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Evaluation of the autonomic nervous system for fall detection

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***Abstract*— Studies show that the proportion of elderly will reach 30% of the total population by 2050 in developed countries, such as France. The elderly live generally alone, thus many health problems related to age are under reported. Falling is one of these problems and several devices have been developed recently, based on accelerometers, in order to detect it and alert carers. In order to improve the detection success of these devices, we propose quantifying autonomic nervous system activity (ANS) using a wearable ambulatory device developed for this purpose. We studied the A.N.S's response on 7 adult subjects during simulated falls and standing-lying transitions. We implemented a classification method using the Support Vector Machine in order to classify these two situations using measured heart rate variability and electrodermal response. Good results (sensibility =70.37%, specificity =80%, positive predictor=73.8%) were obtained using a Polynomial kernel ($p = 5$) for the support vector machine implementation.**

***Index Terms*— Autonomic nervous system(ANS), Wearable device, Fall detection, Support Vector Machine.**

I. INTRODUCTION

THE proportion of the elderly in the population is increasing in developed countries. Many of the elderly choose to stay home rather than go to a retirement home. As they tend to live alone, many health problems related to aging (such as Myocardial infarction, Parkinson'or Alzheimer's disease) are not detected, early enough, thus increasing the mortality rate and adversely affecting the quality of life.

Wearable devices have been developed in response to this growing problem in order to monitor the elderly in their homes. Several devices, such as the AMON system [1], enable the measurement of a range of physiological parameters such as the SpO_2 (oxygen saturation), ECG, blood pressure, skin temperature and/or activity. The purpose of these devices is to monitor the health or the wellness of the subjects, measuring the physiological parameters in order to detect a health problem at an early/latent stage and to send an alarm to alert the remote clinical or related center. One of the major health risks associated with the elderly is falling as it results in many disabling fractures [2] and has major physiological consequences. However, if it is detected in time, much pain and trauma can be averted and the risk of mortality reduced. Fall is defined as a rapid change from the upright/sitting position to the reclining or almost lengthened position [3]. In order to detect this problem, several ambulatory devices have been developed incorporating accelerometers [4]. The sensor [4], developed by the AFIRM team, one of the laboratories contributing to the present research, detects falls using two tri-axial accelerometers placed within a patch attached to the left side of the chest. The latest version of this sensor can detect a fall with a percentage success close to 85%. In order to improve the detection rate of this fall sensor, the authors are studying the ANS activity during simulated falls and standing-lying transitions. Our research seeks to find a classification method that reliably differentiates between these two situations using various physiological signals. We have therefore developed a wearable device for the monitoring of, among of others things, ANS activity.

The ANS is activated unconsciously through the sympathetic (**SNS**) and parasympathetic (**PSNS**) nervous systems in order to maintain homeostasis in the body. The sympathetic system is activated in cases of danger, surprise or stress. The efferent path way in the SNS reacts in order to prepare the body for action, activating the necessary mechanisms such as heart rate acceleration, blood vessels constriction, pupil dilation, perspiration (sweating), etc. On the other hand, the afferent path way carries the sensations as pain or heat to the brain. In contrast, the PSNS is activated in order to enable rest, repose and stock of the energy. The parasympathetic system slows the heart rate, dilates the blood vessels and constricts the bronchi when the need of oxygen decreases.

Several studies have proved the pertinence of measuring the activity of the ANS in order to detect basic emotions [5]. Healey et al [6] evaluated stress levels in car drivers during different kind of driving conditions (rest, highway and city). The recorded physiological signals were electrocardiogram, electromyogram, skin conductance and respiration. Using these signals, the driving stress was classified with a success rate of 97%, the most relevent signals were the heart rate and the skin conductance. Jovanov et al [7] developed a wireless system that monitors stress during the training aircraft pilots and during their routine activities, measuring skin conductivity, instantaneous heart rate and the subject's activity. In our case, we measured the ANS activity using three physiological signals: skin temperature, skin resistance and electrocardiogram, using a wearable device (Fig 1) developped for this purpose.

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II. Materials and methods

A. Wearable device

1) Skin temperature sensor: skin temperature was measured using a thermistor (Betatherm, Réf. 10 K3 MCD2) attached to palm of non dominant hand. The resultant resistance variation produced by the sensor was measured with a Wheatstone bridge in order to produce a voltage corresponding to the resistance. This configuration gave good measurement linearity and accuracy. The temperatures ranged between 22 and 42 degree Celsius. The signal was amplified and filtered with a RC circuit (fc=1KHz).

2) Skin resistance sensor: this signal was measured with a current constant method. The system applied a DC current of 3.3 μA in order to record a voltage proportional to the skin resistance. The value of the current was fixed in order to have a resistance variation beween 0 to 1MΩ. The electrodes used were Ag/AgCl with a diameter of 0.8 mm. The electrodes were placed on the second phalanx of the index and the third digit of the non-dominant hand in compliance with published recommendations [8]. In order to improve the contact surface an isotonic paste was applied. The signal was further buffered and filtered with a RC filter.

3) Electrocardiogram: The electrocardiogram was measured using a classical electrocardiogram circuit and a standard lead II configuration. A Driven Right Leg circuit was implemented in order to increase the SNR, and the ECG signal was finally filtered using a band pass filter between 8 to 16 Hz.

The above three signals were sampled using a Sigma-Delta converter (MAX1400) with a 18-bit resolution and five analogic inputs. The sampling frequency is set to 600 Hz for each input in order to fix the sampling frequency of 200 Hz for the three channels. The signals sampled are send to the microcontroller (PIC18F2580) with a SPI communication. The data frame was sent using a Zigbee device with a baud rate of 57600bps.

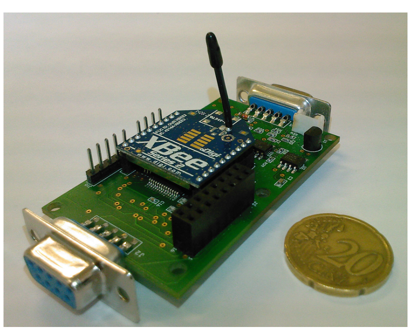

Fig. 1. Wearable ambulatory device developed for the quantification of the ANS; measuring skin temperature, skin resistance and the electrocardiogram.

B. Signal processing

In order to implement the signal processing the algorithms have been developed offline.

1) Skin resistance: The skin resistance signal is mainly associated with the activity of the sweat gland. This activity gives an information about the arousal state of the person. The signal could be analyzed in the following ways [9]:

- Skin resistance level: this is the low variation of the signal.
- Skin resistance response: shows the response produced by a particular stimulus like the fall or another event.
- Non oriented response: the non oriented responses are the responses produced spontaneously without a stimulus.

2) Electrocardiogram: The ECG signal was filtered using a bandpass Butterworth filter with a bandpass frequency from 8 to 16Hz. This numeric filter was implemented in order to set the frequency ranges of the ECG signal for the QRS complex detection. The QRS complex was detected with the Pan-Tompkins' algorithm [10] and the RR times signal extracted detecting the maximal point of the QRS complex in order to built the RR tachogram.

3) Heart Rate Variability: Heart rate variability (HRV) is a complementary non-invasive method commonly used to estimate the ANS activity. Several techniques are currently used in the literature to calculate HRV [11]:

- Frequency domain methods, using either the Fast Fourier Transform (Periodogram or time frequency algorithm) or methods based on the autoregressive model.
- Non linear methods such as the Poincaré Plot.

a) Frequency Domain: The spectral analysis of the heart rate signal is performed on the energies of two different bands of frequencies in order to separately quantify the sympathetic and parasympathetic system activities:

- The measured energy in low frequency band (0.04-0.1 Hz) reflects the activation of both the parasympathetic and sympathetic systems.
- The energy in high frequency band (0.15 - 0.4 Hz), on the other hand, corresponds to the activation of the parasympathetic system alone.

In the present work, the Fourier Transform was used to compute the power spectral density of the heart rate signal that had been reconstructed by a spline cubic interpolation at 10 Hz, and from which the DC component had been removed to facilitate the study of the signal dynamic. The Power spectral density was computed using the short time frequency (STFT) algorithm (1). In this case, f(t) represents the tachogram signal and g(t) the shifting window implemented using a Gaussian window and a standard deviation defined by equation (2) where N is the sample length of the signal f(t) and w the standard deviation of the Gaussian window.

$$Sf(u,\xi) = \langle f,g \rangle = \int_{-\infty}^{+\infty} f(t) g(t-u) e^{-i\xi t} \tag{1}$$

$$w = \sqrt{\frac{N}{4\pi}} \tag{2}$$

b) Poincaré Plot: The Poincaré Plot is a nonlinear method which enables the calculation of the short term variability. It is a representation of the RRn vs. the RRn+1 interval and has the form of an ellipse from which one can measure the standard deviation along its principal axis (SD2) and the orthogonal standard deviation (SD1). The SD1/SD2 ratio is further computed as per the standard methods [12].

C. Support vector Machine

The support vector machine (SVM) is a supervised classification technique developed by Boser and Vapnik [13]. This technique finds the best separating hyperplane between two classes using the samples placed on the edge of each class (Fig 2) in order to maximize the distance that exists between the hyperplan and the nearest points of each classes that is defined as the margin. Let's consider the couple (x_i, y_i) where $x_i \in R^n$ and y_i is a constant that shows the class to which the x_i element belongs. The algorithm consists in determining (w,b) that verify:

$$\begin{cases} w.x_i + b \geq \ \ 1 \Rightarrow y_i = 1 \\ w.x_i + b \leq -1 \Rightarrow y_i = -1 \end{cases} \tag{3}$$

The distance between these two planes is defined as $\gamma = 2/\|w\|^2$ thus maximizing this distance is equivalent to minimizing (4).

$$\min_{w,b} \left\{ \frac{1}{2} \|w\|^2 \right\} \tag{4}$$

In 1995, Cortes et Vapnik [14], introduced a new parameter that considers the wrong classification. This technique introduced the slack variables ξ_i in order to loose the conditions imposed by the equation 3. Finally, the relation 4 can be modified by :

$$\min_{w,b,\xi} \left\{ \frac{1}{2} \|w\|^2 + C \sum_i \xi_i \right\} \tag{5}$$

subject to the following conditions $y_i(w.x_i + b) \geq 1 - \xi_i$.

In the cases where the data are not linearly separable it is possible to modify (3) by the following equation:

$$f(x) = w.K(x) + b \tag{6}$$

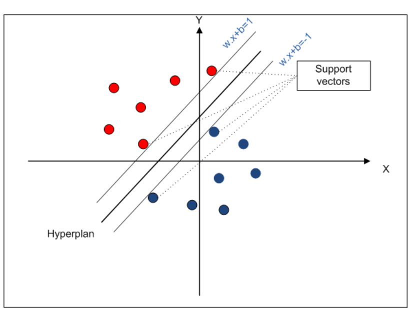

Fig. 2. The margin is maximized ,in order to find the hyperplane, using only the vectors located on the edge of each class.

where the function $K(x)$ is called the kernel function. In our case we used a Gaussian kernel and the Polynomial kernel defined by the equations (7) and (8)

$$K(x_i, x_j) = \exp \frac{\|x_i - x_j\|^2}{2\sigma} \tag{7}$$

$$K(x_i, x_j) = (x_i^T.x_j + 1)^p \tag{8}$$

The Gaussian kernel is modified by the parameter σ. This parameter fixes the standard deviation of the Gaussian curve used. In the case of the Polynomial kernel, the parameter p controls the degree of the polynomial used to implement the non-linear transformation.

III. Experimentation protocol

The experimentation was carried on 7 adult subjects (28 $\pm$7 years). The physiological signals described previously were displayed and recorded during the study. The experimentation has been divided in two parts:

- In the first part, each subject stood in standing position with his eyes closed, during one minute. After one minute, the subject was pushed in order to simulate a fall. The subject remained in the lying position during one minute. The subject's fall was cushioned by a thick mattress, ensuring their safety. For each subject the fall was simulated 6 times.
- In the second part, the subject did a normally standing-lying transition. The event was repeated three times.

A. Feature extraction

For each situation, we extracted a set of features from each signal. For the skin resistance signal we considered 30 seconds before and after each event. We centered the totality of the signal (by subtracting the mean and dividing by the standard deviation) and measured the number of electrodermal responses (EDR's) and the sum of the area related to these responses. In the case of the heart rate variability, we computed the energies in the low and high frequencies bands in order to compute the LF/HF ratio, the LF/(LF+HF) ratio with the STFT and the SD1/SD2 ratio with the Poincaré plot representation 45 seconds before the event. In order to avoid the non stationary problems produced by the change of the position, we evaluated the same features starting with 10 seconds until 55 seconds after the event.

IV. Results

We implemented the SVM in order to classify the two situations (falling down and standing-lying transitions) using the physiological features described above. The SVM was implemented using two types of kernel (Gaussian and Polynomial). For each set of parameters (σ and C for the Gaussian kernel and p and C for the Polynomial kernel), we evaluated the performance of the classifier training on the $S_{1,2...n-1}$ elements and testing on the S_n(leave one out method) following equations(9,10,11).

$$Sensibility(\%) = \frac{TP}{TP + FN} \times 100 \quad (9)$$

$$Specificity(\%) = \frac{TN}{TN + FP} \times 100 \quad (10)$$

$$Positive\ predictivity(\%) = \frac{TP}{TP + FP} \times 100 \quad (11)$$

TABLE I

SVM USING A GAUSSIAN KERNEL

	C=1		
σ	sensitivity	specificity	Positive prediction
0.1	92.59	33.33	71.42
0.2	74.07	40	61.9
0.5	64.28	13.33	64.28
	C=10		
0.1	88.88	33.33	69.04
0.2	74.07	60	69.04
0.5	74.07	53.33	66.66
	C=100		
0.1	88.88	33.33	69.04
0.2	77.77	60	71.42
0.5	66.66	60	64.28

TABLE II

SVM USING A POLYNOMIAL KERNEL

	C=1		
p	sensitivity	specificity	Positive prediction
2	96.29	0	61.90
3	77.77	33.33	61.90
5	74.07	60	69.04
	C=10		
2	74.07	46.66	64.28
3	85.18	53.33	73.80
5	70.37	80	73.80
	C=100		
2	74.07	53.33	66.66
3	70.37	73.33	71.42
5	70.37	73.33	71.42

In the case of the polynomial kernel we observed better results compared with the Gaussian kernel. With $p = 5$ and C=10 we reached a sensitivity equal to 70.3%, a specificity of 80% and the positive predictor was equal to 73%. The non-linear transformation, used to map the data, increases the percentage of good classification in this case. The C parameter allows to soften the constraints improving the results of the clasifier, nevertheless, a high value of C would improve the results but the classifier will be not general falling in the overfitting of the data.

V. CONCLUSION

In the present paper, we presented an approach in order to improve the ratio of the fall detection measuring the activity of the ANS. Therefore, we developed a wearable ambulatory device that measures different physiological signals such as the skin temperature, the skin resistance and the electrocardiogram. We implemented a classification method using the support vector machine in order to differentiate the fall reaction's compared with a normal standing-lying transition. We used two type of kernel (Gaussian and Polynomial). The results show that using the Polynomial kernel with a $p = 5$ and a $C = 10$ we obtained an acceptable positive prediction with equivalent sensibility and specificity. This approach is limited to people whose ANS is not adversely affected by disease, etc. Indeed, with elderly who are treated with beta-blockers, the ANS is impaired and our method is not applicable. As a future work, we hope to make different kind of experimentations in order to study the ANS activity during the daily living activities in the elderly in order to prevent the fall and detect the stress level.

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