Signal Analysis from Wireless ECG System

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Abstract: In this paper a novel mobile ECG analysis system is discussed. Existing stationary systems allow recording high quality ECG signal, but they place patients in an unlikely environment. Known wearable systems do not provide enough freedom as their sensors are connected to a mobile computer by wires. We propose a wireless ECG system with wired sensors and a mobile computer able to perform real-time analysis. Recorded signal is also transmitted to a central server where it can be processed more accurately. Special algorithms, based on well known methods, are proposed for signal filtering, baseline drift removal and P, Q, R, S and T peaks detection.

Key–Words: Electrocardiogram (ECG), QRS complex detection, P-wave, T-wave, R-R intervals, Baseline drift, Mobile systems, Real-time processing, Kalman filter

1 Introduction

Electrocardiogram (ECG) analysis takes the central part of heart disease detection. Rigorous study of ECG signal helps discovering and maintenance of tachycardias, coronary artery disease, myocardial infarction and eventually life extension.

State-of-the-art ECG measurement tools can be roughly divided into 2 general sub-groups: stationary systems designed for hospitals and wearable systems for persistent control. Stationary systems comprise a number of sensors along with data processing and visualisation elements. Though these systems are widely used in practice, generally providing appropriate accuracy, their application area is strongly restricted. Being stationary by design, they cannot be installed into ambulance, as well as cannot be quickly dismantled and set up in a mobile centre. Laboratory resting ECG or stress testing may mislead specialists as some diseases show in patient's natural environment, rather than in a hospital. Many of such measurement systems do not offer data processing for automatic diagnostics of heart disease. Those offering automatic diagnostics require high-quality ECG signal which is not possible to collect by a mobile system operating under harsh conditions.

In order to overcome flaws of the stationary ECG systems, compact wearing ECG sensors have appeared [1]. However, for most cases they lack in accuracy and generally do not offer complex solutions with storage and automatic analysis, that hampers the progress of such solutions. In this work we describe a novel approach, designed for mobile hospitals and ambulances. The proposed system comprises several wireless sensors, connected to the mobile processing computer. Collected data is also transmitted to the central server for data storage and processing. The first processing steps are performed online, e.g. signal filtration and enhancement, and then the data is analysed off-line on the central server, in order to collect statistics on the disease of the particular patient. The system can be also forced to work autonomously, if the central server is not available. The key problem is to diagnose heart disease and to predict various complications. We propose a system, that solves the stated problem using real-time processing with combination of extensive off-line signal analysis. In this article, we focus mainly on data filtering, as it outlines the main scientific interest of this research, which does not reduce the technical novelty of the system architecture.

The rest of the paper is organised as follows. In the second section, the state-of-the-art solutions for ECG measurement are discussed. In the third section, the proposed solution for ECG filtering and analysis is described. In the fourth section, the concluding remarks are emphasised.

2 State of the art

Generally, the ECG systems record the heart electrical activity (beat rate, rhythm, time series). However, the way it is done is constantly evolving. The main challenge for ECG system is to detect and amplify the voltage for the heart beat, based on the measurements on the patient skin. Two main types of systems should be designated: wired (or stationary) and wireless (or wearable) ECG systems. The first widely renowned wearable system was proposed by Holter [4], performing analogue signal measurement and recording and then its wireless transmission. Now, a plenty of systems aimed for long-term ECG recording, are proposed [2].

Many of these systems have their own shortcomings. In hospitals the standard practice is skin preparation (epilation, alcohol wiping, etc.). For wireless systems, it is proven to be ineffective, but the most serious challenge is motion artefacts, that cannot be challenged by these methods of preparation [1, 13].

In this work the problem of pre-processing is posed harshly. Some parts of pre-processing are done by hardware, while other should be done on the software level. For hardware processing, the standard analogue filtering is widely used (low- and high-pass filters), but in order to eliminate more complex artefacts (skin potential difference inside and outside the skin, muscle noise, sensor and cable motion, static electricity), programmatic approach should be used. For carrier line equalisation, low-pass filtering approach are currently used. The most straightforward approach is to use low-pass filtering to eliminate the bias components of the signal frequency, but for most of the real systems an adaptive filter is needed. Some of these approaches are based on moving-window, other are based on the signal model [14].

To enable ECG data analysis, P, Q, R, S and T peaks must be detected. Most of the state-of-the-art methods are based on some kind of a model. The signal can be named as “pseudo-periodic”, as it is likely to be periodic in the sense that the sequence of peaks appearance and the average distance between them are known, but for some diseases, such as arrhythmia, it does not resemble periodic signal. Known methods are based on low frequency signal processing or wavelet transform [12], general machine learning approaches, such as neural networks [3], Hidden Markov models [10] and many others.

3 Proposed solution

We propose a wireless ECG system designed for ECG signal recording and processing in natural environment. It can be divided into three essential parts:

- ECG sensors;
- mobile processing computer;
- central server and database.

Electrocardiogram signal is measured by four sensors: on left arm, on right arm, on left foot and on chest. These sensors are connected by wires to the central device. It serves as data collector, recording signal, and data transmitter, passing data to a mobile processing computer using Bluetooth Smart 4.0 technology. This computer, that can be a mobile phone, in fact, applies lowpass and highpass filtering and visualizes resulted signal in real-time. Proposed rule-based algorithms allows P, Q, R, S and T peaks detection as well. Data from the mobile computer is then sent to the central server where off-line, accurate post-processing, such as Kalman filtering, is performed.

3.1 Filtering

Filtering is an essential part of the ECG pre-processing step. Hereafter we describe initial digital filtering approaches, applied to the signal. The signal, initially acquired from the sensors even in stationary conditions is usually cluttered. The nature of the noise can differ depending on the environment, hardware and patient condition. However, in general we can distinguish three different types of noise that can appear:

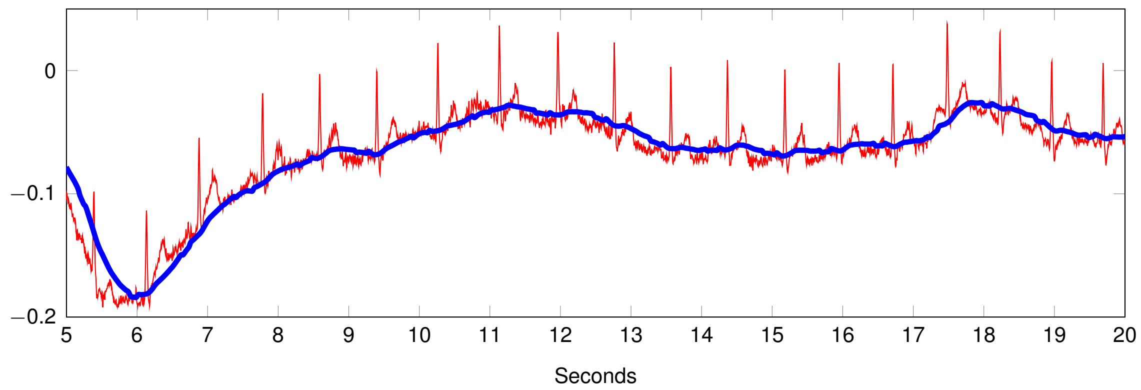

Figure 2: ECG signal carrier estimate

1. high frequency noise, which spectrum is higher than the signal spectrum;
2. low frequency noise, which constitutes a carrier of the ECG signal;
3. noise, which spectrum overlaps with the spectrum of the ECG signal.

First case is well-studied and developed. Usually, high-frequency noise is reduced by using a combination of low-pass and notch filters. Usually high-frequency noise is induced by hardware. In our work we use lowpass finite impulse response Kaiser filter. The group delay of the filter is 83 ms, which opens the doors to the real-time application.

Second type of noise usually appears in the cases when the sensor connection is poor. However, in case of independent measurements of different sensors the overall signal drift may be very significant, because different grounding induces low frequency carrier of the obtained signal. Due to the fact that each of the sensors is earthed independently, the environmental influence is independent as well. Therefore, good sensor connection does not guarantee the adequate carrier level in case of wireless ECG communication. This condition is strengthened by the fact

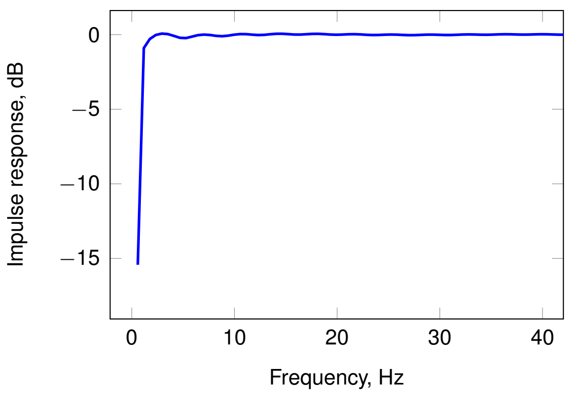

Figure 1: Impulse response characteristic of NW filter

that the measurements are performed in non-clinical conditions. Therefore, high-pass filtering is of high importance in wireless ECG measurements.

Usually high-pass filtering is applied with significant group delay, which may be unacceptable in some cases. For that reason we propose biased Nadaraya-Watson (NW) filtering, which is not based exactly on the frequency spectrum analysis, but on probabilistic basis. The idea is to approximate the carrier using exponential smoothing. Let $x(t) : \mathbb{N}$ $mathbbR$ denote real-values ECG signal.

Here t denotes the discrete time measurements in sample numbers, captured with frequency f. In our work we used signals with $f = 300$Hz. NW filter approximates the carrier by convolving initial signal with Gaussian weights

$$c(t) = (x * w_\alpha)(t) = \sum_{j=1}^{L} w_\alpha(j)x(t - \alpha L + j), \quad (1)$$

where $\alpha \in [0, 1]$ is a bias parameter, $w_\alpha(j) \propto \exp(-\frac{(j-\alpha L)^2}{f^2\sigma^2})$, $\sum_{j=1}^{L} w_\alpha(j) = 1$, and L is filter order.

Parameter α is introduced in order to decrease the delay level. One can see that the group delay in seconds for the described high-pass filter is $\frac{(1-\alpha)L}{f}$. In our work we select the parameter α and σ^2 in the way that the R-peaks and P-peaks amplitude error is lower than 1% (manually checked). In our work $\alpha = 0.75$ and $\sigma^2 = 4$. Impulse response characteristic of the proposed NW is represented on figure 1.

One can see that all the frequencies below 1Hz are suppressed by the filter, ECG spectrum (10Hz-30Hz) is not suppressed. An example of the carrier estimation is provided in figure 2.

The proposed approach is suitable for real-time processing, as it introduce low delay, but drift es-

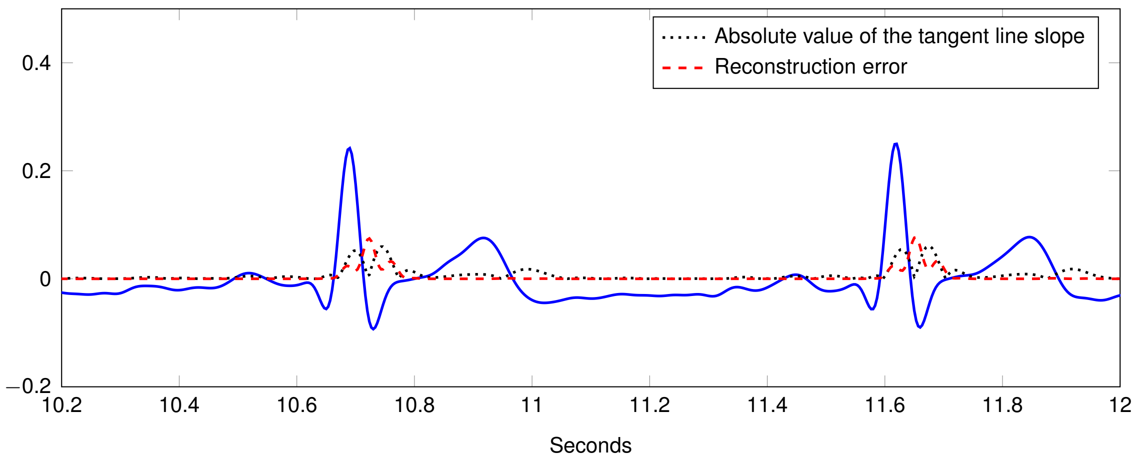

Figure 3: Tangent line slope and reconstruction error

timation can be inaccurate if low-frequency fluctuations overlap with ECG spectrum. In this case more specific cubic-spline interpolation can be applied [8]. However, NW filter is applicable for light-weighted preliminary online processing, as more precise techniques usually introduce significant delay, for example, one heart beat for cubic-spline approach.

3.2 ECG waveform analysis

ECG waveform analysis is based on detection of five characteristic peaks: P, Q, R, S and T, caused by depolarization and repolarization processes during cardiac cycle. Thus, P peaks corresponds to atrial depolarization. Q, R and S peaks, forming QRS complex, correspond to ventricular depolarization. T peak corresponds to ventricular repolarization. Morphology of these peaks: absence of P peak, negative or positive P and T peaks, regularity of R-R interval, helps distinguishing between normal (healthy) heart beat and different heart diseases. More specific U peak is not considered in the present paper being an objective for future work.

Though P, Q, R, S and T peaks detection can be performed automatically by stationary devices, the proposed system is based on mobile devices recording ECG signal outside hospital in natural environment, permanently for a long period of time. Therefore, a real-time lightweight detection algorithm is designed that allows marking peaks and signalling abnormal markups in real-time.

Another problem to be solved by the proposed algorithm is isoline detection. Though isoline drift is eliminated at the previous stage, small changes of isoline level still remain.

Analysis of ECG waveform starts from detecting the most prominent R peak. R peak detection is based on the well-known algorithm by Pan and Tompkins [9]. The original algorithm was modified so it can handle different frequencies and abrupt signal changes, spikes, that can be caused by sensor detaching.

As filtering is performed at the previous stage there is no need in bandpass filtering proposed by Pan and Tompkins. So smoothed squared signal derivative is only used in our algorithm. Derivative and moving-window integration, originally fixed, are parameterized so that their widths depend on frequency f of the input signal. Derivative width equals $h_d = \frac{1}{75}$ seconds and the corresponding transfer function is

$$H(z) = (-z^{-2^{L-1}} - \ldots - 2^{L-1}z^{-1} + \ldots \\ \ldots + 2^{L-1}z^{1} + \ldots + z^{2^{L-1}})/(2^{L+1} - 2), \quad (2)$$

where $L = [h_d f]$. Thus the delay is L samples or h_d seconds.

Similarly, moving-window width equals $h_i = \frac{2}{15}$ seconds and the smoothed R-indicator is calculated as

$$I(t) = (y(t-L) + \ldots + y(t) + \ldots \\ \ldots + y(L+1) + \ldots + y(t+L-1))/2L, \quad (3)$$

where $L = [h_i f]$ and $y(t)$ is the squared derivative. Again, the delay is L samples or h_i seconds. Threshold for the indicator is updated every $h_t = 2$ seconds and calculated as the mean value of the previous $L = [h_t f]$ samples,

$$T = (I(t-L+1) + \ldots + I(t))/L. \quad (4)$$

R peak indicator and the corresponding threshold can be calculated online with total delay of $\frac{11}{75}$ seconds.

With R peaks detected isoline level can be determined between each consecutive R peaks. Isoline detection is based on analysis of linear regression coefficients and reconstruction error. For each sample two linear regressions are built by $r = \left[\frac{f}{75}\right]$ samples backward and forward, respectively. These regressions are characterized by their tangent line slopes α_{bw}, α_{fw} and reconstruction error E_{bw}, E_{fw}. An illustration of α_{bw} and E_{bw} is given in figure 3.

Thresholds are determined for absolute values of α_{bw} and α_{fw} and for errors E_{bw} and E_{fw} as median values over a period of 2 previous seconds. Samples with absolute values of α_{bw} and α_{fw} and errors E_{bw} and E_{fw} below corresponding thresholds are considered as belonging to isoline. Isoline level between consecutive R peaks is calculated as mean value of the inlying isoline samples.

P, Q, S and T peaks are detected when new R peak is found. P and Q peaks are searched to the left from the R peak, S and T — to the right. Detection is based on the normal values of PQ, QSR, ST intervals and P and T waves duration. P and T peaks are maxima and Q and S peaks are minima in the corresponding search areas, depicted in figure 4. P and T peaks are corrected by shifting to the closest zeros of the derivative calculated during R peak detection step.

The final step of peak detection is to classify markup of each R-R interval into two classes: "Correct markup" and "Incorrect markup". This classification is done by applying a set of logical rules listed below.

1. Detected R peaks of the R-R interval (left and right) are both above isoline level.
2. Detected S peak is below isoline level.
3. Detected P peak is above isoline level and smaller than any of the R peaks.
4. Detected T peak is above isoline level and smaller than any of the R peaks.
5. Detected Q peak is below isoline level.
6. Peaks are close to derivative zeros.
7. No peaks higher than T peak between left R peak and T peak.
8. No peaks higher than P peak between right R peak and P peak.
9. No significant peaks between T and P peaks.

The proposed classifier helps discriminating between normal ECG morphology and all other morphologies.

3.3 Post-processing

While lightweight real-time processing is performed by mobile computers, rigorous analysis is done during post-processing stage on computer servers capable to handle all data stored in repositories.

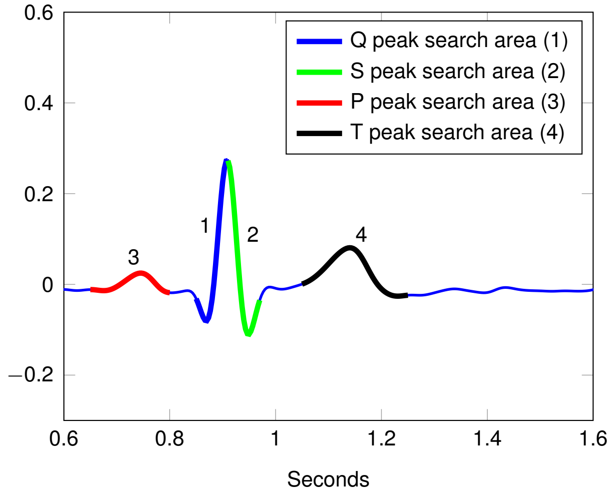

Figure 4: P, Q, S and T search areas

The filters described in 3.1 are not able to suppress noise overlapping with the cardiac components in the frequency domain. As it was mentioned previously, such types of noise is usually induced by muscles contraction. The non-linear Kalman filter-based approaches are proposed in order to overcome these issues. The basic ECG model is close to the framework described in [11] and [7].

We start with calculating mean R-R interval for the ECG signal $x(t)$. An illustration is given in figure 5.

Let n be the mean length is samples of all R-R intervals. It is found by procedures, described in 3.2, because R peak detection is very stable even for noisy data. Then each interval is normalized to the mean length. Due to the periodic nature of the ECG signal, we can parameterize it using "phase" variables. Let each interval be a function of the parameter $\Theta \in [0, 2\pi]$. It is discretized to $\Theta_k = (k-1)\frac{2*\pi}{n}$, $k = 1, \dots, n$. The mean value for each

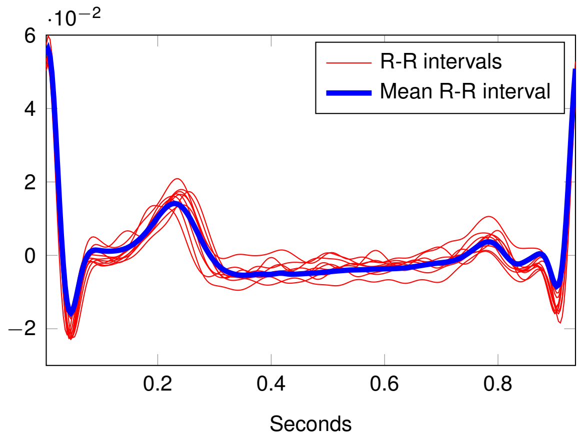

Figure 5: Mean R-R interval

value Θ_k is calculated. For the mean complex we can automatically find all values Θ_k corresponding to P, Q, R, S and T peaks. We denote these points as $\tilde{\Theta}_i$, $i \in \{P, Q, R, S, T\}$. Let $m(\Theta_k)$ be the function of the mean R-R interval.

Consider a dynamic system with hidden variables x_k, y_k, z_k and observed variables $\bar{x}_k, \bar{y}_k, \bar{z}_k$, where x_k, y_k are interpreted as cosines and sines of the "phase" variable and z_k is the value of the ECG signal. Then denote $\cos(\tilde{\Theta}_i), \sin(\tilde{\Theta}_i)$ as $\tilde{x}_i, \tilde{y}_i$. Suppose that the ECG signal hidden variable dynamics are described by equation system (5).

$$\begin{cases} x_{k+1} = \sqrt{1-\omega^2}x_k - \omega y_k = f_x(x_k, y_k, z_k), \\ y_{k+1} = \omega x_k + \sqrt{1-\omega^2}y_k = f_y(x_k, y_k, z_k), \\ z_{k+1} = \omega h(x_k, y_k, \omega_i, \sigma_i, \tilde{x}_i, \tilde{y}_i) + \ldots \\ \qquad \ldots + z_k = f_z(x_k, y_k, z_k), \end{cases} \tag{5}$$

where parameter $\omega = \frac{1}{n}$ corresponds to signal frequency and

$$\begin{aligned} &h(x_k, y_k, \omega_i, \sigma_i, \tilde{x}_i, \tilde{y}_i) = \ldots \\ &\ldots = \sum_{i \in \{P,Q,R,S,T\}} (x_k \tilde{y}_i - y_k \tilde{x}_i) \times \ldots \\ &\ldots \times \omega_i \exp\left(-\frac{(x_k - \tilde{x}_i)^2 + (y_k - \tilde{y}_i)^2}{2\sigma_i^2}\right). \end{aligned} \tag{6}$$

The values $\omega_i, \sigma_i, \tilde{x}_i, \tilde{y}_i$, $i \in \{P, Q, R, S, T\}$ are defined as the solution of optimization problem (7).

$$\begin{aligned} g(\omega_i, \sigma_i, \tilde{x}_i, \tilde{y}_i) = \sum_{k=1}^{n-1} (h(x_k, y_k, \omega_i, \sigma_i, \tilde{x}_i, \tilde{y}_i) + \ldots \\ \ldots + m(\Theta_{k+1}) - m(\Theta_k))^2 \to \min. \end{aligned} \tag{7}$$

Dependency between observations and hidden variables is given by identity transition with additive noise (8),

$$\begin{cases} \bar{x}_k = x_k + \bar{\varepsilon}_x, \\ \bar{y}_k = y_k + \bar{\varepsilon}_y, \\ \bar{z}_k = z_k + \bar{\varepsilon}_z, \end{cases} \tag{8}$$

where vector $\varepsilon = (\bar{\varepsilon}_x, \bar{\varepsilon}_y, \bar{\varepsilon}_z)^T$ represents normally distributed noise.

Denote $t_k = (x_k, y_k, z_k)^T$, $f = (f_x, f_y, f_z)^T$. To estimate t_k we consider two types of Kalman-filtering techniques: Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). Both of them are designed for non-linear dynamic systems.

First, we consider EKF approach. The system (5) is linearized, i.e. $t_{k+1} = f(\mu_k) + \nabla f(\mu_k)(t_k - \mu_k)$. Then Kalman filter "forward-backward" algorithm is

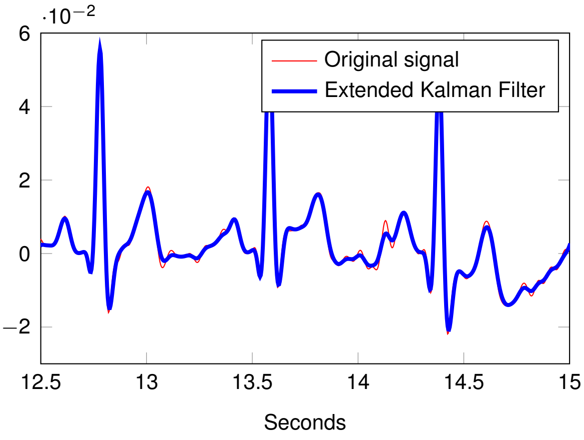

Figure 6: Extended Kalman Filter result

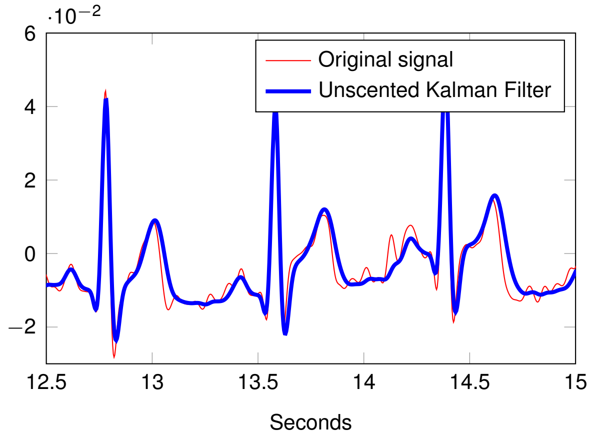

Figure 7: Unscented Kalman Filter result

applied. The observed variable $\bar{z}_k$ and the estimated variable z_k are shown in figure 6.

Contrary to EKF, Unscented Kalman Filter [6] does not need linearization of Kalman filter equations (5) thanks to a well-known unscented transformation method [5]. The method exploits deterministic estimation of data points set, based on the previous ECG signal estimation and data points covariance matrix from the previous step. The forecast is represented as a linear combination of Kalman filter equations (5). ECG waveform for the source and filtered signal are shown in figure 7.

4 Conclusion

Analysis of electrocardiogram benefits prevention and timely treatment of most heart diseases. Stationary ECG analysis systems available in hospitals provide high quality signal, easy to examine. At the same time, such systems place patients in a specially prepared conditions not allowing to record ECG signal in natural environment. Wearable ECG systems can solve this problem, but their usage has considerable difficulties caused by muscle noise, sensor and cable motion, static electricity, etc. In this work a mobile (wearable) ECG analysis system is proposed. From the hardware point of view its novelty is in wireless sensors transmitting signals to a mobile computer. Designed software provide both lightweight real-time and time-demanding off-line algorithms for preprocessing and analyzing ECG signal. Real-time algorithms allow to remove baseline drift, along with high frequency noise, detect P, Q, R, S, and T peaks. A set of rules is proposed to classify good and bad PQRST markups. More powerful Kalman filters are proposed to enhance signal filtering allowing to extract valuable measurements from detected peaks.

In future we aim towards improving filtering and baseline drift removal as well as short-term and long-term predicting of patient state.

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