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SVM-based posture identification with a single waist-located triaxial accelerometer

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ABSTRACT

Analysis of human body 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 o stroke patients, it is crucial to monitor and assess their daily life activities. The main goal of this work is the characterization of basic activities using a single triaxial accelerometer located at the waist. This paper presents a novel postural detection algorithm based in SVM methods which is able to detect and identify Walking, Stand, Sit, Lying, Sit to Stand, Stand to sit, Bending up/down, Lying from Sit and Sit from Lying transitions with a sensitivity of 97% and specificity of 84% with 2884 postures analyzed from 31 healthy volunteers. Parameters and models found have been tested in another dataset from Parkinson's disease patients, achieving results of 98% of sensitivity and 78% of specificity in postural transitions. The proposed algorithm has been optimized to be easily implemented in real-time system for on-line monitoring applications.

1. Introduction

Posture monitoring is useful in order to assess the quality of life of elderly people or patients with mobility problems (Culhane, O'Connor, Lyons, & Lyons, 2005; Najafi et al., 2003; Zijlstra & Aminian, 2007). In stroke patients, for example, it is of main importance the patients' rehabilitation assessment in order to evaluate walking's recovery (Mizuike, Ohgi, & Morita, 2009). On the dependency care area, analyzing postural transitions (PT) like SiSt and StSi are of main importance, since they are also closely associated with fallings (Nyberg & Gustafson, 1995; Cheng et al., 1998). In Parkinson's disease (PD), one of the main consequences which patients suffer are falls in concrete activities, like sit-to-stand (SiSt), stand-to-sit (StSi) or walking, and more concretely, in episodes of Freezing of Gait (FoG). FoG episodes frequently occur after a StSi transition and before walking (Bloem, Hausdorff, Visser, & Giladi, 2004; Grimbergen, Munneke, & Bloem, 2004). Salarian and colleagues points out that an ambulatory system to assess StSi, SiSt and physical activity in PD patients can be of clinical interest (Salarian, Russmann, Vingerhoets, Burkhard, & Aminian 2007).

Many different methods and sensors have been used to analyze human movements. Video (Guzmán, Prado, Porcel, & Cordier, 2009), photography (Nuzik, Lamb, VanSant, & Hirt, 1986), electrogoniometry (Morris, 1973), pressure platforms (Kralj, Jaeger, & Munih, 1990), electromyography (Doorenbosch, Harlaar, Roebroeck, & Lankhorst, 1994; Schenkman, Berger, Riley, Mann, & Hodge, 1990; Wheeler, Woodward, Ucovich, Perry, & Walker, 1985) and stereograph (Kerr, White, Barr, & Mollan, 1994) are some examples. However, these methods are obtrusive for the patient (Godfrey, Conway, Meagher, & O'Laighin, 2008) and for the subsequent analysis of physical activity, as they are used exclusively in laboratory environments (Culhane, O'Connor, Lyons, & Lyons, 2005). Current technology has allowed the manufacture of small devices which can be worn without being cumbersome for the patient. Inertial sensors based in Micro-Electro-Mechanized-Systems (MEMS) such as accelerometers and gyroscopes have become the most utilized tools to analyze human movements (Mathie, Coster, Lovell, & Celler, 2004). Nowadays, inertial sensors are becoming smaller and lighter (Zheng, Black, & Harris 2005). 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 (Yazdi, Ayazi, & Najafi, 1998) (Mannini & Sabatini, 2010). Among inertial sensors, accelerometers can be used as inclinometers in absence of movement, measuring the angle respect gravity, which is very

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useful for activity recognition (Luinge & Veltink, 2005). However, more than one accelerometer is needed in order to know the posture of a person in absence of movement. Moreover, the placement of the sensor is of main importance because it can seriously affect the recognition of some postures (Gjoreski, Luštrek, & Gams 2011). Using a single accelerometer is less bothersome but, as a consequence, a more complex analysis is necessary in order to recognize body postures. There are some static postures like sit or stand that can produce the same signal to a single accelerometer during rest, however analyzing the accelerometer signal during postural transitions, for instance, sitting down or standing up, is necessary to correctly identify the posture.

This work describes an algorithm capable to recognize postures using a single triaxial accelerometer located in the waist. To the best of our knowledge, and as reported on Section 2.1 (Related Work), there is not any algorithm able to recognize posture transitions along with basic DLA activities by means of a single triaxial accelerometer located in the waist, being the waist the best location to wear an accelerometer (Mathie, Basilakis, & Celler, 2001; Yang & Hsu, 2010; Gjoreski et al., 2011). The algorithm implemented is a hierarchical structure of classifiers, which combines techniques of dynamical analysis, like Short Time Fourier Transform (STFT) in order to detect postures transitions. Moreover, a supervised learning method such as Support Vectors Machines (SVM) has been employed to classify eleven activities, including in one hand static postures, such as stand, sit, lying and bent. On the other hand, dynamic postures such as walking, SiSt, StSi, bending down, bending up, sit-to-lying and lying-to-sit have been analyzed and classified. SVM have been optimized in order to allow the algorithm to be implemented in real-time. Parameters of the algorithm have been tuned in order to operate in any person. Two sets of signals have been analyzed, the first one, gathered from healthy people, meanwhile the second one, is obtained from PD disease patients. The algorithm results achieved in the first set are sensitivity above 97% and specificity above 84%, in the second set the results have been reflected in the same way except two activities which will be discussed in Section 4.

This paper is organized as follows, firstly, related work is reported, then, the general algorithm and the calculation of its parameters is described, and then the experiments are explained. Finally, results are shown, which leads to discussion and conclusions.

2. Postural transition identification algorithm

This section is structured as follows: first, related work is presented, then the general algorithm is described and, finally, each part of the general algorithm is detailed.

2.1. Related work

Activity recognition by means of accelerometers has been extensively studied with different body locations and different signal analysis (Preece et al. 2009; Yang & Hsu, 2010; Taraldsen, Chastin, Riphagen, Vereijken, & Helbostad 2012).Related work is organized in these different topics: number of sensors, location, relation with static and dynamic analysis, and classifiers. Finally, some works on walking identification are also reported, since this activity is considered a as a DLA, and it is related with fallings (Nyberg & Gustafson, 1995; Cheng et al., 1998).

Some works have studied physical activity recognition by means of static analysis. Veltink and colleagues analyzed static postures by means of 3 uniaxial accelerometers, 2 of them on the chest, and the other on the thigh (Veltink, Bussmann, de Vries, Martens, & Van Lummel 1996). Baek et al. and Karantonis et al. determined that standing and sitting can be determined by the tilt of a single accelerometer located in the waist (Baek, Lee, Park, & Yun 2004; Karantonis, Narayanan, Mathie, Lovell, & Celler 2006). However, the anatomy of a person affects at the orientation of the accelerometer, and sitting can usually be confused by a standing posture with just one sensor (Gjoreski et al., 2011). Gjioreski and colleagues also described posture recognition using different number of sensors in different locations by means of static analysis, they pointed out how accuracy improves when 2 or more sensors are worn instead of a single accelerometer. Hence, static analysis requires the use of more than one sensor. Nevertheless, identifying postures with a single accelerometer is possible, but location of this accelerometer in the body is of main importance because of comfort reasons. Human motion has been studied with inertial systems in several locations. However, some studies denote the waist as the best location to analyze human movements as it is comfortable and also represents the major human motion since it is close to the centre of mass of a human body (Yang & Hsu, 2010; Gjoreski et al., 2011). According to Mathie and colleagues, in a survey to some volunteers among the different waist positions, they felt more comfortable with the inertial sensor in a lateral of the waist, above the anterior superior iliac spine (Mathie et al., 2001).

Dynamic analysis has to be performed in order to correctly identify postures by means of a single accelerometer. Najafi et al. used discrete wavelet transforms (DWT) to detect postural transitions by means of a chest-attached gyroscope with the purpose of identify a SiSt and a StSi transition (Najafi, Aminian, Loew, Blanc, & Robert, 2002). Frequency analysis, along with an accelerometer and a kinematic model, enabled a completed activity recognition threshold-based algorithm (Najafi et al., 2003). Bidargaggi et al. used reconstruction of the signal by means of DWT to discriminate SiSt and StSi (Bidargaggi et al., 2007). Bao and Intille studied some daily living activities (DLA) by means of Short Time Fourier Transform (STFT) but five accelerometers (Bao & Intille, 2004). Ganea et al. used Dynamic Time Warping (DTW), which compares the signal to some templates finding similarities in the waveform by means of shifting in time samples to correlate the signal samples with template samples. They implemented a SiSt–StSi classifier with a single sensor located in the chest, achieving better results than its prior works. (Najafi et al. 2002; Ganea et al., 2012).

There are several methods to analyze and classify PT or human movement (Preece et al. 2009): threshold-based algorithms, hierarchical methods, decision trees, *k*-nearest neighbor, artificial neural networks (ANN), support vector machines (SVM), Bayesian models, hidden Markov models, or unsupervised learning. In this work, a major focus is to classify with SVM, as it is well-known to be a high performance classifier method (Begg & Kamruzzaman, 2005; Lau, Tong, & Zhu 2008). Many studies with SVM have been reported in the field of activity recognition, although they do not focus in the study of PT. Fleury et al., for example, used SVM by collecting signals from an accelerometer and a magnetometer and other sensors located in a smart home. They detected and identified some DLA such as sleeping, eating or dressing. The posture of the person, however, was not specified (Fleury, Vacher, & Noury, 2010). Doukas et al. and Zhang et al. used SVM in order to detect and identify fallings, without focusing in PT or activity recognition (Doukas & Maglogiannis, 2008; Zhang, Wang, Xu, & Liu, 2006). Ataya and Jallon also used SVM with Gaussian kernels to detect some stationary postures; they used a single accelerometer in a belt (Ataya & Jallon, 2012).

Regarding walking activity, STFT is commonly used to detect an episode of walking. The band of frequencies for detecting walking can vary depending on location the sensor is worn, Moore et al. detected a "walking state" band from 0.5–3 Hz with a sensor located on the left shank (Moore, MacDougall, & Ondo 2008). Najafi however, defined the walking band as the frequencies from 0.6 to 5 Hz while wearing the sensor on the chest (Najafi et al., 2003). Barralon and colleagues studied frequencies from 0.6 to 2.5 Hz with a sensor on the chest too (Barralon, Vuillerme, & Noury 2006). Those studies, however, used the same method regarding the accelerometer. They used the vertical acceleration to analyze the impact against the floor of a step when walking.

2.2. General algorithm

The main goal of the proposed algorithm is to identify eleven postures divided into 2 groups, static postures (Stand, Sit, Bent, Lying) and dynamic postures (Walking, SiSt, StSi, Bending down, Bending up, Lying from Sit, Sit from Lying) by means of a single triaxial accelerometer located at the waist.

Given some initial conditions, i.e. standing, although any other posture could be used, the general algorithm performs a windows capture of the accelerometer signal. Each window is 50% overlapped in order to avoid losing information of events, since an event can occur between two windows. Each window is analyzed through a STFT. The analysis of the STFT can determine if there is no movement, if a PT has occurred, or if the person is walking by analyzing the harmonics on the Power Spectral Density (PSD). Then, if a PT has occurred, vertical axis acceleration (according to orientation set in Fig. 3) is analyzed in order to see whether the person maintains verticality. If the person remains in a vertical position, and has performed a PT, a SiSt or a StSi transition has been detected. A Gaussian kernel SVM model determines whether this transition has been a SiSt or a StSi transition. On the other hand, if the vertical acceleration does not remain vertical, jerk of the anterior axis is analyzed in order to see whether the person is bent, or lying. This feature determines a current state, which will be analyzed in the future, when the vertical axis of the accelerometer recovers its lost verticality. Then the inverse step occurs. If the person was bent, then, the person will return to be in a stand posture. In the same way, if the person was lying, a change in the vertical axis indicates the person is sit. For this reason, when the algorithm determines a state after analyzing some features, this state is stored and analyzed in the next iteration of the algorithm.

The algorithm is a hierarchical structure of classifiers, as depicted in Fig. 1.

$a_i'^x = a_i^x - a_{i-1}^x$, a_i^x is the acceleration on x axis in the *i* sample. Y_W is the mean of *ay* in a window where *ay* is the acceleration on *y* axis or the vertical axis, and Y_{W-1} is the mean of *ay* in the previous window analyzed. *STFTth*, *WIth*, *IAAth*, *JXth* and *Yth* are thresholds which are defined in Section 2.3.2. y_i is the SiSt–StSi classifier output.

The hierarchical structure of classifiers contains 5 classifiers which are described accurately in the next section. A brief description is given below:

- STFT classifier, which detects whether a PT has occurred. According to Najafi, frequencies below 0.68 Hz, corresponds to a PT (Najafi et al., 2003).
- Verticality classifier, which determines whether a person is in a stand posture or a lying/bending posture.
- Bending-Lying classifier, which differentiates lying posture from bending posture by means of the Jerk of an accelerometer axis.
- Walking classifier, which classifies whether a person is walking or not. This classifier depends on 2 indexes, the first one, and by means of a STFT, determines whether the person is walking, the second index excludes false positive cases from bands which are not from the walking band through the Integration of Absolute Acelerometer (*IAA*) (Bouten, Westerterp, Verduin, & Janssen 1994).
- SiSt–StSi classifier, which is performed with a SVM with Gaussian kernel and determines whether a person has executed a SiSt PT, or a StSi PT.

The first four classifiers determine the posture by means of a threshold based classification. Five different thresholds have been fixed, using SVM with linear kernels, one per classifier except the walking classifier, which has 2. The SiSt–StSi classifier also depends on one threshold which is previously fixed (Section 2.3.3).

2.3. Parameters for the general algorithm

Conditions and changes of state on the user's posture/activity are determined by 5 thresholds which have been fixed by means of SVM. Another SVM has been designed for distinguishing a SiSt from a StSi transition. Additionally, an extra threshold is used in

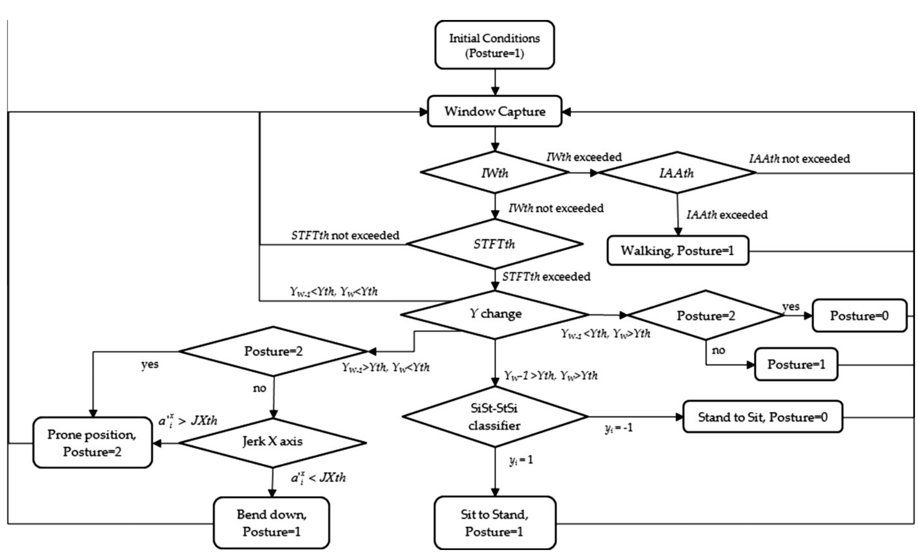

Fig. 1. General algorithm.

order to process the accelerometer signal inputs at the SiSt–StSi classifier which is called, from now on, dynamic threshold (DT).

2.3.1. SVM classification

SVM perform bi-classification tasks by mapping input vectors into a high-dimensional feature space, in which, a hyperplane is constructed to separate and easily classify input vectors (Schölkopf & Smola, 2002). This hyperplane maximizes the classification margin, which maximizes the Vapnik–Chervonenkis dimension, a well-known generalization measure (Vapnik, 1995). At the same time, the hyperplane minimizes the empirical error, i.e. the error committed by the training data. Input vectors $x_i \in \Re^N$ are mapped into a high dimensional feature space Z by $\phi(x_i)$). Output labels are defined as $y_i \in \{1, -1\}$. Optimal hyperplane is determined according to the following optimization problem:

$$minimize\left\{\frac{1}{2}w\cdot w + C\sum_{i=1}^{l}\xi_i\right\} \tag{1}$$

$$Subject\ to\ y_i(w\cdot\varphi(x_i)+b) \geqslant 1-\xi_i,\ \forall i.\xi_i \geqslant 0, \forall i$$

where C is a regularization parameter, which is a trade-off between balance and misclassification error.

In order to solve Eq. (1), its Lagrangian statement is obtained and simplified, transforming it into the following dual problem:

$$maximize\ W(\alpha) = \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i\alpha_j y_i y_j \cdot K(x_i, x_j)) \tag{2}$$

$$Subject\ to\ 0 \leqslant \alpha_i \leqslant C, \quad i = 1, \ldots, l$$

The kernel function $K(xi, xj)$ substitutes the dot product $\varphi(x_i)\cdot\varphi(x_j)$). In this way, input vectors are not needed to be represented in the high dimensional space and only its dot product in this space is required. According to Kuhn–Tucker theorem, data points x_i which corresponds to $\alpha_i > 0$ are called support vectors (SV).

The class of a new pattern is obtained by:

$$f(x) = sign(w\cdot\varphi(x_i)+b) = sign\left(\sum_{i=1}^{l}\alpha_i y_i \cdot K(x_i, x_j) + b\right) \tag{3}$$

In Section 2.3.3, thresholds which classify postures are described. SVM are used by means of a linear kernel $K(xi, xj) = xi \cdot xj$ to set the thresholds. Kernel used for the SiSt–StSi classifier is a Gaussian radial basis function (RBF), due to its wide well performance and generalization capacity, $K(xi, xj) = e^{(-\frac{xi-xj^2}{2\sigma^2})}$, where σ is the width of RBF function. In this paper a major focus is the number of SV, as a high number of SV increases computational burden regarding by real-time SVM classification. SVM have been shown to be a high performance method for bi-classification (Begg & Kamruzzaman, 2005; Lau et al. 2008). Moreover, SVM are easily implementable in a microcontroller (Boni, Pianegiani, & Petri 2007). SVM, in comparison with ANN, find a unique global optimal minimum. ANN can find different solutions in each train not optimizing the problem's solution.

2.3.2. Thresholds description

For PT detection, the sum of power of harmonics below 0.68 Hz and above 0.1 Hz (PT band) on a_i^y and a_i^x is analyzed, where a_i^x is the acceleration on X axis or anterior acceleration and a_i^y the acceleration on Y axis or vertical acceleration. These harmonics are considered to be indicators of a PT when their spectral powers surpass the STFT threshold (*STFTth*).

Harmonics in the walking band determines a possible episode of gait. Thus, an index for walking (*WI*) has been defined as the power of harmonics on a_i^y from 0.68 Hz to 3 Hz divided by the power of harmonics in the PT band. A threshold has been designed to determinate whether the person is possibly walking (*WIth*). Some PT transitions, however, can have harmonics in the band defined as walking band. Therefore, this relation between walking band and PT band deletes these possible false positives if harmonics in the PT band are quite high. On the other hand, very small values on both walking and PT bands can lead to very high values on this index. Consequently, an *IAA* index is introduced to counteract these cases. *IAA* is defined as:

$$IAA = \int_{i=0}^{T}|a_i^x|dt + \int_{i=0}^{T}|a_i^y|dt + \int_{i=0}^{T}|a_i^z|dt \tag{4}$$

where a_i^z is the acceleration on Z axis or lateral acceleration in the i sample. T is the length of the window in samples. A high value on walking index but a small value on the *IAA* index is not considered as a walking episode. Therefore, a threshold on *IAA* (*IAAth*) has been designed in order to check whether the person is actually walking.

Another threshold has been designed to differentiate a person in a prone position and a person in a vertical position (*Yth*). As Fig. 3 shows, Y axis acceleration determinates the verticality of a person due to its confrontation against gravity. Values over *Yth* indicate the person is in a vertical posture (sit or stand), meanwhile values below *Yth* indicate the person is in a prone position. Let be Y_W the value compared to *Yth* in the window W, which is defined as $Y_W = \frac{\sum_{i=1}^{1} a_i^y}{n}$, where n is the window's number of samples, and a_i^y is *ay* in the sample number *i*. When $Y_{W-1} < Yth$ and $Y_W > Yth$, the person is becoming in a prone position. Otherwise, if $Y_{W-1} < Yth$ and $Y_W > Yth$, the person comes from a prone position and is currently in a vertical position.

The last thresholds differentiate a bending down transition from a lying transition. When a person bends down, the dynamics of X axis becomes negative according to the orientation of Fig. 3 and due to gravity. Jerk of X axis is a good indicator to know the trajectory of the body after a Y axis change. Thus, its mean value is compared against a threshold (*JXth*).

The 5 thresholds have been calculated by means of the previously described SVM process on a training dataset, and evaluating another dataset by means of SVM through a linear kernel.

2.3.3. Identification of Sit to Stand and Stand to Sit transitions

Once the General Algorithm determines a window as a candidate to be a SiSt or StSi transition, it has to be analyzed. This window contains 128 samples of accelerometry signal. Windows have duration of 3.2 s at 40 Hz of sampling frequency according to Zhou et al., who recommend this sampling frequency to study human motion (Zhou et al. 2009).

This window length is enough since, according to Kralj's et al., the maximum time of a transition is 3.3 s (Kralj et al., 1990). However, Kerr et al. confirmed that transitions may last up to 2 s in elderly people (Kerr et al., 1994). Thus, windows are 50% overlapped to prevent possible loss of information, since a PT could be shared between two windows. Since the frequency response may surpass the *STFTth* in the current window but the waveform could be distributed in two windows, once the *STFTth* is surpassed, the current and the previous window are analyzed to exactly determine where the PT has occurred. To this end, a dynamic detection is performed and a new threshold is introduced, which is called DT. Fig. 2 shows the detection of the PT performed by DT.

$a_i'^y = a_i^y - a_{i-1}^y$ and t_i is time where a_i^x, a_i^y, a_i^z are sampled. *YMAX* is the maximum value which satisfies Eq. (5). There are parts of the signal which are inputs of the SVM that are flat and do not contain dynamical information of the PT signal. As shown in Fig. 2, only important periods of the PT are analyzed, neglecting those segments which do not contain relevant information.

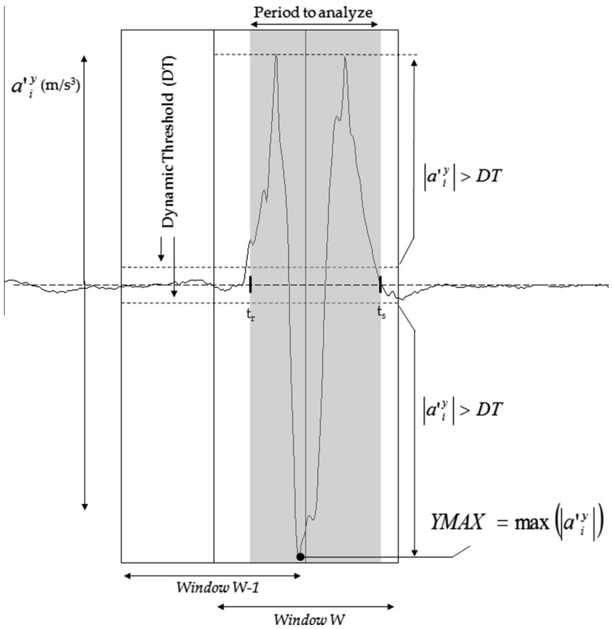

Fig. 2. Posture transition detection by means of DT.

DT is designed as a value which satisfies Eq. (5). Thus, a sweep of values for DT has been tested in order to set DT. With DT = 0, the whole windows data is considered as the SVM input, while a DT value over *YMAX* means, no value of the inertial data is significant, and the algorithm interprets that no transition occurs, as there are not any values which satisfies Eq. (5). The sweep performed is in the interval from $DT = 0.05 \cdot YMAX$ to $0.95 \cdot YMAX$ with Q values. *YMAX* has been generalized for all *YMAX* found as the mean of all *YMAX* found.

Dynamic threshold sets the period where features of the signal must be analyzed. The period to analyze comprises $t_r, \ldots, t_s$ and is given by:

$$\forall t_i \in t_r, \ldots, t_s | a'^{y}_{i}| > DT \tag{5}$$

Subject to $r, s \in \mathbb{N}, \quad r < s$

On the other hand, features for the SVM inputs are a^x_i, which is the anterior acceleration, and $\vec{M} = \sqrt{a_i^{x^2} + a_i^{y^2} + a_i^{z^2}}$, which is the magnitude of the three acceleration axes. Space features for the SVM are defined as $x_i = [a^x_r, \ldots, a^x_s, M_r, \ldots, M_s]$. Length of $t_r, \ldots, t_s$ is around 100 samples, depending on DT, which provokes large number of inputs for a SVM. To lighten the algorithm, vector x_i with $2 \cdot (s + r - 1)$ samples has been resampled to have length $2 \cdot P$, reducing the computational burden. The effect of altering the value P in terms of accuracy will be determined in the experiments. Moreover, $\vec{M}$ and a^x_i have been normalized between 0 and 1.

3. Data treatment

In this section experiments are detailed, the first part reports the process of data collection, which includes materials used to perform the datasets, and the experiments performed. The second part describes the training methods.

3.1. Data collection

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-BarcelonaTech (UPC). This device has been used in prior studies (Samà, Angulo, Pardo, Català, & Cabestany, 2011; Samà et al., 2012; Rodriguez-Martin et al. 2013; Samà et al., 2013; MOMOPA Project, 2010; REMPARK Project, 2013). It has a size of $77 \times 37 \times 21$ mm^3, and weights 78 g, less than a standard smartphone, for example HTC Desire X (137 g), Google Nexus 4 (139 g) or Iphone5 (112 g). The accelerometer used is LIS3LV02DQ, which is 3-axial and has a full scale of ±6G (1G = 9.81 m/s^2). This data is conditioned and digitalized within the encapsulation. The inertial data is stored at 200 Hz of sampling frequency in a μSD Card.

Two datasets have been performed. The first one has been used to train and evaluate the data collected. This dataset was performed by 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). All the volunteers performed the protocol twice. The second time they removed the belt from the waist, and put it on again in order to do the test with the sensor, at least, in a slightly different location. The protocol begins with the person in a stand position, then the person must execute some series of activities including sit, stand, walking bending, lying and PT to go from a posture to other. The test protocol ends with the person in a standing position lasting 4–5 min the whole procedure depending on the volunteer. The sensor is located as shown in Fig. 3.

In order to have a reliable gold standard, the database has been video recorded accurately, with the REMPARK project system (Samà et al., 2013; REMPARK Project, 2013). It consists in sending the exact time to the inertial sensor and to a camera, to have both devices synchronized. Moreover, a visual event is executed in order to ensure a proper synchronization. An application has been used in order to synchronize correctly the inertial signal and the video in a post-process.

A total of 4 h and 36 min of signal and video have been registered. It has been registered the following postures or activities: Stand: 828, Sit: 517, StSi: 458, SiSt: 458, Bend down: 62, Bend up: 62, Walking: 248, Lying: 63, 9-Sit-to-Lying: 63, 10-Lying-To-Sit: 63, Bent: 62.

Fig. 3. Inertial sensor location.

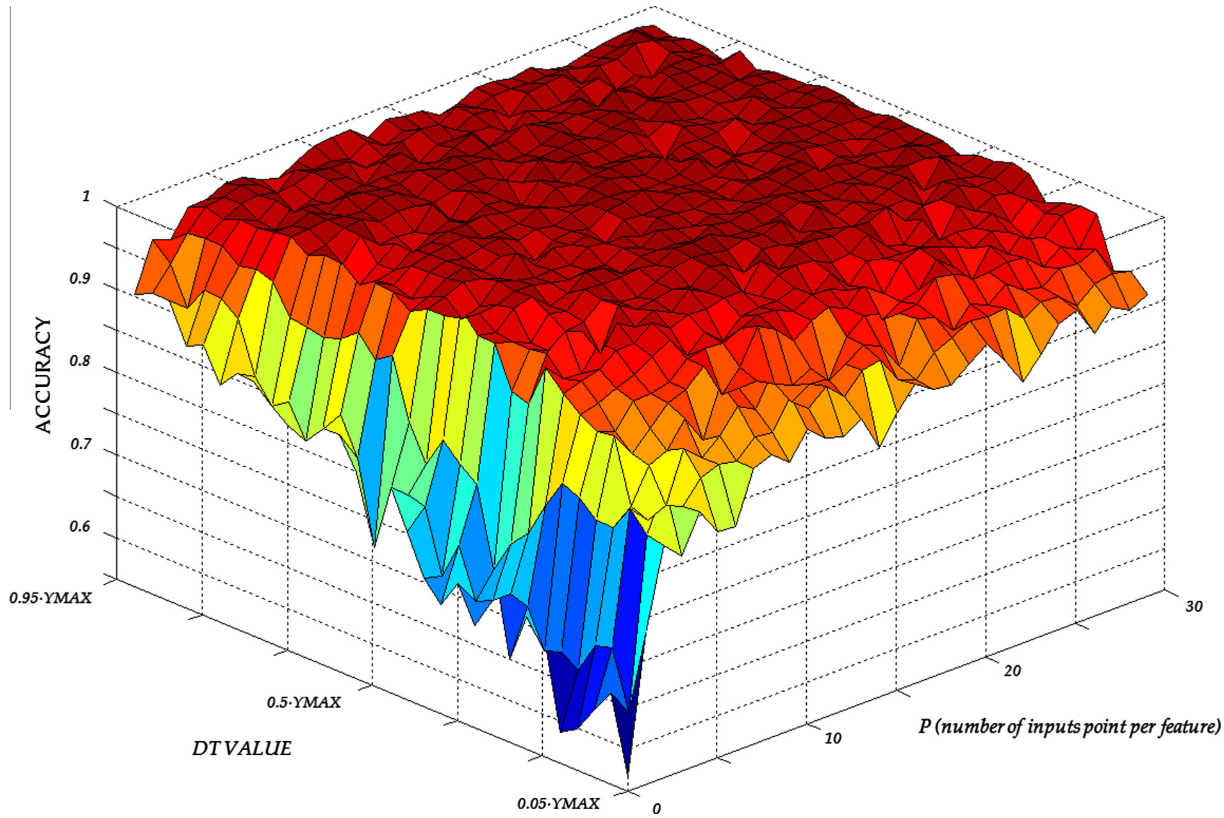

Fig. 4. Relation between accuracy, DT and P.

The second test protocol was performed by 8 patients with PD, who participated in the MoMoPa project (Samà et al., 2012). The entire tests were also video-recorded. The following postures or activities have been registered: Stand: 24, Sit: 125, StSi: 86, SiSt: 86, Walking: 100. This set has been used to evaluate the algorithm performed with healthy people.

3.2. Training methods

In Section 2, the 5 thresholds have been described, and how an SVM has been designed to distinguish a SiSt from a StSi. Finally, DT has been described. In this section it is explained the training and evaluation of data collected in experiments. Firstly, DT is fixed before training models and executing the General Algorithm. To set DT, SiSt–StSi classifier is modeled 30 times for each Q and for each P, being P the number of inputs for the SVM described in Section 2.3.3 and Q the number of steps of the DT sweep. A 75% of the dataset has been used to train the SVM and the 25% left has been used to evaluate parameters calculated of the algorithm. The 5 thresholds are set through linear kernels, and the SiSt–StSi classifier is designed through the Gaussian RBF kernel by means of a SVM, finally, the general algorithm is executed.

Before beginning the training process, and with an established DT, a random selection is performed in the first dataset (healthy volunteers) in order to train 75% of the 62 different tests, and evaluate the 25% left. Then, thresholds for STFT, *IAA*, *WI*, *Y* axis and the Jerk of *X* axis are designed according to the train set.

Features x_i to be trained to determine *STFTth* are values of the PSD below 0.68 Hz found by means of the STFT of the window. To design *IAAth* x_i are values from *IAA* in each window. *WIth* is designed with x_i as the values of WI in each window, product of having calculated the STFT. *Yth* is calculated through the mean value of a_i^y in each window. Finally, JXth is designed by means of the jerk of *X* axis defined as $a_i'^x = a_i^x - a_{i-1}^x$. Since output labels y_i are unbalanced, SVM has been trained by weighting both classes.

After setting thresholds, the SVM model is designed in order to differentiate SiSt and StSi transitions by getting x_i features detailed in Section 2.3.3. Since the SVM model is designed with a Gaussian RBF kernel, C and σ have to be defined to perform the SVM. Since many SVM models may achieve accuracies close to 1, the optimum SVM model is that with fewest SV but within the group of SVM models with accuracies over *max(SVM model accuracy)-5%*. Hence, the SVM model will be lighten and at the same time it will achieve a similar accuracy. Finally, we will obtain 30 SVM models from *P* = 1–30. Then, optimum SVM model is defined by:

$$minimize(SV_P \cdot 2P) \tag{6}$$

where SV_P is the number of support vectors calculated in the training stage of the SVM with the feature space input x_i with length $2 \cdot P$.

Once the 5 thresholds and the SVM model are obtained, the complete algorithm is executed. This procedure is executed 30 times randomly changing the order of data tests in order to check that the parameter tuning process is independent to the training/evaluation set.

Once the first set is evaluated with the 30 models. The second dataset (PD patients) is evaluated 30 times with the 30 models achieved in order to assess whether the thresholds and the SiSt–StSi classifiers are compatible in both sets. Results are shown in the next section.

4. Results and discussions

In this section results of procedures described in Section 3.2 are shown. Dynamic threshold, which was set before the training process begun, is chosen after training 30 times the SiSt–StSi classifier

Table 1
Results of sensitivity and specificity for healthy people.

	Stand	Sit	StSi	SiSt	Bend down	Bend up
Sensitivity	0.97 ± 0.01	0.99 ± 0.00	0.99 ± 0.00	0.99 ± 0.01	1.00 ± 0.00	0.99 ± 0.00
Specificity	0.96 ± 0.02	0.89 ± 0.04	0.84 ± 0.03	0.95 ± 0.03	0.96 ± 0.05	0.92 ± 0.07
	Walking	Lying	Sit to Lying	Lying to Sit	Bent	
Sensitivity	0.98 ± 0.01	0.99 ± 0.00	0.99 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	
Specificity	1.00 ± 0.00	0.97 ± 0.03	0.99 ± 0.01	0.99 ± 0.01	0.99 ± 0.04	

Table 2
Confusion matrix for healthy people.

		REAL										
		Stand	Sit	StSi	SiSt	Bend down	Bend up	Walking	Lying	Sit to Lying	Lying to Sit	Bent
PREDICTED	Stand	0.94	0.03	0	0.01	0	0.01	0.03	0	0.04	0.02	0.01
	Sit	0.05	0.97	0.02	0.02	0	0	0.01	0.02	0.04	0.02	0
	StSi	0.01	0	0.94	0.14	0	0.03	0	0	0.03	0	0.01
	SiSt	0	0	0.04	0.83	0	0.02	0	0	0.01	0	0
	Bend down	0	0	0	0	1	0	0	0	0	0	0
	Bend up	0	0	0	0	0	0.94	0	0	0	0.03	0
	Walking	0	0	0	0	0	0	0.96	0	0	0	0
	Lying	0	0	0	0	0	0	0	0.98	0.01	0	0
	Sit to Lying	0	0	0	0	0	0	0	0	0.87	0	0
	Lying to Sit	0	0	0	0	0	0	0	0	0	0.93	0
	Bent	0	0	0	0	0	0	0	0	0	0	0.98

Table 3
Results of sensitivity and specificity for PD patients.

	Stand	Sit	StSi	SiSt	Walking
Sensitivity	0.99 ± 0.02	0.87 ± 0.03	0,99 ± 0.00	0,98 ± 0.00	0,93 ± 0.00
Specificity	0.25 ± 0.05	0.98 ± 0.00	0,78 ± 0.04	0,94 ± 0.02	1 ± 0.0

Table 4
Confusion matrix for PD patients.

		REAL				
		Stand	Sit	StSi	SiSt	Walking
PREDICTED	Stand	0.69	0.04	0.01	0.03	0.68
	Sit	0.29	0.95	0	0.04	0.14
	StSi	0.01	0.01	0.99	0.12	0.08
	SiSt	0	0	0	0.81	0.04
	Walking	0	0	0	0	0.06

with a different DT and different number of inputs for the SVM. In Fig. 4 it is shown accuracies achieved for every DT value and its relation with the number of input points x_i for the SVM. DT has been chosen to satisfy accuracies over 95%.

As observed in Fig. 4, accuracies with more 3 input points per feature and $DT > 0.3 \cdot YMAX$ are higher than 0.95. Consequently, DT value is set at $DT = 0.3 \cdot YMAX$. Once DT was set, the training process was performed training 30 times the thresholds, the SVM models and executing the algorithm with randomly selected data-set to be trained.

In the following tables results achieved for healthy people are shown. The results shown are the mean of sensitivity and specificity and their standard deviation of the 30 repetitions. The confusion matrix has been calculated by summing the 30 confusion matrixes calculated for each execution of the algorithm. Note that Sensitivity = $\frac{TP}{TP+FN}$, and Specificity = $\frac{TN}{TN+FP}$. TN, TP, FN and FP are True Negative cases, True Positive cases, False Negative cases and False Positive cases respectively.

The algorithm is very sensitive in the eleven activities analyzed as shown by the sensitivity achieved, which is above 97%. However, some false positives can be given according to specificity results at SiSt and StSi. This reflects the complexity of analyzing these transitions with a single triaxial accelerometer located in the waist. Note that confusion matrix shows Sit to Lying may be confused with other activities, such as Stand, Sit, or SiSt. We do not consider it relevant as this transition always leads to Lying posture which is hardly confused with any other posture as seen in confusion matrix, and having very few false positives as shown Lying specificity. The most important static postures which are consequence of determining correctly a PT are Sit and Stand, which directly depend on SiSt and StSi PT. Few cases are confused with any other posture as shown the confusion matrix.

Tables 3 and 4 show the results of evaluating the second dataset (PD patients) with the 30 models calculated from the healthy volunteers set. The general algorithm is executed once for each model. Table 3 shows means and standard deviations of the 30 repetitions and Table 4 shows the sum of the 30 confusion matrixes calculated for each repetition.

As described in Section 3.1 only 5 activities have been performed by the PD patients who formed part of this test. However, a major focus in this paper is to compare SiSt and StSi between healthy volunteers and PD patients. Results are very similar to Table 1 regarding sensitivities and specificities of both activities. This means the models achieved by means of SVM in the first dataset is generalizable to the second set. Results on Table 3, however, are slightly lower than Table 1. This can be explained by the design of DT. DT function is to set the beginning and the end of a PT. When the STFTth is surpassed and there is a possible candidate for being a SiSt or StSi, DT sets the beginning of PT. Due to intrinsic involuntary movements on PD i.e. dyskinesia, DT is not capable to determine an end on the PT. In this case, the whole window of signal would be the inputs for the SVM, being part of x_i insignificant. This can confuse the results of the SVM, such as SiSt or Stand states (see Table 2).

Regarding other activities, it is noted a clear descent in the specifity for stand posture, which is also reflected in the confusion matrix. The walking activity is clearly confused with a stand posture. Unfortunately, walking thresholds are not comparable between first and second set. Due to clear lacks at gait balance, or bradykinesia in PD patients, indexes between the two sets are very different. When the algorithm is executed, walking

Table 5
Confusion matrix for PD patients with specific threshold for Walking.

		REAL				
		Stand	Sit	StSi	SiSt	Walking
PREDICTED	Stand	0.73	0.04	0	0.02	0.11
	Sit	0.08	0.93	0	0.06	0.04
	StSi	0.02	0.01	0.99	0.07	0.03
	SiSt	0	0	0.00	0.81	0.00
	Walking	0.17	0.02	0	0.03	0.82

activity is hardly detected as seen in Table 4, confusing it by a standing activity, provoking a large number of false positives. This is the main reason of low values in specificity in stand posture. Consequently, the walking classifier must be specific for PD, or in other words, the train set must be composed with inertial data belonging to PD patients. In order to emphasize this, another experiment in which the *WIth* and *IAAth* have been empirically set from a PD patient has been performed. The resulting algorithm has been tested with the rest of the patients. Table 5 shows the results of the algorithm after having modified *WIth* and *IAAth*.

5. Conclusions

A new method in order to classify physical activity and posture transition has been presented. At our knowledge, this is the first algorithm which classifies 11 postures including PT with just a single triaxial accelerometer located at the waist, and which its methodology have been tested with PD patients with relevant results. This algorithm has been designed by means of SVM, setting five thresholds through linear kernels in order to classify postures(Stand, Sit, Walking, Lying, Bent, Sit to Lying, Lying to Sit, Bend down, Bend up), and designing a SVM to classify SiSt from StSi. The method is suitable to be implemented in real-time, as solution found has been designed by minimizing the number of SV, lightening the load of calculus of the algorithm. The results achieved are sensitivities above 0.97% and specificities above 84%. Lower results in sensitivity and specifity come from distinguishing SiSt and StSi. However, the algorithm solves the problem of determining these transitions with just an inertial triaxial accelerometer located at the waist. Moreover, a complete algorithm capable to detect and identify 11 activities or postures has been performed. By means of extracted features from the accelerometer, eleven postures or activities, such as Stand, Sit, SiSt, StSi, Bend down, Bend up, Walking, Lying, Lying to Sit, Sit to Lying and Bent can be classified correctly.

The algorithm has been evaluated in 8 PD patients who have performed a total of 39 tests. These patients have performed 5 activities: Stand, Sit, SiSt, StSi and Walking. The results show that the SiSt–StSi classifier works with the same benefits than with healthy people as seen in Tables 3 and 4. However it has been noted that the walking classifier does not work properly, confusing the walking state and the stand state continuously. The proposed algorithm needs to be trained with specific data in order to work correctly as shown in Table 5, achieving accuracies over 0.82 on walking posture. Since the second database is small (8 PD patients compared to healthy volunteers database), a larger database is needed to train the algorithm. REMPARK's project is building a database with 90 PD patients in different countries (Ireland, Israel, Italy and Spain), being one of the largest movement signal databases performed with PD patients. The training methodology has to be tested in a near future in this data base.

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