Method of Extracting Fetal QRS for Single-Lead Abdominal ECG Signal Based On Combined Compressive Sensing and Clustering Analysis

Yapeng Dong

Chengdu University of Information Technology

Wenbo Ju

Chengdu University of Information Technology

Jiancheng Hu

Chengdu University of Information Technology

Lijuan Hu

Sichuan University

Dayu Ding

Chengdu University of Information Technology

Bo Yang (✉ yb71728@cuit.edu.cn)

Chengdu University of Information Technology <https://orcid.org/0000-0002-7719-6916>

Research Article

Keywords: compressive sensing, k-means, mQRS location, fECG detection, double clustering, fQRS correction

Posted Date: July 23rd, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-655594/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Method of Extracting Fetal QRS for Single-lead Abdominal ECG Signal Based on Combined Compressive Sensing and Clustering Analysis

Yapeng Dong¹, Wenbo Ju¹, Jiancheng Hu², Lijuan Hu³, Dayu Ding¹, Bo yang^{1*}

¹School of Electronic Engineering, Chengdu University of Information Technology,
Chengdu, 610255, People's Republic of China

²School of Mathematics, Chengdu University of Information Technology,
Chengdu, 610255, People's Republic of China

³Department of Immunology, West China School of Basic Medical Sciences & Forensic Medicine,
Sichuan University, Chengdu, Sichuan 610041, People's Republic of China

*Corresponding Author: Bo Yang, Email: yb71728@cuit.edu.cn and YapengDong@outlook.com

Abstract

Objective: The fetal electrocardiogram (ECG) is an objective index that reflects a fetus's health status. Non-invasive abdominal ECG (aECG) was obtained by placing silicone electrodes on pregnant women's abdominal wall. However, fetal QRS (fQRS) extraction is very challenging due to maternal ECG interference, motion artifacts, and other noise. **Approach:** This paper introduces a new single-lead non-invasive fQRS extraction method based on compressive sensing and clustering analysis. This method can be applied to portable, low-power remote fetal ECG (fECG) acquisition equipment based on the Internet of Things (IoT). It is mainly divided into the following steps: (1) optimal component extraction of single-channel signal based on compressive sensing theory; (2) location of maternal QRS (mQRS) using the clustering method based on extreme value; (3) maternal ECG (mECG) elimination; (4) The preliminary location of fQRS based on double clustering and the correction of fQRS based on fetal RR interval. **Main results:** The new algorithm proposed in this paper is verified on two publicly available data sets. The averages of these indicators are Se=98.53%, PPV=98.28%, ACC=96.95%, F1=98.43% for the Silesia datasets and Se=97.59%, PPV=97.63%, ACC=95.44%, F1=97.62% for the Challenge datasets A. **Significance:** The results show that it is feasible and reliable to locate fQRS from a single-channel aECG signal under the condition of reducing power consumption. It lays a foundation for implementing the low-power wireless transmission of fECG signal and remote fetal heart rate (FHR) monitoring based on the IoT.

Keywords: compressive sensing; k-means; mQRS location; fECG detection; double clustering; fQRS correction

1.Introduction

Monitoring the changes of FHR during pregnancy is of great significance for real-time monitoring of fetal health status, especially for fetal distress, fetal arrhythmia, fetal bradycardia, fetal tachycardia, fetal hypoxia, and other pathological conditions (Got'E *et al* 1982, Xiaojun *et al* 2018, Dotun *et al* 2018, Ling *et al* 2019). The Doppler Ultrasound technique commonly used for measuring FHR is an active measurement and has not been proved

to be completely harmless, so it can not be used frequently in the clinic (Barnett *et al* 2000, Hamelmann *et al* 2019). The measurement of pregnant women's abdominal electrical signals is a passive, completely non-invasive, and convenient way to collect fECG. The FHR monitoring method from the abdominal signal can be used for a long time compared with other FHR monitoring methods, which can also be measured in the early stage theoretically (Sameni and Clifford 2010, Poiana *et al* 2016, Castillo Encarnación *et al* 2018). The single-lead aECG signal acquisition scheme is convenient to collect and saves costs compared with most existing maternal aECG measurement schemes. This paper's proposed algorithm is suitable for portable single-lead acquisition equipment and remote monitoring schemes of the medical Internet of things based on low power wireless transmission. It makes it possible for pregnant women to monitor the FHR to assess the fetus's health status at any time.

However, although it is more convenient to measure pregnant women's aECG signal, the fECG signal's amplitude is much smaller than that of the mECG signal, and there is a signal overlap between the fECG and mECG in the frequency spectrum. Moreover, the fECG signal of pregnant women's abdomen is also polluted by many kinds of noise, including fetal brain activity interference, mECG interference, uterine contraction interference, electromyogram (EMG) interference, motion artifact interference, and 50Hz/60Hz power line interference (Varanini *et al* 2014, Clifford *et al* 2014). Therefore, it is still very challenging to replace the commonly used Doppler ultrasound detection technology. Many algorithms have been proposed to obtain the FHR by detecting the fQRS complexes in extracted the fECG signal from the maternal aECG signal. The classical fECG extraction algorithm for processing multi-channel aECG signals is independent component analysis (ICA). ICA is a very ambitious approach that aims to reconstruct directly the multiple statistically independent bioelectric source signals. The prerequisite for blind source separation based on ICA is that multiple source signals must be independent. If this premise is violated, the source separation result is invalid (Moore 1981, Hyvärinen and Oja 2000, Mirza *et al.* 2020, Talib *et al.* 2020). The typical algorithms applied to multi-channel aECG are the blind source separation based on ICA and singular value decomposition (SVD) (Lieven *et al.* 2000, Varanini *et al.* 2014) *et al.* Other algorithms based on multi-channel aECG signals include the fQRS detection of maternal aECG signals based on multi-level principal component analysis (Petrolis and Krisciukaitis 2013). Besides, when the number of signal channels is less than the number of signal sources, it is called a low-rank. There are also a variety of processing algorithms for low-rank channels aECG signals (Sameni 2021). Typical examples are the extraction of fetal ECG from time-varying and low-rank non-invasive abdominal records of pregnant women (Fahimeh *et al.* 2018) and the separation of fetal and maternal components of low-dimensional maternal aECG signal (Mantas and Vaidotas 2020) *et al.* For the single-channel maternal abdominal signal, there are generally two kinds of fECG extraction methods. One of them is to use the synchronously collected chest mECG signal as the reference signal, utilizing the adaptive filtering algorithm (Widrow *et al.* 1975, Nannan *et al.* 2017) and the echo state neural network (ESN) (Behar *et al.* 2014) to extract fECG signal and fetal heart rate. Another method is to construct an mECG template signal to eliminate maternal ECG signal interference and extract the fECG

signal. Typical algorithms include multi-step fusion algorithms based on signal quality assessment and fine-tuning (Liu *et al.* 2014); the algorithm combines RR time series smoothing and template matching to detect fQRS single-lead maternal aECG signal (Liu *et al.* 2019) *et al.*. Other single-channel algorithms such as the single-channel ICA can sometimes be used to separate essential components from a time series (Davies and James 2007) and an echo state recurrent neural network trained to indicate fetal QRS complex method (Lukoševičius and Marozas 2014).

This paper proposes a single-channel fQRS extraction algorithm based on compressive sensing and clustering analysis, suitable for portable acquisition equipment and low-power wireless transmission of the Internet of things FHR monitoring scheme. Specifically, firstly, the sparse binary matrix is used to compress a single-channel maternal aECG signal according to the compressed sensing theory, in which the sparse matrix can be easily implemented in embedded devices. Secondly, the reconstructed algorithm proposed in this paper applies the Gaussian redundancy dictionary proposed by Poian *et al.* in 2016, which is three different atomic groups (corresponding to three different scale parameters) constructed from the characteristics of maternal ECG, fetal ECG, and noise. Three kinds of Gaussian redundant dictionaries and SLO reconstruction algorithms (Mohimani *et al.* 2009) reconstruct the compressed signal into three original signals. Thirdly, the optimal maternal aECG signal is the principal component of the preprocessed signals extracted by the PCA algorithm. Fourthly, mQRS is extracted using an extreme values-based clustering algorithm, and the algorithm corrected false-positive and false-negative algorithms. Fifthly, the fECG signal is the residual signal of the mECG template signal constructed by the coherent averaging method, and the fine-tuning algorithm is subtracted from the optimal signal according to the mQRS location results. Sixthly, the preprocessing process of the fECG signal is to use a wavelet adaptive threshold algorithm to filter high-frequency noise and a high-pass filter to filter the low-frequency components below 15Hz. Seventhly, the two clustering results based on local maximum-minimum pair and extreme value are processed by the hard threshold method to get the preliminary location results of fQRS. The location result of fQRS is modified by using the false-positive correction method proposed in this paper. Figure 1 shows the block diagram of the fQRS detection method proposed in this paper.

Fig.1 The structure block diagram of fQRS location using the algorithm proposed in this paper.

2. Materials and methods

2.1 Database

We use the open-access database provided by PhysioNet to evaluate the performance of the proposed approach. Seventy-five non-invasive maternal aECG records with a one-minute length were provided in the 2013 Cardiology Computer Challenge training set A, in which each record contained four channels with a sampling rate of 1kHz and a sampling accuracy of 16 bits. a01-a75 has a reference label of fQRS complex annotated by experts from fECG signals measured from corresponding fetal scalp electrodes in training set A (Silva *et al.* 2013, Clifford *et al.* 2014).

Another database is abdominal and direct fetal ECG records obtained from the Department of Obstetrics at the Medical University of Silesia. The signal records r01, r04, r07, r08, and r10 with a sampling rate of 1kHz and a sampling accuracy of 16 bits from five different pregnant women during 38 to 41 weeks gestation. Each containing four-channel maternal aECG signals, one-channel fECG records directly from the fetal scalp, and fQRS location annotated by a cardiologist team (Goldberger *et al.* 2000, Jezewski *et al.* 2012). The signals evaluate the effectiveness and accuracy of the new algorithm proposed in this paper for single-channel recording with better signal quality pointed out by experts. The selected signals are specifically the second channel of recording r01, the third and fifth channel of recording r04, the third and fifth channel of recording r07, the second channel of recording r08, and the second and third channel of recording r10 are selected respectively. The previous one-minute signal is selected for each channel.

2.2. Compression and reconstruction of maternal aECG

Compressive sensing theory, a new idea for signal compression, indicates that high-dimensional signals that can be sparsely represented are projected to the low-dimensional space using a random observation matrix that satisfies specific conditions. The projection signal containing sufficient information can reconstruct the high-dimensional signal with high probability through the nonlinear optimization method (Donoho 2006, Candes and Wakin 2008, Eldar and Kutyniok 2012). Signal compression problem can be expressed in equation

$$y = \Phi x \quad (1)$$

, in which $y \in R^M$ is the compressed signal; $x \in R^N$ is a segment of the original signal;

Φ is the measurement (sensing) matrix of $M \times N$ with $M \leq N$. The signal compression part of the proposed algorithm can be implemented in embedded devices because the original signal's measurement matrix has the characteristics of simplicity, non-adaptive, and robust versatility.

In general, the selected measurement matrix, which satisfies irrelevance and restricted isometry property (RIP), should satisfy as little compressed data, easy hardware implementation, and robust versatility as possible (Candes and Tao 2005, Devore 2007, Emmanuel *et al.* 2010). It has been proved that the binary sparse random matrix satisfies the condition of the measurement matrix (Indyk 2010, Poian *et al.* 2016). The measurement matrix Φ is constructed through a binary sparse random matrix in which k positions are randomly selected in each column and set to 1 in an $M \times N$ all-zero matrix, which is simple in structure and easy to be stored and constructed. The measurement matrix Φ is used in this paper, in which $k=2$.

The critical concept in compressed sensing theory is sparsity. An appropriate basis function must be selected to ensure the sparsity of the original signal. As long as the original signal's sparse representation x based on the appropriate basis function or redundant dictionary is found, the original signal can be reconstructed. The redundant dictionary is represented as $\Psi = \{\psi_k\}, \psi_k \in R^N$; the sparse representation of the

original signal x is U :

$$x = \Psi U = \sum_k u_k \psi_k \quad (2)$$

The original signal is $x \in R^N$ ($N=1000$), u_k is the coefficient corresponding to the k th atom ψ_k in the redundant dictionary Ψ . If there are at most m non-zero values in the vector $U \in R^L$, $U = \{u_k\}$ elements, the original signal's sparsity x can be expressed $\|U\|_0 \leq m$. The direct observation signal of the original signal x , which can be sparsely represented, can be expressed y :

$$y = \Phi x = \Phi \Psi U = \Theta U \quad (3)$$

in which Θ ($\Theta = \Phi \Psi$) is an information operator or a recovery matrix. The theoretical framework of compressed sensing is shown in figure 2.

Fig.2 Compressed Sensing theoretical framework

The most sparse vector of the original signal corresponding to a particular redundant dictionary can be obtained using an optimization problem (Gurve and Krishnan 2020):

$$\begin{aligned} & \min \|U\|_0 \\ & \text{s.t. } y = \Phi \Psi U \end{aligned} \quad (4)$$

The algorithm based on the ℓ_1 norm includes the minimum basis pursuit (BP) (Mota *et al.* 2011) and the iterative threshold (Yuan *et al.* 2012) in the problem of solving sparse vectors in compressed sensing. There are also some minimum greedy pursuit algorithms based on ℓ_0 norm, such as matching pursuit (MP) (Gui *et al.* 2010), orthogonal matching pursuit (OMP) (Tropp and Gilbert 2007), and sparsity adaptive

matching pursuit (Thong *et al.* 2010). Besides, there is ℓ_p -regularized least squares (ℓ_p -RLS) algorithm (Pant *et al.* 2014). The reconstruction algorithm in our research is the smoothing-based ℓ_0 norm (SL0) (Mohimani *et al.* 2009) proposed by Mohimani *et al.* The main idea of the SL0 algorithm is to approximate the ℓ_0 norm through a series of suitable continuous functions. Therefore, the ℓ_0 norm problem is transformed into optimization problems consisting of a series of Gaussian function clusters solved by convex optimization methods.

mECG signal can be simulated by a linear combination of some Gaussian functions from the mathematical model of the mECG signal (Billah *et al.* 2011). Therefore, the overcomplete Gaussian redundant dictionary Ψ from mECG consists of a series of Gaussian functions in this paper. The redundant dictionary corresponding to the fECG signal can also be composed of Gaussian function clusters because the fECG signal is similar to the mECG signal. The Gaussian function of the k th atom ψ_k in the redundant dictionary Ψ is expressed with $\psi_k(n)$:

$$\psi_k(n) = C_k \exp\left(-\left(\frac{n-a_k}{\sigma_k}\right)^2\right) \quad (5)$$

in which C_k is the normalized constant; σ_k is the parameter that changes the shape of the Gaussian function. The atom $\psi_k(n)$ of the Gaussian redundant dictionary Ψ , which is composed of k unit norm vectors $\|\psi_k\|_1 = 1$, corresponds to a set of scale parameters $\sigma_k \in \{5, 6, 7, 8, 9, 10, 12, 15, 20, 30, 50\}$, ensuring that the Gaussian redundant dictionary Ψ can reconstruct the mECG signal (Poian *et al.* 2014). The Gaussian redundant dictionary is used to recover the fECG signal very well when the scale parameter set is $\sigma_k \in \{2.5, 3, 3.5, 4\}$. The scale parameter set corresponding to the noise component is $\sigma_k \in \{1.6, 2\}$ (Poian *et al.* 2016). All shift parameters a_k ($a_k = \{1, 2, \dots, N\}$) are set up for each scale parameter σ_k in this paper.

The original selected signal X_o is a signal segment with a sampling rate of 1kHz and a time length of 1 minute in the algorithm proposed in this paper. The length of the signal segment x_i ($1 \leq i \leq 60$) intercepting the original X_o is $N=1000$, in which

each signal segment x_i is compressed by using the same binary sparse matrix Φ according to the compressed sensing theory. The complete compressed signal is expressed $Y=[y_1, y_2, \dots, y_{60}]$, which $y_i = \Phi x_i$ represents the compressed signal segment. Three Gaussian redundant dictionaries are constructed according to the three sets of scale parameters σ_k of the Gaussian function. According to the equation $y_i = \Phi \Psi_k U_{k,i}$, the SL0 algorithm solves the compressed signal segment's sparse solution y_i for each Gaussian redundant dictionary $\Psi_k (k = \{1, 2, 3\})$ and measurement matrix Φ . The reconstructed maternal aECG signal $X_k = [x_{k,1}, x_{k,2}, \dots, x_{k,60}]$ consisting of the reconstructed segment signal $x_{k,i} = \Psi_k U_{k,i}$ is shown in figure 3.

Fig. 3 The picture is part of using compressed sensing theory to compress and reconstruct the original signal. (a) The first 6s original signal of the 1st channel in the abdominal fetal ECG record a01 in training set A. (b) the binary sparse random matrix obtains the compressed observation signal. (c) The reconstructed signal with signal-to-ratio (SNR) of 44.98 is obtained according to the Gaussian redundant dictionary composed of a parameter set $\sigma_k \in \{5, 6, 7, 8, 9, 10, 12, 15, 20, 30, 50\}$. (d) The reconstructed signal with signal-to-ratio (SNR) of 41.10 is obtained according to the Gaussian redundant dictionary composed of a parameter set $\sigma_k \in \{2.5, 3, 3.5, 4\}$. (e) The reconstructed signal with signal-to-ratio (SNR) of 39.44 is obtained according to the Gaussian redundant dictionary composed of a parameter set $\sigma_k \in \{1.6, 2\}$.

2.3. Pre-processing of reconstructed aECG signal and principal component extraction

In addition to the main mECG and fECG signals, some other noise components can interfere with the measurement of pregnant women's aECG signal, including power line interference caused by power frequency signal, high-frequency interference of maternal EMG, and fetal EEG, and motion artifact caused by maternal breathing and exercise. It is necessary to reduce the signal's noise component for each reconstructed signal $X_k (k = \{1, 2, 3\})$ before the signal can be used because each reconstructed maternal aECG signal $X_k (k = \{1, 2, 3\})$ is mainly composed of mECG signal, fECG signal, and noise components. Firstly, the wavelet soft threshold de-noising is performed on each reconstructed maternal aECG $X_k (k = \{1, 2, 3\})$ to remove the high-frequency component (Ouyang *et al.* 2002). The wavelet decomposition is then used to remove the baseline interference, including the P wave and T wave of the mECG component and motion artifact interference below 8Hz (Pan and Zhang 1999). Finally, a 50Hz/60Hz notch filter is used to eliminate power line interference. The preprocessing result of a single reconstructed signal $X_k (k = 1)$ is shown in figure 4.

Fig.4 A partial illustration of the preprocessing process of a single reconstructed signal $X_k (k = 1)$. (a) Representative signal after removing high-frequency noise; (b) Removed low-frequency baseline; (c) The pre-processed signal.

The linear dimensionality reduction concept based on principal component analysis maps a high-dimensional signal to a low-dimensional orthogonal space. In this paper, the compressed signal reconstructs three signals with different Gaussian redundancy dictionaries, and the signal-to-noise ratio of the three signals is different. For these three

reconstructed signals, we propose to use the PCA algorithm for dimensionality reduction. After the PCA algorithm processes the preprocessed signal, the result has three subcomponent signals in figure 5. We use the sample entropy to evaluate the subcomponent signal and select the component with the minimum sample entropy as the principal component because the principal component of the original maternal abdominal electrical signal is a pseudo-periodic.

Fig.5 The PCA algorithm results on the three reconstructed signals after preprocessing, in which the subgraph (a) represents the smallest signal on the sample and is also the optimal signal selected. (b), (c) represents other component signals.

We take each signal's average energy as the evaluation criterion to compare and analyze the selected principal component signal and the reconstructed three kinds of signals. The results are shown in figure 6. We use the signal's average energy to measure

PCA's effect and find that the principal component signal's average energy is about three times that of the preprocessed signal. The results show that the principal component signal is the linear combination of the three preprocessed signals and the signal after enhancing the mQRS and fQRS complex. Therefore, we choose the signal with the minimum sample entropy as the optimal signal for the following algorithm.

Fig.6 The figure shows three kinds of reconstructed signals and the signal enhanced with PCA. (a), (b) and (c) The representative pre-processed signal. (d) The first principal component is extracted by the PCA algorithm.

2.4. mQRS location

2.4.1. Clustering-based mQRS location

The clustering algorithm based on extreme value is used to locate mQRS initially, and mQRS correction is used to achieve the accurate location of mQRS to provide the basis for the perfect construction of the mECG template signal in this paper. The optimal signal's extreme value is taken as the unlabeled data set, and the size of the extreme value is taken as the clustering feature. Euclidean distance is used as a measure of similarity to judge the clustering feature. The preliminary extraction of mQRS based on clustering is divided into the following two steps: In the first step, the signal polarity is judged according to the absolute value of the average value of the local maximum or local minimum of the signal X . The local maximum or local minimum is selected as the unlabeled data set according to the signal polarity, and then the k-means (Kanungo *et al.* 2002) clustering analysis is performed in the second step. The specific process is as follows: Firstly, the absolute values of the mean values of the local maximum and the local minimum are calculated respectively in the signal X . If the absolute value of the local maximum's mean is greater than the absolute value of the local minimum's

mean, it indicates that the optimal signal's polarity X is positive, and the local maximum is regarded as an unclassified data set E . On the contrary, it indicates that the optimal signal's polarity X is negative, and the local minimum value is selected as the unclassified data set E . The unclassified data set E is divided into two preset categories, namely mQRS and non-mQRS, in this clustering process. The result of mQRS location extraction based on the clustering method is shown in figure 7.

Fig.7 Some of the results in the process of locating mQRS complex based on clustering are shown in the figure. The '+' represents the local maximum position, and the '*' represents the local minimum position in figure (a). The '*' denotes the non-mQRS class location, and the 'o' indicates that the clustering algorithm finds mQRS locations in figure (b).

2.4.2. mQRS correction

The false-negative and false-positive of the extracted mQRS were corrected as the reference (Liu *et al.* 2012). First of all, the local maximum function or local minimum function is selected to redetermine the maternal R peak position according to the polarity of the optimal signal X and the preliminary location results of the clustering-based mQRS. The local minimum function is used in the local interval of the maternal QRS complex's width range around the R peak position of the clustering result by the polarity of the optimal signal X is negative in our research. The average value RR_m is then calculated according to the RR interval sequence near the median found in the RR interval sequence, which is used as the average value of the whole RR interval sequence in our research. The preliminary locating mQRS is corrected by the

characteristics of each RR interval sequence. The i th R peak of maternal ECG is defined $R_i (i=1,2,\dots,N)$, where N is the number of the R peak extracted by the clustering. Then the i th RR interval sequence of mECG is defined $RR_i = R_{i+1} - R_i (i=1,2,\dots,N)$, set to a much more massive value than R_N . The average value of the absolute value of the R peak amplitude in the mECG signal is defined as Ra . R_i or R_{i+1} which is a falsely detected R peak under the $RR_i \leq a_m \times RRm$ condition. If the $|(R_{i+2} - R_i) - RRm| < |(R_{i+2} - R_{i+1}) - RRm|$ is satisfied, it means that the R_i is the correct position and the R_{i+1} need to be eliminated. Otherwise, this R_i needs to be removed. It is assumed that the amplitude of the signal corresponding to the position R_i is less than $b_m \times Ra$, which indicates that the R peak of this R_i position is also falsely detected.

So, the RR interval average value must be recalculated to update RRm after removing the excess R_i , and the average value Ra of the absolute value of R peak amplitude is updated simultaneously. The purpose of recalculation is to make the parameters RRm and Ra closer to the actual average values. The interval from the starting position of the signal to the first R peak is defined $RR_{head} = R_1 - 1$. The interval from the last R peak of the signal to the cut-off position is defined $RR_{tail} = length(X) - R_N$. The length between RR_{head} and RR_{tail} is different from other RR intervals, so they are treated separately. Whether there is a missing R peak in RR_{head} interval and RR_{tail} interval is judged in this paper. If this condition of $RR_{head} > c_m \times RRm$ is satisfied, it indicates that there must be a missing R peak in the RR_{head} interval. The missing R peak needs to be found in a specific interval $[R_1 - d_m \times RRm, R_1 - a_m \times RRm]$ by the local minimum function. If this condition of $a_m \times RRm < RR_{head} \leq c_m \times RRm$ is satisfied, it indicates that an R peak may be missed in the RR_{head} interval. So, an R peak is searched in the specified search interval

$[1, R_i - a_m \times RRm]$, and a second judgment is made on the search results simultaneously.

If the second judgment condition $abs(Ramp) > b_m \times Ra$ is satisfied, the search result is a missing R peak; otherwise, the interval is regular. The $Ramp$ is the local minimum of the search interval. The process of dealing with RR_{tail} is similar to that of RR_{head} . If the remaining RR_i interval excluding RR_{head} and RR_{tail} is greater than $c_m \times RRm$, it indicates that at least one R peak is lost in the RR_i interval. Otherwise, the RR_i interval is regular. The number m_1 of R peaks that may be missing in the RR_i interval is judged according to the RR_i/RRm value. The m_1 corresponding segments are divided from this RR_i interval, and the search interval of the R peak of each segment is:

$$T_m^n = [R_i + (m + v_m \times n)RRm - h_m \times n \times RRm, R_i + (m + v_m \times n)RRm]$$

($n = 1, 2, \dots, 6, m = 1, 2, \dots, m_1$). The initial value $m = 1, n = 1$ and n add 1 in turn until a suitable R peak is found. The m value is added by 1 to find the next segment's peak until the end after finding a suitable R peak in this previous segment. The pseudo R peaks in 10 uniform segments were calculated separately at the RR_i interval, and six data near the median were taken as average to update Ra . This condition of $abs(Ramp) > b_m \times Ra$ is used to determine whether the searched R peak is finally retained. The proposed false-negative correction algorithm for the RR_i interval is summarized in algorithm 1.

Algorithm 1 The process of false-negative correction for the RR_i interval

Input: R_i, RR_i, RRm, Ra, b_m

Initialization: The number of R peaks that may be missing in the RR_i interval is $m_1 = round(RR_i/RRm) - 1$. $b_m = 0.5$.

if $RR_i > c_m \times RRm$

for $m = 1 : m_1$

for $n = 1 : 6$

The R peak is searched in the interval:

$T_m^n = [R_i + (m + v_m \times n)RRm - h_m \times n \times RRm, R_i + (m + v_m \times n)RRm]$, where the

location of the searched R peak is R_{new} , and the amplitude is $Ramp$ by using the local maximum or minimum function.

```
    if  $abs(Ramp) > b_m \times Ra$ 
         $R_{new}$  is reserved.
        break;
    end if
end for
end for
end if
```

Output: $[R_i, \dots, R_{new}, \dots, R_{i+1}]$

2.5. Elimination of mECG template signal

The coherent averaging method is used to construct the mECG template for the optimal signal X . The two R peaks are selected to extend the selected RR interval to the same length as the maximum RR interval using interpolation when the interval between two consecutive R peak is normal, and the amplitude of the two R peak is also normal. The mECG single template is the average of the RR interval after stretching. The mECG single template is re-stretched to each RR interval's actual length to construct the mECG template signal by connecting them beat by beat. The fine-tuning process (Liu Chengyu *et al.* 2014) is used to achieve the best match between the optimal signal X and the reconstructed mECG template signal. The matching operation shifts the reconstructed mECG template signal to the left or right to achieve maximum correlation with the original signal X . The fECG signal is obtained by subtracting the fine-tuned mECG template signal from the original signal X . The mECG template signal and fECG signal are shown in figure 8.

Fig.8 Part of the result of the extraction process of fECG signal is shown in the figure. (a): The optimal maternal aECG signal is extracted by the PCA algorithm. (b): An mECG template signal is extracted by a combination of coherent averaging and fine-tuning algorithms. (c): The fECG signal is obtained by subtracting the mECG template signal from the pregnant woman's optimal maternal aECG.

2.6. Pre-processing of fECG

The extracted fECG signal is the ECG signal produced by the fetal heart and some other noises that exclude the mECG signal. The wavelet adaptive threshold de-noising method is used to remove the high-frequency components of the fECG signal. Then, a zero-phase high-pass filter is used to remove the low-frequency components below 15Hz in our research. The preprocessing algorithm can effectively remove the noise and obtain a clearer fECG waveform with fQRS. The result of the preprocessed fECG signal is shown in figure 9.

Fig.9 The preprocessing process of fECG signal. (a): The extracted original fECG signal. (b): The preprocessed fECG signal.

2.7. Clustering-based fQRS detection

If the fECG signal's polarity is positive, the local maximum is selected as the unclustered data set. If the polarity of fECG is negative, the local minimum is selected as the unclustered data set. The fECG signal's polarity obtained from the single-channel sample signal selected in our research is positive, so the local maximum is selected as the unclustered data set. The local maximum-minimum pair (Zhang and Yu 2020) and the extreme value are used as clustering features to perform cluster analysis on the unclustered data set in this paper. Three categories are preset in two cluster analysis processes using k-means. The clustering results are shown in figure 10.

According to the local maximum-minimum pair, the location result of clustering is defined as $Pair_i$ ($i=1,2,\dots,n$), where n is the number of selected fQRS categories in the local maximum-minimum pair. The average of the eigenvalue corresponding to all $Pair_i$ positions is defined as $PairM$. The fQRS location for clustering analysis based on the extreme value's characteristics m is the number of selected fQRS in the extreme value. The average of the extreme value corresponding to all $Extreme_i$ positions is defined as $ExtremeM$. The $Pair_i$ position is retained when the extreme value corresponding to the $Pair_i$ position is greater than $0.6ExtremeM$. The $Extreme_i$ position is retained when the eigenvalue of the local maximum-minimum pair of the $Extreme_i$ position is greater than $0.01PairM$. The combination of two kinds of the fetal R peak left by the hard threshold method mentioned above is expressed as $fPeak_i(i=1,2,\dots,k)$, where k is the number of

initially extracted fQRS in fECG. The result of locating fetal R peak by combining clustering and threshold is shown in figure 10.

Fig.10 The figure shows the results of double clustering. The ‘*’ indicates that the clustered fQRS result with extreme value as the clustering feature; the ‘o’ indicates the clustered fQRS results with local maximum-minimum pair as clustering feature in figure (a). The results of excluding redundant non-fQRS positions by performing the threshold processing on the two clustering results are shown in figure (b). The combination of the two fetal R peak position left by the threshold method is shown in figure (c).

The false-positive and false-negative of fQRS were corrected. The idea of false-positive correction for fQRS is to determine the $i+1$ fetal R peak ($fPeak_{i+1}$) of the fECG signal according to the i fetal R peak ($fPeak_i$) and the average value ($fRRm$) of the fetal RR interval. A prerequisite for this idea is that the first fetal R peak position is close to the real fetal R peak position. The fetal RR interval sequence fRR is defined as:

$$fRR_i = fPeak_{i+1} - fPeak_i (i = 1, 2, \dots, k) \quad (6)$$

where $fPeak_{k+1}$ is set to a larger number in order to satisfy the condition of $fRR_k > a_f \times fRRm$. The $fRRm$ is closer to the real fetal RR interval when the mean of the segment at position 3/4 of sorted fetal RR interval sequence is taken as the mean

$fRRm$ of the overall RR interval. The correction process of the false-positive of fQRS is summarized in algorithm 2.

Algorithm 2 The correction of the false-positive of fQRS

Input: fRR fRR_i $fRRm$

Initialization: $n = 2$

while $n < \text{length}(fRR) - 1$

for $i = n : \text{length}(fRR)$

if $fRR_i \leq a_f \times fRRm$

$n = i$

if $\text{abs}((fPeak_i - fPeak_{i-1}) - fRRm) < \text{abs}((fPeak_{i+1} - fPeak_{i-1}) - fRRm)$

$fPeak_{i+1} = 0$; break;

else

$fPeak_i = 0$; break;

end if

else if $a_f \times fRRm < fRR_i < b_f \times fRRm$

When this condition is satisfied, it indicates that the fRR_i interval is regular.

else if $b_f \times fRRm \leq fRR_i < c_f \times fRRm$

When this condition is satisfied, there is one less fetal R peak in the fRR_i interval.

if $\text{abs}((fPeak_i - fPeak_{i-1}) - fRRm) < \text{abs}((fPeak_{i+1} - fPeak_{i-1}) - 2 \times fRRm)$

$fPeak_{i+1} = 0$; break;

end if

end if

end for

$previous = \text{length}(fPeak)$

The location $fPeak_i = 0$ is removed.

$new = \text{length}(fPeak)$

The fRR interval sequence is reobtained for the remaining $fPeak_i$ after the excess $fPeak_i$ is removed.

if $previous == new$

break

end while

Output: The result of the corrected false-positive of fQRS.

The false-positive correction process proposed in our research may lead to a small error between the detected fQRS and the actual fQRS, which can be seen from the false-positive correction results of fQRS in subgraph (b) in figure 11. Therefore, it is necessary to make a micro-correction to the above results to eliminate the error. The fetal R peak positions $fPeak_i (i = 1, 2, \dots, m)$ were obtained from the result of the false-positive correction. The fetal RR interval sequence is obtained according to the method mentioned above in the fetal R peak position sequence $fPeak_i (i = 1, 2, \dots, m)$. Usually,

the average $fRRm_k (k = 1, 2, \dots, n) \quad (n = \text{floor}(m/10))$ of every ten consecutive fetal RR intervals fRR_j was used as the template for the corresponding ten fetal RR intervals in the sequence fRR . However, this $fRRm_n$ is used when there are less than ten fRR_j in the final group. The micro-correction process is summarized in algorithm 3. The results of applying the micro-correction described in algorithm 3 are shown in the subgraph (c) in figure 11.

Algorithm 3 The micro-correction for the false-negative correction result of fQRS.

Input: $fPeak_i$ fRR fRR_j $fRRm_k$ m n δ

Initialization: $n = \text{floor}(m/10)$, $\delta=20$

for $k = 1 : n$

$fRRm_k$ is corrected according to the average $fRRm$ of the overall fetal RR interval.

for $j = (k-1) \times 10 + 1 : (k-1) \times 10 + 10$

$number = \text{round}(fRR_j / fRRm_k)$

If $number=1$ shows that there is no lack of fetal R peak in the fRR_j interval.

if $fRR_j < fRRm_k - \delta$ and $fRR_{j+1} > fRRm_k + \delta$

It shows that the extracted position $fPeak_{j+1}$ is ahead of the actual location, so we search for the next location in the clustering results to replace the false-negative correction location $fPeak_{j+1}$.

Else $number \neq 1$

if $fRR_j < number \times fRRm_k - \delta$ and $fRR_{j+1} > fRRm_k + \delta$

The same micro-correction as above is performed in the case of missed $number$ fetal R peak.

End if

End for

Output: Accurate fetal R peak position $fPeak_i$ except for missed detection.

Fig.11 The figure shows the results of correcting the preliminary results of double clustering. The ‘o’ indicates that the location of fQRS annotated by the expert is in the whole picture. The ‘*’ indicates that the results of detected fQRS by the method based on combining clustering analysis and hard threshold are in figure (a). The false-positive correction results of fQRS are shown in figure (b). The results of the micro-correction are shown in figure (c).

The false-negative correction algorithm of fQRS is consistent with the mQRS correction algorithm 1 in section 2.4.2. It is only necessary to replace the RR interval average RRm of the mECG with the fetal RR interval average $fRRm$ of the fECG. The results of false-negative correction for fQRS are shown in figure 12.

Fig.12 The algorithm proposed in our research is used for the first channel's one-minute signal in the maternal aECG record a01 in training set A. The fECG signal and the location results of fQRS are obtained in this figure, where 'o' is the fQRS location marked by experts, and '*' is the fQRS location extracted by the algorithm proposed in our research.

3.Results

3.1. Evaluation protocol

The corresponding 50ms matching window is constructed with each fQRS location annotated by experts as a center in this paper (Zhang and Yu 2020). If the detected fQRS position is in the corresponding matching window, it indicates that the detected fQRS matches the reference fQRS. The criteria for evaluating the accuracy of the final fQRS location results are sensitivity (Se), positive predictive value (PPV), accuracy (ACC), and F1, following the ANSI/AAMI guideline (ANSI/EC57-2012).

$$Se = \frac{TP}{TP + FN} \quad (7)$$

$$PPV = \frac{TP}{TP + FP} \quad (8)$$

$$ACC = \frac{TP}{TP + FP + FN} \quad (9)$$

$$F_1 = 2 \times \frac{PPV \times Se}{PPV + Se} = \frac{2 \times TP}{2 \times TP + FN + FP} \quad (10)$$

TP is the number of detected fQRS complexes that match the fQRS complexes marked by experts; FN is the number of fQRS complexes that exists but is not detected, which can be calculated by TP subtracting from the number of annotated fQRS complexes; FP is the number of the fQRS complexes that are detected but do not exist. If the detected fQRS complexes are within the 50ms window centered on each actual fQRS complexes position, they are considered to match, then TP+1; If they do not match, it means false detection, then FP+1.

The signal-to-noise ratio (SNR) is the ratio of the signal's useful component to the noise. The performance of the reconstructed signal is evaluated using the SNR.

$$SNR = 10 * \log_{10} \left(\frac{\sum (original_signal)^2}{\sum (reconstructed_signal - original_signal)^2} \right) \quad (11)$$

3.2. Paraments optimization

The threshold-related method proposed in our work has two steps: mQRS correction, fQRS correction. Each step contains some parameters to set. The parameters in every step are fixed, as shown in Table 1 and Table 2. In this paper, the false positive and false negative correction algorithm based on the threshold is used to correct mQRS. The threshold parameters are set according to the known typical waveform width and period of the mQRS complex. The regular maternal RR interval ranges from 0.6s to 1.0s. Bradycardia occurs when the RR interval is greater than 1.5s, and tachycardia occurs when the maternal RR interval is less than 0.5s. Besides, the typical QRS complex's width is 0.06s-0.10s. Table 1 shows the specific parameters set based on the prior values of the maternal ECG waveform characteristics.

Table1 Parameters of mQRS correction algorithm based on threshold

thresholds	Describes	value
a_m	$a_m \times RRm$ represents the minimum of the normal maternal RR interval.	0.55
b_m	$b_m \times Ra$ represents the minimum absolute value of the normal maternal R wave peak.	0.50
c_m	$c_m \times RRm$ represents the maximum value of normal maternal RR interval.	1.55

d_m	(maximum maternal RR interval in the sequence)/ RRm	$d_m < 1.55$
h_m	$h_m \times n \times RRm$ represents the search interval.	$h_m \times n < 1.55$
v_m	$v_m \times RRm$ represents the translation step of the search interval.	0.05

The result sequence of the preliminary location of the fQRS complex using the combined clustering analysis proposed in this paper is preprocessed, and the appropriate value is selected as the threshold, as shown in Table 2.

Table2 Parameters of fQRS correction algorithm based on threshold

thresholds	Describes	value
a_f	$a_f \times fRRm$ approximates the real fetal RR interval.	0.8
b_f	$b_f \times fRRm$ approximates two consecutive fetal RR intervals in the absence of one fetal R peak.	1.7
c_f	$b_f \times fRRm$ represents the maximum value of two consecutive fetal RR intervals in the absence of one fetal R peak.	1.9

3.3 Performance evaluation

The purpose of signal compression using compressed sensing theory is to reduce wireless transmission power in our research. SNR1, SNR2, and SNR3 are used to evaluate the quality of three signals reconstructed by three different Gaussian redundant dictionaries constructed respectively, according to mECG, fECG, and noise. The original signal is compressed with different compression ratio to find a balance point which satisfies both low compression ratio and high SNR as far as possible. a01 and r01 records are compressed and reconstructed with different compression ratios, and the specific SNR results are shown in Table 3 and Figure 13. The effect of different compression ratios on the SNR of the reconstructed signal is studied according to Table 3 and Figure 13. Our study's relative equilibrium point is 75% of the signal compression ratio when the signal-to-noise ratio of the reconstructed signal begins to increase slowly.

Table3 The influence of different compression ratios on the signal-noise ratio of the reconstructed signal on the original signal.

Compression ratio (%)	SNR1(%)		SNR2(%)		SNR3(%)	
	r01	a01	r01	a01	r01	a01
60	37.14	34.60	42.91	41.52	28.59	30.37
65	40.26	37.18	42.92	41.27	33.29	32.69
70	42.40	42.28	42.72	40.66	36.23	38.22
75	46.51	45.26	43.02	41.45	40.25	40.53
80	48.64	45.71	42.65	41.76	42.06	41.41
85	49.03	47.21	42.47	41.94	42.41	43.11
90	50.17	48.25	43.09	42.04	43.25	43.00

Fig.13 The influence of different compression ratios on the signal-noise ratio of the reconstructed signal on the original signal.

Two clinical databases, the abdominal and direct fetal ECG database (adfecgdb) and the 2013 Cardiology Computer Challenge training set (challenge/2013/set-a), are used to verify the proposed method's effectiveness. It should be noted that some signals in the database may be affected by severe artifacts and noise, and some fECG components might be undetected due to improper electrode position. Therefore, it is necessary to select some records and channels with good signal quality to verify the algorithm's performance proposed in our research. So, we choose signals with better quality under the guidance of some experts. The fQRS extracted results of record a01 are shown in figure 14 by using the algorithm proposed in our research. Tables 4 and 5

show the detection results and performance of the selected fQRS containing relatively complete records of useful information in two databases using the proposed algorithm. Each color indicates that multi-channel signals in a record are selected. The new algorithm proposed in our research is verified on two publicly available data sets. the averages of these indicators are Se=98.53%, PPV=98.28%, ACC=96.95%, and F1=98.43% for Silesia data sets, and Se=97.59%, PPV=97.63%, ACC=95.44%, and F1=97.62% for the challenge datasets A. It lays a foundation for the realization of portable FHR monitoring equipment interacting with the hospital.

Table4 Performance metrics of the fQRS detection in *Abdominal and Direct Fetal Electrocardiogram Database*

records	Channel	Se(%)	PPV(%)	ACC(%)	F1(%)	Annotated fQRS	Detected fQRS	fQRS error
r01	2	100	100	100	100	129	129	0
r04	3	97.60	96.83	94.57	97.21	125	126	1
	5	96.00	95.24	91.60	95.62	125	126	1
r07	3	100	100	100	100	127	127	0
	5	100	100	100	100	127	127	0
r08	2	97.73	97.30	95.56	97.73	132	132	0
r10	2	97.66	97.66	95.42	97.66	128	128	0
	3	99.22	99.22	98.45	99.22	128	128	0
average		98.53	98.28	96.95	98.43			

Table5 performance of the fQRS detection on *PhysioNet/CinC Challenge 2013 Set A*

records	Channel	Se(%)	PPV(%)	ACC(%)	F1(%)	annotated fQRS	Detected fQRS	fQRS error
a01	1	96.55	96.55	93.33	96.55	145	145	0
a03	2	99.22	99.22	98.45	99.22	128	128	0
a04	1	100	100	100	100	129	129	0
a05	1	100	100	100	100	129	129	0
a12	1	98.55	98.55	97.14	98.55	138	138	0
	2	97.83	97.12	95.07	97.47	138	139	1
	4	93.48	92.81	87.16	93.14	138	139	1
a15	1	100	100	100	100	134	134	0
a19	2	100	100	100	100	127	127	0
	4	100	100	100	100	127	127	0
a20	4	96.18	94.74	91.30	95.45	131	133	2
a22	1	100	100	100	100	126	126	0
a23	2	97.62	97.62	95.35	97.62	126	126	0
	3	96.03	96.03	92.37	96.03	126	126	0
	4	98.41	98.41	96.88	98.41	126	126	0
a24	2	96.75	96.75	93.7	96.75	123	123	0
	3	96.75	96.75	93.7	96.75	123	123	0
	4	95.93	95.93	92.19	95.93	123	123	0

a25	4	95.20	94.44	90.15	94.82	125	126	1
a35	1	95.15	96.32	91.81	95.73	165	163	2
	2	95.15	96.91	92.35	96.02	165	162	3
	3	96.97	96.07	94.12	96.97	165	165	0
a44	1	98.77	98.77	97.58	98.77	163	163	0
	2	99.39	99.39	98.78	99.39	163	163	0
	3	98.77	98.77	97.58	98.77	163	163	0
	4	97.55	98.15	95.78	97.85	163	162	1
a49	2	99.32	99.32	98.66	99.32	148	148	0
	3	99.32	99.32	98.66	99.32	148	148	0
a65	2	92.36	92.36	85.80	95.83	144	144	0
	4	95.83	95.83	92.00	95.83	144	144	0
a72	1	99.40	99.40	98.81	99.40	167	167	0
	2	99.40	100	99.40	99.70	167	166	1
	3	94.61	96.34	91.33	95.46	167	164	3
average		97.59	97.63	95.44	97.62			

The fourth channel signal under the recoding signal a25 is used to verify the algorithm's extraction performance under some segmental strong noise background. It can be seen from figure 14 that the double clustering joint algorithm and the improved false-positive algorithm proposed in our research for fQRS location can also accurately locate fQRS under the background of strong noise.

Fig.14 fQRS location results are shown in the figure under strong noise interference.

4. Conclusion

The problems of single-channel signal compression and reconstruction, enhancement of mQRS and fQRS complex, maternal R wave detection, and fetal R wave detection based on the application of portable single-lead abdominal electrical signal acquisition equipment on the Internet of thing are proposed. In this paper, a single-lead abdominal fQRS complex localization method based on compressed sensing and clustering is proposed according to the above problems. The compression and reconstruction of single-channel maternal abdominal ECG signal are proposed based on compressive sensing theory, which greatly reduces wireless transmission power consumption. In reconstruction, a method to reconstruct various original signals based on different Gaussian redundant dictionaries is proposed. The single-channel enhanced mQRS and fQRS signals are then obtained by using the principle of PCA reduction and enhancement. Besides, the research results show that the proposed method shows superior visual and statistical performance in the presence of noise. The single-channel fetal ECG signal extraction algorithm proposed in this paper has much practical value, which is especially suitable for low-cost family fetal heart monitoring Internet of things system. However, the algorithm not only has these advantages but also inevitably has its limitations. The algorithm proposed in this paper has not been able to process the data in real-time, and the process of real-time processing of fetal ECG signals remains to be further studies.

References

- Got'E E S, Logvinenko A V, Filimonova N A 1982 role of cardiotocography in the diagnosis of the severity of chronic fetal anoxia during pregnancy *Akusherstvo I Ginekologiya*. **1** 9-12.
- Xiaojun D, Zhiping H, Min L, Chaoqing G, Lin L, et al. 2018 Clinical analysis of prenatal ultrasound diagnosis and pregnancy outcome of fetal arrhythmia. *Contemporary Medicine*.
- Dotun, Ogunyemi, Andrew, Jovanovski, Perry, & Friedman 2018 Temporal and quantitative associations of electronic fetal heart rate monitoring patterns and neonatal outcomes? *The journal of maternal-fetal & neonatal medicine: the official journal of the European Association of Perinatal Medicine, the Federation of Asia and Oceania Perinatal Societies, the International Society of Perinatal Obstetricians*.
- Ling Z, Feng W, Fang H E, Min-Nan Z, Lin-Xia M 2019 Value of fetal spectrum doppler combined with fetal biophysical score in the evaluation of fetal intrauterine hypoxia *Hainan Medical Journal*.
- Barnett S B, Haar G R T, Ziskin M C, Rott H D, Duck F A, Maeda K 2000 International recommendations and guidelines for the safe use of diagnostic ultrasound in medicine *Ultrasound in Med. & Biol.* **26(3)**, 355-366.
- Hamelmann P, Vullings R, Kolen A F, Bergmans J W M, Mischi M 2019 Doppler ultrasound technology for fetal heart rate monitoring: a review. *IEEE Transactions on Ultrasonics Ferroelectrics and Frequency Control* **99** 1-1.
- Sameni R, Clifford GD 2010 A review of fetal ECG signal processing issues and promising directions *Open Pacing Electrophysiol Ther* **3(1)** 4-20.

- Poiana G Da, Bernardini R, and Rinaldo R 2016 Separation and Analysis of Fetal-ECG Signals From Compressed Sensed Abdominal ECG Recordings *IEEE Transactions on Biomedical Engineering* **63(6)** 1269-1279.
- Castillo Encarnación, Morales D P, García Antonio, Luis P, Ruiz Víctor U, & Álvarez-Bermejo José A, et al. 2018 A clustering-based method for single-channel fetal heart rate monitoring. *Plos One* **13(6)** e0199308.
- Varanini M, Tartarisco G, Billeci L, Macerata A, Pioggia G, Balocchi R 2014 A multi-step approach for non-invasive fetal ECG analysis. *Computing in Cardiology Conference. IEEE*.
- Clifford GD, Silva I, Behar J, & Moody G B 2014 Non-invasive fetal ECG analysis. *Physiological Measurement* **35(8)** 1521-1536.
- Moore B 1981 Principal component analysis in linear systems: controllability, observability, and model reduction. *IEEE Transactions on Automatic Control* **26(1)** 17-32.
- Hyvärinen A, Oja E 2000 Independent component analysis: algorithms and applications *Neural Networks* **13** 411–430.
- Mirza S, Bhole K, Singh P 2020 Fetal ECG Extraction and QRS Detection using Independent Component Analysis. *2020 16th IEEE International Colloquium on Signal Processing & Its Applications (CSPA). IEEE*.
- Talib M, Al-Bakri A, Abdullah A K 2020 Enhancement Separation of ECG Signals for Twin Fetuses Based on Modified Blind Source Separation. *2019 4th Scientific International Conference Najaf (SICN). IEEE*.
- Lieven De Lathauwer, Bart De Moor, and Joos Vandewalle 2000 Fetal electrocardiogram extraction by blind source subspace separation. *IEEE Transactions on Biomedical Engineering*.
- Petrolis R, & Krisciukaitis A 2013 Multi stage Principal Component Analysis based method for detection of fetal heart beats in abdominal ECGs. *Computing in Cardiology Conference. IEEE*.
- Sameni R. 2021 Noninvasive Fetal Electrocardiography: Models, Technologies, and Algorithms. In: Pani D., Rabotti C., Signorini M.G., Burattini L. (eds) *Innovative Technologies and Signal Processing in Perinatal Medicine*. Springer, Cham. https://doi.org/10.1007/978-3-030-54403-4_5
- Fahimeh, Jamshidian-Tehrani, Reza, & Sameni. 2018 Fetal ECG extraction from time-varying and low-rank non-invasive maternal abdominal recordings. *Physiological Measurement*.
- Mantas Lukoševičius and Vaidotas Marozas 2020 Blind extraction of fetal and maternal components from the abdominal electrocardiogram: An ICA implementation for low-dimensional recordings *Biomedical Signal Processing and Control* **58** 101836.
- Widrow B, Glover J R, McCool 1975 Adaptive noise canceling: Principles and applications *Proceedings of the IEEE* **63(12)** 1692-1716.
- Nannan Zhan, Jinyong Zhang, Hui, & Li, et al. 2017 A novel technique for fetal ECG extraction using single-channel abdominal recording. *Sensors*.
- Behar, J., Johnson, A., Clifford, G. D., & Oster, J. 2014 A comparison of single-channel fetal ECG extraction methods. *Annals of Biomedical Engineering*, 42(6), 1340-1353.
- Liu Chengyu, Li Peng, Zhao Lina, Di Maria, Costanzo, Zhang Henggui, & Chen Zhiqing 2014 A multi-step method with signal quality assessment and fine-tuning procedure to locate maternal and fetal QRS complexes from abdominal ECG recordings. *Physiological Measurement* **35(8)** 1665-1683.
- Liu H, Chen D, & Sun G 2019 Detection of Fetal ECG R Wave from Single-lead Abdominal ECG Using a Combination of RR Time-Series Smoothing and Template-Matching Approach. *IEEE Access*.
- Davies M E, James C 2007 Source separation using single channel ICA. *Signal Processing Amsterdam*.

87(8) 1819-1832.

Lukoševičius M, Marozas V 2014 Non-invasive fetal QRS detection using an echo state network and dynamic programming *Physiological Measurement* **35(8)** 1685.

Mohimani H, Babaie-Zadeh M, Jutten C 2009 A fast approach for overcomplete sparse decomposition based on smoothed l-0 norm. *IEEE Transactions on Signal Processing* **57(1)** 289-301.

Silva I, Behar J, Sameni R, Zhu T, Moody G B 2013 Non-invasive fetal ECG: The PhysioNet/Computing in Cardiology Challenge 2013. *Computing in Cardiology Conference (CinC), 2013. IEEE*.

Goldberger A L, Amaral L A N, Glass L, Hausdorff J M, Ivanov P Ch, Mark R G, Mietus J E, Moody G B, Peng C K, Stanley H E 2000 PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *Circulation* 101(23) e215-e220.

Jezewski J, Matonia A, Kupka T, Roj D, Czabanski R 2012 Determination of fetal heart rate from abdominal signals: evaluation of beat-to-beat accuracy in relation to the direct fetal electrocardiogram. *Biomedizinische Technik/biomedical Engineering* **57(5)** 383-394 DOI:10.1515/bmt-2011-0130.

Donoho D L 2006 Compressed sensing. *IEEE Transactions on Information Theory* **52(4)** 1289-1306.

Candes, E.J., Wakin, M.B. 2008 An Introduction To Compressive Sampling. *IEEE Signal Processing Magazine* **25(2)** 21-30 DOI: 10.1109/MSP.2007.914731.

Eldar Y C, Kutyniok G 2012 Compressed Sensing: Theory and Applications. *Cambridge University Press*.

Candes E J, Tao T 2005 Decoding by linear programming. *IEEE Trans. Inform. Theory* **51** 4203-4215.

Devore R A 2007 Deterministic constructions of compressed sensing matrices. *Journal of Complexity* **23(4-6)** 918-925.

Emmanuel J Candès, Romberg J K, Tao T 2010 Stable signal recovery from incomplete and inaccurate measurements. *Communications on Pure & Applied Mathematics* **59(8)** 1207-1223.

Indyk P 2010 Sparse recovery using sparse random matrices. *Latin American Conference on Theoretical Informatics. Springer-Verlag*.

Poian G D, Bernardini R, Rinaldo R 2016 Robust reconstruction for CS-based fetal beats detection. *2016 24th European Signal Processing Conference (EUSIPCO). IEEE*.

Curve D, Krishnan S 2020 Separation of fetal ECG from single-channel abdominal ECG using activation scaled non-negative matrix factorization. *IEEE Journal of Biomedical and Health Informatics* **24(3)** 669-680.

Mota J F C, Xavier J M F, Aguiar P M Q, Markus Püschel 2011 Basis Pursuit in sensor networks. *IEEE International Conference on Acoustics. IEEE*.

Yuan L U, Bing-Jie L I, Meng Y E, Guang-Fei L I 2012 Iterative hard threshold algorithm for sparse signal reconstruction based on compressive sensing. *Modern Electronics Technique*.

Gui G, Wan Q, Peng W, Adachi F 2010 Sparse multipath channel estimation using compressive sampling matching pursuit algorithm. *Mathematics*.

Tropp J A, Gilbert A C 2007 Signal recovery from random measurements via orthogonal matching pursuit. *IEEE Transactions on Information Theory* **53(12)** 4655-4666.

Thong T, Do†, Lu Gan‡, Nam Nguyen†, Trac D. Tran† * 2010 Sparsity adaptive matching pursuit algorithm for practical compressed sensing. *Conference on Signals, Systems & Computers. IEEE*.

J. K. Pant, W. Lu and A. Antoniou, 2014 New Improved Algorithms for Compressive Sensing Based on ℓ_p Norm. *IEEE Transactions on Circuits and Systems II: Express Briefs* **61(3)** 198-202.

doi:10.1109/TCSII.2013.2296133.

Billah M S, Mahmud T B, Snigdha F S, Arafat M A 2011 A novel method to model ECG beats using Gaussian functions. *2011 4th International Conference on Biomedical Engineering and Informatics (BMEI). IEEE.*

Poian G D, Bernardini R, Rinaldo R 2014 Gaussian dictionary for Compressive Sensing of the ECG signal. *Biometric Measurements & Systems for Security & Medical Applications. IEEE.*

Poian G Da, Bernardini R, Rinaldo R 2016 Separation and Analysis of Fetal-ECG Signals From Compressed Sensed Abdominal ECG Recordings. *IEEE Transactions on Biomedical Engineering* **63(6)** 1269-1279.

Ouyang S, Song Z, Chen D, Wang J 2002 Application of wavelet soft-threshold de-noising technique to power quality detection. *Automation of Electric Power Systems* **26(19)** 56-60.

Pan Q, Zhang L 1999 Two de-noising methods by wavelet transform. *IEEE Transactions on Signal Processing* **47(12)** 3401-3406.

Kanungo T, Mount D M, Netanyahu N S, et al. 2002 An efficient k-means clustering algorithm: analysis and implementation. *IEEE Transactions on Pattern Analysis & Machine Intelligence* **24(7)** 881-892.

Liu CY, Li LP, Zhao LN, et.al. 2012 A Combination Method of Improved Impulse Rejection Filter and Template Matching for Identification of Anomalous Intervals in RR Sequences. *Proceedings of the annual meeting, American Section of the International Solar Energy Society.*

Zhang Y, Yu S. 2020 Single-lead non-invasive fetal ECG extraction by means of combining clustering and principal components analysis. *Medical & Biological Engineering & Computing.*

ANSI/EC57-2012 Testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms.