FETAL HEART RATE DETECTION USING VPW-FRI

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ABSTRACT

Fetal Electrocardiograms (fECG) are an inexpensive and noninvasive method to determine the heart rate (HR) of the fetus. Large variations in the fetal HR is a good indicator that the fetus is in distress thus allowing for clinical intervention. Although advances have been made in the field of fetal HR detection, more can be done to improve accuracy and efficiency. The Variable Pulse Width - Finite Rate of Innovation (VPW-FRI) method is a suitable method given it deals with pulse parameters such as location, width and amplitude. This allows it to automatically segment and identify the foetal QRS complexes and R peak locations from compressed samples which in turn would yield the fetal HR. Our method, which includes model based denoising and multichannel capability, is comparable to other methods involving machine learning, wavelets and ICA.

Index Terms— ECG, Fetal Heart Rate, Finite Rate of Innovation

1. INTRODUCTION

Fetal Electrocardiograms (fECG) are utilised as a tool for fetal Heart Rate (fHR) and general cardiac monitoring. It was introduced to the clinical setting around three decades ago but its use has not seen the rapid development that was expected [9] especially over such a long time. Invasive fECG is a viable option only during labour thus making noninvasive fECG the only available tool for estimating diagnostic parameters such as fHR. Noninvasive fECG has the advantage of being very low risk. However, it is difficult to detect the fetal QRS complex as it is of very low power in comparison to the maternal QRS. The QRS complex represents ventricular depolarization and is the most obvious part of an ECG tracing which is why it is used for heart rate calculation.

This paper was inspired by the Physionet Challenge 2013, which was to detect R-R intervals and fetal HR from noninvasive fECG. A comprehensive test data set was released where the fetal R peak locations of the noninvasive fECG were annotated. The challenge was a reflection of a lack of significant progress in fECG processing despite the length of time it has been in use and the better understanding of the limitations of using noninvasive fECG for fetal monitoring. There is currently no standard way of measuring fetal HR as this requires a consistently accurate detection of the fetal R peak and therefore the challenge sought to compare and contrast the various methods to find a reliable one.

There were results on the test set of data provided for the Physionet Challenge 2013 but not on the competition set. Several methods were used and maternal ECG removal [10, 12], matched filtering [10, 11] and principal component analysis [10, 12] were amongst the methods used to achieve the best results.

The VPW-FRI algorithm [2, 3, 7] was chosen for this problem due to its ability to parameterize the fECG data and identify individual pulses associated with the fQRS. This is derived from VPW-FRI's Lorentzian pulse model which accounts for various widths and degrees of asymmetry. The pulse model allows VPW-FRI to model signals as a sum of pulses which can be compressed by calculating the four parameters associated with each pulse. For example in regular ECG [2, 3] it has been shown that a single heartbeat with, various morphologies, can be modelled using seven pulses giving 28 parameters. Depending on the HR, this can lead to substantial compression subject to the sampling rate of the data. Compression using multichannel schemes [7] further improves the compression ratio by assuming fixed location of the pulses across various channels.

The capabilities of VPW-FRI was further extended to identify locations and parameters of specific waveforms in the signal which the original VPW-FRI was unable to do. It showed that pulses of differing widths and amplitudes could be separately identified. Therefore, fECG was a prime candidate to test the algorithm given the differing nature of the maternal QRS and the fQRS. This together with the multichannel [7] nature of the data provided a strong basis for VPW-FRI to perform well in R peak detection and thus HR calculation.

This paper is organised as follows. Section 2 will give a brief overview on the multichannel VPW-FRI scheme which will be used in this paper. This will be followed by Section 3 which will outline the fQRS detection method. Section 4 will

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present the data and results and conclusions will be drawn in Section 5.

2. VARIABLE PULSE WIDTH - FINITE RATE OF INNOVATION

Only a summary of the VPW-FRI method in [7] will be shown here for the sake of brevity and extensive discussions can be found in [2, 3, 7].

The VPW-FRI is an extension of the FRI sampling and reconstruction scheme which was designed for a certain class of parametric signals which are not bandlimited. For instance piecewise polynomial signals have discontinuities and jumps, thus having an infinite bandwidth whereby Nyquist sampling theorem is not applicable. The VPW-FRI algorithm expanded upon this to include pulses with variable width by locating the annihilating filter [1, 6] roots inside the unit circle instead of being on the unit circle.

The time domain representation of VPW-FRI can be viewed as

$$\begin{aligned} x(t) &= \sum_{k=0}^{K=1} x_k(t) \qquad (1) \\ &= \sum_{k=0}^{K-1} \sum_{n\in\mathbb{Z}} c_k \frac{a_k}{\pi(a_k^2 + (t - t_k - n\tau)^2)} \\ &+ \sum_{k=0}^{K-1} \sum_{n\in\mathbb{Z}} d_k \frac{t - t_k - n\pi}{\pi(a_k^2 + (t - t_k - n\tau)^2)} \quad , \end{aligned}$$

where a_k, c_k, d_k and t_k are the parameters to be found.

From Eq. (1), it can be seen that the pulse is made up of two components, a symmetric Lorentzian pulse and an asymmetric pulse corresponding to the Hilbert transform of the symmetric pulse.

Only the positive Fourier coefficients are sampled, at or higher than the rate of innovation [1, 3, 6], and the negative frequencies are replaced by the Hilbert transform of the positive frequencies. This allows us to add an additional degree of freedom, asymmetry or d_k, thus expanding the FRI model further.

In this paper, we will use the multichannel approach seen in [7]. Equation (2) shows the single channel version of the annihilating filter.

$$\begin{bmatrix} X[-1] & \dots & X[-K] \\ X[0] & \dots & X[-K+1] \\ \vdots & \ddots & \vdots \\ X[K-2] & \dots & X[-1] \end{bmatrix} \cdot \begin{bmatrix} A[1] \\ A[2] \\ \vdots \\ A[K] \end{bmatrix} = 0, \qquad (2)$$

where $X[k]$, $k = 1, \dots, K$ are the Fourier coefficients, $A[k]$ are the annihilating filter coefficients and K is the number of pulses.

However, in the multichannel case, the root locations, t_k are assumed to be the same across all the channels, thus they could be resolved at the same time using the common annihilator,

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_M \end{bmatrix} \cdot \begin{bmatrix} A[1] \\ A[2] \\ \vdots \\ A[K] \end{bmatrix} = 0, \qquad (3)$$

where $M = 2K$.

The t_k and a_k parameters can be retrieved from the roots of the annihilating filter coefficients [3, 7]. In practice, this is solved using a Singular Value Decomposition (SVD). The $\{c_k\}_{k=0}^{K-1}$ and $\{d_k\}_{k=0}^{K-1}$ coefficients, which are the real and imaginary part of b_k, respectively, can be solved using the Vandermonde system [1, 6] over the complex numbers.

3. FETAL HEART RATE DETECTION

The fECG QRS complex can be found from the multichannel abdominal ECG. The QRS is the most distinctive feature of the fECG and therefore it is the easiest to differentiate. The HR can be calculated from the R-R intervals. This can be achieved by applying the VPW-FRI methods [7] together with some model based width constraints.

All the relevant parameters, t_k, a_k and c_k can be calculated from the samples and specific waveforms can be reconstructed allowing for visual confirmation of the results.

The data is split into $1sec$ segments and each segment is analysed separately. Since the VPW-FRI method outlined in Section 2 has a model based denoising step included, only the baseline wander needs to be removed which we achieve with a 1 Hz low pass filter. This works sufficiently well especially if the goal is to locate and reconstruct only the fetal QRS compelxes.

The SVD which is used as a solution to the common annihilator in Section 2 yields singular values by which we use to discriminate the pulses. The second order derivative of these singular values, $\frac{d^2\Sigma_k}{dk^2}$, as seen in Fig. 1, would show groups of pulses characterized by Eq. (4)

$$\Sigma_k = \sqrt{|c_k^2 + d_k^2|}, \qquad (4)$$

where Σ_k are the singular values from the SVD. The eigenvectors corresponding to the truncated singular values are able to show exact locations, t_k, of the pulses.

In the fECG, any peaks in $\frac{d^2\Sigma_k}{dk^2}$ above a threshold ϵ would be of interest and the remainder of the singular values would be discarded. In most cases, the fetal QRS can be found from the second and third peak, but allowances have to be made for the weaker fQRS pulses which may not be as prominent.

As shown in [7], QRS pulses are associated with the first peak. In this case, this would represent the maternal QRS

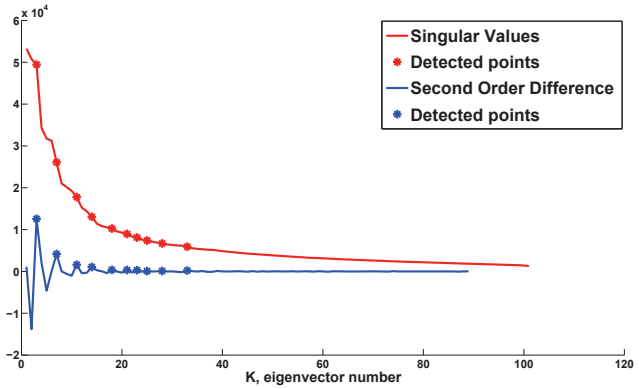

Fig. 1. Singular values of common annihilator

peaks. Therefore, the main maternal QRS pulse would be eliminated by not considering these set of pulses.

Further filtering of the pulses is required and only pulses with a pre-defined width of not more than 15 samples are reconstructed.

This method makes use of all the channels as the common annihilator in Section 2 is being used. This allows channels with prominent fQRS pulses to compensate for channels with noise or weaker fQRS pulses. However, if more than two out of the four channels in this case are noisy, the results will be inaccurate as pulses will not appear as prominently in the singular values.

The algorithm described in this section can be used for compression and detection of pulses which allows for convenience as it can be run from the same model. Also, additional or fewer channels can be used by simply modifying Eq. (3). It also utilizes the ESPRIT noise removal as shown in [3,5,7]. This is further helped by the pruning of the matrix of eigenvectors which serves as a low rank approximation.

4. RESULTS

4.1. Data

The data set from the Physionet Challenge was split into three sets A, B and C where each recording within the set was 60 seconds long. The Set A was a training set with annotations for the fetal R peaks, whereas the Set B was a test set without annotations and finally the Set C was a hidden set which was meant for scoring the competition. In this work, only 25 recordings of the dataset A and 100 recordings of the dataset B were used which comprises of a total of 125 recordings of data.

4.2. Results

The results varied for the data sets. For set A, evaluation was made easier by the presence of annotations. Out of the 25 sets, the algorithm worked well in 19 sets. In the other 6 sets, the algorithm was not able to pick out the fQRS consistently and was not accurate.

Two examples of results from set A can be seen in Figs. 2 and 3. In Fig. 2, the detected fetal R peaks are shown together with the annotations which show a high degree of accuracy. As can be seen even with the R peak at $1.8s$, it could be detected despite being very close to the maternal QRS complex.

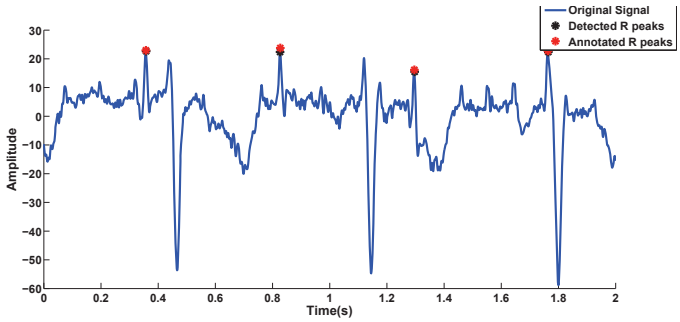

Fig. 2. Fetal QRS reconstruction of signal from Set A of Physionet Challenge 2013

The fQRSs can be reconstructed fairly accurately as well as can be seen in Fig. 3. Again, the fetal R peak around $0.2s$ was reconstructed fairly accurately despite it being in very close proximity to the maternal QRS. This shows the reconstructed pulses were able to detect and capture the morphology of the fQRS. More pulses can be used to improve the accuracy of the reconstruction of the fQRS but trying to detect those pulses would be very difficult and very costly.

Out of the 25 sets, the algorithm was able to consistently pick out the fQRS in 19 sets. There was a fQRS detection rate of 98.2% and the detected pulses were within an accuracy of $\pm$7msec from the Physionet annotated database.

In the remaining 6 sets in which the performance was not as impressive, the detection rate was 41%. This was mainly due to fact that either the pulses were too small to be distinguished by the singular values or the large SNR distorted the small fetal QRS complexes. It has to be mentioned that a more intensive sorting process was attempted based on the widths, amplitudes and locations, but this resulted in overfitting of the data. It became too specific in that it affected the accuracy of results of other recordings.

Since recordings from set B are not annotated, the results will have to be observed and visually inspected for accuracy. As can be seen from Fig. 4 and 5, the algorithm can detect fQRS's of varying prominence. From visual inspection and observation, the results seem to be of roughly the same accuracy as those in set A.

The emphasis on a general scheme designed to handle big volumes of data and real time processing addresses a real concern for mobile health devices and remote monitoring schemes. Given that VPW-FRI is a HR dependant

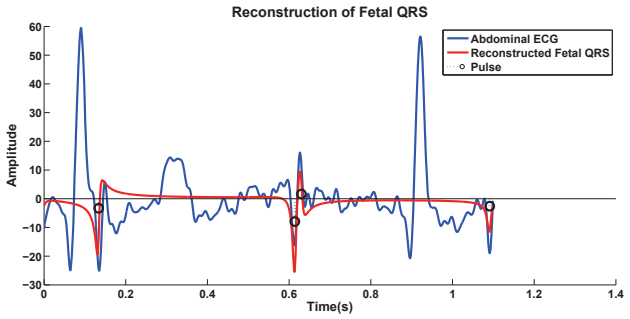

Fig. 3. Fetal R peak detection of signal from Set A of Physionet Challenge 2013 with annotation

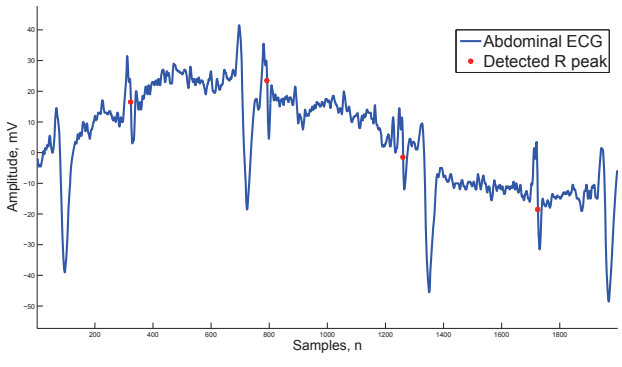

Fig. 4. Fetal R peak detection of signal from Set B of Phy ionet Challenge 2013 without annotation

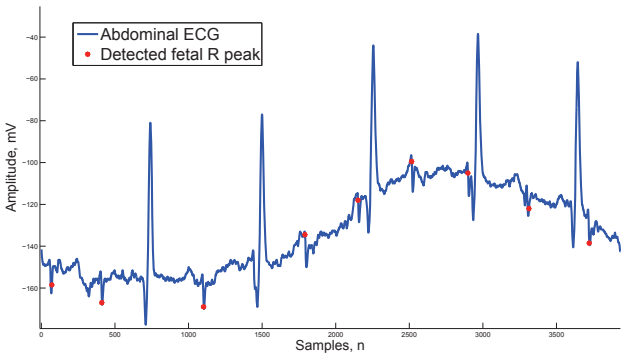

Fig. 5. Fetal R peak detection of signal from Set B of Physionet Challenge 2013 without annotation

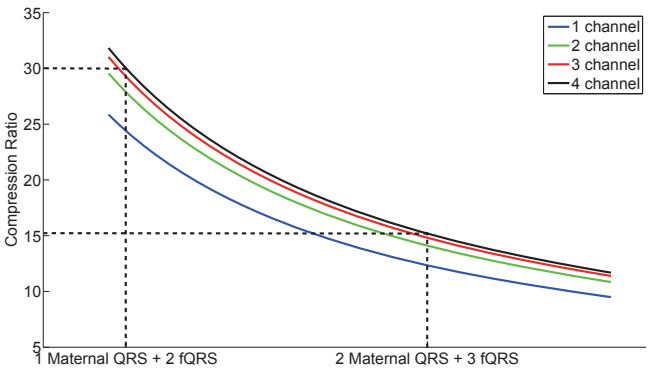

Fig. 6. Compression ratio for Fetal ECG

compression scheme, results can be seen from Fig. 6 that on average only $50 - 80$ samples were being used for compression in each $1sec$ window. Figure 6 shows, as a reference, the compression ratios when a certain number of maternal and fQRS's are present. For example, 2 maternal QRS's and 3 fQRS's translate to a HR of 120 and 180, respectively. The plot assumes a linear increase in HR for both mother and fetus. The compression ratios increase as more channels are added due to the multichannel nature of the algorithm. Also, on average, only $10 - 20$ complex samples per window were used for computation of the results since only location, t_k, is needed. This is in keeping with the idea of a general scheme which is efficient and which has a comparable accuracy to other methods [10–12].

5. CONCLUSION

The achievement of this paper is trying to integrate a sampling and compression scheme, de-noising, multichannel detection and diagnostics into one model. This is being done in pursuit of an efficient algorithm which has many capabilities to reduce computational cost and implementation complexity.

Several of the ideas from the Physionet Challenge contestants with the best scores appear in some form within the VPW-FRI framework. As mentioned in Section 2, the maternal QRS removal [10, 12] appeared in the form of eigenvector selection where the main pulses associated with the maternal QRS were not selected.

Of course improvements can be made which is part of the future work and research to be conducted. A better de-noising scheme could be developed as the current de-noising can only effectively handle signals with 10 dB or more of Additive Gaussian White Noise (AWGN). Also, more specific schemes with regards to certain types of wave or arrhythmia detection could be developed. A balance between generality and accuracy has to be achieved.

Also, additional research that can be done includes real time implementation using [4] which has a polling method for determining Diracs in real time windows. This would be useful for implementation in ECG monitors and devices.

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