8

Impact of Ambulation

In previous chapters we have discussed methods for detecting and recognizing different body movement activities (BMAs) from the analysis of the ECG signal acquired under ambulation. The ECG signals have been analyzed to show that the motion artifacts induced by various BMAs can actually be classified into different types which allows recognition of BMA from the ECG itself. The methods discussed so far deal with the commonplace BMAs performed at a normal pace. The constant normal pace of activity allowed us to exclude more complicated situations arising out of variations in the pace levels of the same BMA. However, in real life, different pace levels of any commonplace BMAs are usually described as slow, normal and fast. This kind of variations in the body movement kinematics may also have some impact on the generation of the motion artifacts in the ECG signal. In this chapter, 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. The impact signal is derived from the ambulatory ECG signal itself. Two approaches have been adopted in this chapter to validate the basic hypothesis that the impact signal does provide a good measure of the pace of ambulation. 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 pace levels. The other method consists of ECG acquisition during treadmill testing at controlled speeds for fixed durations. Ambulatory ECG signals and the required data about the pace of the activity have been acquired from 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 a quantification would also

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help in automated documentation of patient activity levels, which could aid in better interpretation of ambulatory ECG.

8.1 Introduction

Ambulatory 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. The context of ambulation in ECG analysis plays an important role particularly for monitoring with wearable ECG recorders (W-ECG) for which the patient ambulation is quite unencumbered. During monitoring with W-ECG an accurate diary of physical activities is maintained to facilitate better analysis of the ECG 'in context' [43]. It is difficult to provide exact details of the physical activities just by describing a physical activity qualitatively in words and the time stamping of various events by a human user may be quite inaccurate. This difficulty has been solved partially by developing W-ECG systems with evidence based patient activity monitoring in [17, 43, 86, 145]. These systems incorporate accelerometers with ECG recording apparatus, in order to provide information about patient activity levels. However, any exact analysis of the impact of the activity levels as recorded by the accelerometers on the ECG has not been studied yet. Since the primary goal of W-ECG is to monitor ECG signal, it is required to derive a quantitative measure of the quality of the ECG signal rather than just the activity levels being monitored by the accelerometer signals. Here we quantitatively investigate the precise impact of various levels of BMA on the generation of motion artifacts in the ECG signal.

We have shown in Chapter 6, 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. This is based on the fact that different types of body movements affect the skin electrode interface differently. In this chapter, we first define a notion called impact signal which is derived from this RPCA and demonstrate through a number of experiments that the proposed impact signal can be applied for impact analysis of body movement activity (BMA), 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 activities, we perform two different sets of experiments: one using the treadmill test, and the other using commercially available accelerometers. The treadmill test, a benchmark in 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 [16], and hence the activity level of a subject. Accelerometric measurements and treadmill speeds have been shown to be well correlated in [31]. Accelerometry

has been used for studies of body movements in [81, 82, 83]. 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 various types of body movements at three different pace levels: slow, normal and fast. 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. We thus show that 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 development of a simple, low cost, ECG monitoring system which can automatically provide information about BMA from the ECG signal.

The chapter is organized as follows. We describe a method for deriving the impact signal is Section 8.2. In Section 8.3, it is explained how we synchronized the free running clocks of two different systems, the W-ECG equipment and the motion sensor system. The results obtained from various experiments with treadmill and motion sensors are presented in Section 8.4. We discuss about the experimental results and conclusions in in Section 8.5.

8.2 Derivation of Impact Signal

We use the RPCA error signal as derived in Section 6.2, at every R peak locations from the analysis of appropriately time warped ECG beats. We repeat the RPCA based algorithm here for the ease of reading.

Since we use 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 [96] as discussed in Chapter 6. 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

$$C_i = \sum_{k=1}^{i} \alpha^{(i-k)} \underline{r}(k)\underline{r}^T(k) = \alpha C_{i-1} + \underline{r}(i)\underline{r}^T(i), \tag{8.1}$$

where $\alpha,\ 0 < \alpha < 1$ is the *forgetting factor*. . A set of top L eigenvectors of the covariance matrix C_i at i^{th} ECG beat is derived using Eq. (8.1). Let $E_i = [\underline{e}_{i1}\ \underline{e}_{i2} \dots \underline{e}_{iL}]_{M_0 \times L}$ 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 $\{\underline{e}_{i1},\ \underline{e}_{i2}, \dots, \underline{e}_{iL}\}$. The error in approximation

$$\epsilon(i) = |\underline{r}(i+1) - (E_i E_i^T)\underline{r}(i+1)| \tag{8.2}$$

provides a measure of the level of motion artifact in the ECG, i.e. the impact of body movement in ambulatory ECG signal. The error $\epsilon(i)$ defined in Eq. (8.2) is called the impact signal for the i^{th} beat. The impact signal could be non-uniform on the time scale due to the beat to beat variations in the heart rate. The exact time instant of the impact signal can be calculated from the R peak location corresponding to the beat index i in the ECG signal. Then it is possible to compare the impact signal with the accelerometer signals at same time instances.

8.3 Synchronization of Impact and Motion Data

We have explained how we acquire the motion data from accelerometers in Chapter 5. 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

1. the impact is measured at every heart beat duration of which is variable and
2. 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 non-uniform sampling rate of the impact signal $\epsilon(i)$, the impact signal is upsampled to 242Hz (sampling frequency of the W-ECG) using a cubic spline interpolation. For comparison between the impact signal and the acceleration signals, the interpolated impact signal is downsampled to 25Hz (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 RR interval may vary with time for an individual. As the motion sensor and ECG acquisition starting times could be slightly different, it is also essential to have an automatic means to calculate the time delay between them.

The location of the peak of the cross-correlation between the acceleration data $\beta_k(n)$ [see Chapter 5 for definition of $\beta_k(n)$] and the time warped impact signal $\epsilon(n)$ is used as a measure of this time delay to synchronize the ECG and motion sensors. Having synchronized these two different types of 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.

8.4 Experimentations

Continuous lead-II ECG signals are recorded as described in Sections 5.4 and 5.6 for the direct motion sensing and the treadmill experiments involving the variations in the pace levels of the BMA. The results for these two types of experiments are reported separately. Data are collected 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 Chapter 6. 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 [20, 65, 97]. In [65], an adaptive, model based technique is provided for estimation of width and shape parameters of the QRS complex. Autoregressive modeling of envelopes of coefficients of discrete cosine transform of the QRS complex is discussed in [97]. Application of a neural network for classification of normal and abnormal ECG beats is given in [20]. Having detected the ectopic beat, one may discard 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 an ectopic one, alternately.

8.4.1 Experiments on the Treadmill

In the experiment involving the treadmill, our endeavor is to find a relation between the impact signal and the treadmill speed for quantification of the impact signal. Most subjects take 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 affects their gait for reactive stabilization, and results in increased motion artifacts. Subsequently, the subject adjusts to the motion of the treadmill and this steady state behavior is studied in this chapter. We report our findings for healthy subjects and cardiac patients separately as below.

Case I (Healthy Subjects)

Data from healthy volunteers are acquired with different treadmill speeds at zero inclination. Once the subject is settled on the treadmill, the impact

signal ϵ shows an increase in amplitude with increasing treadmill speed. This is illustrated in Fig. 8.1, in which are plotted the mean impact signal m_j, along with the standard deviation σ_j, for j^{th} 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 strength of impact signal 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 work 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.

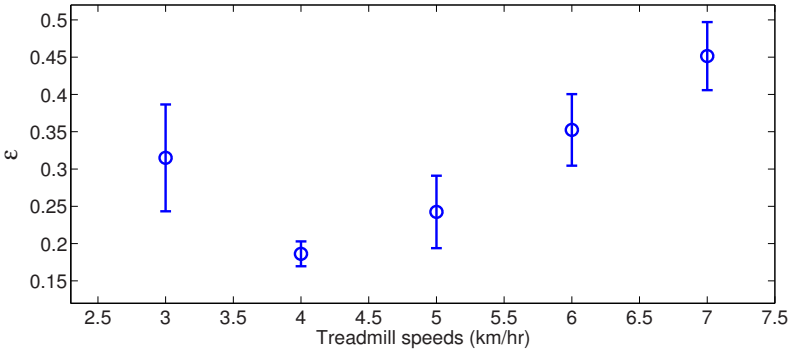

Fig. 8.1. Illustration of the relation between the impact signal and treadmill speeds for a subject walking at different speeds on a treadmill. The large dot represents the mean value of the impact signal (ϵ), with the vertical bars representing the standard deviations around the mean. The horizontal 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.

Case II (Cardiac Patients)

Patients who undertook the stress test could barely complete three stages of the Bruce protocol. The impact signal for one such subject is shown in

Fig. 8.2(a). As in case of normal subjects, ϵ increases with increasing treadmill speed. From the plot of mean impact signal m_j in Fig. 8.2(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 speed irrespective of whether the QRS complexes of the subjects are normal or abnormal. There is a small treadmill inclination associated with the Bruce protocol, which increases gradually with every stage. We ignore this inclination, as magnitude of this slope is very small at the first few levels of the protocol.

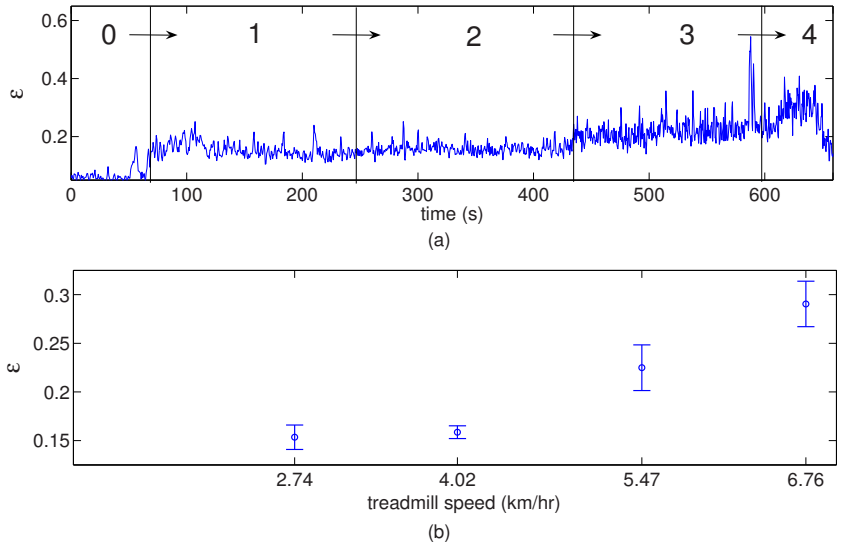

Fig. 8.2. Plots of the impact signal ϵ for a cardiac patient whose treadmill test is terminated after 30 seconds into the fourth stage of the Bruce protocol. The first stage in both plots shows a comparatively large value of ϵ, due to the initial adjustment issues of the subject on the treadmill. (a) 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.

The treadmill exercise involves putting the heart through a certain amount of stress, with peak heart rates touching 150 beats per minute. Such a stress may result in temporary morphological changes in the ECG, more so in case of patients with an ischemic heart disease [32]. 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 the motion artifact, 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.

8.4.2 Experiments with Motion Sensors

In our experiment with motion sensors, since our objective is to evaluate the applicability of ambulatory ECG monitoring, some typical BMAs are chosen as explained in Section 5.4. The impact signal is derived from the ECG signal described in Section 8.2, while the acceleration signals are analyzed according to the procedure given in Section 8.3. 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 $\gamma_k(n)$.

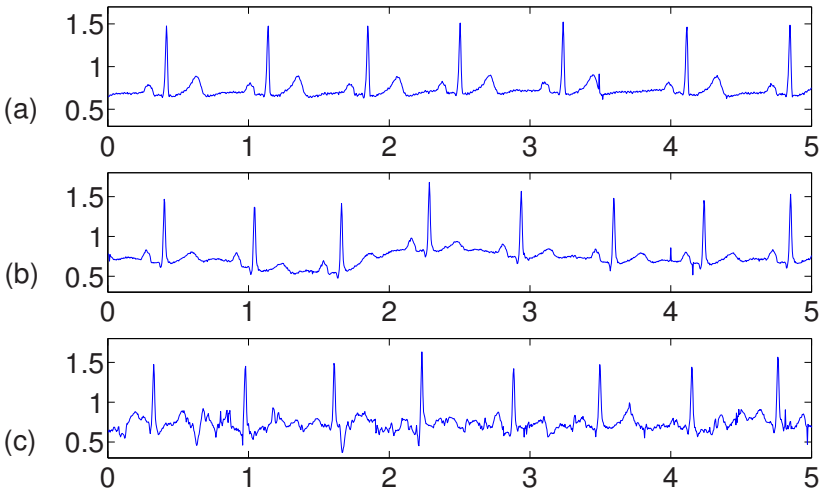

Fig. 8.3. Illustration of ECG signal for a normal subject while different ambulation activities. (a) sedentary ECG signal without any body movement, (b) ambulatory ECG signal of the same subject while moving his left arm, (c) ambulatory ECG signal of the same subject while walking. The horizontal axes are time in seconds in all plots shown.

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. 8.3. The sample ECG under a sedentary

condition without any body movement is shown in Fig. 8.3(a). The corresponding ECG trace for the same subject while moving his left arm is shown in Fig. 8.3(b). Fig. 8.3(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.

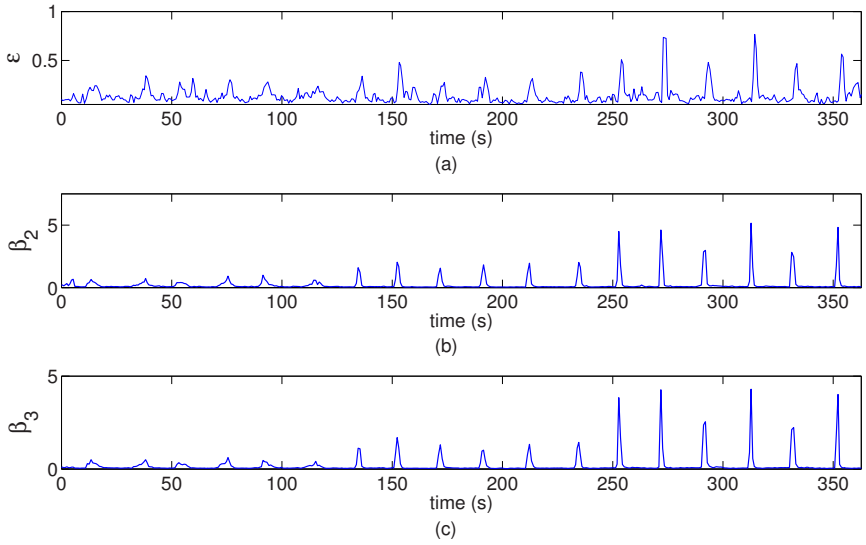

Fig. 8.4. Illustration of impact signal ϵ for change in posture alternating between sitting down and standing up three times each with three different levels: slow (0-120s), medium (120-240s) and fast (240-360s). (a) Impact signal derived from the ambulatory ECG signal, norm of acceleration (m/s^2) for sensor attached at (b) right leg, and (c) frontal waist. (©2007 IEEE)

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. 8.4(a), while the corresponding accelerations $\beta_k(n)$ are shown in Fig. 8.4(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 very easily. 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 is allowed

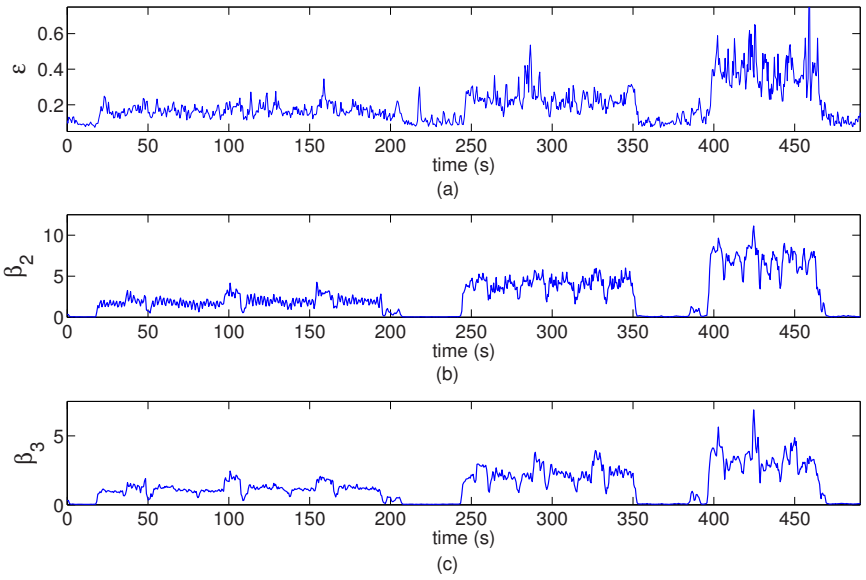

Fig. 8.5. Illustration of impact signal ϵ for climbing stairs with three different paces: slow (18-206s), medium (244-352s) and fast (395-470s). (a) Impact signal derived from the ambulatory ECG signal, norms of acceleration (m/s^2) for sensor attached at (b) right leg, and (c) frontal waist. (©2007 IEEE)

after finishing each level. The impact signal $\epsilon(n)$ for this activity for a subject and the corresponding acceleration signals $\beta_k(n)$ are shown in Fig. 8.5. From the amplitudes of signals in the figure and their time spans it is apparent that the impact signal does quantify 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.

We now consider rotation of the torso at the waist, with both hands firmly at the hips (so that they do not move with respect to the trunk), at three different intensities: slow, medium and fast, with a little rest in between. The impact signal $\epsilon(n)$ for a subject and corresponding accelerations $\beta_k(n)$ from the motion sensors placed at right leg and frontally at the waist are shown in Fig. 8.6. The relative variation in amplitude across the three paces of movement remains similar for all motion sensors. Specifically, the twisting body movement is well represented by the sensor placed on the waist, and the corresponding impact on ambulatory ECG is evident from the amplitudes of the impact signal for the three different levels of motion activity.

Next, we look at the impact of the 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 consider

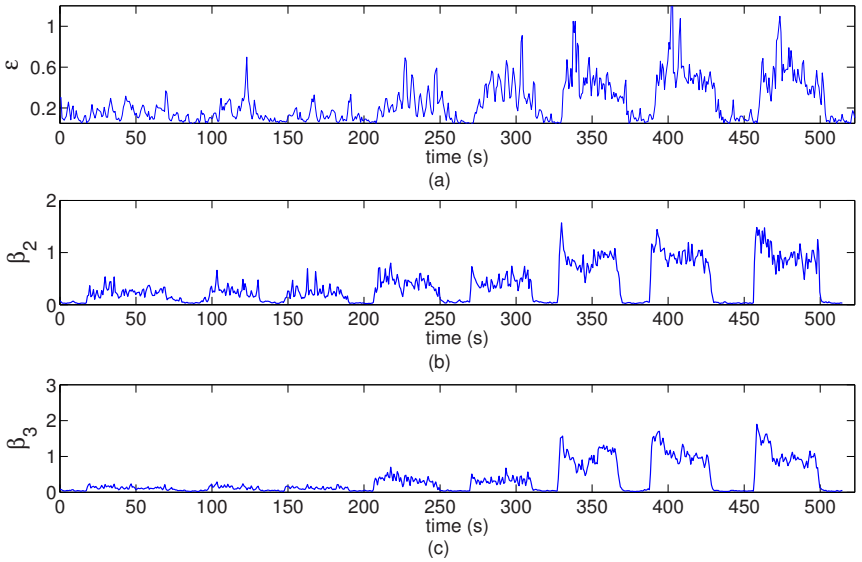

Fig. 8.6. Impact signal ϵ while twisting the torso at the waist with three different paces: slow (17-191s), medium (206-312s), and fast (326-500s). (a) Impact signal derived from the ambulatory ECG signal, norms of acceleration (m/s^2) for sensor attached at (b) right leg, and (c) frontal waist. The troughs intervening the high magnitude regions correspond to the resting time between consecutive action phases. (©2007 IEEE)

arm movement with flexion at the shoulder joint parallel to the sagittal plane of the body. For this purpose, the subject is 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 is maintained throughout the different extents of arm movement, with the other arm kept at rest by the side of the body. An instance of the impact signal $\epsilon(n)$ for this activity involving the right arm, with corresponding acceleration signal $\beta_1(n)$ and displacement signals $\delta_1(n)$ [see Chapter 5 for definition] of the sensor placed on the right arm are shown in Fig. 8.7. Except in the case of very small extent of movement, the magnitudes of acceleration for the other extents are nearly at the same level. There is a discernible increase 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. Hence, it is not just the pace (as quantified by the acceleration) that determines the motion artifacts, the extent of motion (such as stride length, etc.) also plays an important role in determining the impact of the body movement on the ECG data. A similar exercise is 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 previously. It may be useful to adopt a different lead configuration for this case.

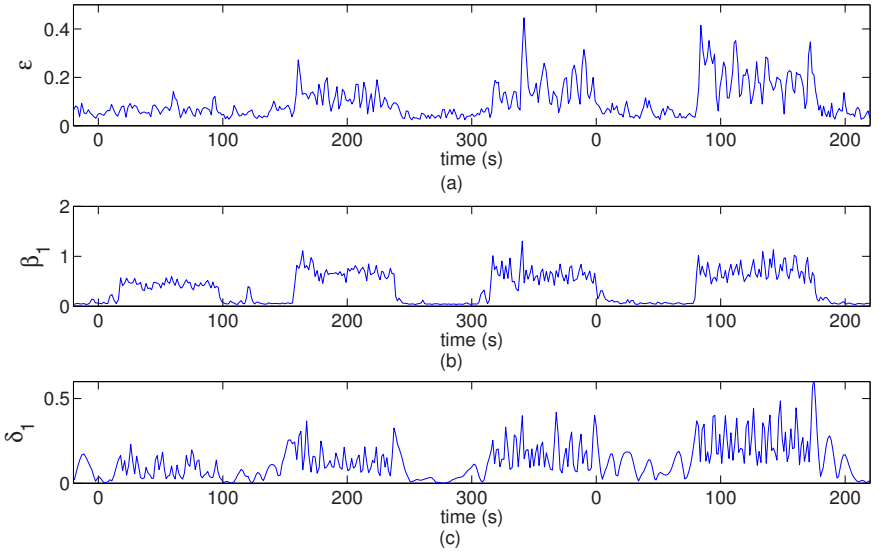

Fig. 8.7. Illustration of impact signal ϵ for right arm movement with four different extents with similar pace (very small:8-48s, small:78-120s, moderate:156-200s, wide:340-388s). (a) Impact signal derived from the ambulatory ECG signal, (b) norm of acceleration (m/s^2) for sensor attached at right arm, and (c) norm of displacement (m) for the sensor attached at right arm.

Now we study the combined effect of the pace of motion and the extent of the body movement on the acquired ECG data. Analysis of the impact for different strides (extents) and speeds of walking also indicates an increase in the amplitude of impact signal with the 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 impact signal $\epsilon(n)$ is almost proportional to treadmill speed (see Fig. 8.1), this is an expected result. An illustration of the impact of walking is given in Fig. 8.8. The plot shows that an increased stride length (or extent of motion) has a greater impact on the generation of motion artifact than the pace of activity. The increased stride length while walking automatically requires an increased movement of arms for reactive stabilization of the body and hence the skin at electrode contact is involved in further stretching and contraction.

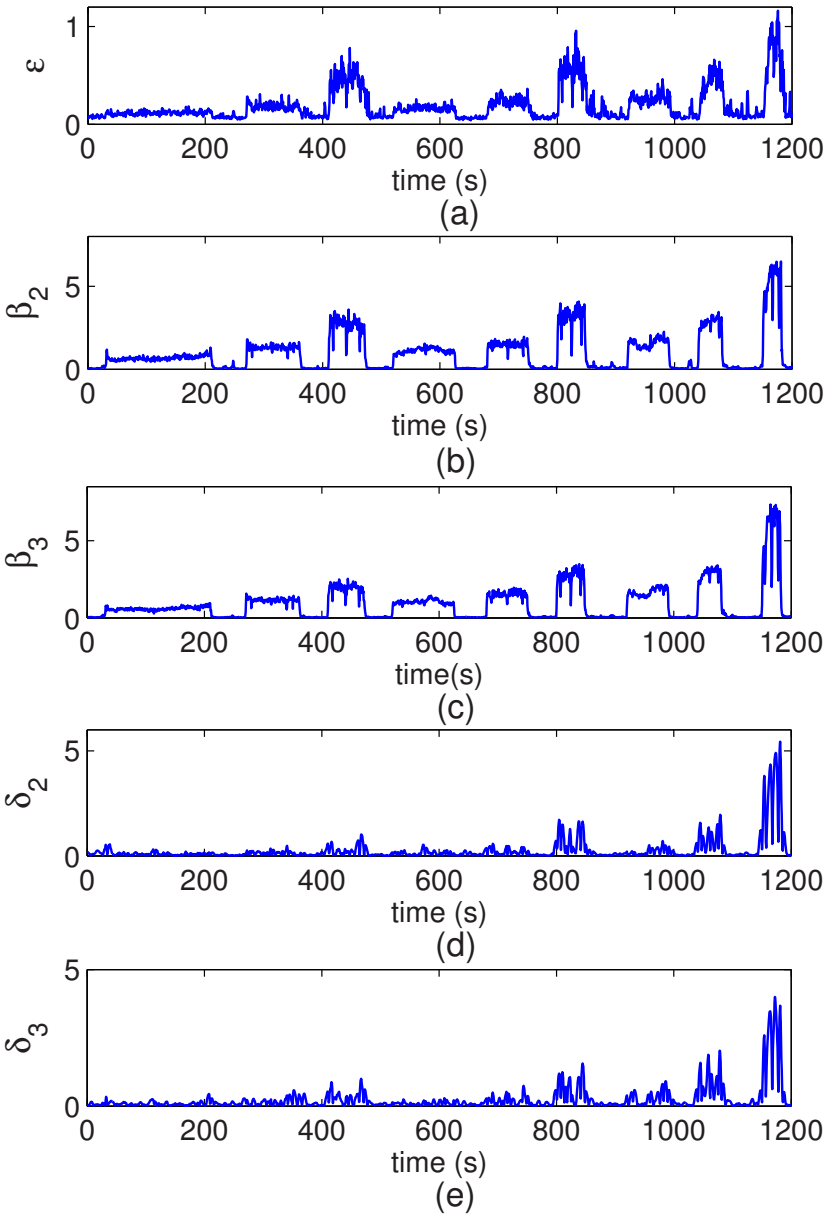

Fig. 8.8. Illustration of impact signal ϵ for walking with three different stride-lengths: 1, 2 and 3 ft. and at three different speeds: slow (1 ft: 25-207s, 2 ft: 265-358s and 3 ft: 405-470s), medium (1 ft: 515-621s, 2 ft: 675-747s and 3 ft: 795-843s) and fast (1 ft: 915-987s, 2 ft: 1035-1078s and 3 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, and (c) frontal waist, displacement as a function of time, captured by the motion sensor placed at (d) right arm, and (e) frontal waist. For (a), (b) and (c):

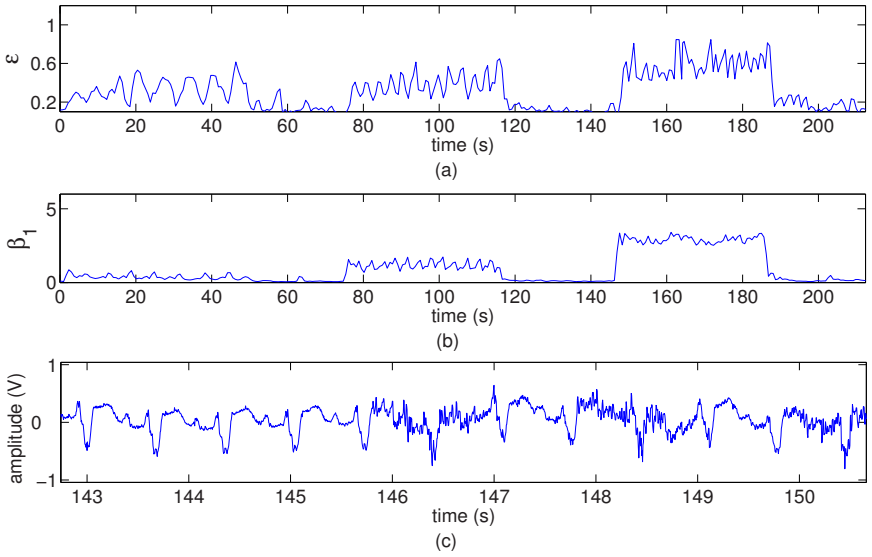

Fig. 8.9. Illustration of the impact signal ϵ of a cardiac patient for right arm movements at three different speeds : slow (0-50s), medium (75-120s) and fast (144-190s). (a) Impact signal derived from the ambulatory ECG signal, (b) norm of acceleration (m/s^2) for sensor attached at right arm, (c) a snapshot of the ECG signal recorded during this activity. Note the abnormal QRS morphology.

The motion sensor experiment also involves patients with cardiac disorders and anomalous QRS complexes. Since there is no existing protocol as yet and this experiment is not conducted under medical supervision, it is ensured that the overall intensity levels of the activity are lower for the selected patients to avoid undue physical stress. Fig. 8.9(a-c) shows the results for the movement of right arm as in Section 5.4 at three different 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 of healthy subjects. The RPCA method is largely unaffected by the vastly different QRS morphology in case of the 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 takes place and what the subject is actually trying to do at that instant. The scatter plot of the impact signal for the

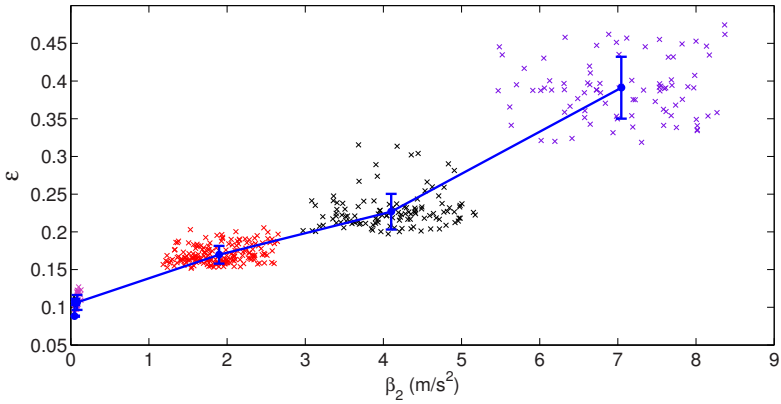

Fig. 8.10. Scatter plot of the magnitude of the impact signal ϵ as a function of norm of instantaneous acceleration while climbing stairs for the sensor attached at the right leg. Note the well defined clusters around the large dots, which represent the mean value of ϵ over 15 beats. The trend appears 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 $0.2g$.

experiment on climbing stairs vs. norm of acceleration in Fig. 8.10 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 smoothing are illustrated in Fig. 8.11 and Fig. 8.12, associated with the activities of walking and twisting of torso, respectively. The linear relationship shows that the impact signal can be used for quantification of motion. Comparing Fig. 8.11 and Fig. 8.12, we note from the range of the impact signal 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 $\beta_k(n)$ and the impact signal $\epsilon(n)$ indicates a strong 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 proves 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 Section 5.4.2, this is used in

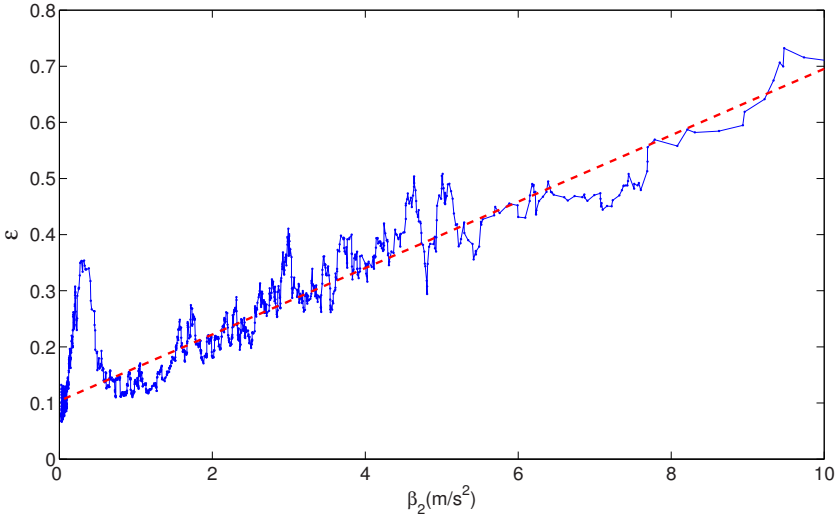

Fig. 8.11. Plot of the magnitude of the impact signal ϵ as a function of norm of instantaneous acceleration while walking for the sensor attached at the right leg. This indicates that as the activity level goes up, so does the motion artifact. The trend appears to be a linear one. (©2007 IEEE)

all plots to time synchronize the acceleration and impact signals. One of the plots showing cross-correlation between the acceleration signal and the impact signal while climbing stairs is shown in Fig. 8.13. In order to synchronize with the ECG data, we observe from the plot that the accelerometer data must be time shifted forward by 9.6s.

Presented in Table 8.1, is a summary of the global mean (μ) and standard deviation (σ) of the coefficient of cross-correlation (ρ) and slope (ω) of the line best fitting impact ϵ against acceleration data β, for climbing stairs and walking when experimented on different subjects. The cross-correlation values are high, while the low values of the standard deviation of ρ indicate less inter-personal variation. In other words, the impact signal is well correlated for most of the subjects. Standard deviation values for slope ω are marginally 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.

8.5 Discussions

We have studied the impact of body movements on generation of motion artifacts in ambulatory ECG recordings, and reported our observations on the

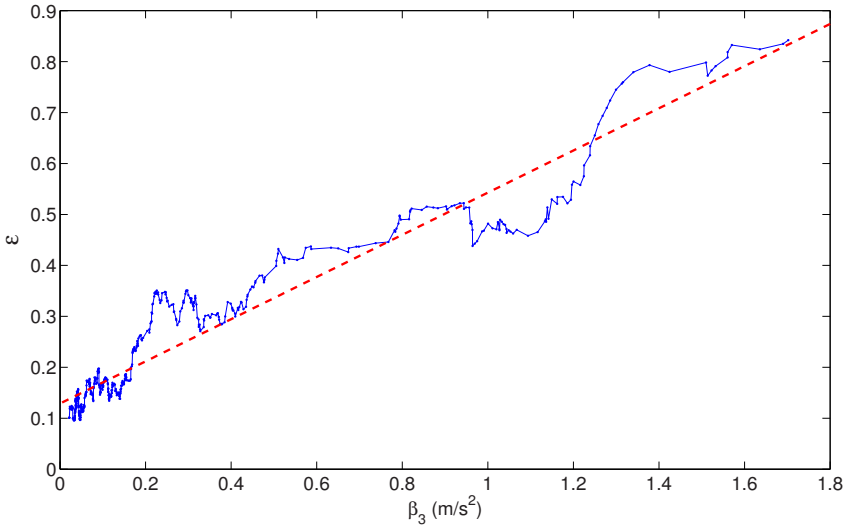

Fig. 8.12. Plot of the magnitude of the impact signal ϵ as a function of norm of instantaneous acceleration for the twisting at waist movement for the sensor attached frontally at the waist. Note that the acceleration values are much smaller (about 0.1-0.2g) compared to the previous plot as the movement at the waist is much slower than that at the leg. (©2007 IEEE)

Table 8.1. Means (μ) and standard deviations (σ) of the coefficients, ρ and ω for climbing up stairs and walking across different subjects. The columns hand, thigh and waist signify the placement of the motion sensor.

Coefficients		**Correlation (ρ)**			**Slope (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

quantification of body movements using the impact signal. The amplitude of the impact signal is shown to be very well correlated with the accelerations 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. The results from the treadmill experiment also indicate that the impact analysis is able to successfully adapt

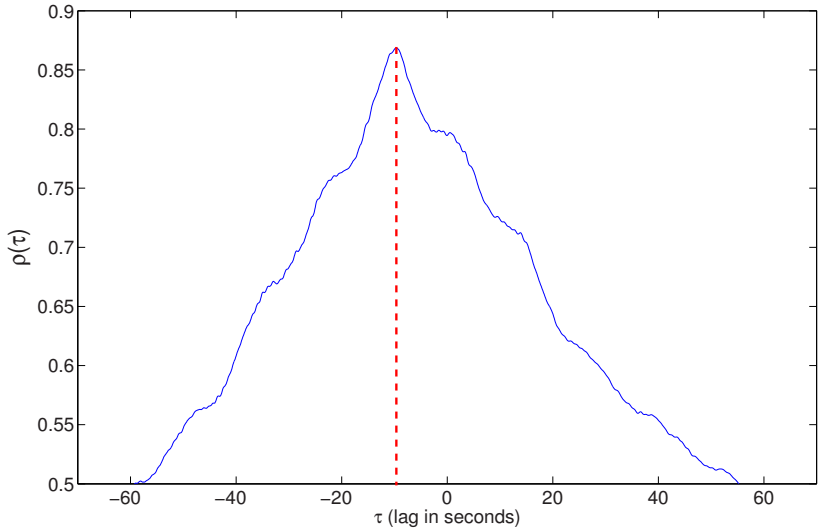

Fig. 8.13. Plot of the cross-correlation between the acceleration signal β and the impact signal ϵ as a function of lag (τ) in seconds for the activity of climbing stairs. The dashed line indicates the maximum correlation, which also gives the time lag between the two signals for the purpose of synchronization. The plot takes triangular shape as expected since the two signals have inherent rectangular shape due to step changes in the levels. (©2007 IEEE)

to stress induced morphological ECG variations, and can be applied even at high activity levels.

The impact signal has been presently used for measuring an extraneous activity superimposed on regular heart activity, be it normal or abnormal. Data sets from both healthy subjects and cardiac patients have been obtained to corroborate our hypothesis. Quantification of the impact signal from cardiac patients requires further analysis pertaining to detections for ectopicity and rhythm disturbances. We observe that the impact signal is unaffected by abnormal QRS morphologies, if they are regular and periodic. However, the method does not work in case of abnormalities like ventricular bigeminy where ectopics occur very frequently. Also, 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 an abnormal gait results due to difficulty in adjusting to the jerky start of the treadmill. 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.

We have limited our studies to single lead (lead-II) observations. However, additional activities could be analyzed if more than one ECG leads are available.