Preliminary results from a proof of concept study for fall detection via ECG morphology

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Abstract—**Falls are a major problem in later life. Early fall detection systems are increased over the years as undetected falls can have severe consequences for the fallers. Fall detection systems are based mainly on posture detection using accelerometers and gyroscopes. Alternatively, this study aims to understand if it is possible to detect posture changes using only electrocardiogram (ECG) morphology, which is significantly associated with moving from one position to another. This paper presents preliminary results of a feasibility study aiming to investigate at what extend it was possible to detect lying and standing position, using wearable devices to observe ECG morphology alterations. According to the literature, 29 ECG features were extracted. 11 healthy subjects (aged 19-36 years) were monitoring while lying down and standing up. ECG and accelerometer signals were recorded continually using a chest wearable monitoring device, the BioHarness M3 (ZephyrTech, NZ).Variations in the ECG features while the subjects lay down and stood up were analysed with the parametric statistical paired T-test. The results of the current study suggested that 4 ECG features were effective in detecting changes while lying down or standing up. Linear Discriminant Analysis (LDA) was used to generate a classifier based on these ECG features to detect automatically the changes while lying down or standing up with total classification accuracy, sensitivity and specificity rates of 77.3%, 81.8%, and 72.7% respectively. The results obtained from the current study support a preliminary proof of concept and pave the way to more complex studies aiming to detecting real falls using ECG variations.**

Keywords— **ECG morphology, posture detection, accidental falls, Linear Discriminant Analysis (LDA)**

I. Introduction

Falls are a serious major health problem especially in later life, when in community dwelling old adults the fall rate is more than 30%[1, 2]. The number of old adults increases at an accelerating rate and falls represent a costly issue with serious negative consequences for quality of life[1]. Falls are estimated to cost the NHS more than £ 2.3 Billion per year, affecting the family members and carers of people who fall as well, since minor injuries (28%), soft injures (11%) and fractures (5%) frequently occur after a fall[1]. In this context, assistive devices that could help to relieve this health problem are necessary. Indeed, fall detectors are being persuaded.

A fall detection system can be defined as an assistive device whose main objective is to alert when a fall event has occurred[3].

The number of studies on fall detection has increased dramatically over recent years. According to the existing literature, current fall detectors are sensors deployed in the environment such as cameras, floor sensors, infrared sensors, microphones and pressure sensors or miniature electronic sensor-based devices that are worn with or on top of clothing. However, sensors deployed in the environment are limited to those places where the sensors have been previously deployed and privacy is not a major concern[3]. On the other hand, the wide majority of wearable devices are in the form of accelerometers and gyroscopes, which have no other direct benefits for elderly health conditions; moreover, elderly are not willing to continuously wear a device that spies on them just because a fall may happen.

There is evidence that the most frequent co-morbidities for patients hospitalized for a fall are cardiovascular diseases (CVD) [4]: hypertension (63%), coronary atrial fibrillation (30%), artery disease (25%) and congestive heart failure (20%). Among other biomedical signals, electrocardiogram (ECG) is the most used for CVD. This suggests that developing a solution for fall detection basing on ECG monitoring may result in a more sustainable approach. Instead the falls could be detected using a system for ECG monitoring that is eventually in place for other CVD monitoring purposes.

Moreover, although 31% of falls are due to accidents and the causes of 27% of falls remain unclear, the remaining 42% are due to transient problems, which are clearly related to health states, including those related to cardiovascular system (CVS) conditions [5]: gait/balance disorders or weakness (17%), dizziness/vertigo (13%), drop attacks (9%), postural hypotension (3%). There is evidence that these physiological conditions, particularly dizziness/vertigo [6] or postural hypotension [7], can be detected through the study of the ECG.

Therefore, differently from previous studies, we aimed to investigate the potential of ECG to detect postural changes (lying and standing) in order to use ECG as mean to detect postural changes and subsequently falls; in fact, ECG is largely used to monitor elderly people, in hospital and in the community, and there is wide consensus that ECG monitoring is beneficial for the early detection of CVD worsening [8-

11], as opposed to the use of only accelerometers or gyroscope.

Therefore, the first step we took in order to develop a model to automatically detect falls was to understand if ECG features were able to detect changes in body posture in particular during lying and standing positions. This paper presents those very preliminary results, which while proving the concept will need further developments in order to be directly applied to real falls in the elderly.

II. Methods and materials

A. Study Design

The study was conducted on 11 subjects (8 females and 3 males) with an average age of 28.7±10.7 years old. There were no obese persons (BMI 22.33±2.79) and there were not taking medication for the duration of the study. The following inclusion criteria were used to enrol the volunteers: with an age between 18 and 40 years old, no consumption of drugs or alcohol before the experiment or other self-reported diseases that potentially influencing the ECGs.

This study was approved by the Biomedical and Scientific Research Ethics Committee of The University of Warwick (reference number REGO-2014-1039), assuring the anonymity and no side effects or possible disadvantages for the subjects. All subjects were carefully instructed about the study protocol and the informed consent was given prior to the examination.

ECG and accelerometer signals were recorded in the two positions (lying down and standing) using a commercial wearable device, the BioHarness M3 (ZephyrTech, NZ).

The ECG was segmented, according to the accelerometer signals in the two phases (lying and standing). Ten ECG beats recorded after 5 minutes of lying down or standing were analysed using in-house software developed in MATLAB version R2014a (The MathWorks Inc., Natick, MA). For each beat (Fig 1), ECG features were extracted (Table 1).

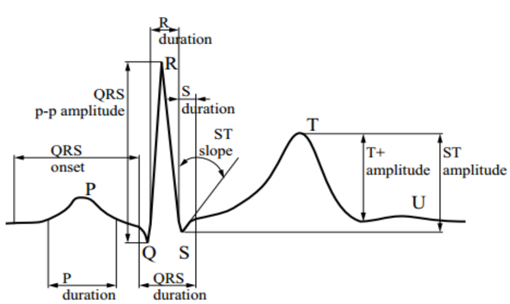

Fig. 1 ECG features[12]

Table 1 ECG features derived

N	ECG Features
1	P wave onset
2	P wave duration (ms)
3	QRS wave onset
4	QRS wave duration (ms)
5	Q wave duration (ms)
6	R wave duration (ms)
7	S wave duration (ms)
8	R’ wave duration (ms)
9	S’ wave duration (ms)
10	P+ wave duration (ms)
11	QRS wave deflection (ms)
12	P+ wave amplitude (µV)
13	P- wave amplitude (µV)
14	QRS wave peak to peak amplitude (µV)
15	Q wave amplitude (µV)
16	R wave amplitude (µV)
17	S wave amplitude (mV)
18	R wave amplitude (µV)
19	S wave amplitude (µV)
20	ST segment amplitude (µV)
21	2/8 ST segment amplitude (µV)
22	3/8 ST segment amplitude (µV)
23	T+ wave amplitude (µV)
24	T wave amplitude (µV)
25	QRS wave area (µV)
26	T wave morphology (µV·ms)
27	R wave notch existence [-2, 2] (%)
28	Delta wave confidence
29	ST segment slope [-90, 90] (deg.)

B. ECG Feature Selection and Statistical Analysis

The mean and standard deviation for each ECG feature (over 10 beats) were calculated for each subject in the two different positions. All the statistical analysis was performed by IBM SPSS statistics 22. A parametric paired T-test was run on all the data and only the features that changed significantly ($p<0.05$) for all the subjects were selected. In order to represent the trend of the features the following convention was adopted: two arrows pointing down (↓↓) were used to indicate a significant decrease in the feature while standing. Two arrows pointing up were used in case of significant increase (↑↑).

C. Classification and Model

After selecting the ECG features that changed significantly ($p<0.05$), the correlation matrix was calculated in order to select uncorrelated features for the development of an automatic classifier to detect automatically when a subject was lying down. The method used was the Linear Discriminant Analysis (LDA). LDA aims to find linear combinations of the input features that can provide an adequate separation between two classes, in the current study, lying down vs standing up. The discriminant function used by LDA was built up as a linear combination of the variables that seek to maximize the differences between the classes[13]. The performance of the classifier was evaluated by computing the rate of correctly recognized lying down (true positives, TP), the rate of correctly recognized standing up (true negatives, TN), the rate of non-recognised lying down (false negative, FN) and the rate of standing classified as lying down (false positive, FP) [13-15]. These four counts constitute a confusion matrix [13-15].

Finally positive predictive value, negative predictive value, total classification accuracy, sensitivity and specificity rate were calculated as shown in Table 2.

Table 2 Binary classification performance measures

Measure	Abbreviation	Formula
Total Classification Accuracy	ACC	$\frac{TP+TN}{TP+TN+FP+FN}$
Sensitivity	SEN	$\frac{TP}{TP+FN}$
Specificity	SPE	$\frac{TN}{FP+TN}$
Positive Predictive Value	PPV	$\frac{TP}{TP+FP}$
Negative Predictive Value	NPV	$\frac{TN}{TN+FN}$

Total classification accuracy represents the ability of the classifier to discriminate between the two sessions, sensitivity refers to the ability to identify records while lying down and specificity refers to the ability to identify records while standing[13].

To estimate the performance measures leave-one-out cross validation was performed.

III. RESULTS

The results are reported in Table 3. The T-test analysis revealed that the following four ECG features (Rwave (μV), STinterval (ms),Twave (ms) and Twave (μV)) changed significantly ($p<0.01$) between lying down and standing up. All the selected features increased significantly while lying down as shown by the trends reported in Table 3.

Table 3 ECG feature analysis

ECG Feat.	Standing up		Lying down			
	Mean	**SD**	**Mean**	**SD**	**T***	**P-val.**
Rwave(μV)	0.078	0.004	0.108	0.002	↑↑	<0.01
STinterval (ms)	282.7	8.29	314.9	3.313	↑↑	<0.01
Twave(ms)	203.2	11.1	217.7	5.388	↑↑	<0.01
Twave(μV)	0.015	0.002	0.025	0.001	↑↑	<0.01

The correlation matrix showed that Twave (ms) and Twave (μV) were significantly correlated ($\rho<0.01$) with STinterval (ms) and Rwave (μV) respectively. The classifier achieving the highest accuracy is based on the subset of features, STinterval (ms) and Rwave (μV) with sensitivity rate of 81.8%, specificity rate of 72.7%, and total accuracy classification of 77.3%.

The classification rule can be expressed as follows:
the record is classified as lying down if:

$$0.05*STwave - 0.302*Rwave - 14.912 > 0 \quad (1)$$

Furthermore, the classification rule could be represented as in Fig. 2, if a subject's score on the discriminant function is close to 0.8, then probably the subject was lying down.

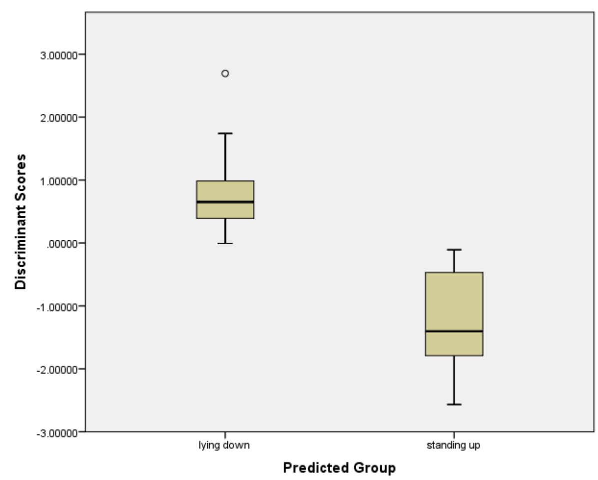

Fig. 2 Box plots illustrating the distribution scores for the two groups

IV. CONCLUSIONS

This paper presents the preliminary results of a proof of concept study investigating where ECG morphology changed significantly while lying down or standing up in order to investigate in principle if wearable ECG sensors can be used to automatically detect postural changes (lying and standing) and subsequently falls, instead of using accelerometers.

It is well established that a change in body position causes a change in the position of the heart [16], therefore, the aim of this study is to quantify those changes in a control population and to show that these changes in ECG features (Rwave(μV), ST interval(ms)) can be used in principle to detect changes in positions (lying vs standing). This is an interesting result as ECG is widely used also to monitor other adverse cardiovascular events and is widely accepted among elderly people. In other words, since assistive devices that could help to relieve the fall problem are necessary and the health devices on the current market present privacy concerns and they are only limited to the detection of falls based on accelerometer signals, an ECG sensor could provide a perfect combination of detecting falls and cardiovascular problems which are quite frequent among the elderly.

In conclusion, this study is the first step to understand if ECG morphology could be used to detect postural changes, starting with studying only two distinct positions (lying vs standing). The results presented in this study encourage us to study the ECG morphology not only in real-life scenario as in different postural changes but also in simulating falls.

Therefore, further studies are necessary to understand how ECG features changes in transition postural changes and in elderly subjects simulating falls.

It is worth of highlighting that the model presented in this paper was trained only to detect ECG significant changes in two distinct postural positions (lying vs standing). This informed the design of more complex studies aiming to extend this approaches to more realistic scenarios, including: enrolling older subjects, eventually suffering from other cardiovascular diseases; inserting other experimental conditions more significant for falls (i.e. lying down voluntarily, vs lying down after a fall), integrating this approach based on ECG with other signal sensing.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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