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Walk Detection With a Kinematic Sensor: Frequency and Wavelet Comparison

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Abstract— **This study is included in the framework of Health Smart Homes which monitor some physiological or not physiological parameters of elderly people living independently at home. In this study we will focus on the walk detection. Walk activity is one parameter to evaluate the health of patient. For example, the total time of walk during a day allows assessing quickly if the subject is mobile rather than immobile. To reach this goal we used a kinematic sensor placed on the chest recording the movements of the subject. The data are analyzed by six algorithms to detect walk phases: two based on Fourier analysis and the others using a wavelet decomposition (DWT and CWT). All algorithms are described and the performances are evaluated on real data recorded with 20 elderly people. Results show that the method using the DWT decomposition is the most efficient (78.5% in sensitivity and 67.6% in specificity).**

I. INTRODUCTION

During the past ten years, the elderly population has increased in developed countries, increasing dramatically the burden on specialized structures. To face this situation the health and social policies are promoting home healthcare. The Health Smart Home concept [1] proposes a solution to supervise elderly people at home, through remotely monitoring physiological parameters, such as cardiac frequency or arterial oxygen saturation, and by launching alarms when necessary. Moreover it must also be able to perform fall detection [2], and to evaluate the level of autonomy level of the patient, assuming that the daily physical activity is linked to the health status and the quality of life [3]. The patient's autonomy may be estimated using the Activity of Daily living (ADL) scale [4]. Currently, it is subjectively evaluated by the physician during an interview. This task is operator-dependant, thus it would be preferable to perform it objectively using sensors and adapted data processing. The walk is a good estimator of the level of activity, either in quantity (period of walk per day) or in quality (frequency, celerity). There are two main approaches to walk detection in home either using infrared sensors spread into the accommodation [5][6] or a set of sensors worn by the subject [7]. Wearable sensors, being attached to the subject, are more specific and can measure physiological/biomechanical parameters which may not be accessibles using ambient sensors.

The purpose of this study is to detect the walk through real-time analysis of the signals from wearable accelerometers. We address two algorithms (Fourier- and Wavelet-transform) and assess their performances, in term of sensitivity an specificity, on daily living data from 20 elderly people.

II. MEASUREMENTS AND METHODS

A. Subjects and materials

This study was performed in an elderly institution. 20 participants (eighteen females, two males, 79±7 years old) were enrolled. Informed consent was obtained from all subjects. For the comparison of our algorithms, the patients performed different daily activities (walking on the flat, sitting on different chairs, standing, lying, picking objects in a refrigerator or a shelf) at their own usual place, indoor (institution). A video camera recorded all trials. The periods of walk were indexed manually by an engineer (resolution 1 s). A walk phase is labelled when the subject perform a least two steps in a row. Comparison was made with the data delivered by the algorithms to calculate the sensitivity and specificity.

In all studies, an ACTIMOMETER [8] (sensor measuring both ACTIvity and MObility, based on a ”fall sensor” [2] developed in the TIMC laboratory, was placed on the chest under the left armpit of the subject. This sensor includes three orthogonally oriented accelerometers (ADXL213, Analog Device) and produces: anteroposterior acceleration (a_{AP}), mediolateral acceleration (a_{ML}) and vertical down acceleration (a_V) data. The sampling frequency can be adjusted according to the phenomenon studied. In this study, the fastest body movements occur when walking with a signal frequency ranged from 0.6 Hz to 2.5 Hz [9].

Consequently, to prevent aliasing problem, we follow the Shannon sampling theorem:

$$F_E \geq 2 * F_{max} = 5Hz$$

During our experiments, the sampling frequency was fixed to 20 Hz, to maintain a sufficient accuracy of our algorithm.

B. Walking classification algorithm

The walking event occurs mainly in the sagittal plane [10] and is characterized either by the foot impacts on the floor (information on a_V) or by chest oscillations (information on a_{AP}). So, frequency analysis is the more efficient method to

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detect this activity. We developed four algorithms to detect periods of walking in a signal containing many other activities. MoeNilsen [11] showed that the vertical axis is more sensitive (greater RMS acceleration) than the anteroposterior and the mediolateral for all speed ranged from 0 to 2 m/s. Based on that comment we selected the vertical acceleration a_V to assess the performance of the different algorithms.

1) Short Term Fourier Transform: STFT was used by DeVaul [12] who developed a model to classify a range of user activity states, including sitting, walking, biking.

Based on the STFT (Cf. equation 1), we proposed an algorithm to detect walk periods among other daily activities in a long period of time.

$$STFT(t', f) = \int_t x(t) \cdot e^{-2\pi i f t} \cdot w(t - t')dt \qquad (1)$$

where $x(t)$ is the signal to analyze and w an apodization function (Hanning).

The figure 1 describes the algorithm based on the STFT.

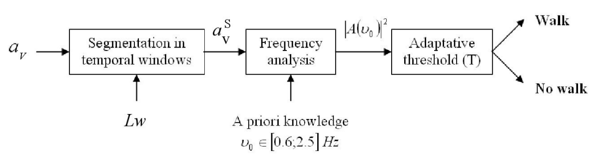

Fig. 1. Classifier of walk/no walk activities using a STFT analysis. The signal a_V is segmented into temporal windows a_V^S . The spectral analysis determines a peak amplitude value ($|A(\nu_0)|^2$) with a frequency (ν_0) ranging from 0.6 to 2 Hz [9]. A walk activity is detected if the $|A(\nu_0)|^2$ is above the adaptative threshold (T) otherwise an activity is deemed "no walk".

As describe in [13], we defined an adaptative threshold (T) as follows:

$$T = \frac{1}{\tau}\left[\frac{b.Lw}{2}\right]^2 \qquad (2)$$

where τ is an attenuation coefficient, b the amplitude of the input signal (a_V^S) and Lw the length of the apodization window (Hanning). A walk phase is defined (§II-A) as at least two steps which corresponds to three peaks on the a_V signal. Since the lower frequency of the walk is 0.6 Hz [9] we fixed $Lw = 3s$ in this. The threshold (T), applied on each STFT estimation, decides if a walk period was occurred or not. This algorithm will be called $STFT_T$.

2) Short Term Fourier Transform with Threshold: However, in the last section, since the value of T is adapted according to the amplitude b of the input signal (eq.2), a noise with a small amplitude can be classified as "walk" if its frequency content is included in [0.6;2] Hz [9]. To overcome this problem, we define a constant threshold T_b to test b: the amplitude of the input signal:

If $b < T_b$	Then NO WALK
Else If $\vert A(\nu_0)\vert^2 > T$	Then WALK
ELSE	NO WALK
End If	

This algorithm will be called $STFT_T^{T_b}$.

The accuracy of these two algorithms ($STFT_T$ and $STFT_T^{T_b}$) depends on the value of τ (eq. 2) as depicted on figure 5.

3) Discrete Wavelet Transform: Discrete wavelet transformation of a signal $x(t)$ is defined as :

$$x(n) = \sum_{j=1}^{J}\sum_{k\in\mathcal{Z}} d_j(k)\cdot\psi^*(n - 2^j k) + \sum_{k\in\mathcal{Z}} a_j(k)\cdot\phi^*(n - 2^j k) \quad (3)$$

where $j \in \mathcal{Z}$ and $k \in \mathcal{Z}$ represent the resolution, J is depth of level, ψ is the synthesis (reconstruction) wavelet function and ϕ is the scaling function

Sekine et al. [14] attempted to classify walking on the ground level from walking on a stairway using a waist acceleration signal. Recently Coley et al. [15] proposed a method to detect the same parameter using a gyroscope.

Sekine et al. method is based on a ratio between the power of the detail signals and the total power in the anteroposterior direction. In this study, we compute a similar ratio called R^{DWT} of the power of the details between level 3 and 4, and the total power of details as follows:

$$R^{DWT} = \frac{\sum_{j=\alpha}^{\beta} d_j^2}{\sum_{j=1}^{J} d_j^2} \qquad (4)$$

with $\alpha = 3$, $\beta = 4$ and J=8 in this study.

"Walk" and "No Walk" are discriminated by a threshold $TRDWT$. Actually, if $R^{DWT} > TRDWT$ then a walk period is detected otherwise its a no walk phase.

The properties of the wavelet transform rely on the selected analyzing wavelet. As mentioned in the paragraph II-A, a walk period is at least two steps that is why we have chosen a wavelet with two main oscillations: db10.

The figure 2, shows a trivial accelerometric signal where a subject performs six phases of walk. Below the detail coefficients for 8 levels. We can see easily that the details level 3 with high values correspond to walk periods.

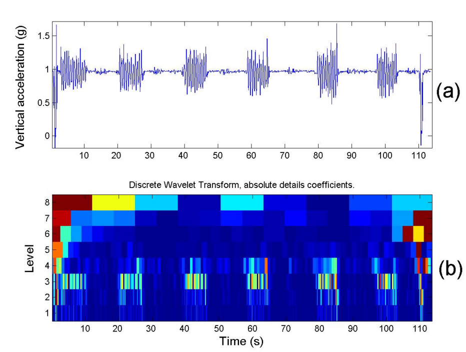

Fig. 2. (a): vertical acceleration (g). The subject performed six walk phases with a pause between each of them. At the beginning and the end a small vertical jump was performed. (b): DWT absolute details coefficients on the eight levels.

Sometimes, the ratio R^{DWT} is above the threshold $TRDWT$ even if there is no walk because of the recording noise of the sensor. To prevent this effect we propose to remove all the DWT coefficients below an absolute threshold determined in a pilot study. This algorithm will be called $DWT^{\dagger}$.

The performances of both algorithms (DWT and $DWT^{\dagger}$) depending of the parameter $TRDWT$ are presented on the figure 5.

4) Continuous Wavelet Transform: The continuous wavelet transform of a monodimensional signal $x(t)$, provides a decomposition of the signal at different scales [16]. As seen in the equation 5, the transformed signal is a function of two variables, τ and s , the translation and scale parameters, respectively.

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^* \left(\frac{t-\tau}{s}\right) dt \qquad (5)$$

The approach to detect the period of walk is the same as the DWT method. We asses a ratio (R^{CWT}) between the power of small scales (high frequencies) and the total power of the scales.

"Walk" and "No Walk" are discriminated by a threshold $TRCWT$. If $R^{CWT} > TRCWT$ then a walk period is detected otherwise its a no walk phase.

The figure 3, shows the CWT compute on the same input signal (Fig. 2) for 64 scales.

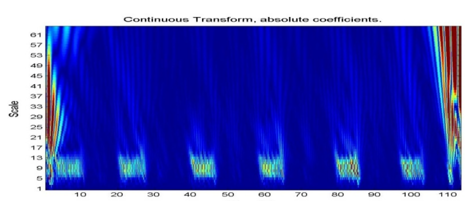

Fig. 3. CWT computed with 64 scales on the signal depicted in figure 2(a). During the walk periods, most of the energy is concentrated between the scales 5 and 13 (α and β respectively in equation 4). But on this example, the subject was a healthy young adult who walked quite quickly. The lower speed of walk of elderly people implies lower frequency on the vertical acceleration. That is why we have increased the β value from 13 to 20.

To prevent the same effects presented in the subsection II-B.3, we propose to cancel the smallest CWT coefficients, further named ($CWT^{\dagger}$).

The performances of both CWT and $CWT^{\dagger}$ algorithms depend of the parameter $TRCWT$ are presented on the figure 5.

III. RESULTS

The result of the CWT-based detection applied on the test signal (Fig. 2(a)) is depicted on the figure 4.

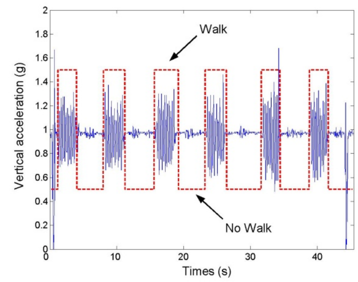

Fig. 4. Results of the detection using de CWT method. The solid line represents the input signal (vertical acceleration). The Y-axis values 1.5 and 0.5 of the dashed line correspond to the WALK and NO WALK periods respectively .

The accuracy of our six methods ($STFT_T$, $STFT_T^{T_b}$, DWT, $DWT^{\dagger}$, CWT and $CWT^{\dagger}$) was assessed during an experiment with twenty elderly people who performed daily activities. We compared the outputs of the different algorithms to the reference videotape (Cf. §II-A). Two indices were used to evaluate the accuracy the sensitivity and the specificity.

The sensitivity (defined as the ability of the system to correctly identify the true walk sample in the input signal) and specificity (defined as the ability of the system not to generate false detection of walk) were estimated. Actually, we compare all the samples of the input signal to the reference and count the number of True Positives (TP), False Negatives (FN), True Negatives (TN) and False Positives (FP) to finally compute the sensitivity and specificity as:

$$Se = \frac{VP}{VP + FN} * 100 \qquad Sp = \frac{VN}{VN + FP} * 100$$

These two criteria were assessed for the six proposed methods and different values of the parameters τ (eq. 2) for both $STFT_T$ and $STFT_T^{T_b}$ methods, $TRDWT$ and $TRCWT$ for the DWT- and CWT-based analysis respectively.

All results are summarized in a Receiver Operating Characateristic (ROC) curve (Fig. 5).

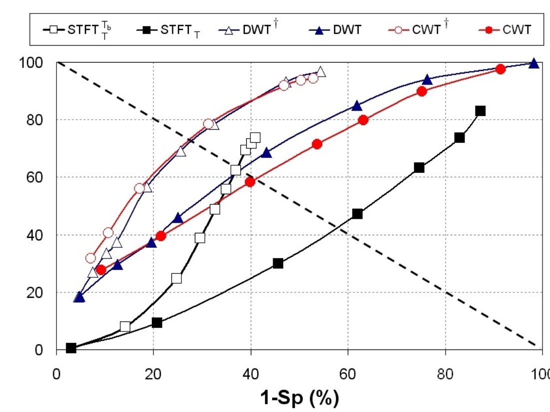

Fig. 5. ROC curve of the three basic methods (CWT, DWT, STFT). The curves with unfilled points represent the different methods using the thresholding.

The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test is (the true positive rate is high and the false positive rate is low).

Based on this comment, We can see (Fig. 5) that for all methods using a threshold increase both Se and Sp. Moreover it shows that $CWT^{\dagger}$ and $DWT^{\dagger}$ are roughly equivalent and $STFT_T^{T_b}$ less accurate.

A quantitative comparison is given in the table I which presents the best operating points (closer to the dashed line) for the six methods.

TABLE I
BEST SENSITIVITY AND SPECIFICITY VALUES FOR EACH METHOD

Method	Sensitivity (%)	Specificity(%)
CWT	58.2	60.1
DWT	68.7	56.7
$STFT_T$	47.1	38.0
$CWT^{\dagger}$	78.4	68.7
$DWT^{\dagger}$	78.5	67.6
$STFT_T^{T_b}$	62.3	63.0

IV. DISCUSSION AND CONCLUSION

We have presented six methods for detecting walk periods; two were based on a wavelet transforms (CWT and DWT) and the others on Fourier Transform (STFT). We also presented their performances obtained on 20 elderly people. Results show that CWT and DWT with thresholds give similar better results than the other ones. The best operating point for these two methods generates 78.5% in sensitivity and around 68.0% in specificity. However, the absolute value of these two criteria are very sensitive to the reference signal. Indeed, as mentioned in the section II-A, a time incertitude (maximum error $\pm 0.5s$) can occur during the indexation of the walk periods. Since the sample frequency is equal to 20 Hz, up to twenty samples can be misclassified because of an error in the reference signal.

Although the $CWT^{\dagger}$ and $DWT^{\dagger}$ methods exhibit same performances, the CWT suffers some limitations. It is more processor time consuming. The table II gives the average computation time required to analyze 1h of recording.

TABLE II
COMPUTATION TIME OF THE STFT, DWT AND CWT

Method	Mean (s/1h of recording)	Standard deviation
CWT	23.9	1.1
DWT	1.1	0.1
$STFT$	0.6	0.1

Because the CWT is computed with 64 scales and only 8 for the DWT, the computation time is drastically higher. For this reason we decided to exclude this approach.

With regards to the STFT methods, the length of the analysis window (*Lw*) influences the performances. Indeed, if *Lw* is smaller than the period of the walk, no walk will be detected. If the window is too long, it can contain both ”walk” and ”no walk” activities.

The advantages of the methods are that 1) only one accelerometer attached to the chest is sufficient to detect the walk periods, 2) the value of the parameters (τ, $TRDWT$ and $TRCWT$) were fixed once for all the subjects, 3) classification of walking detection in elderly people could be performed, and 4) it worked well even with some elderly people who had a limited locomotion (walking stick and/or Total Knee Prosthesis (THP) and/or Total Hip Prosthesis (THP))

In conclusion, we can better extract walking phases from others daily activities using a ratio based on CWT coefficients and thus assess objectively one autonomy criterion.

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