stroke. 26 (1995) 838–842. doi:10.1161/01.STR.26.5.838.

[5] P.-T. Cheng, M.-Y. Liaw, M.-K. Wong, F.-T. Tang, M.-Y. Lee, P.-S. Lin, The sit-to-stand movement in stroke patients and its correlation with falling, Arch. Phys. Med. Rehabil. 79 (1998) 1043–1046. doi:http://dx.doi.org/10.1016/S0003-9993(98)90168-X.

[6] A. Salarian, H. Russmann, C. Wider, P.R. Burkhard, F.J.G. Vingerhoets, K. Aminian, Quantification of tremor and bradykinesia in Parkinson's disease using a novel ambulatory monitoring system., IEEE Trans. Biomed. Eng. 54 (2007) 313–322. doi:10.1109/TBME.2006.886670.

[7] A.J. Manson, P. Brown, J.D. O'Sullivan, P. Asselman, D. Buckwell, A.J. Lees, An ambulatory dyskinesia monitor, J. Neurol. Neurosurg. Psychiatry. 68 (2000) 196–201. doi:10.1136/jnnp.68.2.196.

[8] N. Giladi, A. Nieuwboer, Understanding and treating freezing of gait in parkinsonism, proposed working definition, and setting the stage., Mov. Disord. 23 (2008) 423–425. doi:10.1002/mds.21927.

[9] S. Beeby, G. Ensell, M. Kraft, N. White, MEMS. Mechanical Sensors, Artech House, 2004.

[10] N. Yazdi, F. Ayazi, K. Najafi, S. Member, Micromachined Inertial Sensors, Proc. IEEE. 86 (1998) 1640–1659.

[11] A. Godfrey, R. Conway, D. Meagher, G. OLaighin, Direct measurement of human movement by accelerometry., Med. Eng. Phys. 30 (2008) 1364–1386. doi:10.1016/j.medengphy.2008.09.005.

[12] M. Bachlin, M. Plotnik, D. Roggen, I. Maidan, J.M. Hausdorff, N. Giladi, et al., Wearable Assistant for Parkinson's Disease Patients With the Freezing of Gait Symptom, Ieee Trans. Inf. Technol. Biomed. 14 (2010) 436–446. http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5325884.

[13] A. Salarian, H. Russmann, F.J.G. Vingerhoets, C. Dehollain, Y. Blanc, P.R. Burkhard, et al., Gait assessment in Parkinson's disease: toward an ambulatory system for long-term monitoring., IEEE Trans. Biomed. Eng. 51 (2004) 1434–1443. doi:10.1109/TBME.2004.827933.

[14] N. Bidargaddi, L. Klingbeil, A. Sarela, J. Boyle, V. Cheung, C. Yelland, et al., Wavelet based approach for posture transition estimation using a waist worn accelerometer., 29th Annu. Int. Conf. IEEE EMBS. 2007 (2007) 1884–1887. doi:10.1109/IEMBS.2007.4352683.

[15] B. Najafi, K. Aminian, F. Loew, Y. Blanc, P.A. Robert, Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly, IEEE Trans. Biomed. Eng. 49 (2002) 843–851. http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=1019448.

[16] M. Aloqlah, R.R. Lahiji, K. Loparo, M. Mehregany, A headband for classifying human postures., 32nd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (2010) 382–385. doi:10.1109/IEMBS.2010.5628011.

[17] G. Bieber, P. Koldrack, C. Sablowski, C. Peter, B. Urban, Mobile physical activity recognition of stand-up and sit-down transitions for user behavior analysis, Proc. 3rd Int. Conf. PErvasive Technol. Relat. to Assist. Environ. - PETRA '10. (2010) 1. doi:10.1145/1839294.1839354.

[18] M.J. Mathie, J. Basilakis, B.G. Celler, A system for monitoring posture and physical activity using accelerometers, 23rd Annu. Int. Conf. IEEE EMBS. 4 (2001) 3654–3657. doi:10.1109/IEMBS.2001.1019627.

[19] C.C. Yang, Y.L. Hsu, A review of accelerometry-based wearable motion detectors for physical activity monitoring., Sensors. 10 (2010) 7772–7788. doi:10.3390/s100807772.

[20] H. Gjoreski, M. Lustrek, M. Gams, Accelerometer Placement for Posture Recognition and Fall Detection, in: 2011 Seventh Int. Conf. Intell. Environ., 2011: pp. 47–54. doi:10.1109/IE.2011.11.

[21] J. Cabestany, J.M. Moreno, C. Perez, A. Sama, A. Catala, REMPARK: When AI and Technology Meet Parkinson Disease Assessment, in: 20th Int. Conf. Mix. Des. Integr. Circuits Syst., 2013.

[22] D. Rodríguez-Martín, A. Samà, C. Pérez-López, A. Català, J. Cabestany, A. Rodríguez-Molinero, Identification of Postural Transitions Using a Waist-Located Inertial Sensor,

in: Int. Work Conf. Artif. Neural Networks. Lect. Notes Comput. Sci., Springer-Verlag, 2013: pp. 142–149.

[23] M.J. Mathie, A.C.F. Coster, N.H. Lovell, B.G. Celler, Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement, Physiol. Meas. 25 (2004) 1–20. http://www.ncbi.nlm.nih.gov/pubmed/15132305.

[24] D. Rodríguez-Martín, A. Samà, C. Pérez-López, A. Català, Identification of sit-to-stand and stand-to-sit transitions using a single inertial sensor., Stud. Health Technol. Inform. 177 (2012) 113–117. http://www.ncbi.nlm.nih.gov/pubmed/22942040.

[25] P.H. Veltink, H.B. Bussmann, W. de Vries, W.L. Martens, R.C. Van Lummel, Detection of static and dynamic activities using uniaxial accelerometers., IEEE Trans. Rehabil. Eng. 4 (1996) 375–385. http://www.ncbi.nlm.nih.gov/pubmed/8973963.

[26] J. Baek, G. Lee, W. Park, B. Yun, Accelerometer Signal Processing for User Activity Detection, Knowledge-Based Intell. Inf. Eng. Syst. Lect. Notes Comput. Sci. 3215 (2004) 610–617.

[27] D.M. Karantonis, M.R. Narayanan, M. Mathie, N.H. Lovell, B.G. Celler, Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring., 28th Annu. Int. Conf. IEEE EMBS. 10 (2006) 156–167. http://www.ncbi.nlm.nih.gov/pubmed/16445260.

[28] L. Bao, S.S. Intille, Activity Recognition from User-Annotated Acceleration Data, Comput. Lect. Notes Comput. Sci. 3001 (2004) 1–17.

[29] R. Ganea, A. Paraschiv-lonescu, K. Aminian, Detection and Classi fi cation of Postural Transitions in Real-World Conditions, 20 (2012) 688–696.

[30] M.M. Hoehn, M.D. Yahr, Parkinsonism: onset, progression, and mortality, Neurology. 17 (1967) 427–427. doi:10.1212/WNL.17.5.427.

[31] D. Rodríguez-Martín, C. Pérez-López, A. Samà, J. Cabestany, A. Català, A Wearable Inertial Measurement Unit for Long-Term Monitoring in the Dependency Care Area, Sensors. 13 (2013) 14079–14104. doi:10.3390/s131014079.

[32] H. Zhou, H. Hu, Human motion tracking for rehabilitation—A survey, Biomed. Signal Process. Control. 3 (2008) 1–18. doi:10.1016/j.bspc.2007.09.001.

[33] A. Kralj, R.J. Jaeger, M. Munih, Analysis of standing up and sitting down in humans: Definitions and normative data presentation, J. Biomech. 23 (1990) 1123–1138. doi:10.1016/0021-9290(90)90005-N.

[34] A.M. Khan, Y.-K. Lee, S.Y. Lee, T.-S. Kim, A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer., IEEE Trans. Inf. Technol. Biomed. 14 (2010) 1166–72. doi:10.1109/TITB.2010.2051955.

[35] S.J. Preece, J.Y. Goulermas, L.P.J. Kenney, D. Howard, K. Meijer, R. Crompton, Activity identification using body-mounted sensors--a review of classification techniques., Physiol. Meas. 30 (2009) R1–33. doi:10.1088/0967-3334/30/4/R01.

[36] K.-T. Song, Y.-Q. Wang, Remote Activity Monitoring of the Elderly Using a Two-Axis Accelerometer, in: Proc. CACS Autom. Control Conf., Tainan, 2005.

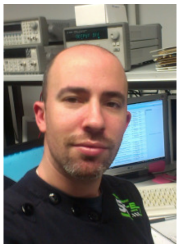
[37] P. Casale, O. Pujol, P. Radeva, Human Activity Recognition from Accelerometer Data Using a Wearable Device, in: Proc. 5th Iber. Conf. Pattern Recognit. Image Anal., 2011: pp. 289–296.

[38] M. V Albert, S. Toledo, M. Shapiro, K. Kording, Using mobile phones for activity recognition in Parkinson's patients., Front. Neurol. 3 (2012) 158. doi:10.3389/fneur.2012.00158.

[39] V.N. Vapnik, The Nature of Statistical Learning Theory, second, Springer-Verlag, New York, 1995.

[40] A. Boni, F. Pianegiani, D. Petri, Low-Power and Low-Cost Implementation of SVMs for Smart Sensors, IEEE Trans. Instrum. Meas. 56 (2007) 39–44.

[41] D. Rodriguez-Martin, A. Samà, C. Perez-Lopez, A. Català, J. Cabestany, A. Rodriguez-Molinero, SVM-based posture identification with a single waist-located triaxial accelerometer, Expert Syst. Appl. 40 (2013) 7203–7211. doi:10.1016/j.eswa.2013.07.028.



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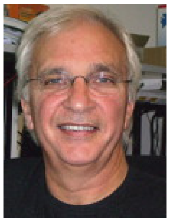

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Highlights

- Posture Transition identification is performed by means of a tri-axial accelerometer located in the waist.
- A hierarchical structure of classifiers allows to determine the human posture.
- SVM techniques have been used to set parameters of the algorithm.
- The algorithm allows different locations along waist's left side.
- The algorithm is focused on Parkinson's disease patients.