A Stochastic Fusion Technique for Removing Motion Artefacts from the Measurements of a Wireless ECG

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***Abstract*— Wireless electrocardiograms are useful for several practical applications in the healthcare domain. However, their usefulness is often limited by the quality of data that can be extracted from them. One of the main factors affecting the quality of ECG data is the inclusion of movement induced artefacts. In this paper we propose an adaptive filter to improve the quality of measurements. We propose to use motion or inertial sensors to capture the movements which affect the electrodes of a wireless ECG. Thus, we regard measurements from a 3D accelerometer and a 3D gyroscope as indication of the magnitude of noise artefacts in the outputs of a wireless ECG and use them to estimate and remove the movement artefacts. The paper presents the design and implementation of the filter, which we used to improve actual measurements we took whilst different subjects carried out various everyday activities (walking, running, riding a bicycle, and climbing up and down a staircase).**

I. Introduction

Wireless electrocardiograms (ECGs) are finding a large number of applications in the healthcare domain, such as monitoring patients with Parkinson Disease [1], [2], seizure and epilepsy [3], [4], [5], [6], and ambulatory needs [7], [8]. There are several aspects which make wireless ECGs suitable for these applications, two of them being (1) the ease with which the sensor nodes can be deployed in settings which are otherwise difficult or impermissible to wired deployments and (2) the ability to monitor the actual condition of patients while they are moving and carry out everyday activities unhindered, so that symptoms which may not easily be revealed in clinical settings where patients are normally resting and relaxing while measurements are taken from them can be revealed. Similarly, a wireless ECG can be deployed for a long time and sufficient measurements and statistics can be gathered.

But mobility brings with it some formidable challenges, one of them being the inclusion of motion-induced artefacts into the useful data. Depending on the placement of the sensors (electrodes), motion can affect them in different ways: (1) They can be subject to undesired vibrations; (2) there can be loose contacts and a change in the characteristic of the medium interfacing the sensor and the measurand being monitored (for example, a change in the skin conductance due to the contraction of muscles or sweat); (3) a gradual, microscopic displacement of the sensors from their original (and perhaps, preferred) position; and (4) improper alignments between the sensors and the measurand. Even though an extensive body of work exists on processing the measurements of electrocardiograms in clinical settings, the removal of movement-induced artefacts, nevertheless, is an ongoing and active research area. Fig. 1 highlights the challenges to which we refer. We employed a wireless ECG with 5 leads (the Shimmer platform) to measure the cardiac activities of a healthy adult person while doing a routine warm-up (skipping, stretching, and push-ups). Even though the measurements, which are taken from three different places in the chest, appear to be different from each other, it is clear that all of them underwent a gradual drift over time. Furthermore, a closer look into the short-term evolution of each measurement set reveals the existence of a considerable short-term variation as a result of the inclusion of motion artefacts into the useful data, as can be seen in Fig. 2.

In this paper, we apply an adaptive minimum mean square error filter and employ measurements from 3D accelerometer and 3D gyroscope to remove both the short-term effect of movement-induced artefacts from the measurements of a

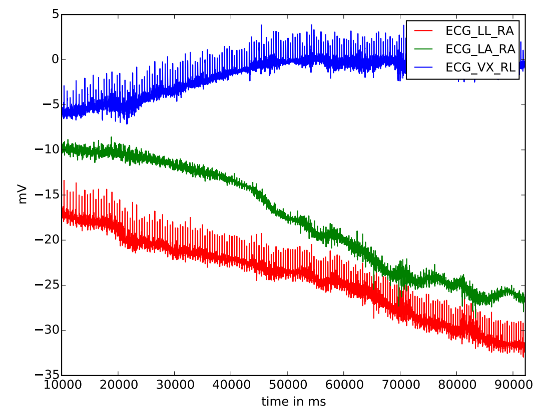

Fig. 1: A gradual drift in the baseline of the measurements of a wireless electrocardiogram taken from three different places in the chest.

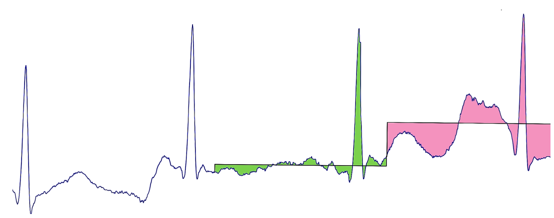

Fig. 2: A closer look at the effect of movement artefacts on the quality of ECG measurements.

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wireless ECG. Our premises is the following: The main cause of distortion in a wireless ECG during movement is the movement itself. The more vigorous the movement, the most likely the distortion becomes. Consequently, by establishing a correlation between the measurements from ECG and an accelerometer (or a gyroscope), it is possible to identify and correct movement produced artefacts. The paper presents our approach as well as initial experiment results and discusses the insight the experiment results reveal. The remaining part of this paper is organised as follows: In Section II, we review related work. In Section III, we present the estimation concept we adopt to filter movement generated noise artefacts. In Section IV we briefly discuss how the filter parameters are obtained from actual measurements. In Section V, we present and discuss experimental results, and, finally, in Section VI, we give concluding remarks and identify some open issues which we aim to address in future.

II. Related Work

Most existing approaches in processing measurements obtained from wireless ECGs focus on correcting long-term drifts (the gradual change in the reference line of the ECG waveform) mainly by employing digital high-pass and band-pass filters, wavelet analysis, and polynomial fitting. Our review of state-of-the-art in this section, however, focuses on advanced signal processing techniques.

Poungponsri and Yu [9] combine an adaptive filter, a wavelet transform, and a neural network to reduce the effect of uncorrelated and non-stationary noise both on the quality of ECG measurements and on the efficiency of the adaptive filter. But their study relies on simulated signal. Baraniak et al. [10] employ a least mean square (LMS) adaptive filter to minimise the effect of noise stemming from a power-line. Their main contribution is determining the upper and lower bounds of the convergence factor μ of the adaptive filter assuming that the noise has a stationary statistics. Romero et al. [11] make a comparative, experimental study of the performance of different variants of least mean square filters (LMS, normalised LMS, and signed LMS). They alternatively employ the outputs of an accelerometer and a skin conductance sensor to model noise. For analysing the performance of the filters, they use hit rate and accuracy of heartbeat detection. In their analysis they first took ECG measurements while healthy subjects were relaxing and sitting. Secondly, they obtained measurements from accelerometers and skin-conductance sensors while the subjects were moving. Thirdly, they mixed the measurements from the wireless ECG with the measurements of the accelerometer and supplied both the mixed measurements and the measurements from the accelerometer to the different filters. Lastly, they applied a heartbeat detection algorithm on both the unmixed and the filtered ECG measurements and compared the results. The same methodology was applied with the measurements of the wireless ECG and the skin-conductance sensor. The researchers observed that the signed LMS adaptive filter produced the best performance when the measurements from the skin conductance sensor were taken as motion artefacts. Tong et al. [12] carry out a similar study, but this time, real 2D accelerometers and skin conductance sensors were embedded into ECG electrodes and all measurements were taken simultaneously. The measurements from the two heterogeneous sensors were then supplied to a least mean square error filter to correct the actual measurements of the ECG. The main idea was to adjust the weight of the filter in accordance with the outputs of the skin conductance sensor and the accelerometer. The filter, however, was given a fixed convergence factor. As a validation, the authors compared the L2-norm and max-min statistics of both the filtered and unfiltered ECG measurements.

In summary, there is a shared and growing interest in the research community to employ motion sensors in order to model and remove movement-induced artefacts from the measurements of a wireless ECG. Even though a significant portion of the proposed approaches target the removal of long-term and gradual drifts from base-lines, some of them also target short-term distortions. The latter approaches, however, rely on simulated measurements or on measurements which were taken independently and mixed at a latter stage for the purpose of demonstration. In contrast, we first establish the mathematical basis for the use of an adaptive mean-square error filter and employ inertial sensors (accelerometers and gyroscopes) to simultaneously measure the cardiac activities and the accelerations and angular velocities to which the electrodes of the wireless ECG are subjected during measurement.

III. Estimation Concept

When compared to the frequency at which the measurand (the ECG output) is typically sampled, the speed of the motion affecting the electrodes of a wireless ECG (or in general, the speed of the subject) is significantly low. This observation enables us to assume that for a specific observation window, say for a duration of $100\,\mathrm{ms}$, the samples taken from a movement sensor exhibit stronger correlation with each other than the correlation exhibited between the samples of the wireless ECG. Furthermore, if we suppose that the predominant noise artefacts in the measurements of a wireless ECG are motion artefacts and that these artefacts are correlated with the measurements taken from a movement sensor (an accelerometer or a gyroscope), then, the motion artefacts in the ECG measurement also exhibit strong correlation with the samples of the motion sensors for the specified observation period. If we fix this observation duration as the duration between two heartbeats, then from the above statements we can further assert that the statistics we gather from the samples of the motion sensor during this period can be considered adequate to estimate and remove the motion artefacts included in the ECG measurements.

A. Establishing Model Coefficients

Hence, in order to estimate the motion artefact (from now on we simply use the term noise as long as the context is clear) included in each ECG sample, we propose to use an adaptive FIR filter the weights of which can be determined

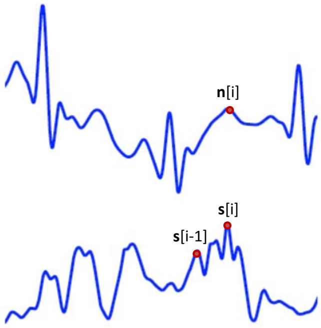

Fig. 3: The estimation of movement artefacts from the samples of inertia sensors. As long as there is a covariance between the samples of the inertia sensor and the noise included in the ECG measurements, the type of sensor (tilt, accelerometer, gyroscope, etc.) employed to measure the movement affecting the ECG measurement is irrelevant.

by the statistics associated with the samples of the movement sensors belonging to a single observation period.

Suppose we model the i-th sample of the wireless ECG as a random variable **r**[i] containing, among other things, the desired (or true) measurand **m**[i] and the undesired motion artefact, **n**[i]:

$$\mathbf{r}[i] = \mathbf{m}[i] + \mathbf{n}[i] \tag{1}$$

Both **m**[i] and **n**[i] cannot be known except in a probabilistic sense. The estimate of **n**[i], $\hat{\mathbf{n}}[i]$, can be expressed as:

$$\hat{\mathbf{n}}[i] = \sum_{k=1}^{K} \alpha_i[k]\mathbf{s}[i-k+1] \tag{2}$$

where $\mathbf{s}[i-k+1]$ is associated with the $(i-k+1)$ sample of the movement sensor and K is the total number of samples between the peaks of two heartbeats. We can also express Equation 2 in a matrix form as follows:

$$\hat{\mathbf{n}}[i] = (\alpha_i)^T \mathbf{s}_i \tag{3}$$

where the subscript indices refer to the K coefficients and movement samples we use for estimating the i-th noise sample. α_i can be determined by minimising the difference between the actual and the estimated noise in the mean square error sense:

$$E\left\{\mathbf{e}_n^2[i]\right\} = E\left\{(\mathbf{n}[i] - \hat{\mathbf{n}}[i])^2\right\} \stackrel{!}{=} \ minimum \tag{4}$$

If we insert Equation 2 into Equation 4 and differentiate with respect to α_i and set the result to zero, we shall obtain the values of all α_i which minimise the error. In order to illustrate this, consider Fig. 3 where we wish to estimate the noise corrupting the i-th ECG sample (i.e., **n**[i]). If we take only two samples of an inertial sensor for this task and linearly combine them to estimate $\hat{\mathbf{n}}[i]$, we shall have:

$$\hat{\mathbf{n}}[i] = \alpha_i[1]\mathbf{s}[i] + \alpha_i[2]\mathbf{s}[i-1] \tag{5}$$

Hence, the mean square error can be expressed as:

$$E\left\{\mathbf{e}_n^2[i]\right\} = E\left\{[\mathbf{n}[i] - (\alpha_i[1]\mathbf{s}[i] + \alpha_i[2]\mathbf{s}[i-1])]^2\right\} \tag{6}$$

In order to determine the coefficients $\alpha_i[1]$ and $\alpha_i[2]$ which minimise the mean square error, we differentiate Equation 6 with respect to $\alpha_i[1]$ and $\alpha_i[2]$ and set the result to zero, which yields the following:

$$\begin{aligned} E\{\mathbf{n}[i]\mathbf{s}[i]\} &= \alpha_i[1]E\{\mathbf{s}^2[i]\} + \alpha_i[2]E\{\mathbf{s}[i]\mathbf{s}[i-1]\} \\ E\{\mathbf{n}[i]\mathbf{s}[i-1]\} &= \alpha_i[1]E\{\mathbf{s}[i]\mathbf{s}[i-1]\} + \alpha_i[2]E\{\mathbf{s}^2[i-1]\} \end{aligned} \tag{7}$$

If we let $E\{\mathbf{n}[i]\mathbf{s}[i-j]\} = R_{ns}[i(i-j)]$ and $E\{\mathbf{s}[i]\mathbf{s}[i-j]\} = R_{ss}[i(i-j)]$, then we can express the above equation in a matrix form as follows:

$$\begin{bmatrix} R_{ns}[ii] \\ R_{ns}[i(i-1)] \end{bmatrix} = \begin{bmatrix} R_{ss}[ii] & R_{ss}[(i-j)i] \\ R_{ss}[i(i-j)] & R_{ss}[(i-1)(i-1)] \end{bmatrix} \begin{bmatrix} \alpha_i[1] \\ \alpha_i[2] \end{bmatrix} \tag{8}$$

From Equation 8, we can determine the coefficients by taking the inverse of the square matrix of the right term:

$$\alpha_i = \mathbf{R_{ss}}^{-1}\mathbf{R_{ns}} \tag{9}$$

The significance of the terms in Equation 9 should be clear: $\mathbf{R_{ss}}$ corresponds to the covariance between the samples of the inertial sensor and $\mathbf{R_{ns}}$ is the covariance between the noise and the samples of the inertial sensor. In general, if we take K samples from the inertial sensor into consideration to estimate $\hat{\mathbf{n}}[i]$, Equation 7 can be generalised as:

$$\begin{aligned} E\{\mathbf{n}[i]\mathbf{s}[j]\} = \ & \alpha_i[1]E\{\mathbf{s}[i]\mathbf{s}[j]\} + \alpha_i[2]E\{\mathbf{s}[i-1]\mathbf{s}[j]\} + \cdots + \\ & \alpha_i[j]E\{\mathbf{s}^2[j]\} + \cdots + \alpha_i[K]E\{\mathbf{s}[i-K+1]\mathbf{s}[j]\} \end{aligned} \tag{10}$$

Alternatively, $E\{\mathbf{n}[i]\mathbf{s}[j]\}$ in Equation 10 can be expressed as:

$$E\{\mathbf{n}[i]\mathbf{s}[j]\} = E\{\mathbf{r}[i]\mathbf{s}[j]\} - E\{\mathbf{m}[i]\mathbf{s}[j]\} \tag{11}$$

because

$$\mathbf{n}[i] = \mathbf{r}[i] - \mathbf{m}[i] \tag{12}$$

The advantage of Equation 11 is that the covariance between the true measurand and the movement measured by the inertia sensor – $E(\mathbf{m}[i]\mathbf{s}[j])$ – can be taken as weak since we are concerned primarily with that type of movement which directly affects the interface between the electrodes of the ECG and the skin (the body may exert but the sensor may poorly capture the exertion as a whole; the heart rate may also increase even when the body does not exert). The implication of this assertion is that Equation 9 can be expressed in terms of measurable quantities only.

B. Updating Model Coefficients

As the movement affecting the electrodes of the ECG changes, so should the filter coefficients be updated. Since determining the covariance matrices is normally computationally intensive, the more efficient technique would be to iteratively update the coefficients. This can be done by propagating belief into the future and by comparing the accuracy of our belief with the reality. The basic premises for belief propagation is that the change in the parameters being estimated is a gradual rather than a wild or haphazard process. In other words, there is a correlation between the predicted and the actual values of the parameters.

Suppose, based on the statistics we established with the $i-1$ samples of the wireless ECG and the inertia sensor we predict the filter coefficients for the i-th noise sample and we label the predicted vector as α_i^p. Notice that the vector contains the K filter coefficients. Suppose also after we received the i-th sample from the inertia sensor, we computed the optimal filter coefficients and label the coefficient vector as α_i^m. Because of our assumption about the gradual change of the movement affecting the ECG electrodes, we expect the difference between the predicted and the actual coefficients to be very small. Thus,

$$\mathbf{e}_\alpha[i] = \alpha_i^m - \alpha_i^p \tag{13}$$

We have now two types of errors: the first arising from the difference between the actual noise and the estimated noise (refer to Equation 4) and the second arising from the gradual change in the noise artefacts and the difference between the predicted and the "actual" filter coefficients (refers to Equation 13). We make it our objective to minimise these two errors with respect to the predicted filter coefficients under the constraint:

$$\mathbf{n}[i] = \left(\alpha_i^p\right)^T \mathbf{s}_i \tag{14}$$

(Equation 14 is a variant of Equation 3, but here the relationship is ideal). Thus, the total error of our estimation can be expressed as [13]:

$$J[i] = \|e_\alpha[i]\|^2 + \lambda\left[(\mathbf{r}[i] - \mathbf{m}[i]) - \left(\alpha_i^P\right)^T \mathbf{s}_i\right] \tag{15}$$

where λ is a Lagrange multiplier. Notice that the term inside the square bracket in Equation 15 is zero, so the significance of λ will be clear shortly. Hence, the prediction of the coefficients to estimate $\mathbf{n}[i]$ should be so determined that $J[i]$ is minimum. This can be achieved by differentiating Equation 15 with respect to α_i^p and setting the result to zero:

$$\frac{dJ[i]}{d\alpha_i^p} = 0 \tag{16}$$

From which we have:

$$\alpha_i^m = \alpha_i^p - \frac{1}{2}\lambda\mathbf{s}_i \tag{17}$$

In order to determine λ, we can express $\mathbf{n}[i]$ in terms of Equation 17:

$$\begin{aligned}\mathbf{n}[i] &= \left(\frac{1}{2}\lambda\mathbf{s}_i + \alpha_i^m\right)^T \mathbf{s}_i \\ &= \frac{1}{2}\lambda\|\mathbf{s}_i\|^2 + \hat{\mathbf{n}}[i]\end{aligned} \tag{18}$$

This is because $\hat{\mathbf{n}}[i] = \left(\alpha_i^m\right)^T \mathbf{s}_i$. Rearranging the terms in Equation 18 yields:

$$\lambda = \frac{2\left[\mathbf{n}[i] - \hat{\mathbf{n}}[i]\right]}{\|\mathbf{s}_i\|^2} \tag{19}$$

Finally, the prediction error can be expressed as:

$$\alpha_i^p = \frac{1}{2}\frac{\mathbf{e}_n[i]}{\|\mathbf{s}_i\|^2}\mathbf{s}_i \tag{20}$$

Figure 4 displays the architecture of the adaptive filter we designed to remove movement artefacts from the measurements of a wireless ECG. In the next section we provide an account of how we actually determined the filter parameters.

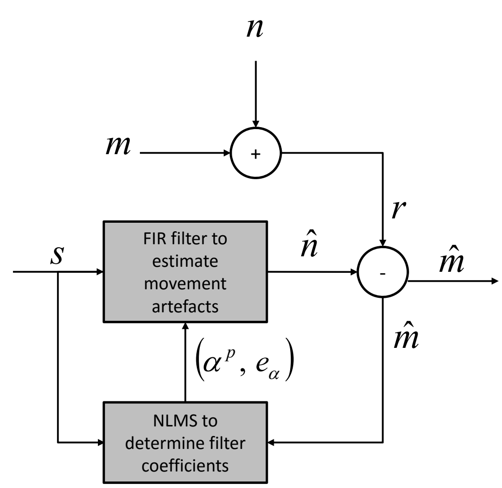

Fig. 4: The structure of the adaptive filter we designed to remove movement artefacts from the measurements of a wireless ECG. FIR: finite impulse response. NLMS: non-linear mean square estimator.

IV. Implementation

Cardiac action potentials exhibit strong regularities under normal conditions. Therefore, it is possible to predict the entire samples of a single heartbeat from the statistics of previous heartbeats and the samples of the movement sensor associated with them. We employed the covariance and autocorrelation functions to estimate the parameters given in Equations 8 and 20.

A normal cardiac rhythm consists of P, QRS, and T waves. The P wave corresponds to the contraction of atrial muscles to pump blood into the right and left ventricles. The QRS wave complex corresponds, predominantly, to the contraction of ventricular muscles as they pump blood into the lung and the rest of the body. The T wave corresponds to the repolarisation of the ventricular muscles. Of these waves, the intensity of the QRS wave is the largest, and, therefore, the less likely wave to be affected by noise. If we remove this wave complex by setting a threshold and regard the remaining samples as the outcomes of a random variable, the statistics of this random variable (for example, the variance) can be used to characterise the "noisyness" of the samples

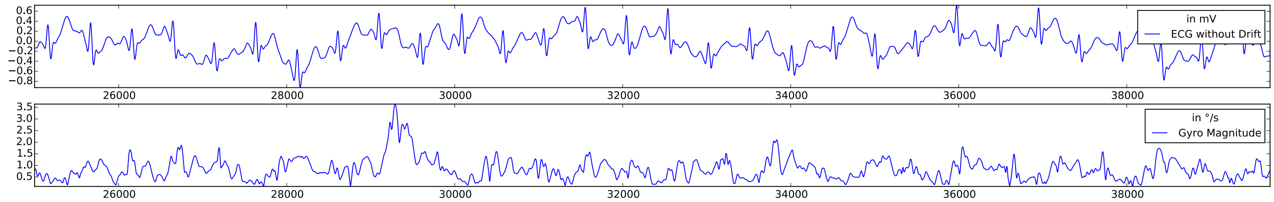

Fig. 5: The covariance between the measurements taken from a wireless ECG (top) and a 3D gyroscope attached between two of the ECG electrodes (bottom). The subject was climbing up a staircase.

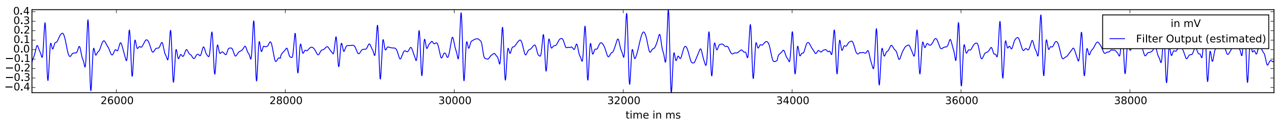

Fig. 6: The measurements of the wireless ECG in Fig. 5 after the movement artefacts are removed by the adaptive filter. The motion artefacts are estimated with the help of the angular velocity of the subject measured by a 3D gyroscope .

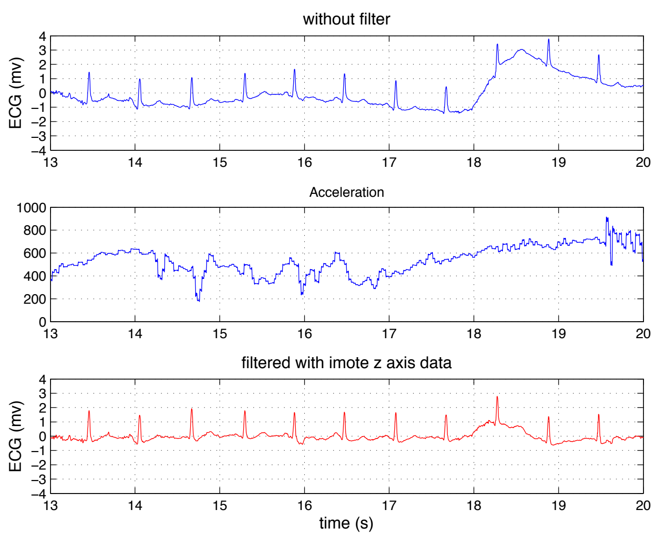

Fig. 7: The removal of motion artefacts from the ECG measurements of a person running. Top: The unfiltered ECG measurement. Middle: The corresponding measurement from one of the axes of a 3D accelerometer (the axis directed towards the earth's gravity). Bottom: The filtered ECG measurements.

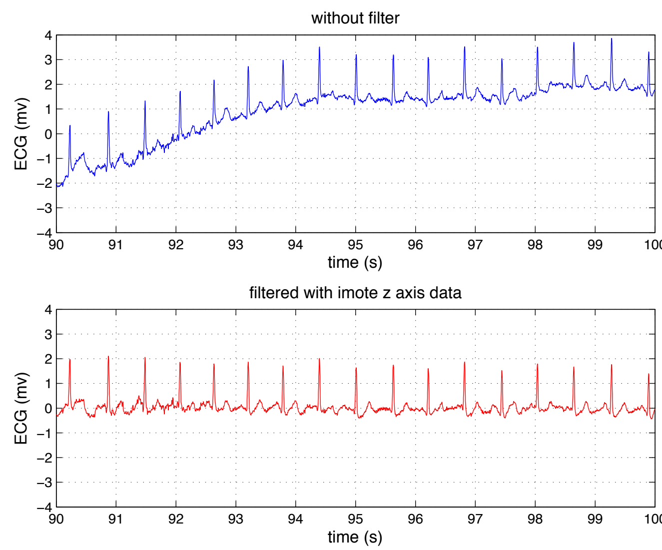

Fig. 8: The removal of motion artefacts from the ECG measurements of a person who was riding a bicycle. The motion artefacts are estimated with the help of one of the axes of a 3D acceleration (the axis directed towards the earth's gravity).

(a small variance around zero means the presence of a small noise component; a large variance, on the other hand, is an indication of the existence of a significant noise component). Similarly, if we regard the samples coming from a movement sensor for the same observation period, we can regard the samples as the outcomes of a random variable pertaining to movement. Hence, the samples collected between the peaks of two heartbeats can be used to establish the statistics of both the noise inside the ECG measurements and the corresponding movement which induces the noise in the ECG. Once these statistics are available, constructing the covariance, variance, and autocorrelation is possible.

V. Experiment Results and Evaluation

We use the Shimmer and IMote2 platforms for our experiments. The first integrates a wireless ECG (with 5 leads), 3D accelerometer, and 3D gyroscope, all of which can be sampled synchronously. The sensor platform is small enough to be placed between two electrodes to measure the movement which introduces artefacts into the ECG measurements. The disadvantage of using all the sensor in the Shimmer platform is that the platform can be placed between any of the pair of electrodes. The use of a separate platform (IMote2) for the inertia sensors is that multiple platforms can be placed between multiple pairs of electrodes at the same time. However, this option is cumbersome and synchronising the two heterogeneous platforms during sampling is difficult. The measurements representing movement artefacts can be obtained in different ways, for example, by fusing the measurements of accelerometers and gyroscopes. However, this technique introduces bias. If the movement type is known a priori, then the fusion technique can be optimised but if the movement is random (which is usually the case in everyday activities), then the fusion technique may not produce comparable outcomes in all situations. In our experiments, we decided to consider the output of each sensor separately. To remove the components of accelerations and rotation which have nothing to do with the movement artefacts in the ECG readings (such as gravity) and to translate local reference frames into a global reference frame, we applied the filter proposed by Madgwick et al. [14].

As a sanity test for our approach, first we took ECG measurements from a person who was at rest and relaxing, and determined the heart rate. For a healthy adult person, the heart rate varies between 50 and 100 beats a minute, which corresponds to a duration of 600 to 1200 ms per beat. At a sampling rate of 512 Hz, the wireless ECG produces between 307 to 614 samples per beat, which contains sufficient statistics. Then we separately measured the acceleration and rotation (with respect to the z-axis, which is parallel to the earth's gravity) of random movements of different intensities and mixed the results with the resting ECG readings, and supplied the noisy ECG readings to our adaptive filter. We then took actual readings from all the sensors while the same person carried out different activities (free walking, bicycle riding, running, climbing up a staircase, and climbing down a staircase). We discarded the measurements of the first 10 seconds to exclude the effects of undesirable activities from our analysis. Depending on the intensity of the activities, the duration of the useful measurements ranged from 60 to 130 s. Figs. 5 and 6 display the raw noisy ECG measurements taken while a subject was climbing up a staircase, the magnitude of rotation taken from a 3D gyroscope, and the filtered ECG measurements. In this case we used the integrated gyroscope to measure rotation. Fig. 7 shows the same set of measurements for a subject running. However, here we employed a separate accelerometer to capture the movement of the subject. Likewise, Fig. 8 displays the unfiltered and filtered ECG measurements for a subject riding a bicycle. Initial visual inspection in all cases confirms that all the heart beats of the subject could be detected. Moreover, whereas the P and T waves tend to vanish in the unfiltered measurements, they could be determined using our approach.

VI. Conclusion and Future Work

In this paper we employed an adaptive filter to improve the measurements of a wireless ECG. The coefficients of the filter were obtained by modelling measurements from 3D accelerometers and 3D gyroscopes as noise artefacts distorting the ECG measurements. We took actual measurements while a person was walking, running, riding a bicycle, and climbing up and down a staircase and correlated the ECG measurements with measurements associated with acceleration and angular rotation using the Shimmer and IMote2 platforms. One of the issues which is not sufficiently addressed in this paper is the analysis of the filter accuracy. We used the autocorrelation function and the duration of the ECG measurements as the basis for estimating the actual heart bit rate which we then compared with the heart rates we estimated with the unfiltered and filtered ECG measurements. A more plausible approach will be employing an external reference. This will be left as our future work.

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