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Modified Block Compressed Sensing for Extraction of Fetal Electrocardiogram from Mother Electrocardiogram Using Block Compressed Sensing Based Guided FOCUSS and FAST-Independent Component

Muhammad Tayyib, Muhammad Amir, Musyyab Yousufi, Suheel Abdullah

Faculty of Engineering and Technology; International Islamic University Islamabad; 44000, Pakistan; phone: +92 51 9019100; e-mails: Muhammad.tayyib@iiu.edu.pk, m.amir@iiu.edu.pk, musyyab.bsee1662@iiu.edu.pk, suheel.abdullah@iiu.edu.pk

Sarmad Maqsood

Department of Software Engineering, Kaunas University of Technology, Kaunas 51368, Lithuania; phone: +370 624 77480; e-mail: sarmad.maqsood@ktu.edu

Muhammad Irfan

Faculty of Engineering and Technology; International Islamic University Islamabad; 44000, Pakistan; e-mail: mirfan@iiu.edu.pk

Corresponding author: muhammad.tayyib@iiu.edu.pk

Fetal electrocardiogram extraction from abdominal electrocardiogram is perilous task for tele-monitoring of fetus which require in-depth understanding. Conventional source separation methods are not efficient enough to separate fetal electrocardiogram from huge multi-channel electrocardiogram signals. Due to huge amount of data, source separation techniques along with compression methods are used, however, the use of compressed sensing depends on the sparsity of signal. Electrocardiogram signal is not sparse in original form; therefore, it is made co-sparse for processing. This paper proposes block compresses sensing based reconstruction of fetal electrocardiogram from abdominal electrocardiogram, the novelty of this paper is in the form of using guided frequency filter for removing interdependency between multichannel electrocardiogram signals. The use of Walsh sensing matrix made it possible to achieve high compression ratio. Experimental results prove that even at very high compression ratio, successful fetal electrocardiogram reconstruction from raw electrocardiogram is possible. These results are validated using peak signal to noise ratio, signal to interference and noise ratio, and mean square error. This shows the framework, compared to other algorithms such as current blocking compressed sensing algorithms, Rakness based compressed sensing algorithm and wavelet algorithms, can greatly reduce code execution time during data compression stage and achieve better reconstruction.

KEYWORDS: Fetal ECG; Compressed Sensing; BCS-GFOCUSS; Source separation; Classification.

1. Introduction

Cognitive impairment caused by fetal hypoxia during the perinatal period remains a serious health problem worldwide [18]. The growth of fetus is tracked by closely monitoring the difference in the fetal electrocardiogram (ECG), morphology, heart rate, dynamic behavior, and heart sound during perinatal period. ECG allows the interpretation of the heart electrical activity far beyond just heart rate and heart rate variability. The analysis of mother ECG (MECG) is quite simple, electrodes directly placed on chest give distinct signals for health monitoring. Obtaining fetus-ECG (FECG) is entirely different, as FECG is to be extracted from MECG using source separation algorithms which is quite complex. Using FECG signal analysis, the actionable deformities during fetal growth i.e. deceleration, fetal intrauterine hypoxia, loss of high frequency variability, ischemia, and distress, can be distinguished.

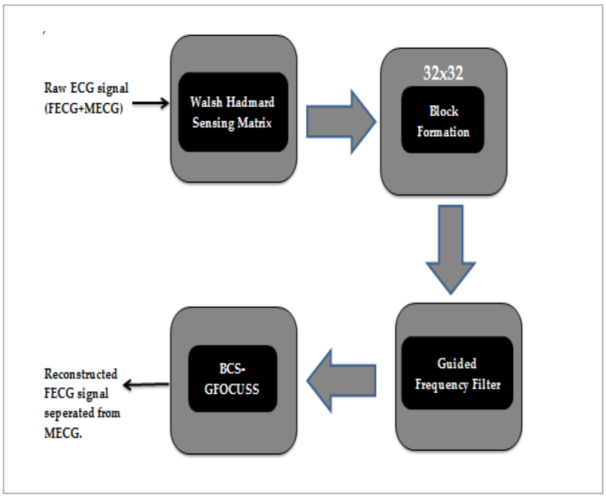
EEG based Brain Computer Interface (BCI) has shown significant importance in recent years for health-care monitoring, including early detection of seizure, trauma, Alzheimer, and stroke [20]. After the advent of ECG in early 90's, there have been significant improvement in the standards of ECG signal monitoring. ECG plays vital role in the detection of many anomalies in the functionality of heart, however long-term ECG signals (in some cases fourteen days) is compulsory for close observation and diagnosis of certain diseases [21]. Moreover, today's ECG equipment's uses high sampling frequency for recording, enforcing to deal with huge amount of data and with the increasing computation capabilities. This huge data entails incredible threat in data monitoring, storing, processing, and transmitting which is not economically efficient. Consequently, to deal with this, several compression techniques have been proposed in the literature.

A suitable compression method can significantly reduce the proportion of ECG signals. However, majority of the conventional compression methods are not suitable for wireless transmission of ECG signals due to their complexity. Competent compression methods usually promote either high energy consumption or low compression [4]. Therefore, forging an efficient compression method with ability to fast processing and less computational complexity is in high demand. With the advent of Compressed sensing (CS), all these problems are addressed in most suitable manner [11]. Mathematically, CS is the dimensionality reduction of sensing technique that uses a usually random, linear transformation to map original vectors into smaller vectors of measurements that are enough to reconstruct the original signal [10]. CS is a novel signal processing method for the efficient compression and signal reconstruction with minimum error by finding the closest possible solution to the undetermined linear problem.

CS was first introduced by Donho [6] and Candes [2] in 2006. CS is competent enough to successfully compress and reconstruct the signal having sparse representation in certain bases. After presentation of the CS theory, there have been tremendous amount of work done using CS reconstruction methods. The introduction of CS to ECG have caught the eye of researchers in recent years, with this in mind there have been vast number of publications in the areas of reconstruction, encoding and sampling. In contrast to the compression process, the reconstruction of CS is computationally complex. Zhang et al. [26] proposed the concept of Block Spare Bayesian Learning (BSBL) for the reconstruction of raw FECG. This method exploits the use of intra-block correlation that is present in the sparsity pattern of wavelet domain and uses BSBL to reconstruct the FECG signal. Craven et al. [3], have used the concept of adaptive dictionary learning for the reconstruction of ECG. This adaptive method determines the location of the QRS complex and selects the most appropriate dictionary which results in more refined reconstruction. Very recently, Eftekharifar et al. [8], have used the block sparse model which claims that using raised cosine kernel for the construction of sparse bases instead of wavelet or Gaussian families, better performance can be achieved. Pareschi et al. [16], have introduced the concept of Rakness based model that can improve the reconstruction performance. Rakness is the ability of the linear transformation to collect the energy of the signal. By using Rakness based reconstruction model, the amount of information for each measurement is increased. Thus, it reduces the number of measurements for transmission, however it has some significant impact on the time window duration of the computational cost, nevertheless the hardware cost.

Although CS has achieved some success in adult ECG telemonitoring [26], however, it suffers from the telemonitoring of FECG. This conflict is due to the strict energy constraint and the non-sparsity of the raw FECG signal. The use of filtering for increasing the energy component of FECG is not encouraged due to limited energy. For CS algorithms, this indicates that compression should be done with minimum pre-processing. Due to the non-sparsity of the raw FECG, the reconstruction quality of CS algorithms suffers. Raw FECG is different from normal ECG due to the presence of strong noise and unavoidable interference. Recording from abdominal electrodes consist of MECG and FECG, both superimposed on each other. FECG is comparatively smaller in magnitude, extracting the fECG from the MECG in the presence of noise is thus a difficult problem. Different methods have been introduced for this purpose in literature, state of the art are, adaptive filtering, Wavelets, Blind Source Separation (BSS), Principle Component Analysis (PCA), Independent Component Analysis (ICA), and sparse redundant information [18]. Blind Source Separation (BSS) [15], separates the abdominal signal into three components, FECG, MECG, and noise. However, if the abdominal signal does not carry these three components, the BSS algorithms fails to separate the FECG from MECG. The ICA based blind source separation [17], was proposed to distinguish FECG from the maternal ECG, however, ICA lacks its ability due to nonstationary nature of FECG and the presence of white noise. The adaptive filtering algorithm has been used for the adaptive noise cancellation from abdominal signal [1]. This method uses the combination of linear combiner and adaptive noise cancellation to update the weights, however, this approach does not consider the sparsity of FECG and only use a single chest sensor as the MECG reference.

Figure 1
Flow diagram of proposed method



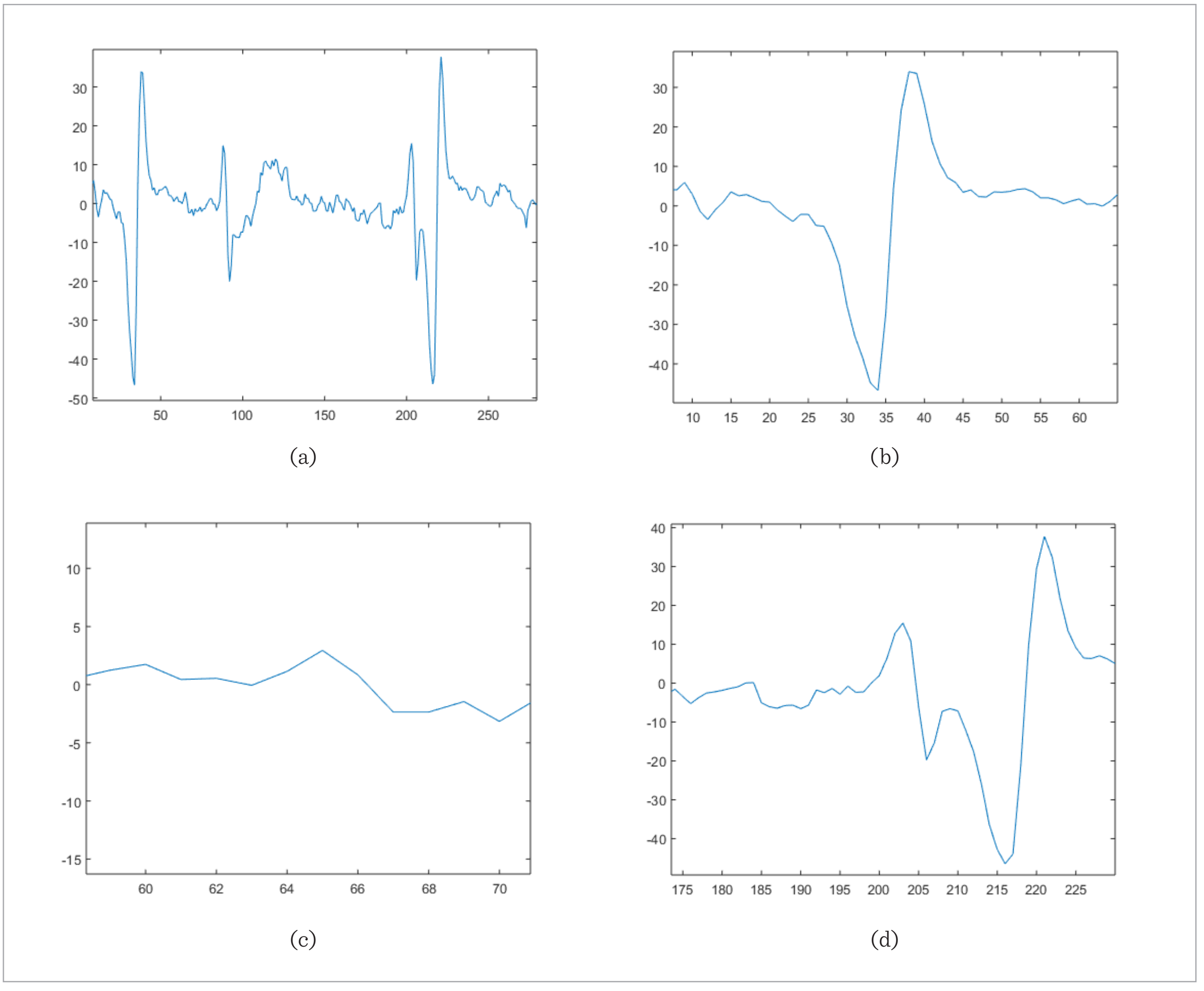
The adoption of wavelet-based techniques is also been widely used for source separation, in the literature. Yu et al. [25], proposed to enhance the MECG components before the extraction of FECG, this result in optimize wavelet scale. Procedure is not fully automated and require some manual assistance in some cases. Moreover, this specific method does not give any glimpse of FECG extraction. The block compressed sensing was introduced to overcome the memory issues by dividing the ECG signal into small non-overlapping blocks [26]. The independent sampling of these blocks is achieved using similar or unique measurement matrices. BCS effectively reduce the memory requirement compared to the non-BCS algorithms by introducing unique and efficient measurement matrices. This results in high speed reconstruction and substantial less encoding complexity. The use of parallel processing also increases the process of encryption [12].

A raw FECG signal can be viewed as contaminated by noise. Figure 2 shows the segment of raw FECG recording, in which non-zero segments from 20-50, 80-95, and 200-230 time points can be clearly seen. Remaining segment can be viewed as concentration of zero blocks. The whole signal is thus clean signal contaminated by noise, therefore, block partition is unknown in FECG monitoring. Hence, raw FECG can be modeled as block sparse signal with block partition and unknown noise.

There are various methods used in the literature for the efficient reconstruction of EEG signal from

Figure 2

Closeup of second channel daisy dataset(a) Segments of first 250 time points of the recording. (b) Subsegment containing the QRS complex of MECG. (c) Subsegment containing the QRS complex of FECG. (d) Subsegment containing the QRS complex of FECG contaminated by the QRS of MECG



sparse reconstruction using compressed sensing, however, there are limitations to these in terms of high compression ratio, whenever algorithms try to achieve reconstruction from high compression, they face degradation in signal, in [19], accelerated double temporal based sparse reconstruction is done for EEG signal. The use of schattern-p norm made it useful technique in terms of execution time, however, this technique is prone to noise in high compression ratio. Although results are prominent in terms of SNDR, and NMSE, however, these are limited to only specific data set, therefore improvement could be done. Compressed sensing have wide range of applications in wireless communication, in [12], authors have presented comprehensive literature review of cognitive and wireless application for compressed sensing domain, the method proposed is distortion rate QCS (DR-QCS). The research is based on three sections, first section covers the CS techniques for wireless applications, in second part, data gathering, and lossy compression is addressed. In last section of paper, architecture based on multi-user detection and spectrum sensing are discussed. This study provides value able insight to the current trends of CS, however, there is not practical simulation presented by authors.

The idea of compressed sensing-based compressor for ECG signals was proposed in [11], authors have presented linear method based system architecture that is applicable even at 75 percent compression. The use of compressor is validated by the fact the very small amount of data is used for compression, this although provides efficiency in terms of compression and power consumption, however, this method is prone to errors on different architecture. To improve the quality of recovered signal, kronecker based approach is used. This idea is further explored in [12], where for the reconstruction of signal, enhanced weighted greedy analysis pursuit algorithm is used. The problem addressed here is to solve the weighted optimization problem using enhanced greedy algorithm in the presence of impulsive noise. The comparative analysis of this method is presented with other algorithms, however, there is lack of comparison between advanced techniques, therefore, this method could be categorized as application/technique specific method where comparing it with state of the art methods may results in deteriorating performance.

In this paper, we propose a modified iterative re-weighted l_1-norm minimization for the BCS framework in conjunction with guided frequency filter to smooth the blocks. Using l_1-norm encourage the sparsity of desired signal along with guided frequency filter which removes the blocking artifacts. We also extend the joint reconstruction of Multi-lead ECG signal exploiting the high correlation present in the ECG signals. To validate the proposed algorithm performance, state of the art performance matrices is used, which clearly indicates that proposed method outperforms the reconstruction quality from existing methods. Extensive simulations are performed for the reconstruction, FECG separation and performance evaluation.

The rest of the paper is organized as follows, the BCS-framework is explained in Section 2, Section 3 consists of proposed method, detailed experimental results are discussed in Section 4, and finally conclusion is drawn in Section 5.

2. Compressed Sensing

Compressed sensing is comparatively new signal processing paradigm offering more possibilities than any other compression method. The theory of CS relies on the assumption that if the subjected signal is exactly or approximately sparse in appropriate basis, then the reconstruction below the Shannon Nyquist theorem sampling is possible. Sparsity in the signal's representation leads to the reduced degree of freedom. Majority of signals are not sparse by nature, so they are made sparse by choosing a suitable basis matrix and thus transformation results in the sparsity of signal in that domain. This is achieved by selecting a suitable basis matrix $\Psi \in \mathbb{R}^{N\times M}$. The real valued signal $\Psi \in \mathbb{R}^{N\times M}$ is said to be k-sparse if it can be represented as, $x = \Psi$ have k (k<<N) non-zero entries, where, $c \in \mathbb{R}^{M}$ is the coefficient vector, with $\|c\|_0 < k$ and $\| \|_0$ is l_0 norm indicate the number of non-zero entries. The sparse representation of multiple channel model can be represented as,

$$X = \Psi C. \tag{1}$$

where, $X = [x_1, x_2, \dots, x_P] \in \mathbb{R}^{N\times P}$ is data matrix considering P channels and N-dimensional FECG signal, $\Psi = [\psi_1, \psi_2, \dots, \psi_P] \in \mathbb{R}^{N \times N}$ is orthonormal basis vector, $\Psi = [\psi_1, \psi_2, \dots, \psi_P] \in \mathbb{R}^{N \times N}$ represents the sparse coeffecient vector for each signal. The compressed signal is obtained using compressed sensing theory, as,

$$Y = AX, \tag{2}$$

where, $Y = [y_1, y_2, \dots, y_P] \in \mathbb{R}^{m \times P}$ is compressed data, $A \in \mathbb{R}^{m \times N}$ is the sensing matrix (m << N) indicating dimension far less than the original data, and P represent the original signal. Combining Equations (1) and (2),

$$Y = AX = A\Psi C. \tag{3}$$

To ensure a stable recovery, the sensing matrix must satisfy the restricted isometry property (RIP) [6]. The sparse matrixes involve less computation and are memory efficient. All most all of the real-world signals are contaminated with noise, so in order to represent these signals, Equation (3) can be written more appropriately as,

$$Y = AX + \eta = A\Psi C + \eta, \tag{4}$$

where η is noise vector modeling the errors occur during the acquisition or in CS framework.

The recovery of compressed signal from measurement vector Y is ill posed problem due to m << N. This results in undermined system which has infinitely many solutions. It was suggested that to recover such problems, convex optimization techniques can be applied only of it satisfy the following condition: m > OK log (N), where O is some constant and ratio m/N is called compression ratio (CR). The convex optimization problem formed is as follows,

$$min\|C\|_0 \; s.t \; Y = AX + \eta = A\Psi^{-1}C + \eta, \tag{5}$$

where, Ψ^{-1} is the inverse transform. This is an NP-hard problem and to exactly recover the sparse signal following model is used,

$$min\|C\|_1 \; s.t \; Y = AX + \eta = A\Psi^{-1}C + \eta, \tag{6}$$

In Equation (6), $\|.\|_1$ is the l_1-norm.

3. Block Compressed Sensing

In recent years, numerous CS reconstruction algorithms have been proposed. The use of Basis Pursuit (BP) for reconstruction gives better results, but due to computational cost BP is not frequently used. Gradient Projection for Sparse Reconstruction (GPSR), Orthogonal Matching Pursuit (OMP), and stage-wise orthogonal matching pursuit (st-OMP) speeds up the computations but suffer severely with reconstruction quality. The gradient descent-based methods [12-13], were proposed in literature that are comparatively fast and gives better quality. These methods divide the function into smaller subfunctions, which can be solved separately with efficiency and less computational cost. However, these algorithms suffer during reconstruction from blocking artifacts that are introduced during the regrouping of these subproblems [14]. It can cause loss in vital information. Recently, iterative thresholding algorithm based on smoothed projected land-weber for Block Compressive Sensing (BCS-SPL), was proposed to address these problems, which can efficiently achieve sparsity and smoothness using filters and hard thresholding [20]. This algorithm like gradient based methods solve subproblem separately and during recovery the hard thresholding cause significant loss of information.

To address the above-mentioned shortcomings, we propose modified BCS algorithm to solve subproblems as single unit. This not only achieve better performance but also results in less computations [19]. To avoid the blocking artifacts upon reconstruction, Guided Frequency Filter (GFF) is proposed. In our previous work we have proposed to remove these artifacts using median filter [24]. The reconstruction performance is improved using GFF filter [23]. GFF filter is the frequency domain filter adopted from the guided filter theory. The proposed method is variant of FOCUSS algorithm with GFF filtering incorporated in every iteration. The proposed method is validated using statistical matrices i.e. PSNR, SINR and correlation, which clearly shows that proposed method outperforms the BSBL-BO, Rakness, BCS-SPL, BCS-DWT and BCS-DCT algorithms. In BCS, FECG signals are distributed into k×k blocks that are sampled using sequential walsh-hadmard matrix [9].

The proposed method removes the blocking artifacts and work as smoothing operator, whereas, applying FOCUSS directly as reconstruction algorithm leads to blocking artifacts. In this paper, we proposed to overcome these artifacts by incorporating GFF filter in each iteration. Using BCS, the FECG signal x_i is divided into k×k non-overlapping blocks containing $z = k^2$ time points. Let $A_k \in \mathbb{R}^{m_k \times N}$ the measurement matrix, in our case it is sequential walsh-hadmard matrix, where m_k are the number of measurements per block. Then $y_i = A_k x_i$ give the projection of x_i onto the measurement matrix. Equation (5) represent the problem that is solved using FOCUSS algorithm. The optimization problem and reconstruction is done using Lagrangian method, which reconstruct as $\hat{x} = \Psi^{-1}C$. The novelty of proposed method is that FOCUSS in its pure form does not involve any smoothing operator for the removal of artifacts in each iteration, we have successfully incorporated the GFF filter in each iteration. The cost function for such iterative problem is formulated as,

$$\min_{c_i} \|c_i\|_1 \ s.t\ y_i = A_k \Psi c_i + \eta. \tag{7}$$

for more general scenario, Equation (7) can be written as,

$$\min_{c_i} \|c_i\|_1 \ s.t\ y_i = A_k \Psi c_i. \tag{8}$$

The iterative reconstruction problem is formulated as,

$$\min_{x_i} f(x_i) = \|\Psi x_i\|_1 \ s.t\ \ y_i = A_k \Psi. \tag{9}$$

Equation (9), give sparse solution by taking l_1-norm of signal with respect to sparsity basis Ψ and keeping the equality constraints in check. To solve this constrained non-linear optimization problem, Lagrangian method is used and GFF filter is applied in each iteration for smoothing. The Lagrangian is defined as,

$$L(x_i, \lambda) = f(x_i) + \lambda^T (A_k x_i - y_i), \tag{10}$$

where λ is a vector containing Lagrangian multipliers. Let x_i^* be the minimizing solution, the necessary condition for Lagrangian requires (x_i^*, λ) be the stationary points of Lagrangian function. This is given as,

$$\frac{\partial L}{\partial x_i} = 0, s.t. \frac{\partial L}{\partial \lambda^*} = 0. \tag{11}$$

The partial derivative of $L(x_i, \lambda)$ w.r.t x_i is given as

$$\frac{\partial L}{\partial x_i} = \frac{\partial F}{\partial x_i} + {A_k}^T \lambda. \tag{12}$$

The objective function is obtained using decomposition,

$$f(x_i) = \|\Psi x_i\|_1 = \sum_{j=1}^{n} |\psi_j x_i|, \tag{13}$$

where ψ_j is the row vector of Ψ. The gradient vector of objective function after decomposition is obtained as,

$$\frac{\partial f}{\partial x_i} = \Psi^T \Pi(x_\psi) \Psi x_i, \tag{14}$$

where Π represent the diagonal matrix of size n× n.

$$\Pi(x_\psi) = diag|x_\psi|^{-1}, \tag{15}$$

where $x_\psi = \Psi x_i$. Refereing to Equation (12) and Equation (15), we can write,

$$\frac{\partial L}{\partial x_i} = \Psi^T \Pi(x_\psi) \Psi x_i + {A_k}^T \lambda, \tag{16}$$

considering the Lagrangian in Equation (10), we may write as,

$$\frac{\partial L}{\partial x_i} = A_k x_i - y_i. \tag{17}$$

From Equation (11), (16), and (17), the stationary points must satisfy,

$$\Psi^T \Pi(x^*_\psi) \Psi x^*_i + {A_k}^T \lambda^* = 0 \tag{18}$$

$$A_k x^*_i - y_i = 0. \tag{19}$$

From Equation (18)

$$x^*_i = -(\Psi^T \Pi(x_\psi) \Psi)^{-1} {A_k}^T \lambda), \tag{20}$$

using this expression in Equation (19)

$$\lambda^* = -(\mathrm{A}_k(\Psi^T\Pi(x_\psi)\Psi)^{-1}\mathrm{A}_k{}^T)^{-1}\mathrm{y}_i. \tag{21}$$

Using this expression for λ^* in Equation (20),

$$x^*{}_i = -(\Psi^T\Pi(x_\psi)\Psi)^{-1}\mathrm{A}_k{}^T(\mathrm{A}_k(\Psi^T\Pi(x_\psi)\Psi)^{-1}\mathrm{A}_k{}^T)^{-1}, \tag{22}$$

defining $\Gamma_{\psi A}$, the recursive form of x^*, for iterative scheme is given as,

$$x^{(j+1)}{}_i = \Psi^{-1}\Pi^{-1}(x^j{}_\psi)\Gamma_{\psi A}{}^T(\Gamma_{\psi A}\Pi^{-1}(x^j{}_\psi)\Gamma_{\psi A}{}^T)^{-1}\mathrm{y}_i. \tag{23}$$

Although solving Equation (23) is not straight forward, but in literature to solve such approach, relaxation method is suggested. Relaxation method solves the problem by approximating the difficult problem into simple problems.

Unlike FOCUSS algorithm, Equation (23) gives an approximation of each FECG signal at individual iteration by incorporating smoothing filter. As Lagrange multiplier is used to solve the FOCUSS algorithm, we name it as BCS-GFOCUSS.

Algorithm 1. Proposed Algorithm

1) **function** $x^{(k+1)}$ = BCS-GFOCUSS $x^{(k)}$, y, A_k, Ψ)
2) $\hat{x}^{(k)} = GFF(x^{(k)})$
   for each block i
3) $\lambda_i^{(k)} = \Pi^{(-1)}(x_\psi)$, $x_\psi = \Psi\hat{x}_i$
4) $x_i^{(k+1)} = \Psi^{-1}\Gamma_{\psi A}^T\,(\Gamma_{\psi A}\Pi_i^{(k)}\Gamma_{\psi A}^T)^{-1}y_i$
5) Terminate when $|\ \exp^{(k+1)} - \exp^{(k)}\ | < 10^{(-2)}$ where $\exp^{(k+1)} = \frac{1}{N}\,\|x^{(k+1)} - \hat{x}^{(k)}\|_2$

4. Experiments

For the extraction of FECG from MECG, we have used publicly available dataset [5]. This benchmark dataset has wide reputation for such tasks, the DaISy dataset contain barely visible FECG. To show the diversity of the proposed algorithm, these datasets prove efficiency under different scenarios. All the simulations are performed on MATLAB 2017a, with 8Gb RAM. The validity of proposed algorithm is verified by comparison with existing compressed sensing algorithm i.e. BSBL, Rakness, BCS-SPL, BCS-DWT and BCS-DCT. For the compression in each case, sequential Walsh Hamdard matrix is used as sensing matrix. Due to the excessive amount of simulations, we only present reconstruction results of BSBL-BO and Rakness bases compressed sensing.

Normally MSE is used as performance indicator for sparse sensing prospect. In our work reconstruction quality is not the final goal, so reconstructed signal is further processed for clean extraction of FECG. MSE shows infidelity in the structured signal [22], so it is difficult to see errors in the final reconstructed recording. Thus, we develop more direct approach by extracting FECG form raw signal as well as from reconstructed signal and calculating the SINR vs correlation between both.

4.1. Daisy Dataset

Daisy dataset is the most used data for the telemonitoring of FECG [5]. Figure 2 shows the segments of daisy dataset. In this dataset, two not clearly visible FECG QRS complex are present which are overshadowed by two MECG QRS complexes. By observing we can clearly state that this dataset is not sparse and almost its every entry is non-zero. This poses serious difficulty for the CS recovery algorithms. For compression, we have used 125x250 sequential Walsh Hadamard matrix.

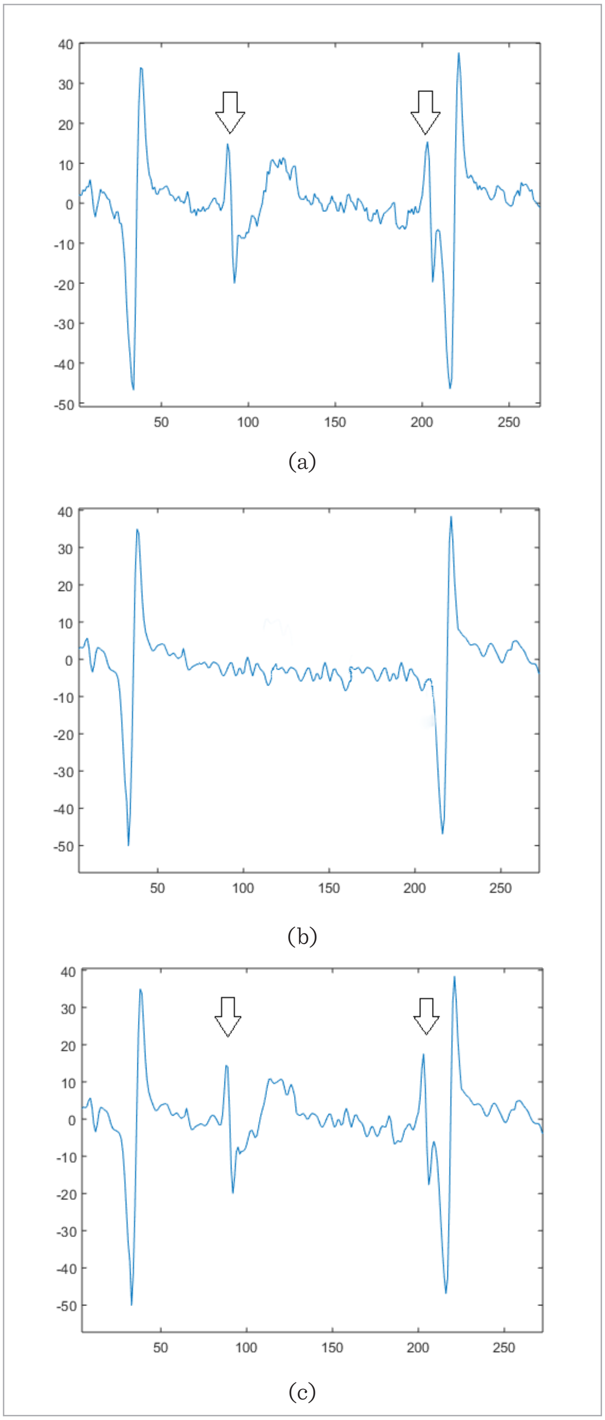
For BCS-GFOCUSS, we have defined the block size of 32x32 for the partition of each ECG signal. As ECG data is very similar due to monitoring of same source with different angles, so using intra-block correlation results in better performance. This can be seen in Figure 3.

The comparison is done with two sets of algorithms, first lot contain non-blocking CS algorithms and second one contains blocking CS algorithms. Due to excessive amount of result, only results of BSBL-BO and Rackness CS are presented in Figure 4. To justify the claimed results, we have have incorporated same sensing matrix for the compression of DaISy dataset and then used BCS-GFOCUSS to reconstruct it.

DaISy dataset contain prominent MECG activity prominent in all recordings of Figure 5(a). The recordings show very feeble FECG which is not very

Figure 3

Comparison of original and reconstructed segments by BCS-GFOCUSS (a) Raw fECG segment (b) Reconstructed fECG exploiting intra-block correlation (c) Reconstruction avoiding intra-block correlation



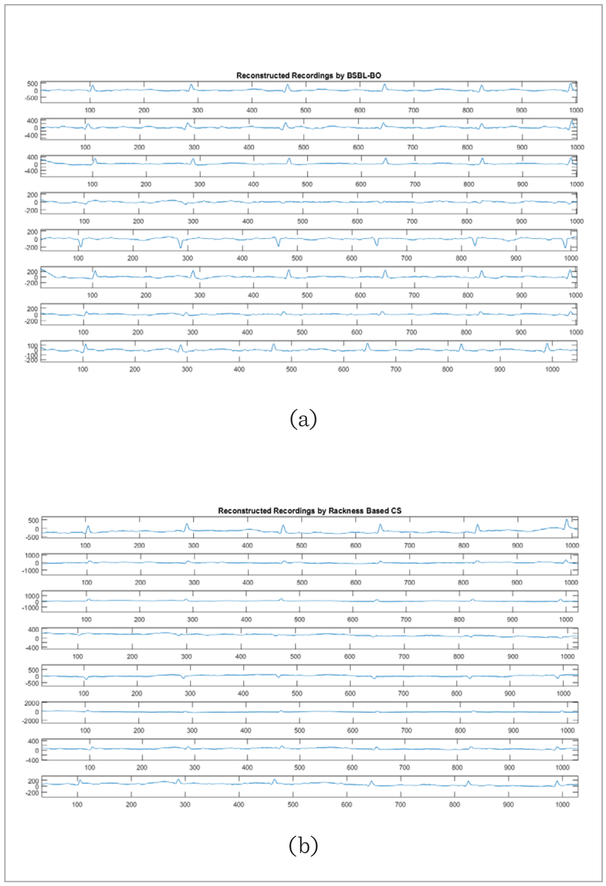
(a)

(b)

(c)

Figure 4

Reconstruction of FECG signal (a) BSBL-BO (b) Rakness based compressed sensing



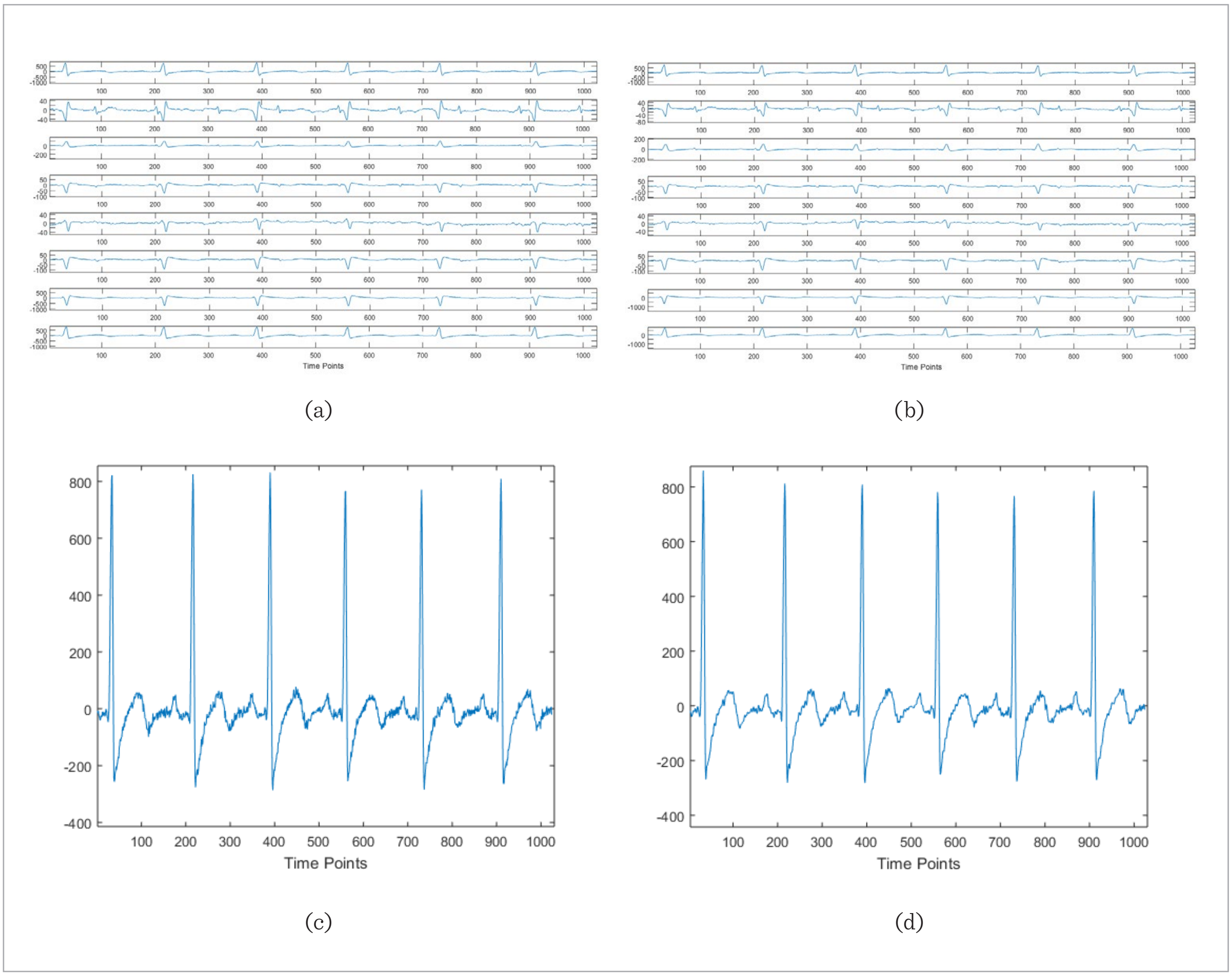
(a)

(b)

clear in first five readings, however fourth one dominated by baseline deviation probably due to maternal respiration. Figure 5 (b) shows all the reconstructed recordings using BCS-GFOCUSS, which do not show any distortion visibly and shows prominent reconstruction. By checking the reconstruction quality with statistical analysis, there are slight errors. The final goal of our work is extracting clean FECG from reconstructed FECG recordings, so this does not pose any serious issue. The extraction results are shown in Figure 5(d), which clearly advertise the prominent QRS complexes without any residual noise effects. For comparison, same method is repeated on original FECG recordings and results are shown in Figure 5(c) clearly indicate the same FECG patterns. Even baseline wanders are recovered well.

Figure 5

Comparison of original and reconstructedsegments by BCS-GFOCUSS (a) Raw fECG segment (b) Reconstructed fECGexploiting intra-block correlation (c) Reconstruction avoiding intra-blockcorrelation MECG, (d) Reconstruction avoiding intra-block correlation for fECG



The outcome of the proposed algorithms is source separation of FECG from MECG. This is achieved by using GIFT toolbox as a source separation toolbox [7]. GIFT is publicly available toolbox, with excellent results in source separation. FAST-ICA algorithm is used to extract IC's from raw FECG dataset and from reconstructed BCS-GFOCUSS algorithm. FECG and MECG are separated using FAST ICA, it can be seen in Figure 6, that there is very minute amount of difference between raw and reconstructed IC's almost indistinguishable by naked eye. FAST-ICA is used in deflation mode and six different IC's were extracted where fourth one is the FECG. Same procedure was performed on all the comparison algorithms, as seen in Figure 6, all these algorithms fail to achieve the task.

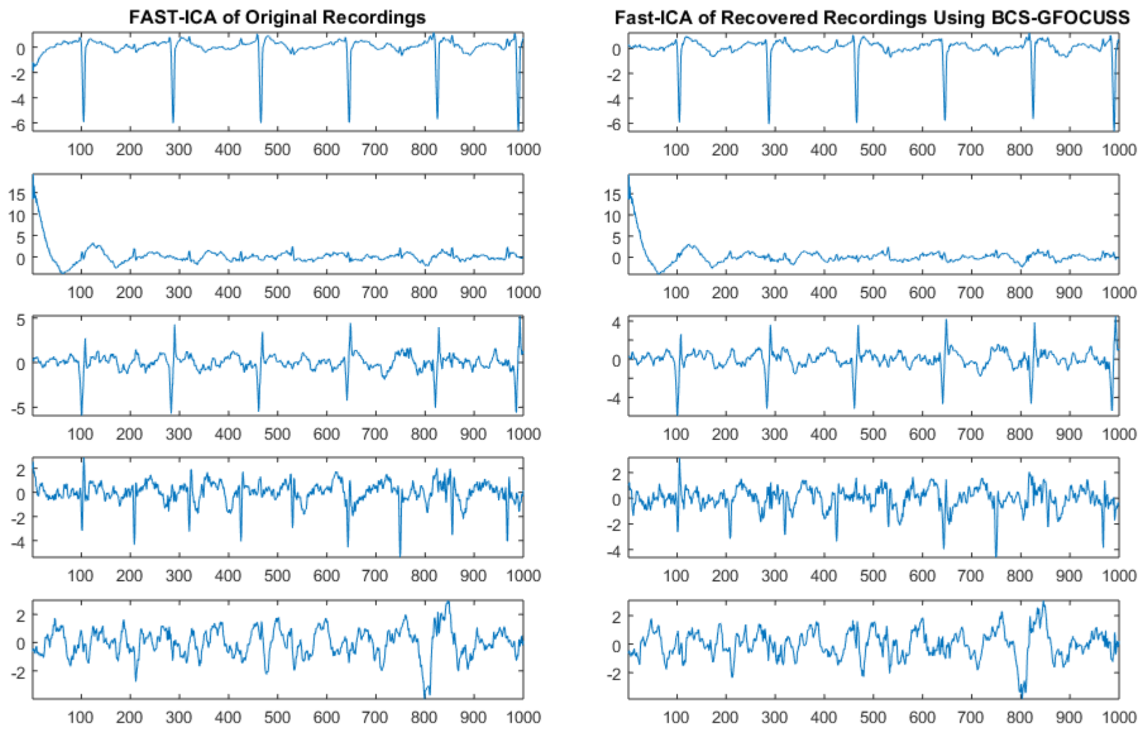
4.2. Performance Evaluation

In this paper, we have successfully extracted FECG from MECG using DaISy dataset. The main question rises in the form that either same algorithms will perform well using different dataset, as the amount of correlation in fetus may vary due to pregnancy period, position of fetus and random muscle move-

Figure 6

Comparison of FAST-ICA decomposition of original dataset and reconstructed dataset by BCS-GFOCUSS (a) ICs of recovered dataset (b) ICs of the original dataset

The fourth IC in both (a) and (b) are the extracted FECG from both original and reconstructed dataset



(a) (b)

ment. Since BCS-GFOCUSS totally rely on correlation structure to improve its performance. These questions are answered by evaluating the experimental results using different statistical measurements. The aim of BCS-GFOCUSS is on applications where low coding optimization techniques are required to optimize available resources. As non-overlapping blocks in BCS reduces amount of data, computation, and power, hence, in all our simulations non-overlapping block of 32x32 is used. To test the performance of proposed algorithm, we have used peak signal to noise ratio (PSNR) and signal to interference and noise ratio (SINR). SINR in our case is the ratio between the power of FECG to combined power of MECG and noise/interference. The results are shown in Table 1, at SINR value of -35 dB. It can be clearly observed, in the presence of strong noise FECGs are still recovered maintaining high fidelity.

Compression ratio (CR) also plays vital role in the successful recovery of compressed signal. CR is defined as,

$$CR = \frac{N - M}{N} \times 100, \tag{24}$$

where N is the length of raw FECG signal and M is the length of the reconstructed FECG signal. In case of sensing matrix, CR varies by changing the values of M from 25 to 90, while N is fixed to 512. To validate the results, we have performed same scenario for 20 times to avoid any errors. Walsh Hadamard sensing matrix and DaISy dataset is used for all the simulations.

Table 1

Quantitative measures for sparse signal recovery of EEG signals

Method	Compression Ratio	MSE	PSNR	SNR(dB)	Mean	Std
BCS-DWT	2:1(50%)	0.02517	32.36	-11	1.76e-05	2.47e-06
	3.4:1(70%)	0.02832	30.64	-15	8.48e-05	1.15e-06
	5:1(80%)	0.04717	28.19	-19	6.02e-05	1.78e-06
BCS-SPL	2:1(50%)	0.02471	33.30	-12	1.63e-05	1.47e-06
	3.4:1(70%)	0.02781	31.77	-17	6.54e-05	1.15e-06
	5:1(80%)	0.03843	28.66	-20	6.06e-05	1.68e-06
BSC-FOCUSS	2:1(50%)	0.01173	35.42	-15	8.47e-04	1.99e-05
	3.4:1(70%)	0.01837	33.65	-20	7.03e-04	2.29e-05
	5:1(80%)	0.02176	29.66	-22	2.76e-04	1.54e-05
BSBL-BO	2:1(50%)	0.003725	38.71	-25	2.79e-04	3.55e-05
	3.4:1(70%)	0.006521	35.14	-28	9.47e-04	4.99e-04
	5:1(80%)	0.007413	33.63	-32	5.03e-04	3.29e-04
Rakness	2:1(50%)	0.003545	41.48	-25	1.66e-03	2.57e-04
	3.4:1(70%)	0.004618	38.92	-26	7.53e-03	1.29e-04
	5:1(80%)	0.006717	36.85	-29	6.06e-03	1.23e-04
DTSR	2:1(50%)	0.002451	49.21	-32	1.56e-03	2.37e-04
	3.4:1(70%)	0.006341	49.54	-31	8.58e-04	1.25e-04
	5:1(80%)	0.006817	47.32	-32	7.02e-04	1.68e-04
DR-QCS	2:1(50%)	0.005545	42.58	-28	1.56e-03	2.37e-04
	3.4:1(70%)	0.004714	40.72	-27	8.58e-04	1.25e-04
	5:1(80%)	0.007783	39.55	-32	7.02e-04	1.68e-04
CS-based compressor	2:1(50%)	0.02521	45.21	-31	9.47e-04	1.99e-04
	3.4:1(70%)	0.002145	44.44	-28	6.03e-04	1.29e-04
	5:1(80%)	0.003561	42.14	-30	1.76e-03	2.54e-04
ewGAP	2:1(50%)	0.001122	50.25	-34	1.79e-03	2.55e-04
	3.4:1(70%)	0.002140	48.47	-35	9.47e-04	1.99e-04
	5:1(80%)	0.002265	43.21	-37	6.03e-04	1.29e-04
BCS-GFOCUSS	2:1(50%)	0.001025	51.24	-35	1.76e-03	2.54e-04
	3.4:1(70%)	0.001541	49.75	-6	9.46e-04	1.98e-04
	5:1(80%)	0.002169	45.74	-39	6.02e-04	1.27e-04

5. Discussion

The size of the block plays an important role in the performance of the algorithm. Most of the CS algorithms deals with unknown block structure. Hence, they try to find true block structure compromising the accuracy. BCS-GFOCUSS create user defined arbitrary blocks, which may differ from true block structure. After many experiments and simulations, it was noted that best results are obtained when block size is 32x32.

Most of the raw signals are not sparse, especially in the presence of noise. To reconstruct such signals, generally two types of approaches are adopted. First one is to take some threshold point below whose all values are made zero, which in case of FECG is not possible as we have seen that FECG signal may have very small amplitude. Second approach is to reconstruct the signal in transform domain, the success of which rely on the sparsity level of representation coefficients. However, in most of the cases, sparse coefficients are still not sparse enough. This results in few large amplitude coefficients and large amount of small amplitude coefficients, which in case of further processing, results in the failure of source separation of FECG from MECG. Unlike these scenarios, BCS-GFOCUSS directly reconstruct the non-sparse signals unlike resorting to above two strategies. High quality reconstruction allows this method for further signal processing and pattern recognition used for clinical diagnosis. Very clearly it can be observed the block structure and intra-block correlation plays crucial role in the high-quality reconstruction. Furthermore, it is observed, that unlike existing CS algorithms, BCS-GFOCUSS even perform better at high compression ratio.

The ability of proposed BCS-GFOCUSS to tackle strong noise and high-quality reconstruction even at high compression (very less measurements) has interesting mathematical implications. There are infinite many solutions to undetermined problem, in case of sparse solution, CS algorithms works but when solution is not sparse, it is more challenging and difficult. This study shows that using Walsh Hadamard sensing matrix, the transformed domain shows better sparsity and using block structure with intra-block correlation it is possible to reconstruct estimated solution that is almost equal to original signal.

6. Conclusion

Extraction of FECG from abdominal ECG is challenging task, this study proposes BCS-GFOCUSS framework for the extraction of FECG from MECG. ECG signal being non-sparse and contaminated by noise is difficult to handle using conventional CS approach, using Walsh sensing matrix this method explores the efficient reconstruction of FECG signal after compression. Based on the proposed method, experimentation is done using statistical analysis and results are compared with state-of-the-art compression methods. The novelty of this method is based on using guided frequency filter which provide distinct signal that is not interdependent on the multi-channel property of ECG. Simulations are done on the well-known FECG data set which shows that proposed algorithm is easy to incorporate, moreover, the results indicate that reconstruction accuracy of proposed method is more compare to Rakness, BSBL-BO, BCS-FOCUSS, BCS-SPL and BCS-DWT. The biggest advantage of using BCS-GFOCUSS is that even at high compression ratio, excellent reconstruction could be achieved that is not possible using conventional compressed sensing algorithms.

References

1. Blöcher, T., Zhou, K., Krause, S., Stork, W. An Adaptive Bandpass Filter Based on Temporal Spectrogram Analysis for Photoplethysmography Imaging. 2018 IEEE 20th International Workshop on Multimedia Signal Processing (MMSP), 2018, https://doi.org/10.1109/MMSP.2018.8547129
2. Candès, E. J. Compressive Sampling. In Proceedings of the International Congress of Mathematicians, 2006, 3, 1433-1452. https://doi.org/10.4171/022-3/69
3. Craven, D., McGinley, B., Kilmartin, L., Glavin, M., Jones, E. Adaptive Dictionary Reconstruction for Compressed Sensing of ECG Signals. IEEE Journal

of Biomedical and Health Informatics, 2016, 21(3), 645-654. https://doi.org/10.1109/JBHI.2016.2531182 https://doi.org/10.1109/JBHI.2016.2531182

4. Craven, D., McGinley, B., Kilmartin, L., Glavin, M., Jones, E. Energy-efficient Compressed Sensing for Ambulatory ECG Monitoring. Computers in Biology and medicine, 2016, 71, 1-13. https://doi.org/10.1016/j.compbiomed.2016.01.013
5. De Moor, B., De Gersem, P., De Schutter, B., Favoreel, W. DAISY: A Database for Identification of Systems. Journal A, 1997, 38, 4-5.
6. Donoho, D. L. Compressed Sensing. IEEE Transactions on Information Theory, 2006, 52(4), 1289-1306.https://doi.org/10.1109/TIT.2006.871582
7. Eichele, T., Rachakonda, S., Brakedal, B., Eikeland, R., Calhoun, V. D. EEGIFT: Group Independent Component Analysis for Event-Related EEG Data. Computational Intelligence and Neuroscience, 2011. https://doi.org/10.1155/2011/129365
8. Eftekharifar, S., Rezaii, T. Y., Beheshti, S., Daneshvar, S. Block Sparse Multi-Lead ECG Compression Exploiting Between-Lead Collaboration. IET Signal Processing, 2018, 13(1), 46-55. https://doi.org/10.1049/iet-spr.2018.5076
9. Fayed, S., Youssef, S. M., El-Helw, A., Patwary, M., Moniri, M. Adaptive Compressive Sensing for Target Tracking Within Wireless Visual Sensor Networks-Based Surveillance Applications. Multimedia Tools and Applications, 2016. 75(11), 6347-6371. https://doi.org/10.1007/s11042-015-2575-8
10. Huang, L., Lin, Q., Zhang, X., Shuai, P. Fast Ambiguity Resolution for Pulsar-Based Navigation by Means of Hypothesis Testing. IEEE Transactions on Aerospace and Electronic Systems, 2017, 53(1), 137-147. https://doi.org/10.1109/TAES.2017.2649698
11. Izadi, V., Shahri, P. K., Ahani, H. A compressed-sensing-based compressor for ECG. Biomedical engineering letters, 2020, 10, 299-307. https://doi.org/10.1007/s13534-020-00148-7
12. Leinonen, M., Codreanu, M., Giannakis, G. Compressed Sensing with Applications in Wireless Networks. Foundations and Trends in Signal Processing, 2019, 13(1-2). https://doi.org/10.1561/2000000107
13. Luo, X., Wang, D., Zhou, M., Yuan, H. Latent Factor-Based Recommenders Relying on Extended Stochastic Gradient Descent Algorithms. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2020, 1-11. https://doi.org/10.1109/TSMC.2018.2884191
14. Mohagheghian, F., Deevband, M. R., Samadzadehaghdam, N., Khajehpour, H., Makkiabadi, B. An Enhanced Weighted Greedy Analysis Pursuit Algorithm with Application to EEG Signal Reconstruction. International Journal of Imaging Systems and Technology, 2020, 1-13. https://doi.org/10.1002/ima.22438
15. Naziya, M., Srujana, M. A New Design and Implementation On Convolution Blind Source Seperation. International Journal of Research, 2017, 4(14), 198-203.
16. Pareschi, F., Mangia, M., Bortolotti, D., Bartolini, A., Benini, L., Rovatti, R., Setti, G. Energy Analysis of Decoders for Rakeness-Based compressed Sensing of ECG Signals. IEEE Transactions on Biomedical Circuits and Systems, 2017, 11(6), 1278-1289. https://doi.org/10.1109/TBCAS.2017.2740059
17. Safari, A., Hesar, H. D., Mohebbi, M., Faradji, F. A Novel Method for R-peak Detection in Noisy ECG Signals Using EEMD and ICA. 2016 23rd Iranian Conference on Biomedical Engineering and 2016 1st International Iranian Conference on Biomedical Engineering (ICBME), 155-158. https://doi.org/10.1109/ICBME.2016.7890948
18. Sana, F., Ballal, T., Shadaydeh, M., Hoteit, I., Al-naffouri, T. Fetal ECG Extraction Exploiting Joint Sparse Supports in a Dual Dictionary Framework. Biomedical Signal Processing and Control, 2019, 48, 46-60. https://doi.org/10.1016/j.bspc.2018.08.023
19. Tayyib, M., Amir, M., Javed, U., Akram, M. W., Yousufi, M., Qureshi, I. M., Ullah, H. Accelerated Sparsity Based Reconstruction of Compressively Sensed Multichannel EEG Signals. Plos One, 2020, 15(1), e0225397. https://doi.org/10.1371/journal.pone.0225397
20. Unde, A. S., Deepthi, P. P. Fast BCS-FOCUSS and DBCS-FOCUSS with Augmented Lagrangian and Minimum Residual Methods. Journal of Visual Communication and Image Representation, 2018, 52, 92-100. https://doi.org/10.1016/j.jvcir.2018.02.009
21. Unde, A. S., Deepthi, P. P. Block Compressive Sensing: Individual and Joint Reconstruction of Correlated Images. Journal of Visual Communication and Image Representation, 2017, 44, 187-197. https://doi.org/10.1016/j.jvcir.2017.01.028
22. Wang, Z., Bovik, A. C. Mean Squared Error: Love It or Leave It? A New Look at Signal Fidelity Measures. IEEE Signal Processing Magazine, 2009, 26(1), 98-117. https://doi.org/10.1109/MSP.2008.930649

23. Xue, J., Xie, X., Li, G., Wang, Z. Guided Frequency Filter for Block-DCT Compressed Capsule Endoscopic Images. 2018 IEEE Biomedical Circuits and Systems Conference (BioCAS), 2018, 1-4. https://doi.org/10.1109/BIOCAS.2018.8584768

24. Yousufi, M., Amir, M., Javed, U., Tayyib, M., Abdullah, S. Ultrasound Compressive Sensing Using BCS-FOCUSS. 2018 IEEE 4th International Conference on Computer and Communications (ICCC), 2018, 174-178. https://doi.org/10.1109/CompComm.2018.8780883

25. Yu, Q., Guan, Q., Li, P., Liu, T. B., Si, J. F., Zhao, Y., Wang, Y. Q. Wavelet Optimization for Applying Continuous Wavelet Transform to Maternal Electrocardiogram Component Enhancing. Chinese physics b, 2017, 26(11), 118702. https://doi.org/10.1088/1674-1056/26/11/118702

26. Zhang, Z., Jung, T. P., Makeig, S., Rao, B. D. Compressed Sensing for Energy-Efficient Wireless Telemonitoring of Noninvasive Fetal ECG via Block Sparse Bayesian Learning. IEEE Transactions on Biomedical Engineering, 2012, 60(2), 300-309. https://doi.org/10.1109/TBME.2012.2226175