Editorial Manager(tm) for Annals of Biomedical Engineering
Manuscript Draft

Manuscript Number: ABME1350R1

Title: Impact of Ambulation in Wearable-ECG

Article Type: Research Article

Section/Category:

Keywords: Ambulatory ECG, activity levels, body movement, impact signal, motion artifacts, principal component analysis, acceleration, treadmill test.

Corresponding Author: Tanmay D Pawar,

Corresponding Author's Institution: IIT Bombay

First Author: Tanmay Pawar

Order of Authors: Tanmay Pawar; Anantakrishnan N. S.; Subhasis Chaudhuri; Siddhartha P Duttagupta; Tanmay Pawar

Manuscript Region of Origin:

Abstract: Ambulatory ElectroCardioGram (ECG) analysis is adversely affected by motion artifacts induced
due to body movements. Knowledge of the extent of motion artifacts could facilitate better ECG analysis.
In this paper, our purpose is to determine the impact of body movement kinematics on the extent of ECG motion artifact by defining a notion called impact signal. Two approaches have been adopted in

this paper to validate our experiments. One of them involves measuring local acceleration using motion sensors at appropriate body positions, in conjunction with the ECG, while performing routine activities at different intensity levels. The other method consists of ECG acquisition during Treadmill testing at controlled speeds and fixed duration. Data has been acquired from both healthy subjects as well as patients with suspected cardio-vascular disorders. In case of patients, the treadmill tests were carried out under the supervision of a cardiologist. We demonstrate that the impact signal shows a proportional increase with the increasing activity levels. The measured accelerations obtained are also found to be well correlated with the impact signal. The impact analysis thus indicates the suitability of the proposed method for quantification of body movement kinematics from the ECG signal itself, even in the absence of any accelerometer sensors. Such quantification would also help in automatic documentation of patient activity levels, which could aid in better interpretation of ambulatory ECG.

Dear Dr. Pawar:

Your manuscript, "Impact of Ambulation in Wearable-ECG," by Tanmay D Pawar (Corresponding Author), Tanmay Pawar; Anantakrishnan N. S.; Subhasis Chaudhuri; Siddhartha P Duttagupta; , has been reviewed by an Associate Editor and referees who specialize in the subject matter addressed by the submitted material. The general and specific comments of each referee are included with this email (at bottom). The referees feel the study addresses an important issue. In addition, they agree that the results are interesting, but some revisions are required before the manuscript can be accepted.

The acceptance of your manuscript for publication will depend upon a favorable review of your revision by the Associate Editor and possibly the referees. Please be sure to include a detailed response to the referees' comments.

Submit your revision at http://abme.edmgr.com

Your Username is: tanmaypawar
Your Password is: viplab

Click Author Login.

We congratulate you and your colleagues on an excellent study.

Sincerely,
Dr. Raymond Ideker and Dr. Larry V. McIntire, Editor
Annals of Biomedical Engineering

Authors' response to the review

We are very much thankful to the editors for their encouraging words. We are also thankful to the reviewers for encouraging comments and constructive comments about our work. Here we give a detailed response to each of the comments and suggestions made by reviewers.

Comments for the Author:

Reviewer #1: This paper describes an interesting aspect of measuring the patient's physical activity based on noise from the recorded ECG-signals. The work carried out is done in a proper way, and is documented acceptably. However, it is not mentioned what type of ECG equipment and ECG electrodes are used. Those are important factors in how the actual measurements of the ECG-signals are influenced by motion artefacts, and hence for the measurements of the physical activity by the principles used in this paper, those can be quite different with other types of equipment. If possible, different types of ECG recorder and electrodes should be used at the same test person in order to validate this method.

Answer: We agree with the reviewer's concern about possible variations due to use of different ECG recorders. However, we have specified the frequency range and sampling frequency specifications for the ECG recorders used in our studies. We think that these are the most important parameters, particularly, the lower cut-off frequency (0.05Hz) of the ECG recorder (since the motion artifacts are concentrated in <10Hz) for the given application. We have now also mentioned that we have used disposable foam-pad electrodes for ECG recording, which are widely used for ambulatory ECG recording.

Reviewer #2: The manuscript 'Impact of Ambulation in Wearable-ECG' by Pawar et al. is well written and certainly of interest for the ABME audience.

I have, however, some concern with the MS:

(1) Introduction, first sentence: The authors state that today's active lifestyle is associated with an increase of cardiovascular disorders. Is there any evidence for that? Pls. cite the source!

Answer: We agree that the use of the word **'associated'** is unsubstantiated and hence we now remove it and corrected the sentence to '…today's active lifestyle **and** the increase in cardiovascular disorders…'

(2) P12, last sentence of the paragraph: displacement should be gamma, not beta?!

Answer: Thanks for the correction, we have now changed it to 'displacement \gamma_{k}(n)'.

(3) The presentation of the results (page 12) appears to be qualitative rather than quantitative. The authors show a number of figures (4-9) that display example traces of impact signal and acceleration. I don't think all these graphs are really necessary. It is probably more appropriate to focus on group statistics as in table 2.

Answer: We agree with the reviewer. But this being the first of a kind report of such an investigation, we feel that the general readers of ABME will find these plots very useful in future bench marking efforts. Other two reviewers seem to have liked them. Nonetheless, we have removed one plot (Fig. 6 in earlier version of the manuscript) during revision.

(4) Fig. 11 and 12. It would be more interesting to see group averages and error bars.

Answer: Purpose of these plots is to know the near linear relationship between acceleration and the impact signal. Hence they are retained. Group average behavior for another study has already been given, as suggested, in Fig. 10.

(5) Fig. 13 is not very informative. I think most interested readers would be familiar with cross-correlation functions.

Answer: Figure removed as suggested.

(6) It would be interesting for the reader to see some ECG traces with and without movement artifacts.

Answer: We have now added sample ECG traces as suggested (Fig. 4).

(7) P15: The conclusion is quite long (almost one page). The authors should not repeat hypothesis, methods and results and limit this section to their main findings.

Answer: Done as suggested.

(8) I did not find any statement regarding subject / patient consent or ethics committee agreement.

Answer: We have now clarified it in Section II- Data acquisition. "In the case of patients, treadmill testing was done using the Bruce protocol in the clinical setup **with prior permission from the ethics committee of the hospital** under strict medical supervision, with simultaneous monitoring of vital parameters such as heart rate and blood pressure, and other stipulations in accordance with the AHA guidelines [21]. **The procedure and the purpose in this experiment were explained to the patients and their consents for the same were obtained by the hospital**."

Reviewer #3: The proposed paper is well structured however i would like that the authors take into account the following corrections and comments:

corrections:

in page 4:

line7: correct the corresponding sentence as follows: is derived from the RPCA method. We then demonstrate... – **Done as suggested.**

line 27: have been shown in [16] to be well correlated.. – **Done as suggested.**

line 44: for the development of a simple... – **Done as suggested.**

In page6:

line14: that which have been done in [12],[13], here both the experiments and the purpose are different. – **Done as suggested.**

Lines 15 up to 22: try to reformulate the sentence [Here.......the impact analysis] it is not very clear. – **It has been redrafted and the presentation is improved.**

line 37: and the gradient – **Done as suggested.**

in page7:

line 18: mix of the cardiac signal—**Done as suggested.**

line 33: to feature alignment, it is required—**Done as suggested.**

in page8

line 14: define in the formula 2 the error e(i) – **Done as suggested.**

line 19: in the analysed ECG signal. – **Done as suggested.**

line 25: this subsection focuses on .... – **Done as suggested.**

line 56: the writing of the equation in formula 4 is not clear. – **The equation has been appropriately modified and properly explained.**

in page 22: correct the legend in the table: gradient instead of grade – **Done as suggested.**

Comments:

in p6 line 38: precise what the value of the target heart rate. Try to give examples of signs of instability and other parameters.

Answer: Now we have added there. "The target heart-rate is calculated as 0.85X(220− age of patient in years) for each patient."

in p7 line 20: precise where it has been demonstrated. is it your result? if not provide a reference.

Answer: Yes, it is our result in [11] and [12], and now we have mentioned it there. “It has also been demonstrated in [11], [12] that motion artifact subspaces for different body movements are separable,..”

in p7 line 38: there are limits in which heart rate is considered normal, what are these limits you have chosen in your application?

Answer: Now we have provided the range of the heart-rate which we encountered in our ECG data sets. “In our experiments presented here, we encountered the heart-rate variations from 64 to 160 (under treadmill test) beats per minute.”

in p8 line 51: explain briefly why a time window of 8seconds is used.

Answer: Reason for selecting a time-window of 8 seconds is now explained there, **“**We have observed that the maximum time required to complete one cycle of any body movement activity was \approx 5 seconds, considering that each of the activities are periodic in nature. Therefore, we expect that the useful information in the acceleration signal lies in the spectrum band \ge 0.2Hz. Since we are interested in capturing accelerations due to movements of body only, we suppress the undesirable lower frequency components (< 0.2Hz) of the acceleration using the time-window of 8 seconds.”

in p10 line 27: give a brief description of such standard preprocessing techniques.

Answer: Now we have described these techniques there: “In [23], an adaptive, model based technique is proposed for estimation of width and shape parameters of the QRS complex. Autoregressive modeling of envelops of discrete cosine transform coefficients of the QRS complex is proposed in [24]. Application of a neural network for classification of normal and abnormal ECG beats is proposed in [25].”

in p11 line 14-15: How 68% cases is obtained? explain briefly.

Answer: We have now tried to explain it in brief, “If **for a given speed of the treadmill**, the impact signal is assumed to be Gaussian distributed, this would mean that, given the measure of the impact signal \epsilon, one can correctly identify the treadmill speed in more than 68% cases as the area of a Gaussian probability density function within the range [m-\sigma, m + \sigma] is about 0.68.”

in p12 line 31-32: precise how the posture change can be identified from the plot. Is it by successive peaks?

Answer: Yes. “From the plot of the impact signal, the exact instants when the posture changes were effected can be identified **by successive peaks**.”

Impact of Ambulation in Wearable-ECG*

Tanmay Pawar, N. S. Anantakrishnan, Subhasis Chaudhuri and Siddhartha P. Duttagupta

Department of Electrical Engineering, Indian Institute of Technology-Bombay, Mumbai - 400076. INDIA.

Phone: +91 22 2576 7401, 7402

Fax: +91 22 2572 3707

Email: tanmaypawar@iitb.ac.in, (ananthaks, sc, sdgupta)@ee.iitb.ac.in

*A preliminary version of the manuscript under very restrictive cases of validation with motion sensors and involving healthy subjects only has earlier been presented at IEEE EMBC (Engineering in Medicine and Biology Conference) - 2007 held at Lyon, France on 23-26 Aug. 2007.

Abstract

Ambulatory ElectroCardioGram (ECG) analysis is adversely affected by motion artifacts induced due to body movements. Knowledge of the extent of motion artifacts could facilitate better ECG analysis. In this paper, our purpose is to determine the impact of body movement kinematics on the extent of ECG motion artifact by defining a notion called impact signal. Two approaches have been adopted in this paper to validate our experiments. One of them involves measuring local acceleration using motion sensors at appropriate body positions, in conjunction with the ECG, while performing routine activities at different intensity levels. The other method consists of ECG acquisition during Treadmill testing at controlled speeds and fixed duration. Data has been acquired from both healthy subjects as well as patients with suspected cardio-vascular disorders. In case of patients, the treadmill tests were carried out under the supervision of a cardiologist. We demonstrate that the impact signal shows a proportional increase with the increasing activity levels. The measured accelerations obtained are also found to be well correlated with the impact signal. The impact analysis thus indicates the suitability of the proposed method for quantification of body movement kinematics from the ECG signal itself, even in the absence of any accelerometer sensors. Such quantification would also help in automatic documentation of patient activity levels, which could aid in better interpretation of ambulatory ECG.

Index Terms

Ambulatory ECG, activity levels, body movement, impact signal, motion artifacts, principal component analysis, acceleration, treadmill test.

Impact of Ambulation in Wearable-ECG*

I. Introduction

Recently, significant interest has been generated in Holter or wearable ElectroCardioGram (W-ECG) studies, driven by today's active lifestyle and the increase in cardiovascular disorders. There are two major problems associated with Holter ECG recording. One of them is the contamination of the ECG signal due to motion artifacts induced by the body movements of the subject during ambulation. Owing to spectral overlap between the artifacts and the ECG signal, linear filters cannot be used to effectively minimize motion artifacts. To ensure that the Holter ECG recorder does not impede the subject's daily activities, a recent focus in ambulatory cardiac monitoring is on highly miniaturized, wearable ECG data acquisition systems. The *Silicon Locket*, which weighs just under 100 grams is one such available system [1]. Although this makes patient ambulation quite unencumbered, the problem of motion artifacts in the ECG data remains as this is generated due to variable contact resistance between the stretching or contracting skin and the electrode. Motion artifact reduction in W-ECG has been a topic of active research, and several methods have been used, with limited success.

The other common shortcoming in W-ECG monitoring is the documentation of daily patient activities; an accurate diary is desired to facilitate better analysis of the ECG 'in context' [2]. Conventional Holter monitoring systems rely on manual time stamping of activities, which is unreliable. W-ECG systems with patient-activity monitoring attempt to address this problem, by incorporating accelerometers with ECG recording apparatus, in order to provide evidence based information about patient activity levels [2], [3], [4], [5]. Techniques exploring the recognition of specific activities and postural changes of the subject from the ECG itself have been discussed in [6], [7], [8], [9], [10], [11], [12], but these methods do not aim at detecting intensity levels of the activity. In this paper, we quantitatively investigate the precise impact of different levels of body movement activity on the generation of ECG motion artifacts, with a view to overcoming both these problems mentioned earlier.

It has been shown in [13], that it is possible to detect the onsets of body movements, or transitions from one movement to another, from the ECG signal itself using a recursive principal component analysis (RPCA) based method [14]. This is based on the fact that different types of body movements affect the skin-electrode interface differently. In this paper, we first define a notion called impact signal which is derived from the RPCA method. We then demonstrate through a number of experiments that the proposed impact signal can be applied for impact analysis of body movement activity, and consequently, for determining different levels of body movements from the ECG signal itself. We show that it is a measure of induced motion artifact on the ECG signal.

For quantifying subject activity, we have performed two different sets of experiments; one using the treadmill test, and the other using commercially available accelerometers. The treadmill test, a benchmark in exercise-stress testing for cardiac patients, is calibrated in terms of energy expenditure for standard test protocols, like the Bruce Protocol. The output from triaxial accelerometers on the human body have been quantified as a function of energy expenditure in [15], and hence the activity level of a subject. Accelerometer activity and treadmill speeds have been shown in [16] to be well correlated. Accelerometry has been used for studies of body movements in [17], [18], [19]. We report our observations on the magnitude of the impact signal in relation to the walking speed of the subject in the treadmill test, as well as the recorded accelerations while performing several types of body movements at three different intensity levels: slow, normal and fast. We thus show that body movement activity (BMA) levels can be quantified from the ECG signal itself using the impact signal, without using any sophisticated motion sensors. In other words, we demonstrate that it is, indeed, possible to have a truly unencumbered ambulatory cardiac monitoring system without the use of multiple inputs from accelerometers tethered to the body, with activity detected from just a single lead of the ECG. This is useful for the development of a simple, low cost, ECG monitoring system which can automatically provide information about BMA from the ECG signal.

The paper is organized as follows: Section II provides details of the apparatus and the protocols used for data acquisition. The method used to obtain the impact signal from the ECG and processing of the accelerometer data is described in Section III. The results and discussion are presented in Section IV. The paper concludes in Section V.

II. Data Acquisition

The specifications of the ambulatory ECG recorder used in this study are as follows: single-lead, bandwidth- 0.05 to 106 Hz, sampling frequency- 242 Hz, A/D conversion- 12 bits/sample [1].

The Lead-II ECG configuration was chosen to maintain consistency, and also to capture motion artifacts from the lower body. Disposable foam-pad electrodes are used for the same purpose. We have followed two different procedures for motion quantification, one measuring accelerations using motion sensors, the other using a treadmill.

Accelerations were measured using *MTx*® motion trackers from *Xsens Motion Technologies*® placed at appropriate positions on the body. The *MTx*® motion tracker senses linear acceleration along 3 axes along with the 3-D rotations of the sensor co-ordinate system in a fixed local co-ordinate system (LCS). The fixed LCS has its positive (+ve) X pointing toward the local magnetic North, +ve Y toward the West and +ve Z pointing upwards. All accelerations and rotations were measured at 32-bit resolution and sampled at 25Hz. A blue tooth wireless interface was used to transmit data. Very recently, a similar data acquisition system has been used for ambulation analysis and assessment of human ankle and foot [20].

Motion sensors were placed on the upper arm(s), right thigh and the waist (below the navel). The waist sensor measured the local acceleration at the waist while twisting, and the general acceleration of the subject's body during other activities. The accelerometers at the arm(s) and on the thigh measured local accelerations in these parts. Motion trackers were tightly strapped at their respective positions on the subject's body to prevent slippage or any relative motion between the sensor and the body. However, it was also ensured that the subject faced minimal discomfiture after wearing the ECG electrodes and the motion sensors, such that the usual body movement of the subject remains unaffected. For better understanding of events recorded by motion sensors as well as for *post facto* verification, all activities of the subjects were time-stamped and recorded using a video camera. The starting and ending times for ECG and motion recording were noted down for data analysis. The experimental setup is illustrated in Fig. 1, with the motion sensor apparatus and electrodes of the W-ECG recorder firmly secured at appropriate locations on the body of a subject.

In the first set of experiments involving motion sensors, each of the following BMAs were performed at three different levels of pace: slow, normal and fast.

1) change in posture from sitting on a chair to standing up, and vice versa,
2) up-down movement of one of the two arms, left or right, parallel to the sagittal plane, with the other hand at rest
3) walking on a level floor,

4) twisting the torso at the waist while standing, as a common body stretching activity,
5) climbing up and down the stairs,

A total of 5 healthy male subjects in the age group of 22 to 27 years and 2 cardiac patients of ages 31 and 62 years participated in this experiment. The subjects were requested to avoid undue tightening of muscles of freely movable limbs, to avoid extra EMG noise due to muscle stiffness. It should be noted that though the activities in the list above are apparently similar to those which have been done in [12], [13], here both the experiments and the purpose are different. Here we vary the pace of performing the BMAs to analyze the corresponding impact on generation of motion artifacts in ECG whereas the previous works are intended for recognition of commonplace BMAs in routine life and hence the exact impact of the variations in the pace levels has not been studied.

In our second set of experiments, the ECG of a subject was monitored while walking at controlled speeds for fixed durations on a Treadmill (Quinton®). Data was acquired from 5 healthy volunteers in the age group from 22-26 and 9 cardiac patients in the age group of 39-63. In the case of patients, treadmill testing was done using the Bruce protocol in the clinical setup with prior permission from the ethics committee of the hospital under strict medical supervision, with simultaneous monitoring of vital parameters such as heart rate and blood pressure, and other stipulations in accordance with the AHA guidelines [21]. The procedure and purpose in this experiment were explained to the patients and their consents for the same were obtained by the hospital. The Bruce protocol subjects the patients to increasing levels of stress by increasing the speed and the gradient (treadmill inclination), as given in Table I. For the cardiac patients, the test was terminated as soon as the target heart rate was reached, or when signs of instability were observed in the ECG or in the other parameters for example, significant ST level and slope changes, substantial increase in blood pressures as decided by the trained physician, patient complaining about breathlessness, angina, pain in legs or chest. The target heart-rate is restricted to $0.85 \times (220 - age\ of\ patient\ in\ years)$ for each patient. Stress-ECG data from the healthy volunteers was obtained using a treadmill exercise protocol that was physically less taxing than the conventional Bruce protocol used in the clinical setup. The protocol was devised considering the lack of medical supervision and online parameter monitoring facilities in the laboratory setup. The gradient was set to zero throughout the test, and each stage was limited to two minutes compared to three minutes in the Bruce protocol. There were 5 stages in all for a total duration of 10 minutes, starting from 3 km/hr to 7 km/hr in increments of 1 km/hr at every stage. The heart rate of the subjects was monitored every minute, using a pressure sensor attached to the chest, communicating via infrared to a display device that could be worn on the wrist for easy viewing of the heart rate in beats per minute. Accelerometers were not connected during the treadmill exercise since the motion is directly measurable from the treadmill, and to ensure that movement on the treadmill was not cumbersome.

III. Experimental Method

We note that slow body movements may induce motion artifacts of smaller magnitude whereas quick body movements are likely to induce larger motion artifacts. At rest, there are usually no motion artifacts at all. Thus different levels of body movements may have different impact on the motion artifacts and hence on the ambulatory ECG signal. The ambulatory ECG signal can be modeled as an additive mix of the cardiac signal and the motion artifacts induced by body movements [11], [12]. It has also been demonstrated in [11], [12] that motion artifact subspaces for different body movements are separable, and can be effectively represented by a set of the top few (6-8) eigenvectors, which can be learned through principal component analysis (PCA). We have used the impact signal obtained through recursive PCA to gauge these different levels of the motion artifact.

A. Derivation of Impact Signal

Since we are using PCA based method which is sensitive to feature alignment, it is required that the input data vectors have the same dimension. The ECG beats are therefore time synchronized with respect to R-peak in each beat, and resampled to a fixed length of M_0 samples, to account for possible Heart Rate Variability (HRV). The value of M_0 is chosen based on the normal heart-beat duration and the given sampling rate of the ECG recorder. In our experiments presented here, we encountered the heart-rate variations from 64 to 160 (under the stress test) beats per minute. The R-peaks in the ECG signals are detected using a modified Pan-Tompkins algorithm [22]. The current ECG beat length is estimated as the duration between the current R-peak and the previous one.

In order to estimate the principal components, the covariance matrix C_i is recursively computed from the i^{th} length normalized and mean-subtracted ECG beat $\underline{r}(i)$ as

$$C_i = \sum_{k=1}^{i} \alpha^{(i-k)} \underline{r}(k) \underline{r}^T(k) = \alpha C_{i-1} + \underline{r}(i) \underline{r}^T(i), \tag{1}$$

where $\alpha,\ 0 < \alpha < 1$ is the *forgetting factor*. Past data is forgotten faster for smaller α. A set of top L eigenvectors of the covariance matrix C_i at i^{th} ECG beat is derived using (1). Let $E_i = [\underline{e}_{i1}\ \underline{e}_{i2} \ldots \underline{e}_{iL}]_{M_0 \times L}$ be the set of top L eigenvectors arranged in a non-ascending order of magnitudes of the corresponding eigenvalues. To quantify the variation in the ECG signal due to motion artifacts, we obtain from the next ECG beat $\underline{r}(i+1)$ the component that lies in the span $\{\underline{e}_{i1},\ \underline{e}_{i2}, \ldots, \underline{e}_{iL}\}$. The error in approximation

$$\epsilon(i) = |\underline{r}(i) - (E_{i-1} E_{i-1}^T) \underline{r}(i)| \tag{2}$$

provides a measure of the motion artifact level in the ECG i.e. the impact of body movement in ambulatory ECG signal. The error $\epsilon(i)$ defined in (2) is called the impact signal for the i^{th} beat in this paper. The impact signal could be non-uniform on the time-scale as the heart rate may change with time for a particular subject, with time instants calculated from the R-peak locations of the corresponding beat indices i in the analyzed ECG signal.

B. Processing Accelerometer Data

This subsection focuses on procedures involved in computing local acceleration signals at a position with reference to the body. The motion sensor system described in Section II records accelerations in sensor axes and rotations of the sensor axes in the fixed local co-ordinate system (LCS). Since the sensor axes are rotating with the body during movements, all accelerations are converted to the fixed LCS using the rotation matrix of direction cosines for each individual sensor. Let $R_k(n)$ be the 3×3 rotation matrix in the fixed LCS and $\underline{a}_k(n) = [a_{kx}(n)\ a_{ky}(n)\ a_{kz}(n)]^T$ be the 3-axes acceleration vector recorded at nth sample for the kth accelerometer (at a suitable body position) respectively. It may be noted that the time index 'n' is different from the heart beat index 'i' discussed in the previous subsection. The corresponding accelerations $\underline{a'}_k(n) = [a_{kX}(n)\ a_{kY}(n)\ a_{kZ}(n)]^T$ in the LCS can be computed as

$$\underline{a'}_k(n) = R_k(n) \underline{a}_k(n). \tag{3}$$

Measured accelerations $\underline{a}'_k$ have static components corresponding to gravity and general translation of the body, as well as dynamic components associated with local limb motion. To account for only the local limb movements, the static components are suppressed by local mean subtraction, calculated over a moving time-window of 8 seconds, from each element of the acceleration $\underline{a}'_k(n)$. We have observed that the maximum time required to complete one cycle of any body movement activity is ≈5 seconds, considering that each of the activities is periodic in nature. Therefore, we expect that the useful information in the acceleration signal lies in the spectrum band $\geq$ 0.2Hz. Since we are interested in capturing accelerations due to movements of body only, we suppress the undesirable lower frequency components ($<$ 0.2Hz) of the acceleration using the time-window of 8 seconds. The local mean subtracted acceleration due to the motion of the k^{th} limb is given by $\underline{a}''_k(n) = \underline{a}'_k(n) - \overline{a}_k(n)$, where the local mean signal $\overline{a}_k(n)$ is given by

$$\overline{a}_k(n) = \frac{1}{8f_s + 1} \sum_{j=n-4f_s}^{n+4f_s} \underline{a}'_k(j), \tag{4}$$

where f_s=25Hz is the sampling frequency for the motion sensor and hence $[-4f_s,\ 4f_s]$ is the 8 seconds time window over which the signal is to be averaged out. The movement of the k^{th} limb (sensor) is quantified in terms of the norm of the acceleration vector $\beta_k(n) = |\underline{a}''_k(n)|$. In this paper, k=1 refers to the sensor at the right arm, k=2 to the right leg sensor, k=3 is the sensor at the waist and k=4 refers to the sensor at the upper left arm. Hence, we would like to relate the impact signal $\epsilon(i)$ in the recorded ECG, as discussed in the previous subsection, to the limb motion $\beta(n)$ and show that they are highly correlated.

To study the behavior of motion artifacts with respect to extent of movement, displacements of individual sensors need to be obtained. The extent is defined as the distance between two extreme positions during limb movement. The relative position of the kth sensor at the nth sample, $\underline{p}''_k(n)$ is computed by simple discrete integration of the corresponding accelerations $\underline{a}''_k$ twice in time using the trapezoidal rule.

The extent of a body movement from the initial position is computed as the norm of vector $\underline{p}''_k(n)$, as $\gamma_k(n) = \|\underline{p}''_k(n)\|$. The envelope of $\gamma_k(n)$ gives the extent of the body movement. While $\beta(n)$ is a measure of the instantaneous motion of a limb, $\gamma(n)$ could be viewed as a measure of the combined effect of physical stretching of the surrounding skin along with contraction of the associated limb muscles.

C. Synchronization of Impact Signal and Motion Measures

We again reiterate the fact that for the impact signal, we use the index 'i' to denote time axis, while we use the index 'n' to denote time while measuring acceleration. This is due to the fact that

(a) the impact is measured at every heart beat and

(b) the sampling frequencies for the ECG and the motion sensors are different.

The two indices are related in time as $n = \kappa(i)$, where κ is a function of the time instances of occurrence of each QRS complex in the input ECG. In order to synchronize the acceleration and impact signals, we need to calculate the cross-correlation ρ between them.

To compensate for sampling differences between the ECG and accelerometer data while computing ρ, the impact signal is upsampled to 242 Hz (sampling frequency of the ECG recorder) using cubic spline interpolation, and then downsampled to 25 Hz (sampling frequency of the motion sensor). This two stage process is required because the impact signal is non-uniformly sampled on the time-scale as the R-R interval may vary with time for an individual. As the motion sensor and ECG acquisition start times could be slightly different, it is also essential to have an automatic means to calculate the time delay between the two start times. The location of the peak of the cross-correlation between the motion sensor data $\beta_k(n)$ and the time warped impact signal $\epsilon(i)$ was used as a measure of this time delay to synchronize the ECG and motion sensors. Having synchronized the two sensors, the index function $\kappa(i)$ can be easily computed from the warped impact signal. The usefulness of the function $\kappa(i)$ will be clear in the next section when the data from two different sensors are compared at a given instant of time.

IV. RESULTS

Continuous Lead II ECG signals are recorded as described in Section II for the Treadmill and the BMA Tests. The results for these two experiments are reported separately. Data are collected both from healthy subjects as well as patients with cardiac disorders. In case of patients, ectopicity in QRS complexes are manifested as major spikes in the impact signal, as mentioned in [13]. To obtain a correct estimate of the impact in these cases, ectopics have to be separated from the input data stream by standard preprocessing techniques discussed in the literature [23], [24], [25]. In [23], an adaptive, model based technique is proposed for estimation of width and shape parameters of the QRS complex. Autoregressive modeling of envelops of discrete cosine transform coefficients of the QRS complex is proposed in [24]. Application of a neural network for classification of normal and abnormal ECG beats is proposed in [25]. Having detected the ectopic beat, one may simply discard the abnormal spikes in the impact signal. However, owing to the inability in handling frequent ectopics, the method is not found to work well in subjects where ventricular bigeminy is observed, i.e. one normal QRS complex followed by one ectopic, alternately.

A. Experiments on the Treadmill

In the experiment involving the treadmill, our endeavour was to find a relation between the impact signal and the treadmill speed for quantification of the impact signal. Most subjects took some time to adjust to the movement on the treadmill during the first stage of the exercise due to the sudden and jerky start, which consequently affected their gait for reactive stabilization, and resulted in increased motion artifacts. We report our findings for healthy subjects and cardiac patients separately as below:

1) Case I (Healthy Subjects): Data from healthy volunteers are acquired with different treadmill speeds at zero inclination. Once the subject was settled on the treadmill, the impact signal (ϵ) showed an increase in amplitude with increasing treadmill speed. This is illustrated in Fig. 2, in which are plotted the mean impact signal estimates (m), along with the standard deviation (σ), for a given treadmill speed. This clearly demonstrates that as the human motion activity increases, it can be easily captured from the impact signal derived from the ECG signal itself. The discrepancy in the plot at the beginning is due to jerky start of the treadmill as explained earlier. The variance of the impact signal strength at a given treadmill speed, shown in this plot, makes a very interesting observation. We observe that, for the jth speed

$$m_j + \sigma_j < m_{j+1} - \sigma_{j+1}.$$

If for a given speed of the treadmill, the impact signal is assumed to be Gaussian distributed, this would mean that, given the measure of the impact signal ϵ, one can correctly identify the treadmill speed in more than 68% cases as the area of a Gaussian probability density function within the range $[m - \sigma,\ m + \sigma]$ is about 0.68. Given that we are working with a single lead ECG recorder, this can be considered quite an accurate measurement technique. Computing the cross-correlation between the impact signal and the treadmill speeds yields a typical correlation coefficient of $\rho = 0.95$, which also indicates a strong collinearity among them.

2) Case II (Cardiac Patients): Patients who undertook the stress test could barely complete 3 stages of the Bruce Protocol. The impact signal for one such subject is shown in Fig. 3(a-b). As in case of normal subjects, ϵ increases with increasing treadmill speed. From the plot of mean impact signal estimates (m) in Fig. 3(b), we find that

$$m_j + \sigma_j < m_{j+1} - \sigma_{j+1}$$

described in Case I, again holds true. The discrepancy in the value of ϵ in the first stage as explained earlier is also observed here. This suggests that the impact signal provides a good estimate of treadmill speeds irrespective of whether the QRS complexes of the subject are normal or abnormal.

There is a small treadmill inclination associated with the Bruce protocol, which increases gradually with every stage. We have ignored this inclination, as magnitude of this slope is very small at the first few levels of the protocol.

The treadmill exercise involves putting the heart through a certain amount of stress, with peak heart rates touching 150 beats per minute. Such stress may result in temporary morphological changes in the ECG, more so in case of patients with ischemic heart disease [21]. The nearly linear trend of the impact signal with respect to the treadmill speed despite these morphological variations can be explained by the fact that these changes are gradual compared to motion artifacts, and the RPCA method adapts itself to gradual variations. From this we conclude that the impact signal provides a good estimate of activity levels even when the heart is subjected to high levels of stress.

B. Experiments with Motion Sensors

In our experiment with motion sensors, since our objective was to evaluate the applicability in ambulatory ECG monitoring, some typical BMAs were chosen as explained in section II. The impact signal is derived from the ECG signal described in Section III-A, while the motion data was analyzed according to the procedure given in Section III-B. The goal here is to determine a relationship between the impact signal $\epsilon(i)$ with the kinematic measures like acceleration $\beta_k(n)$ and displacement $\gamma_k(n)$.

Before we quantify the effect of ambulation on the acquired ECG, we illustrate the effect by plotting the ECG traces for a normal subject with and without the body movement in Fig. 4. The sample ECG under a sedentary condition without any body movement is shown in Fig. 4(a). The corresponding ECG trace for the same subject while moving his left arm is shown in Fig. 4(b). Fig. 4(c) shows the effect of walking for the same subject. It is quite clear from the plots that the corresponding ECG traces are very different in terms of ambulation artifacts.

First, we look at the impact of posture changes, requiring subjects to sit down and stand up alternately at three different intensity levels: slow, medium and fast, with a motion pause of nearly 20 seconds in between. The impact signal for a subject due to these posture changes is shown in Fig. 5(a), while the corresponding accelerations $\beta_k(n)$ are shown in Fig. 5(b-c). We observe that the magnitude of the impact signal follows the pattern of the acceleration $\beta_k(n)$, i.e. low, medium and high, indicating that the impact signal is a quantitative measure of the levels of the body movement similar to acceleration. From the plot of the impact signal, the exact instants when the posture changes were effected can be identified by successive peaks. This can be verified from the accelerometer data.

Next, we analyze the act of climbing up and down on a staircase of 36 steps, again at three different intensity levels. A rest period of 30 seconds was allowed after finishing each level. The impact signal for this activity for a subject and the corresponding acceleration signals $\beta_k(n)$ are shown in Fig. 6. From the amplitudes of signals in the figure and their time spans it is apparent that the impact signal quantifies the different levels of body movement while climbing stairs. For slow motion, both the impact signal and the acceleration measures are less in magnitude. They both increase proportionately as the pace increases.

Next, we look at the results of impact analysis of extent of body movement on the ECG signal. Arm movements have a larger extent as compared to usual leg and waist movements, as the shoulder joint is one of the most freely movable joints in the human body with a large range of motion (ROM). Hence we considered arm movement with flexion at the shoulder joint parallel to the sagittal plane of the body. For this purpose, the subject was asked to swing one of the arms to different angular extents: very small ($\pm 10^o$ from rest), small ($\pm 30^o$), moderate ($+60^o$ to -45^o) and wide ($+90^o$ to maximum ROM angle backward). Approximately the same pace was maintained throughout the different extents of arm movement, with the other arm static, at rest by the side of the body. An instance of the impact signal for this activity involving the right arm, with corresponding acceleration and displacement signals of the sensor placed on the right arm are shown in Fig. 7. Except in case of the very small extent of movement, the acceleration magnitudes for the other extents are more or less at the same level. However, there is a discernible variation in the amplitudes of the corresponding impact signal, associated with the increasing displacement levels. That shows the impact of extents, e.g. very small, small, moderate and wide movements of right arm on the ECG signal. A similar exercise was also performed with the left arm. However, for the lead-II configuration, the impact signal is not as sensitive to left arm movements as compared to right arm movements, as reported in [13]. It may be useful to adopt a different lead configuration for this case.

Analysis of the impact for different strides (extents) and speeds of walking also indicates an increase in impact signal amplitude with increase in acceleration. In addition, one also observes that for the same pace of the stride, a longer stride results in increased motion artifacts. A shorter but quicker stride may result in the same walking speed as a longer but slower stride. Looking at this from the perspective of the treadmill experiment, and considering that ϵ was almost linearly related to treadmill speed (see Fig. 2), this is an expected result. An illustration of the impact of walking is given in Fig. 8.

The motion sensor experiment also involved patients with cardiac disorders and anomalous QRS complexes. Since there is no existing protocol as yet and this experiment was not conducted under medical supervision, it was ensured that the overall intensity levels of the activity were lower for the selected patients, to avoid undue physical stress. Fig. 9(a-c) shows the results for the right hand movement activity as in II.(2) at three speeds, from a patient with a prosthetic aortic valve and a left-bundle branch block (LBBB). From the ECG, we can observe that the QRS duration is more than twice that of a normal subject, the R-wave amplitude is smaller than normal, and the S-wave is predominant. However, the resulting trends are similar to that from healthy volunteers. The Recursive PCA method was largely unaffected by the vastly different QRS morphology in case of cardiac patient data. Motion artifacts being an external influence at the superficial level of the skin, it must have similar effects on the ECG for both healthy subjects as well as those with cardiac abnormalities.

In our next attempt to analyze the acquired data, we remove the time dependence and plot the impact signal as a function of the instantaneous acceleration. This should ideally remove the human bias as we no longer know when a particular acceleration took place and what the subject was actually trying to do at that instant. The scatter plot of the impact signal for the experiment on climbing stairs vs. norm of acceleration in Fig. 10 shows the presence of well-defined clusters corresponding to different magnitudes of acceleration, underlining the fact that ϵ is a proper representative of activity levels. It is also clear that mean values of ϵ provide better estimates of activity levels than instantaneous values, although instantaneous values of the impact signal provide a fairly accurate indication of initiation or cessation of activity periods. An alternative representation of the impact signal and the corresponding norm of instantaneous acceleration after temporal smoothening is illustrated in Fig. 11 and Fig. 12, associated with the activities of walking and torso twisting, respectively. The linear relationship shows that the impact signal can be used for quantification of motion. Comparing Fig. 11 and Fig. 12, we note from the impact signal range that a smaller acceleration at the waist due to stretching of the body while twisting, causes a similar impact on the skin-electrode interface, as a larger acceleration at the leg while walking. At zero acceleration, a finite value of error (≈ 0.1) is observed, analogous to background noise, which can be attributed to the beat-to-beat variability in the human ECG even at rest.

Plotting the cross-correlation between the acceleration signal and the impact signal indicates a strong linear correlation between the two quantities in time, with a typical correlation coefficient of 0.80. The location of the peak on the correlation plot also proved to be a good estimate of the time delay between the starting of motion and ECG data, as verified from the video recording of the experiment. As mentioned in III-C, this has been used in all plots to time synchronize the acceleration and impact signals.

Presented in Table II, is a summary of the global mean (μ) and standard deviation (σ) of the coefficients of cross-correlation (ρ) and linear regression (ω) for the motion signals from representative sensors for climbing stairs and walking. The cross-correlation values are high, while the low values of the standard deviation of ρ indicate less person to person variation. In other words, the impact signal is well correlated for most of the subjects. Standard deviation values for ω are higher, indicating higher interpersonal variability in this regard. This implies that the method requires individual specific calibration for more accurate quantification of patient activity levels.

V. Conclusions

We have studied the extent of impact of body movements on generation of motion artifacts in ambulatory ECG recordings, and reported our observations on the quantification of body movements using the impact signal. The amplitude of the impact signal is shown to be very well correlated with the acceleration magnitudes at the limb locations, a fact that is verified by analyzing the signal amplitudes in time synchronization. The impact signal also shows a linear trend with the treadmill speed in case of the stress test, further validating the idea of motion quantification from the ECG data itself.

We have restricted ourselves to subjects with normal posture and gait, and results may be different in case of individuals with defects in gait. An indication of this fact is the discrepancy observed in the first stage of the treadmill test, where abnormal gait results due to difficulty in adjusting to the jerky start of the treadmill. Also for the chosen lead configuration, it is found that movements of right-arm have a greater impact as compared to similar movements of the left arm due to proximity of the sensor. Finally, we have limited our studies to single lead (lead-II) observations, and now plan to develop an equally miniature multi-lead ECG system. Additional activities could be analyzed if more than one ECG lead were available.

Acknowledgment

Partial research funding under the scheme of *Swarnajayanti* fellowship is gratefully acknowledged. Authors are thankful to Dr. M. J. Gandhi, Dr. Mohanty and other staff at Nanavati Hospital, Mumbai for their help in collecting patient data under the Bruce Protocol. Authors are thankful to the reviewers for their constructive suggestions.

References

[1] M. Shojaei-Baghini, R. K. Lal, and D. K. Sharma, “A Low-Power and Compact Analog CMOS Processing Chip for Portable ECG Recorders,” in *A-SSCC’05*, Hshinchu, Taiwan, Nov. 2005.

[2] J. Healey and B. Logan, “Wearable Wellness Monitoring Using ECG and Accelerometer Data,” in *Proceedings of the 2005 Ninth IEEE International Symposium on Wearable Computers (ISWC’05)*, Osaka, Japan, Oct. 2005.

[3] T. Yoshimura, Y. Yonezawa, H. Maki, H. Ogawa, I. Ninomiya, and W. M. Caldwell, “An ECG electrode-mounted heart rate, respiratory rhythm, posture and behavior recording system,” in *26th IEEE EMBC*, San Francisco, CA, USA, Sept 2004, pp. 2373–2374.

[4] J. Muhlsteff, R. S. O. Such, M. Perkuhn, H. Reiter, J. Lauter, J. Thijs, G. Masch, and M. Harris, “Wearable approach for continuous ECG and Activity Patient-Monitoring,” in *26th IEEE EMBC*, San Francisco, CA, USA, Sept 2004, pp. 2184–2187.

[5] J. Boyle, M. Karunanithi, T. Wark, W. Chan, and C. Colavitti, “An Observational Trial of Ambulatory Monitoring of Elderly Patients,” in *12th International Conference on Biomedical Engineering (ICBME)*, Singapore, Dec. 2005.

[6] F. Jager, G. B. Moody, and R. G. Mark, "Detection of Transient ST Segment Episodes During Ambulatory ECG Monitoring," *Computers and Biomed. Res.*, vol. 31, pp. 305–322, 1998.

[7] M. Astrom, J. Garcia, P. Laguna, and L. Sornmo, "ECG Based Detection of Body Position Changes," *Signal Processing Report*, vol. SPR-48, pp. 1–34, November 2000.

[8] J. Garcia, M. Astrom, J. Mendive, P. Laguna, and L. Sornmo, "ECG-Based Detection of Body Position Changes in Ischemia Monitoring," *IEEE Trans. on Biomed. Engg.*, vol. 50, no. 6, pp. 677–685, June 2003.

[9] M. Astrom, J. Garcia, P. Laguna, O. Pahlm, and L. Sornmo, "Detection of Body Position Changes using the Surface Electrocardiogram," *Medical and Biological Engineering and Computing*, vol. 41, pp. 164–171, 2003.

[10] V. S. Nimbargi, V. M. Gadre, and S. Mukherji, "Characterization of ECG Motion Artifacts Using Wavelet Transform and Neural Networks," in *Indian Conference on Medical Informatics and Telemedicine*, Kharagpur, West Bengal, India, 2005.

[11] T. Pawar, S. Chaudhuri, and S. P. Duttagupta, "Analysis of Ambulatory ECG Signal," in *28th IEEE EMBC*, New York City, New York, USA, Aug.-Sept 2006, pp. 3094–3097.

[12] ——, "Body Movement Activity Recognition for Ambulatory Cardiac Monitoring," *IEEE Trans. on Biomed. Engg.*, vol. 54, no. 5, pp. 874–882, May 2007.

[13] T. Pawar, N. S. Anantakrishnan, S. Chaudhuri, and S. P. Duttagupta, "Transition Detection in Body Movement Activities for Wearable ECG," *IEEE Trans. on Biomed. Engg.*, vol. 54, no. 6, pp. 1149–1152, June 2007.

[14] W. Li, H. H. Yue, S. Valle-Cervantes, and S. J. Qin, "Recursive PCA for Adaptive Process Monitoring," *Journal of Process Control*, vol. 10, no. 5, pp. 471–486, October 2000.

[15] C. V. C. Bouten, K. T. M. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen, "A Triaxial Accelerometer and Portable Data Processing Unit for the Assessment of Daily Physical Activity," *IEEE Transactions On Biomedical Engineering*, vol. 44, no. 3, pp. 136–147, March 1997.

[16] R. Fensli, T. Frsnes, C. Hadland, and T. Gundersen, "Wearable Activity Sensor based on Triaxial Accelerometer," in *Scandinavian Conference in Health Informatics, SHI*, AalBorg, 2005.

[17] M. J. Mathie, A. C. F. Coster, N. H. Lovell, and B. G. Celler, "Detection of daily physical activities using a triaxial accelerometer," *Medical and Biological Engineering and Computing*, vol. 41, no. 3, pp. 296–301, May 2003.

[18] ——, "Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement," *Physiological Measurement*, vol. 25, no. 2, pp. R1–R20, April 2004.

[19] M. J. Mathie, B. G. Celler, N. H. Lovell, and A. C. F. Coster, "Classification of basic daily movements using a triaxial accelerometer," *Medical and Biological Engineering and Computing*, vol. 42, no. 5, pp. 679–687, September 2004.

[20] H. M. Schepers, H. F. J. M. Koopman, and P. H. Veltink, "Ambulatory Assessment of Ankle and Foot Dynamics," *IEEE Transactions On Biomedical Engineering*, vol. 54, no. 5, pp. 895–902, May 2007.

[21] G. Fletcher, G. Balady, A. EA., B. Chaitman, R.Eckel, J. Fleg, V. Froelicher, A. Leon, I. P. na, R. Roxanne, D. Simons-Morton, M. Williams, and T. Bazzarre, "Exercise Standards for Testing and Training: A Statement for Healthcare Professionals From the American Heart Association," *Circulation*, vol. 104, pp. 1694–1740, 2001.

[22] J. Pan and W. L. Tompkins, "A Real-Time QRS Detection Algorithm," *IEEE Trans. on Biomedical Engineering*, vol. 32, no. 3, pp. 230–236, March 1985.

[23] P. Laguna, R. Jane, and P. Caminal, "Adaptive Feature Extraction for QRS Classification and Ectopic Beat Detection," in *Computers in Cardiology*, 1991, pp. 613–616.

[24] J. S. Paul, M. R. S. Reddy, and V. J. Kumar, "Automatic Detection of PVC's using Autoregressive Models," in *19th IEEE EMBC*, 1997, pp. 68–71.

[25] H. Chow, G. Moody, and R. Mark, “Detection of Ventricular ectopic beats using Neural Networks,” in *Computers in Cardiology*, 1992, pp. 659–662.

List of Tables

List of Figures

Fig. 1. Illustration of the experimental setup. Motion trackers (small orange objects) are strapped on the upper arms and the waist. The bigger object hanging at the waist where the left hand touches is the bluetooth interface for motion sensors. The single lead ECG recorder is attached to the front right side of the waist. The entire experiment is recorded on video to capture stray events not recorded by the motion sensor.

TABLE I

THE BRUCE PROTOCOL

Level	Time(mins)	Speed(kmph)	Gradient(%)
1	0-3	2.74	10
2	3-6	4.02	12
3	6-9	5.47	14
4	9-12	6.76	16
5	12-15	8.05	18
6	15-18	8.85	20
7	18-21	9.65	22

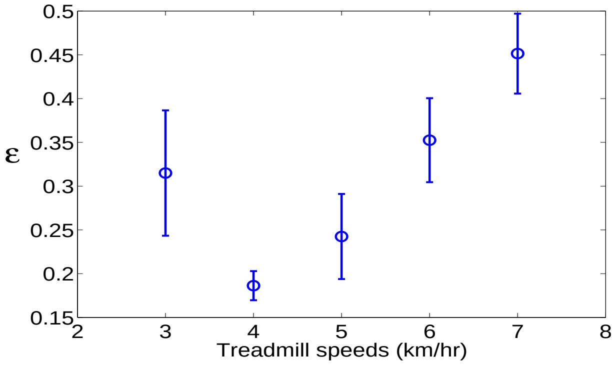

Fig. 2. Illustration of the relation between the impact signal and treadmill speeds for a subject walking at different speeds on a treadmill. The large dot represents the mean value of the impact signal (ϵ), with the vertical bars representing the standard deviations around the mean. The horizontal axis is the treadmill speed in km/hr. The first stage on the treadmill shows a larger value of ϵ, due to the initial discomfort of the subject on the treadmill.

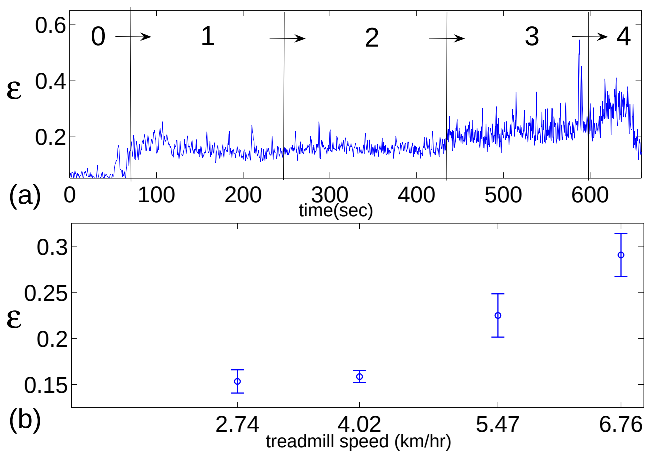

Fig. 3. Plots of the impact signal (ϵ) for a cardiac patient whose treadmill test was terminated after 30 seconds into the fourth stage of the Bruce Protocol. The first stage in both plots shows a comparatively large value of ϵ, due to the initial adjustment issues of the subject on the treadmill. (a) Plot of ϵ vs. time in seconds on the treadmill. The corresponding stages are indicated by numbers at the top, with '0' indicating resting conditions. (b) Plot illustrating the relation between ϵ and treadmill speeds. The large dot represents the mean value of the ϵ, with the vertical bars representing the standard deviations.

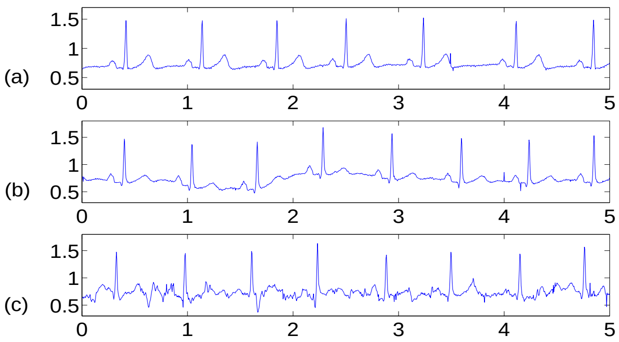

Fig. 4. Illustration of ECG signal for a normal subject while different ambulation activities. (a) sedentary ECG signal without any body movement, (b) ambulatory ECG signal of the same subject while moving his left arm, (c) ambulatory ECG signal of the same subject while walking. The horizontal axes are time in seconds in all plots shown.

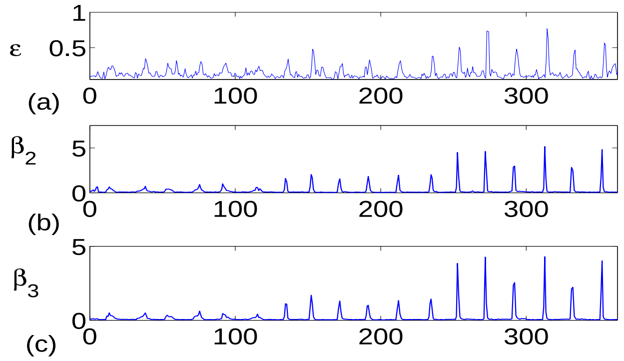

Fig. 5. Illustration of impact signal (ϵ) for change in posture alternating between sitting down and standing up three times each with three different levels: slow (0-120s), medium (120-240s) and fast (240-360s). (a) impact signal derived from the ambulatory ECG signal, norm of acceleration (m/s^2) for sensor attached at (b) right leg, (c) waist. The horizontal axes are time in seconds in all plots shown.

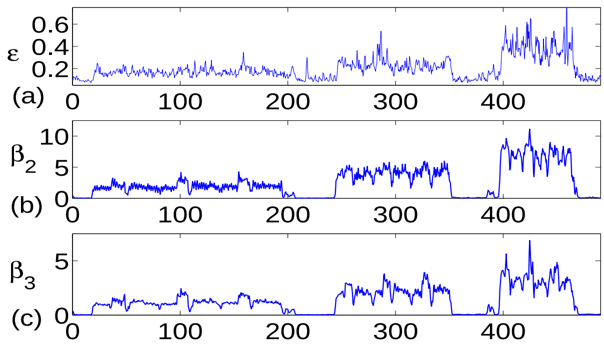

Fig. 6. Illustration of impact signal (ϵ) for climbing stairs with three different paces: slow (18-206s), medium (244-352s) and fast (395-470s). (a) impact signal derived from the ambulatory ECG signal, norms of acceleration (m/s^2) for sensor attached at (b) right leg, (c) waist. The horizontal axes are time in seconds in all plots shown.

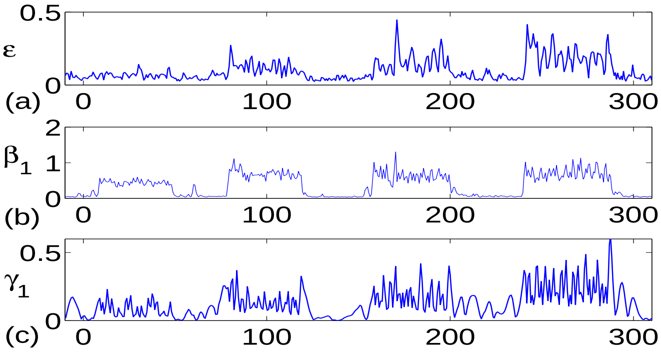

Fig. 7. Illustration of impact signal (ϵ) for right arm movement with four different extents with similar pace (very small:8-48s, small:78-120s, moderate:156-200s, wide:340-388s). (a) Impact signal derived from the ambulatory ECG signal, (b) norm of acceleration (m/s^2) for sensor attached at right arm, (c) norm of displacement (m) for the sensor attached at right arm. The horizontal axes represent time in seconds in all plots shown.

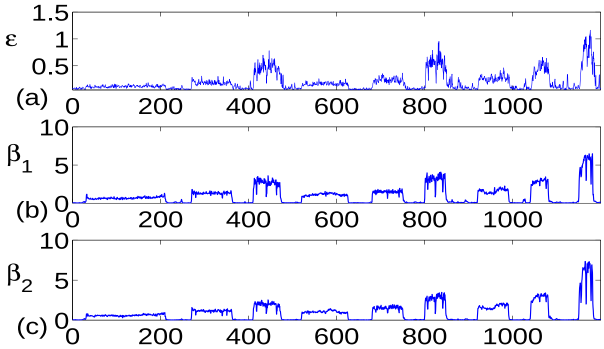

Fig. 8. Illustration of impact signal (ϵ) for walking with three different stride-lengths: 1, 2 and 3 ft. and at three different speeds: slow (1 ft: 25-207s, 2 ft: 265-358s and 3 ft: 405-470s), medium (1 ft: 515-621s, 2 ft: 675-747s and 3 ft: 795-843s) and fast (1 ft: 915-987s, 2 ft: 1035-1078s and 3 ft: 1145-1180s). (a) impact signal derived from the ambulatory ECG signal, norms of acceleration (m/s^2 for sensor attached at (b) right arm, (c) waist. The horizontal axes indicate time in seconds.

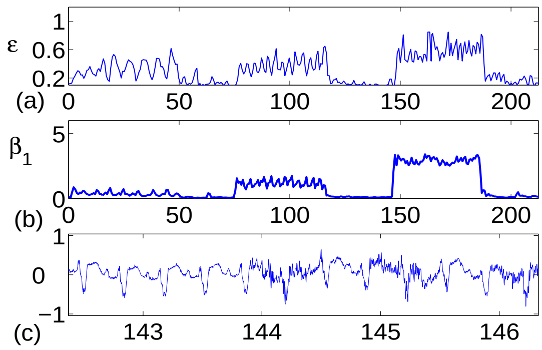

Fig. 9. Illustration of the impact signal (ϵ) of a cardiac patient for right arm movements at three different speeds : slow (0-50s), medium (75-120s) and fast (144-190s). (a) impact signal derived from the ambulatory ECG signal, (b) norm of acceleration (m/s^2) for sensor attached at right arm, (c) a snapshot of the ECG signal recorded during this activity. Note the abnormal QRS morphology, and the increase in motion artifacts after 144s due to initiation of activity. The horizontal axes indicate time in seconds.

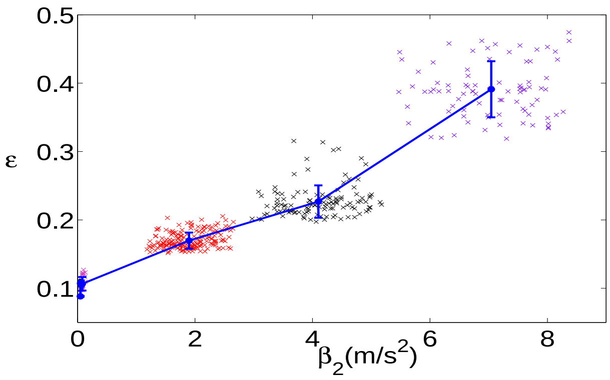

Fig. 10. Scatter plot of the magnitude of the impact signal (ϵ) as a function of norm of instantaneous acceleration while climbing stairs at three paces, for the sensor attached at the right leg. Note the well-defined clustering around the large dot, which represents the mean value of ϵ over 15 beats. The trend appears to be more or less linear, and the vertical bars representative of the standard deviation of ϵ indicate separability of acceleration levels at a resolution of nearly $0.2g$.

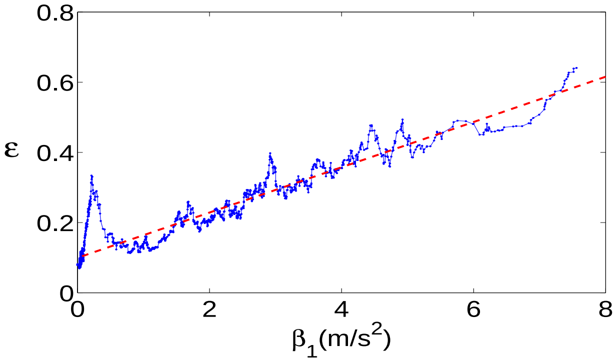

Fig. 11. Plot of the magnitude of the impact signal (ϵ) as a function of norm of instantaneous acceleration while walking, for the sensor attached at the right leg. This indicates that as the activity level goes up so does the motion artifact. The trend appears to be a linear one.

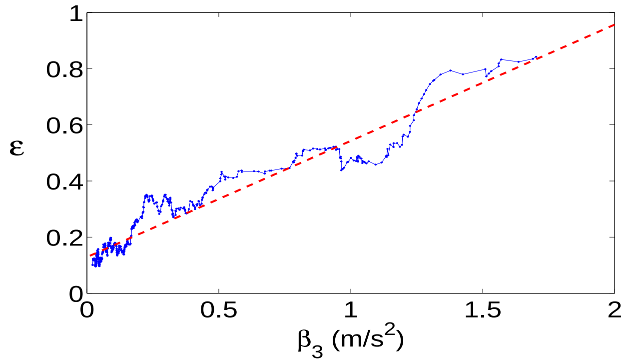

Fig. 12. Plot of the magnitude of the impact signal (ϵ) as a function of norm of instantaneous acceleration for the twisting at waist movement, for the sensor attached frontally at the waist. Note that the acceleration values are much smaller (about 0.1-0.2g) compared to the previous plot as the movement at the waist is much slower than at the leg.

TABLE II

MEANS (μ) AND STANDARD DEVIATIONS (σ) OF THE COEFFICIENTS, ρ AND ω FOR CLIMBING UP STAIRS AND WALKING ACROSS DIFFERENT SUBJECTS

Coefficients		**Correlation (ρ)**			**Regression (ω)**		
Activity		**Hand**	**Thigh**	**Waist**	**Hand**	**Thigh**	**Waist**
Climb	μ	0.8226	0.8090	0.8150	0.1337	0.0655	0.1297
	σ	0.0195	0.0161	0.0176	0.0368	0.0222	0.0408
Walk	μ	0.8517	0.8027	0.7985	0.1989	0.1548	0.1779
	σ	0.0278	0.0628	0.0512	0.0599	0.0675	0.0471