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Design & Analysis of Multimode Monitoring of Electrocardiogram (ECG) and Electromyography (EMG) Signals with USB interface or Human Computer Interaction System

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Abstract: ***The electrocardiogram (ECG) and electromyography (EMG) is an important physiological signal that helps determine the state of the cardiovascular & muscular system; however, this signal is often corrupted by interfering noise. Baseline wander is a commonly seen noise in ECG & EMG recordings and can be caused by respiration, changes in electrode impedance, and motion. Baseline wander can mask important information from the ECG & EMG, and if it is not properly removed, crucial diagnostic information contained in the ECG & EMG will be lost or corrupted. Therefore, it is vital to effectively eliminate baseline wander before any further processing of ECG such as feature extraction. The simplest method of baseline wander (drift) removal is the use of a high-pass filter that blocks the drift and passes all main components of ECG though the filter. The main components of ECG include the P-wave, QRS-complex, and Twave. Specifically, the PR-Segment, ST-Segment, PR-Interval, and QT-Interval are considered as the main segments of the ECG. Each of these intervals/segments has its corresponding frequency components, and according to the American Health Association (AHA), the lowest frequency component in the ECG signal is at about 0.05Hz. However, a complete baseline removal requires that the cut-off frequency of the high-pass filter be set higher than the lowest frequency in the ECG; otherwise some of the baseline drift will pass through the filter. The frequency of the baseline wander high-pass filter is usually set slightly below 0.5Hz.Therefore, knowing that the actual ECG & EMG signal has components between 0.05Hz and 0.5Hz, the fore mentioned simple approach for baseline removal distorts and deforms the ECG & EMG signals.***

Keywords: Electrocardiogram (ECG), Surface Electromyography (SEMG), Motor System, Matlab

1. Introduction

Chronic conditions are becoming the first problem of public health in western countries. This situation is the result of changing demographic trends and population aging, changes in consumption patterns and risk behaviors, rapid urbanization and social disintegration and the globalization of health issues. The economic costs associated to the treatment of these patients are a burden that not only threatens the sustainability of health systems but also imposes challenges to the patients and their families. Our current health care structures, too focused in the healing of acute conditions, do not facilitate the management of chronic patients. There is little or no co-ordination among different health care levels, patient empowerment is a priority, prevention and regular follow-up are not frequent and community support is not considered. New emerging models of health care provision for chronic patients take all these components into account to achieve productive interactions between informed activated patients and proactive practice teams. There are experiences demonstrating the feasibility and benefits of such model. Within the project, the chronic patient model will correspond to either Chronic Pulmonary Obstructive Disease or Congestive Heart Failure or both. The focus will be set in the monitoring facilities of the different vital signs to ensure adequate follow-up at a distance. To this end, the URSAFE system includes sensors (ECG, Oxygen saturation and fall detection) linked to a Portable Base Station (PBS) through UWB (Ultra Wide Band) techniques. Each sensor will include software for signal processing and alarm management; it has been agreed that a regular poll coming from the UWB associated to each sensors will regularly check if an alarm has been set at the sensor SW module. In case an alarm has been effectively raised, the UWB module then initiates the transmission scenario between the local monitoring network (including all the monitoring devices) and the medical service center (using different transmission bridges that are the PBS and either indoor or outdoor dedicated networks).

2. Method Used

Figure 1 shows the framework of the proposed method. As it can be seen in Figure 1, the first step of the proposed method is an adaptive notch filter, designed to form sub signals of the ECG, as described later. Next, as shown in Figure 1.

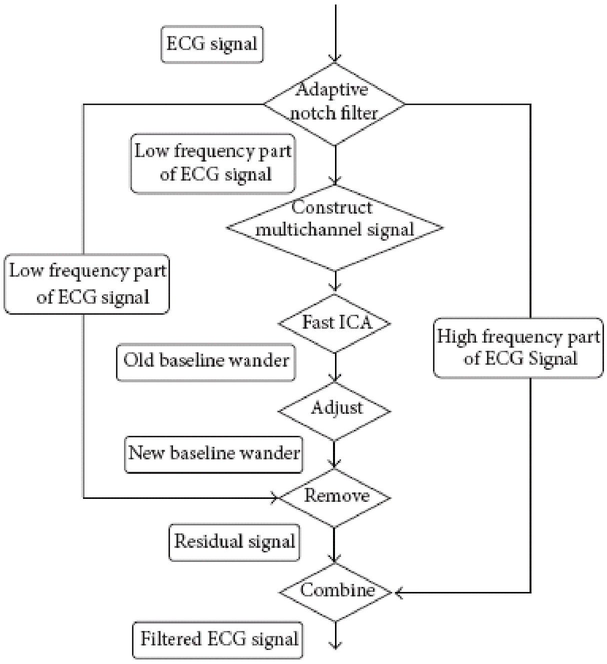

Figure 1: Flowchart diagram of proposed method

The proposed method utilizes ICA to remove the baseline drift. Considering the noisy nature of the typical raw ECG signal, in this study, sub signals in low frequencies of the ECG are formed and these filtered signals are, then, formed by an adaptive notch filter, and then used as the input to the ICA algorithm. Moreover, with regard to the inputs fed to the ICA algorithm, in this study, only a single-channel ECG signal is available. Therefore, knowing that ICA requires multichannel signals to process as its input, in order to use ICA to remove baseline wander, one needs to build multichannel signals from the single-channel ECG. In order to address this issue in the proposed method, a systematic process was created in addition, as shown in Figure 1, the independent component formed by the ICA as the output, which is originally labeled as the baseline wander, needs to be further adjusted to form a better estimate of the baseline wander. This is due to the fact that, while one of the components resembles the baseline drift, it is unlikely that any of the original components detected by the ICA is "purely" the baseline wander. The specific steps shown in Figure 1 are further described below. (a) Form sub-signals of ECG using an adaptive notch filter: as shown in Figure 1, the adaptive notch filter [25, 26] is designed and customized to form the sub signal. The reason for using the adaptive notch filter is its flexibility as well as its relatively superior performance compared with other filters. As mentioned above, applying the ICA algorithm on a sub-signal of the ECG has the advantage of reducing the errors coming from multi-channel signals in estimating the baseline wander. (b) Construct multi-channel signals: applying ICA requires that the signals are multi-channel ones. However, in many ECG processing applications only the single-channel ECG signal is available and/or processed. The proposed method applies the methodology in [11] to construct multi-channel signals by delaying the single-channel signal. In our study, the multi-channel signals are constructed using sixty signals, which are delayed 10 sample points (83 ms) of the original signal in succession. (c) Adjust the baseline wanders extracted by ICA: the baseline wander extracted by ICA is an approximation of the true baseline wander because (1) there will be some errors in the resulting component due to the fact that the estimation process used in the ICA (in particular in the first few attempts) may be non optimal; (2) in the ICA analysis there may be more than one maximum in the estimation function and, therefore, the true baseline wander may not be located accurately; (3) the constructed multi-channel signals cannot convey all information about the baseline wander and, as such, the proposed process may alleviate the issues associated with the non-optimal construction of multi-channel signals. The 10-sample shift of the signals provides large enough variations between the multi signal components to alleviate the issues concerning dependencies for ICA processing.

3. Independent Component Analysis (ICA)

Independent component analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed non gaussian and mutually independent and they are called the independent components of the observed data. These independent components, also called sources or factors, can be found by ICA. ICA is superficially related to principal component analysis and factor analysis. ICA is a much more powerful technique, however, capable of finding the underlying factors or sources when these classic methods fail completely. The data analyzed by ICA could originate from many different kinds of application fields, including digital images, document databases, economic indicators and psychometric measurements. In many cases, the measurements are given as a set of parallel signals or time series; the term blind source separation is used to characterize this problem. Typical examples are mixtures of simultaneous speech signals that have been picked up by several microphones, brain waves recorded by multiple sensors, interfering radio signals arriving at a mobile phone, or parallel time series obtained from some industrial process.

4. Medical Requirement Constraint

The present document focuses on the definition of the signal processing needs for the development of tele-monitoring applications. This task shall include in a complementary way, both medical requirements as well as technical feasibility. The following sections adopt a medical point of view and provide basis for drawing the technical system specifications. It has particularly led to some adaptation of the initial system architecture and has orientated the signal processing application SW. The medical aspects of the context (it will be updated and completed throughout this document); it will help to define a first stage for the signal processing activity specifications. The sensors of interest and the associated biomedical data in the scope of this study are the baseline-selected devices: The processing associated to each device has to be considered. But as we will further underline, the most demanding signal from both medical and technical points of view (medically full of information and most complex to analyze) is the ECG. First we will highlight the "medical" objectives of an automated monitoring, that is to say what kind of events have to be analyzed, detected, and recognized. Then with the clarified medical objectives in the scope of URSAFE we will present the steps followed for the signal processing activity study. This part will finally help support the technical specification of the software modules dedicated to biomedical data monitoring.

5. Medical Support Provided Through The Use of wearable & Continuous Monitoring Devices

The efficiency of the whole URSAFE concept from medical cost reduction as well as patient way of life improvement has been proved in deliverable D1. Particularly focusing on the signal processing activities, we have to detail some fields of application of the system. This section recalls in which situations this system could be required to satisfy the two initial objectives of the project: hospitalization costs reduction and patient quality of life by avoiding visits to the hospital.

6. Case Study

Case 1

After a by-pass heart operation, the (usually elderly) patient comes at home after some days and earlier than she/he would have been back without the use of the U-R-Safe platform. The continuous monitoring at home allows during the initial dates the rhythm of the evolution to be continuously monitored. A nurse comes from time to time to the home of the person to assure her/him. When the person does not feel comfortable a first contact is established with the voice processing system. A series of simple but critical questions is set by the machine and answered by the person. This information is transmitted to the Hospital or other Medical Service and the Medical doctor in charge of the case decides either to send the emergency or to settle the case by phone. After some days of home follow-up the person can quit her/his home and drive a normal life: visit family, shopping, travelling. The whole system is following her/him: the communication is conducted outdoors via the GPRS system. To avoid excess transmission of data, automatic transmission is triggered on events or manually when the person feels less comfortable. The same procedure based on voice processing is also followed in the outdoors case. By doing so for the first several weeks after the operation the person is better followed up (continuously) with lower cost (the hospital bed cost for 2-3 days versus monitoring for several days – presently precursor services come with costs of the less than 2 Euro per day, that even for weeks of monitoring is considerably lower than the cost of a hospital bed for 2-3 days).

Case 2

A diabetic person is in rural area. A satellite communication system is the means to establish the contact to the home of this person. In a normal case the personal base station is measuring diabetes. At a certain moment a case of hypoglycemia appears. Then the Satellite Communication is activated. According to the position of the home either a confident neighbor is invited to come or the emergency service (that can be in this case the rural medical doctor or helicopter help). Again information gained through the voice processing before collapse and glucose automatic measurements are fed to the Service center. Electromyography is a muscle examination method which tracks and interprets electrical activity that provides to muscle contractions. Surface electromyography (SEMG) is widely used as a diagnostic tool in estimation of muscle strength, calculation of muscle fatigue and ergonomics, sports physiology and rehabilitation. Obtaining and examining carefully EMG signals provide valuable information in determining and examining abnormalities in the muscle and motor system. In this research, a computer based, instrumentation system has been designed for EMG signals which are taken from the patient's arm muscle. The aim of the hardware is to provide, transfer to computer and view the EMG information of the patients received over the USB port. The essential hardware and software was created to perform the system. On the phase of obtaining the signal, EMG signals that were received from the surface electrodes over the patient's arms have been subjected to various filtering and amplification processes to transport from the transmission channel to the environment that the signal will be displayed. The EMG signal was translated from analogue to digital and was transferred to the computer with USB. After transforming analogue signal to digital, obtained data was filtered with MATLAB in the digital media and provided to display in the computer with the prepared software interface. According to my research: (i) Facial expression and human emotion analysis, (ii) Eye movement and gaze tracking, (iii) Speech recognition and synthesis ,(iv)Virtual reality (VR) and augmented reality (AR) interaction,(v) Driver assisted multimodal interface,(vi) Multimodal interface for disabled and elderly people. Noise can compromise the extraction of some fundamental and important features from biomedical signals and hence prohibit accurate analysis of these signals. Baseline wander in electrocardiogram (ECG) signals is one such example, which can be caused by factors such as respiration, variations in electrode impedance, and excessive body movements. Unless baseline wander is effectively removed, the accuracy of any feature extracted from the ECG, such as timing and duration of the ST-segment, is compromised. This paper approaches this filtering task from a novel standpoint by assuming that the ECG baseline wander comes from an independent and unknown source. The technique utilizes a hierarchical method including a blind source separation (BSS) step, in particular independent component analysis, to eliminate the effect of the baseline wander. We examine the specifics of the components causing the baseline wander and the factors that affect the separation process. Experimental results reveal the superiority of the proposed algorithm in removing the baseline wander.

7. Conclusion

An ECG dataset of human volunteer undergoing lower body negative pressure (LBNP) [28] as a surrogate of hemorrhage was employed to verify the effectiveness of removing baseline wander. This data set was created under Institutional Review Board approval. The LBNP dataset consisted of a total of 91 subjects. Each subject had a single vector lead ECG recording collected at the sampling rate of 500Hz. The baseline wander in ECG signals demonstrated significant level of variations in the amplitude over the course of the LBNP experiment. During LBNP, subjects are exposed to increasing negative pressure to their lower bodies. This causes a redistribution of blood volume to the lower extremities and abdomen causing a decrease in blood pressure and cardiac output and resulting in an increased respiratory rate. The results of the proposed method are compared with a reference method, called robust locally weighted regression [29], which is often treated as one of the most robust and commonly used methods to remove baseline drift. The robust locally weighted regression method employs two techniques: the local fitting of polynomials and an adaptation of iterated weighted least squares to remove the baseline drift.

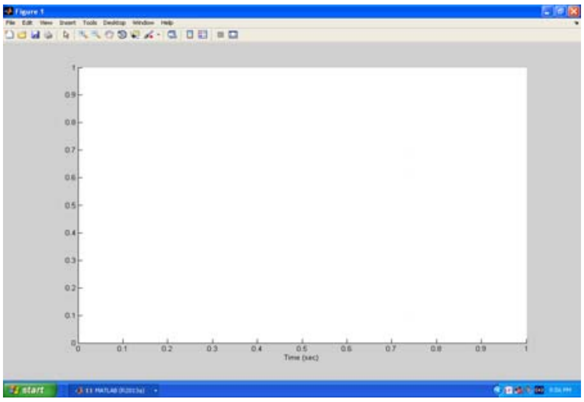

Figure 2: Schematic diagram of proposed method

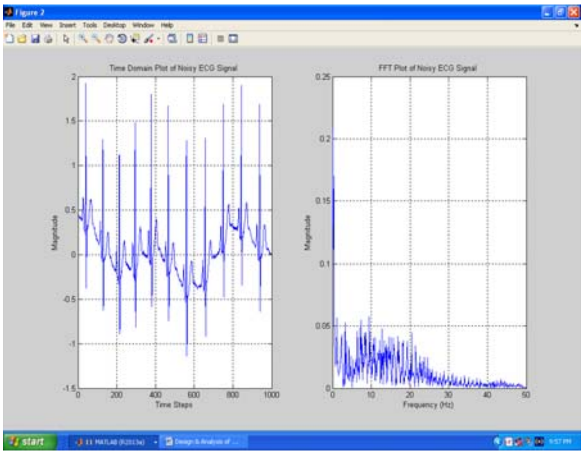

Figure 3: Schematic diagram of proposed method

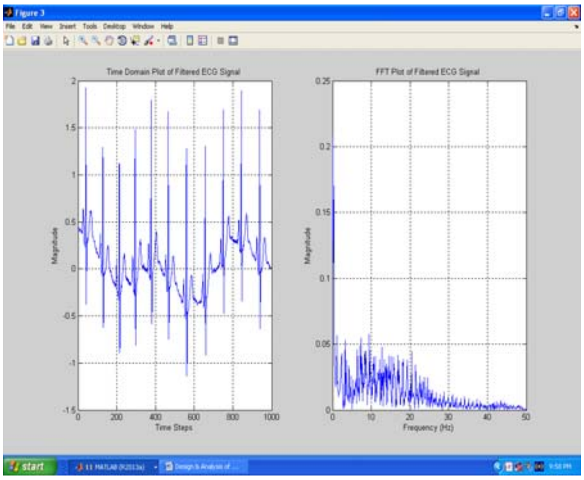

Figure 4: Schematic diagram of proposed method

Figure 5: Schematic diagram of proposed method

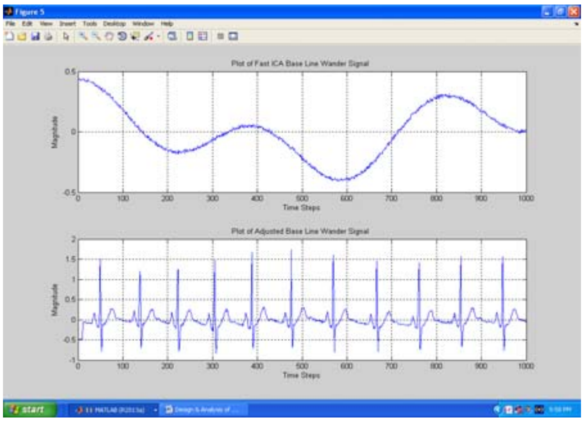

Figure 6: Schematic diagram of proposed method

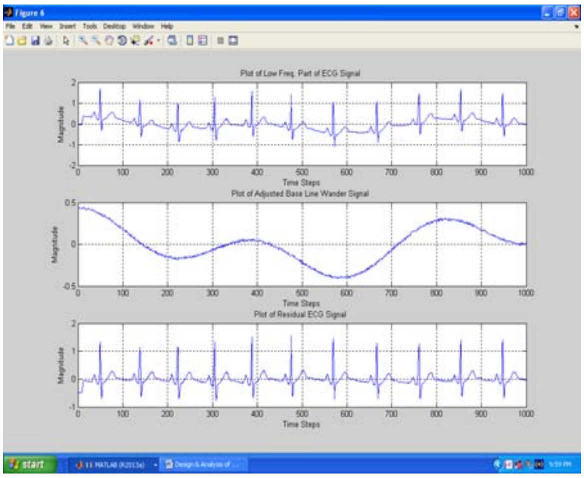

Figure 7: Schematic diagram of proposed method

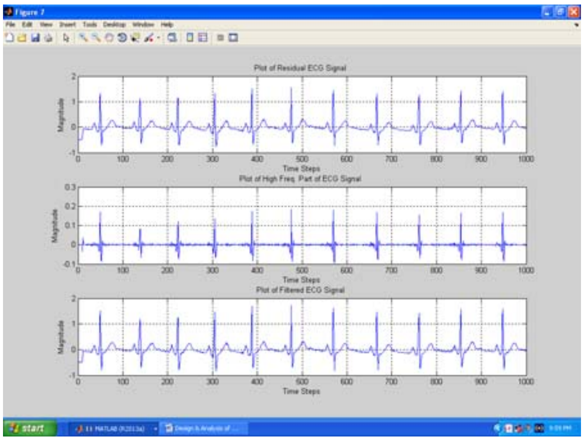

Figure 8: Schematic diagram of proposed method

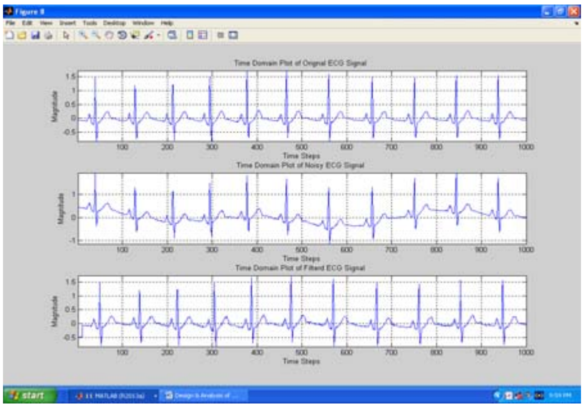

Figure 9: Schematic diagram of proposed method

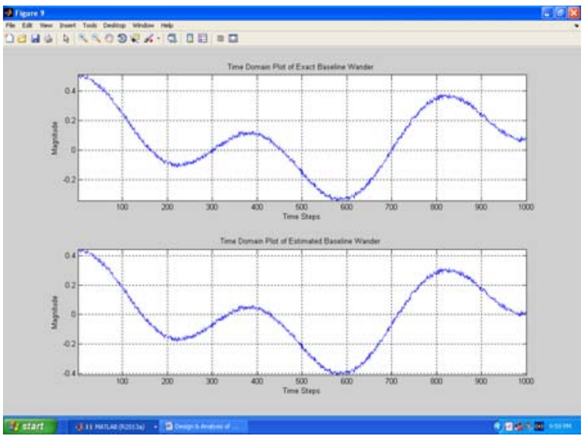

Figure 10: Schematic diagram of proposed method

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