Separation and Analysis of Fetal-ECG Signals From Compressed Sensed Abdominal ECG Recordings

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Abstract- *In the paper, Assessment of fetal health conditions through electrocardiography allows to discover possible distress or congenital heart defects during pregnancy .A novel system for the compression and analysis of the Abdominal Fetal Electrocardiogram (fECG) using Compressive Sensing (CS).We propose to apply the ICA directly in the compressed domain to extract the source components from the multi-channel novel framework for the compression of abdominal fECG recordings jointly with real time beat detection and classification. Results allow us to conclude that the proposed framework may be used for compression of abdominal f-ECG and to obtain real time information of the fetal heart rate, providing a suitable solution for low-power tele monitoring applications minal fECG.*

I. INTRODUCTION

Assessment of fetal health conditions through electrocardiography is a useful clinical diagnostic method, which allows to discover possible distress or congenital heart defects in early stages of pregnancy and during delivery. Fetal heart rate (fHR) monitoring and detection of the fetal electrocardiogram (f-ECG) may be able to provide early detection of fetal arrhythmias, making it possible to treat them with drug administration or to pre-schedule the delivery.

In abdominal f-ECG recording, the electrical signal generated by the fetal heart is measured by non-invasive electrodes placed on the mother's abdomen surface. This kind of measurement is clearly suitable for long-term observation as well as for at-home monitoring during all pregnancy. However, the f-ECG signal acquired from the mother's abdomen is typically characterized by a very low SNR. In fact, signals recorded by this method are always a mixture of noises generated, for instance, by fetal brain activity, myographic signals (both from the mother and the fetus), movement artifacts and maternal ECG. Moreover, the fetal component is usually smaller compared to the maternal one, since the fetal heart is smaller than the adult, and is typically attenuated by tissues in the path to the measuring electrodes.

Advanced techniques are required for abdominal fetal ECG signals analysis due to the typical complexity and variability of recorded signals. two abdominal recordings from the Physionet Challenge database . In the fetal heart beat is barely visible, while it can be seen clearly The duration, amplitude, and morphology of the fetal QRS complex is similar to the maternal one, but with a smaller amplitude and QRS width. Moreover, fetal and maternal beats may overlap in time, making even harder to detect the fetal QRS complexes. Signal processing techniques for non-invasive f-ECG are still an active field of research, as reported .The possibility to obtain clean f-ECG signals by non-invasive abdominal measurements has been demonstrated in . It has been shown that the use of signal processing techniques may improve the quality of f-ECG waveforms from abdominal recordings and make it comparable to that achievable through the use of a scalp electrode.

Combining advanced signal processing techniques and noninvasive acquisition of f-ECG through abdominal electrodes may allow at-home continuous monitoring using technologies such as wireless body sensor networks (WBSNs), which have been recently proposed for adult monitoring of physiological signals during everyday activities . A WBSN is composed of a varying number of sensors which measure and compress physiological signals (e.g., the ECG signal). Signals are then typically sent to a nearby smart phone to allow its transmission to a remote terminal via the Internet. WBSN sensors have typically many constraints, one of which is low energy consumption. Moreover, since ultra low power radio devices, with low communication capacity, are commonly used for transmission, another constraint is that the transmitted physiological signal should be largely compressed.

II. LITERATURE SURVEY

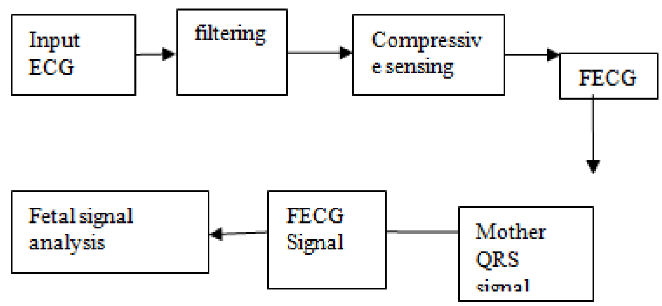
1. We sought to evaluate the accuracy of a novel system for measuring fetal heart rate (FHR) and ST-segment changes using noninvasive electrodes on the maternal abdomen. Continuous fetal heart rate (FHR) monitoring during labor is utilized in85% of labor episodes in the United States and represents the standard of care,1 although there is scant *evidence to demonstrate that the use of the technology improves newborn or maternal outcomes.*

2. Recent technological advances in sensors, low-power integrated circuits, and wireless communications have enabled the design of lowcost, miniature, lightweight, and intelligent physiological sensor nodes. These nodes, capable of sensing, processing, and communicating one or more vital signs, can be seamlessly integrated into wireless personal or body networks (WPANs or WBANs) for health monitoring. These networks promise to revolutionize health care by allowing inexpensive, non-invasive, continuous, ambulatory health monitoring with almost real-time updates of medical records via the Internet.

3. The increasing use of wireless networks and the constant miniaturization of electrical devices has empowered the development of Wireless Body Area Networks (WBANs). In these networks various sensors are attached on clothing or on the body or even implanted under the skin. The wireless nature of the network and the wide variety of sensors offer numerous new, practical and innovative applications to improve health care and the Quality of Life. The sensors of a WBAN measure for example the heartbeat, the body temperature or record a prolonged electrocardiogram.

4. Compressive Sensing (CS) is a newly introduced signal processing technique that enables to recover sparse signals from fewer samples than the Shannon sampling theorem would typically require. It is based on the assumption that, for a sparse signal, a small collection of linear measurements contains enough information to allow its reconstruction. Combining the acquisition and compression stages, CS is a very promising technique to develop ultra low power wireless bio-signal monitoring systems.

A novel framework for the Com pressive Sensing of abdominal multi-channel f-ECG recordings jointly with the detection and classification of fetal and maternal beats. The proposed method is summarized in the block diagram. Extending our previous work , to overcame the limitations of classical Compressive Sensing framework for f-ECG signals, we introduce a new universal dictionary that permits to successfully increase compression while maintaining a reconstruction quality which does not affect the detection performance. The dictionary comprises two classes of Gaussian-like functions. modeling the fetal and mother ECG. Fetal heart rate estimation requires to separate the fetal and maternal beats from the acquired ECG signals. We model the recorded ECG signals as a mixture of independent components (ICs) given by the mother's and fetal heart beat signals, as well as other noise sources. We show that it is possible to perform Independent Component Analysis (ICA) directly in the compressed sensed domain, with no performance loss than using the original signals. Our scheme operates on small blocks of compressed coefficients, and estimates the compressed independent components, thus reducing computational complexity and permitting low delay detection and reconstruction. Finally, from the compressed independent components, we separate the maternal and fetal beats by checking the activated atoms during reconstruction within the CS framework. Although the focus of this paper is the design of a low-power and low-complexity acquisition/ detection real-time system, the performance loss with respect to non real-time procedures, which apply off line post processing techniques and several detection refinement stages, is acceptable, besides the fact that the proposed approach does not require training, it is completely automatic and can be used for real-time analysis with a small delay.



The fetal heart rate (fHR) and the morphological analysis of the fetal electrocardiogram (fECG) are two of the most important tools used nowadays in clinical investigations to examine the health state of the fetus during pregnancy. The fHR is the mostly used parameter in fetal monitoring, since 1818 [1]. While the fHR track shows a predictive value of almost 99% for the fetal well being investigation, an abnormal fHR has a predictive value of only 50%. Hence, it provides relatively poor specificity in detecting the fetal distress [2]. Additional information about the fetal well being can be obtained by analyzing the morphology of the fECG signal, which was recently introduced in clinical practice for fetal monitoring. Its clinical relevance was demonstrated by a series of clinical studies [3], randomized controlled trials [4–8] and prospective observational studies [9–18], which prove that clinical fetal monitoring based on both fHR and fECG morphology analysis, especially the ST waveform analysis, leads to the reduction in the number of operative vaginal deliveries, smaller rate of metabolic acidosis at birth, less blood samples performed during labor, and fetal morbidity reduction. The standard procedure to record the fHR is the cardiotocography (CTG), sometimes known as electronic fetal monitoring [19]. When necessary to investigate both the instantaneous fHR and the fECG morphology, an invasive fetal monitoring method that uses a wire electrode attached to the fetal scalp [20], after the membrane rupture, is preferred. However, both methods have important drawbacks: (i) the fHR obtained via CTG has the potential problems of reliability and accuracy [21, 22]; in addition, the beat-to-beat variability of fHR is not present in the CTG traces [23, 24]; hence, rapid variations of the fHR cannot be detected; (ii) the second recording technique is invasive [20]; thus, it can put the life of both the mother and the fetus in danger (e.g., possible infections can lead to different complications).

III. SOFTWARE MODULE WITH EXPLANATION

MATLAB (matrix laboratory) is a fourth-generation high-level programming language and interactive environment for numerical computation, visualization and programming. MATLAB is developed by Math Works .It allows matrix manipulations; plotting of functions and data; implementation of algorithms; creation of user interfaces; interfacing with programs written in other languages, including C, C++, Java, and Fortran ;analyze data; develop algorithms; and create models and applications. It has numerous built-in commands and math functions that help you in mathematical calculations, generating plots and performing numerical methods.

Model-Based Design is a process that enables faster, more cost-effective development of dynamic systems, including control systems, signal processing, and communications systems. In Model-Based Design, a system model is at the center of the development process, from requirements development, through design, implementation, and testing. The model is an executable specification that you continually refine throughout the development process. After model development, simulation shows whether the model works correctly. When software and hardware implementation requirements are included, such as fixed-point and timing behavior, you can automatically generate code for embedded deployment and create test benches for system verification, saving time and avoiding the introduction of manually coded errors. The first step in modeling a dynamic system is to fully define the system. If you are modeling a large system that can be broken into parts, you should model each subcomponent on its own. Then, after building each component, you can integrate them into a complete model of the system. For example, the demo house heat example model of the heating system of a house is broken down into three main parts:

- Heater subsystem
- Thermostat subsystem
- Thermodynamic model subsystem

The most effective way to build a model of this system is to consider each of these Subsystems independently.

Identifying System Components

The second step in the modeling process is to identify the system components. Three types of components define a system:

• **Parameters —** System values that remain constant unless you change them
• **States** — Variables in the system that change over time
• **Signals —** Input and output values that change dynamically during a simulation

In Simulink, parameters and states are represented by blocks, while signals are represented by the lines that connect blocks. For each subsystem that you identified, ask yourself the following questions:

- How many input signals does the subsystem have?
- How many output signals does the subsystem have?
- How many states (variables) does the subsystem have?
- What are the parameters (constants) in the subsystem?
- Are there any intermediate (internal) signals in the subsystem?

Once you have answered these questions, you should have a comprehensive list of system components, and you are ready to begin modeling the system.

Modeling the System with Equations

The third step in modeling a system is to formulate the mathematical equations that describe the system. For each subsystem, use the list of system components that you identified to describe the system mathematically.

Your model may include:

- Algebraic equations
- Logical equations
- Differential equations, for continuous systems
- Difference equations, for discrete systems
- You use these equations to create the block diagram in Simulink.

Building the Simulink Block Diagram

After you have defined the mathematical equations that describe each subsystem, you can begin building a block diagram of your model in Simulink. Build the block diagram for each of your subcomponents separately. After you have modeled each subcomponent, you can then integrate them into a complete model of the system.

Running the Simulation

After you build the Simulink block diagram, you can simulate the model and analyze the results. Simulink allows you to interactively define system inputs, simulate the model, and observe changes in behavior. This allows you to quickly evaluate your model.

Validating the Simulation Results

Finally, you must validate that your model accurately represents the physical characteristics of the dynamic system. You can use the linearization and trimming tools available from the MATLAB command line, plus the many tools in MATLAB and its application toolboxes to analyze and validate your model.

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