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A WAVELET-BASED PATTERN RECOGNITION ALGORITHM TO CLASSIFY POSTURAL TRANSITIONS IN HUMANS

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ABSTRACT

Elderly people can be monitored at home to detect autonomy issues in their behavior. In addition to the environmental sensors (presence and movements in a room, temperature in the flat, light, etc.), we developed an inertial and magnetic based central of sensors to monitor the activity of the person. This article presents a wavelet-based pattern recognition algorithm that work on the data of this central to detect the postural transitions occurring in the daily life. We constructed four patterns: (1) for stand to sit, (2) for sit to stand, (3) for stand to lying down and (4) for lying down to stand. With this, we are able to detect theses changes, and to infer (as we consider that the subject is stand-up when the sensor is turned on) its posture. We also have, with these sensors, an idea of the activity of the person in each frame of time (immobile, moving, etc.). To test this algorithm and verify that the patterns are independent of the subject, we asked fifteen people to reproduce a scenario and we present, in the last section of this article, the results obtained. Results of an experiment are also given to show a mean good classification rate of 70% for this method.

1. INTRODUCTION

The constant growing of life expectancy in the world creates a lack of places and workers in institutions equipped to care of elderly people. To prevent overpopulation problems, researcher teams all over the world work on ways to keep elderly people at home. Geriatrics ask researchers to design sensors and algorithms to appreciate the evolution of the person in his environment and detect the appropriate moment to organize the admission in an institution.

Abnormal situations in the behavior of the person should be detected by smart sensors and smart homes. Smart Homes have demonstrated that a measure of the activity of a person at home can be relevant [1]. Inertial and magnetic sensors have been used in the past to detect and reproduce movements of a part of the human body (a limb for instance) with uses in virtual reality. In telemedicine they can be used to analyze movements of the person (for example Sit-to-Stand and Stand-to-Sit [2], or to detect distress situations such as fall [3]. This paper aims at using such sensors to detect the postural transitions of a human (Sit to Stand, Stand to Sit, Lying down, Standing Up, Walking) with only one point of measurement, to reduce the inconvenience for the user that has to keep the sensor all the time.

This detection has been realized using a wavelet-based pattern recognition algorithm. This kind of algorithms has been applied in a large variety of application such as handwritten and printed characters recognition in different languages [4].

2. MATERIALS: ACQUISITION SYSTEM ACTIM6D

2.1 Sensors

ACTIM6D (Actimetry in six dimensions) is an home-made acquisition circuit board continuously delivering six signals. The first three signals are from a tri-axes $\pm 1.5g$ to $\pm 6g$ accelerometer (MMA7260Q, Freescale). The $\pm 2g$ resolution is software selected and gives us a $0g$ value at $V_{ss}/2$ with a sensitivity on each axis of $600mV/g$. The other three signals are from a tri-axis $\pm 6Gs$ magnetometer (HMC1053, Honeywell), with a sensitivity of $1.0mV/V/Gs$. The magnetic field measured is the Earth one. The three outputs from the magnetometer are amplified to give $\pm 0.6Gs$ in full-scale.

2.2 Description

Data are acquired to a frequency of $100Hz$ with a DAC of 10 bits for both sensors by a Microchip micro-controller. This frequency is largely sufficient considering that human movements in daily living occurs in the bandwidth $[0.8-5Hz]$ (for a sensor on the upper part of the body) [5]. These collected data are stored on a SD/MMC Memory Card. Figure 1-a and 1-b illustrate this circuit.

All this system is autonomous: it is powered by two coin-cell batteries and not connected to a computer (as it stores data on the memory card). The data on the memory card have to be stored by 512 bytes block. We store $0.5s$ on one sector. A 1GB card allow an autonomy of about 11 days. The battery consumption has been reduced by entering in sleep mode when waiting for acquisition. This allow about fifteen hours of autonomy with two CR2025 batteries (250mAh only). For the experimental sessions, it can be easily fixed on the body of the subject. The size of the circuit board has been highly reduced (we can deduce it with the sizes of the battery and of the MMC on the figure).

2.3 Positioning

This central is kept immobile on the subject body and worn into a pocket under his left armpit (shown by the pink point on Fig. 1-c). This position has been chosen for two reasons: the first is that it is as comfortable as possible for the subject (the card is very light and small), so it can be used for long time measurements and the second is that the movements of

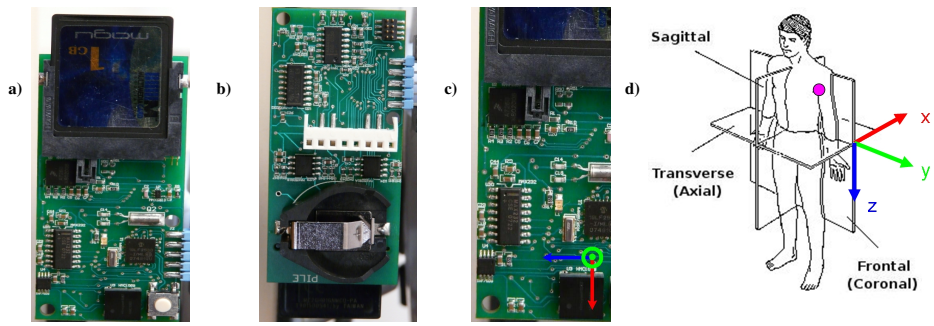

Figure 1: ACTIM6D and its positioning on the subject. (a): front side of the circuit board, (b): back side of the circuit board, (c): Positioning of the subject basis on the circuit board, (d): Positioning of the subject basis

the trunk are the most interesting for our application, as we want to detect changes of posture.

This figure also illustrates the position of the three axis that are created by the central, and that can be described as "the subject basis" ; and finally the orientation of the three axes on the circuit board (for both inertial and magnetic sensors – Fig. 1-d) that corresponds to this subject basis. We chose the different axis as reference to the roll, pitch and yaw axes of an aircraft. As in aeronautic, **x** is the roll axis, **y** is the pitch axis and **z** the yaw axis.

3. SIGNAL PROCESSING OF INERTIAL AND MAGNETIC SENSORS

3.1 Filtering process of accelerometers and magnetometers signals

Both sensors are acquired to 100 Hz in order to be compatible with other applications that the one presented in this article. However, as previously written, for a sensor placed on the upper part of the body, the bandpass necessary for a good analysis of the system is limited to $5Hz$ [5].

For this reason, both signals are filtered using a sixth order low-pass butterworth filter with a cut-off frequency of $5Hz$. This kind of filter has been chosen for its flatness in the bandwidth and the order of the filter is selected to be optimal.

3.2 Transformation of the magnetometers signals

3.2.1 Magnetometers signal and Quaternion

Our algorithm consists in a pattern recognition using wavelets, on two different signals: the accelerometer signal, that varies with the movements of the subject because of the acceleration that is implied to do such a movement ; and the magnetometer signal that varies because when the subject moves, its position against the fixed earth magnetic field is modified. When the subject do the movement to stand up, we want only a three dimensional pattern of its movement. If we consider the magnetometer signal without any modification, this pattern will be modified with a rotation of the subject around the axis of his chest. Indeed, this pattern will depend on the position of the subject with respect to the north direction.

To compensate this modification of the pattern and become invariant with a rotation around the chest axis, we consider the quaternion representation of the movement for the magnetometer signal. This representation will give us an information on the three dimensional rotation that has been realized during the movement and so will not vary with the position of the subject.

In two dimensions, we can write a rotation using the complex numbers. To represent a combination of three rotations in $\mathbb{R}^3$, Hamilton introduced a fourth dimension to form an hypercomplex algebra over real numbers defined by $\mathbb{H} = \{a+bi+cj+dk \mid [a,b,c,d] \in \mathbb{R}^4\}$ with $i^2 = j^2 = k^2 = ijk = -1$.

With that construction, a quaternion is able to represent a rotation in the 3D space, without singular representation (as for Euler angles). If we consider a composition of three rotations that form a movement in the 3D space, we can write this transformation as a simple rotation around one axis. Let's consider two vectors $\mathbf{B_1}$ and $\mathbf{B_2}$. From these vectors we can define a new basis $(\mathbf{i},\mathbf{j},\mathbf{k})$ as follow:

$$\begin{pmatrix} \mathbf{i} & = & \frac{\mathbf{B_1}}{\|\mathbf{B_1}\|} \\ \mathbf{j} & = & \frac{\|\mathbf{B_1}\|^2\mathbf{B_2}-(\mathbf{B_1}\cdot\mathbf{B_2})\mathbf{B_1}}{\|\|\mathbf{B_1}\|^2\mathbf{B_2}-(\mathbf{B_1}\cdot\mathbf{B_2})\mathbf{B_1}\|} \\ \mathbf{k} & = & \frac{\mathbf{B_1}\wedge\mathbf{B_2}}{\|\mathbf{B_1}\wedge\mathbf{B_2}\|} \end{pmatrix} \quad (1)$$

Let's now consider $\mathbf{b_1}$ and $\mathbf{b_2}$, the projection of respectively $\mathbf{B_1}$ and $\mathbf{B_2}$ in this new basis. The rotation from $\mathbf{b_1}$ to $\mathbf{b_2}$ can be written, in $(\mathbf{i},\mathbf{j},\mathbf{k})$, as a rotation around $\mathbf{k}$ of angle θ with:

$$\theta = \arccos\left(\frac{\mathbf{b_1}\cdot\mathbf{b_2}}{\|\,\mathbf{b_1}\,\|\,\|\,\mathbf{b_2}\,\|}\right) \quad (2)$$

Thus, such a rotation of angle θ and principle axis $\mathbf{k} = (k_x \quad k_y \quad k_z)^T$ will be associated to the quaternion

$$Q = \left(\cos\left(\tfrac{\theta}{2}\right) \quad \sin\left(\tfrac{\theta}{2}\right)k_x \quad \sin\left(\tfrac{\theta}{2}\right)k_y \quad \sin\left(\tfrac{\theta}{2}\right)k_z\right)^T \quad (3)$$

With this representation, whatever could be the starting position regarding the magnetic north, as we will compute the transformation between two moments in 3D, the pattern will be the same for a given movement.

In the following parts, we will use this transformation on the magnetometers signals.

3.3 Data segmentation

3.3.1 Segmentation Criterion

The ACTIM6D device is realized to be used on long-term measurement. Analyzing the whole signal to find the patterns that correspond to the postural transition should create a too

large amount of computation (while more that 80% of the signal is meaningless) and also should induce a lot of false detections.

For this reason, the first process that is applied to the filtered signal is a segmentation that will determine the possible positions of the postural transitions. While occurring a postural transition, the variations of the accelerometers are higher (due to the force that is being created by the wearer to perform this movement).

Noticing it, the segmentation is done by analyzing the standard deviation of the norm of the accelerometers. This norm evolves with the time (with the dynamical component of the accelerometer induced by the movement of the body).

3.3.2 Segmentation of the signal

From several realization of each movements (by the same person), we computed the respective standard deviation s_{ass} and s_{all}, respectively for Stand to Sit and Lying Down, allowing to take the decision with the following criterion:

Let $N_Accelero_i$ be the norm, at the window number i and s_i the standard deviation of the data inside this window:

$$\text{Segmentation}_i = \begin{cases} 1 \text{ if } 0,5 \cdot s_{ass} \leqslant s_i \leqslant 1,5 \cdot s_{ass} \\ 2 \text{ if } 0,5 \cdot s_{all} \leqslant s_i \leqslant 1,5 \cdot s_{all} \\ 0 \text{ else} \end{cases} \quad (4)$$

The threshold of detection with half more and less of the initial values have been chosen with preliminary experimentations to reduce the number of false detections without non-detection.

However, this segmentation is not sufficient. Indeed, for example, tying the shoes or getting an object on the floor both create a false detection that will be canceled by the classification algorithm that follows.

3.4 Walk Detection

3.4.1 Walking periods detection

Walking give a frequency content in the bandwidth $[0.8;5\text{Hz}]$ [5]. We used the Short Term Fast Fourier Transform (STFFT) on the norm of the accelerometers, that greatly represent this oscillation during walking, with the acceleration due to the movement of the chest added to the gravity. As we are interested in an analysis on long-term of the activity of the person, we consider large windows (5 seconds), to detect the walking periods that correspond for example to a movement from a room to another and not only one step to take something in the kitchen.

We first windowed the signal using hamming window, which Fourier transform contains a first rebound extremely weak (comparing to the a rectangular window that have sinc as Fourier transform). We included an aliasing zone in the running window (to compensate the apodization of the window).

This STFFT is computed on the bandwidth $[0.8;5\text{Hz}]$ (M frequencies). The transform is then:

$$X(\omega_j,\tau) = \int_{\mathbb{R}} x(t)w(t-\tau)e^{-j\omega_j t}dt,\ \tau \in \mathbb{R}, \omega_j \in [0.8;2\text{Hz}] \quad (5)$$

Afterward, the decision is taken by overtaking a threshold, s_{marche}. The output signal is given by:

$$S(\tau) = \begin{cases} 1 \text{ if } \sum_{j=1}^{M} X(\omega_j,\tau) > s_{marche} \\ 0 \text{ else} \end{cases} \quad (6)$$

That is to say if the frequency content in the considered bandwidth is sufficient to override the given threshold (determined by preliminary experimentations).

3.4.2 Walking periods and segmentation

As the temporal windows are large for the detection of walking periods (5 secs), if a window contains 3 secs of walking and a postural transition, we will miss the postural transition. Indeed, it is useless to analyze (for the postural transitions) a window that have been detected as walking. But the proximity of a postural transition with walking could be a reason of miss-detection of the transition.

To correct this, when a walking period is detected, the first and the last two seconds of the signal are analyzed more precisely to detect the beginning and the end of the walking episodes. This improves the detection of the transitions on sequences like up & Go but also in real life because no-one really stop his movement before sitting down after walking for example.

4. PATTERN RECOGNITION

4.1 Wavelet Analysis of Inertial and Magnetic Signals

Wavelets have been introduced by Morlet and Grossman to override the problems of the Fourier transform and provide a time-scale analyzing tool able to represent the local variations of a signal and operate on non-stationary ones. For this, we define a mother function ψ, well localized in frequency and time space, and we define a base from this function by translating and dilating it ($\psi_{a,b}(t) = \frac{1}{a}\psi\left(\frac{t-b}{a}\right)$, with $a > 0$) and computing the coefficients of the transformation of the signal x with $C_{a,b} = \int_{-\infty}^{+\infty} x(t)\psi_{a,b}(t)dt$

These coefficients create a two dimensional signal giving information on the energy at a given time b and a given scale a. If we consider an adapted wavelet, when searching for maximal surfaces on this two dimensional signals, we can localize in time and scale the apparition of the pattern [6].

To do so, we will create patterns adapted to each postural transitions that we are looking for and we will look for each patterns in the windows determined by the segmentation algorithm.

4.2 Analyzed Data

The data to analyze are two multidimensional functions of time:

- The filtered accelerometer signals: a 3 dimensional vector $\mathbf{A} = (A_x \quad A_y \quad A_z)^T$ where A_v stands for the projection of the acceleration sensed by the accelerometer on the v axis on the body fixed basis.
- The quaternion representation of the movement acquired by the tri-axis magnetometer, a four-dimensional signal that represents the quaternion of the movement between $t = 0$ (beginning of the frame of time) and the current sample. For this signal, we only consider the angle θ, reproducible between two movements.

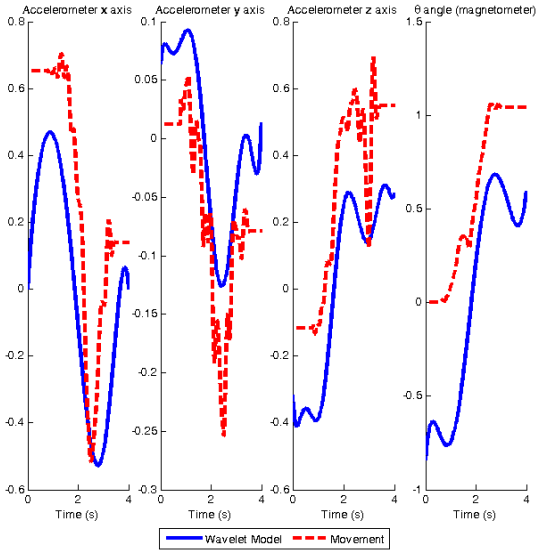

Figure 2: Mother wavelets for the four signals of the transition standing up from the bed. The dashed lines are the signals obtained from the mean of 10 realizations of the same movements and the straight lines are the mother wavelets given by the interpolation

4.3 Patterns Definition

We decided to use the wavelet transform to classify the different patterns to recognize. We have four different patterns that correspond to the transition: (1) Sit to Stand, (2) Stand to Sit, (3) Lying down, (4) Standing up from the lying position.

For each of these four patterns we have four signals. These transitions are supposed to be isolated by the first process: the segmentation. From the segmentation results, we obtain a piece of signal, recognized as possible transition that is either Sit-stand/Stand-sit or Lying down/standing up. The classification process will determine if a real transition occured trying to detect the presence of a pattern in the piece of signal.

To define these four patterns, we asked a volunteer to realize these transitions ten times, we meaned these realizations and then we interpolated the four signals from this mean realization to obtain the wavelets. To do the interpolation, we need two different informations: the basis used to interpolate the signal (polynomial, cosines, etc.) and the degree of the interpolation (the number of coefficients). These two parameters, for each signals, have been determined empirically by analyzing firstly the shape of the signal (the most important point in the pattern recognition is to keep this shape as intact as possible). This shape give us an information on the kind of basis to use. Then, the second point, the degree, was determined by comparing the interpolated signal with the original signal and computing the error between both (and minimizing it). An example of such construction is given, for standing up from the bed, on figure 2.

5. CLASSIFICATION ALGORITHM

The previous models are designed one time (for a population). Once realized, we can classify the possible postural transitions detected by the segmentation algorithm. This

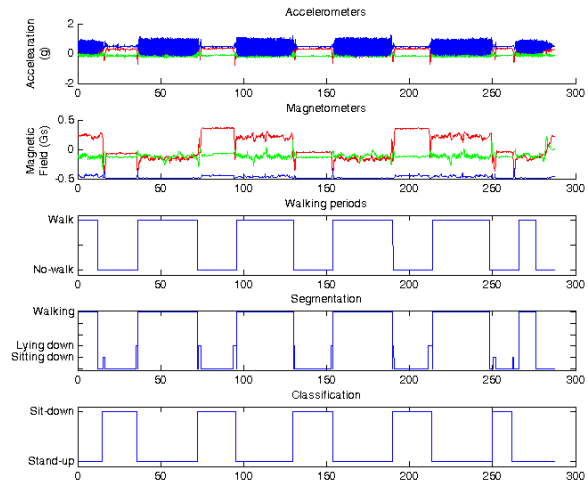

Figure 3: Results of the different phases of the algorithm, from the raw signal to the posture classification and the walk detection

classification is based on the wavelet transform. For each window determined by the segmentation algorithm as possibly containing a transition, we perform the wavelet transform of the signal using the model adapted to the previous posture (sit, stand or lie down) and to the kind of movement detected by the segmentation algorithm. Then, in this set of coefficients, we try to find local maximal surfaces (of sufficient amplitude determined by the standard deviation of the surrounding coefficients). If such a surface is present, we consider a detection for this signal and this transition. The final detection of the transition is performed if the four models are detected in the four signals at the same time (position b in the wavelet transform) and at a same scale (a in the wavelet transform).

The advantages of such a classification is that:

- We have only one model that is not dependent of the speed of realization of the transition. The scale factor a will try to fit the shape whatever its speed could be. Only the way to perform the transition (and so the shape of the signal) is important. For a same transition between two subjects of a same population (young and healthy, elderly people...), this will not change.
- Except for the segmentation algorithm, our process does not depend on many pre-defined coefficients that have to be adapted from one subject to another to be optimal.

For an Up&Go experimentation, the whole results of the different phases of the process are given by Fig. 3

6. EXPERIMENTS AND RESULTS

6.1 Experimental protocol

This algorithm has been tested, to evaluate its performances, on fifteen healthy subject that volunteered for this experimentation. Within these 13 subjects, 6 were women and 7 men, with the following statistics: age: 30.4 $years \pm 6$, weight: 69.7 $kgs \pm 7.5$, size: $1.76m \pm 0.08$. The subjects were asked to reproduce movements of daily life inside the

Health Smart Home of Grenoble. The whole experimental session was filmed by five webcams for indexation and verification. The flat was especially equipped with two chairs (firm, without armrest, height of the sit: 45 *cm*, angle sit/back: 10°), placed at 90° one with respect to the other) and a bed (firm, height: 46 *cm*). The two chairs are used to show the independence of the algorithm against the position of the chair. The scenario was as follow:

- Realize five Up & Go from the chair number one (an Up & Go is defined as follow: the subject is sat down on the chair, he stand up, walk for 4 *m*, turn around, come back, turn around the chair and sit down again),
- A series of five sequences on the bed: the subject walk to the bed, lye down (on the back), stay in this position a few seconds, move on the bed on the left and on the right, stay immobile on the back, stand up and finally walk back to the initial position,
- Stand-up in the living room, the subject has to tie up his two shoes and pick-up a pen from the floor.

6.2 Results

	Incorrect Classification	Correct Classification
Sit to Stand and Stand to Sit		
Incorrect Segmentation	8% (10)	10,4% (13)
Correct Segmentation	6,4% (8)	75% (93)
Lying down and Standing up from bed		
Incorrect Segmentation	13,4% (15)	17,8% (20)
Correct Segmentation	4,4% (5)	64,2% (72)

Table 1: Confusion matrix for the postural transition classification

Table 1 describes the results of the experimentations. The algorithms give a good classification rate of 65% for the transitions Lying down and Standing up from the bed, and 75% for the transitions Sit to Stand and Stand to Sit. This difference is due to the fact that the transition with the lying position are more difficult to detect because of their complexity from one part (with the decubitus part), and because they contain also a sitting transition (and depending on the way to realize the global movement, it can be done with a little stop between both phases).

Moreover, we can see that a large part of the bad classification are due to a bad segmentation. This can be explained by the differences between the subjects in the "strength" of the movement. It will change the acceleration due to the transition. For instance, we could have a subject that sit very slowly and carefully on the bed before the decubitus and on the contrary someone who literally jump on it.

Finally, the transitions are classified correctly in 70% of the cases for the global experiment, using the models and the coefficients for the segmentation obtains by the measurement of ten of each transitions performed by one subject that did not perform the whole experimental protocol.

7. CONCLUSION

We have described a complete process to detect postural transitions, from the signals of an accelerometers and a magnetometers. The segmentation part is performed by analyzing the standard deviation of a slicing window of the accelerometer signal and the classification part is based on detecting the pattern of the transition using the wavelet transform of the signal with an adapted mother wavelet.

Finally, we obtained a correct classification rate of 70% on an experiment involving 13 subjects. We also noticed that the segmentation part was the weakest point of the algorithm because it is responsible of a large part of the errors.

Futures works include the integration of the algorithms into the micro-controller and the improvement of the segmentation coefficients, by considering more signals to understand how to reinforce this part.

This work is a part of a largest classification algorithm implying this sensor and other environmental and location sensors in a flat. With a whole set of 18 sensors, we classify, using Support Vector Machines, the Activities of Daily Living (resting, sleeping, having a meal, hygiene, communicating, eliminating and dressing/undressing) with a correct classification rate of 86%. Improving the postural transitions detection could improve this classification results. This whole work aims at helping elderly people at home by monitoring their activities of daily living and detecting their loss of autonomy as earlier as possible.

Acknowledgments

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