# Modified sparse representation for ECG reconstruction in telemonitoring

Sushree Satvatee Swain
Department of Electrical Engineering
National Institute of Technology
Rourkela, India
ssatvatee16@gmail.com

Dipti Patra
Department of Electrical Engineering
National Institute of Technology
Rourkela, India
dpatra@nitrkl.ac.in

***Abstract*—Presently ECG signal telemonitoring is one of the essential branch in telemedicine system. So it is highly desirable to construct a robust telemonitoring system through wireless body area network (WBAN) with consumption of less energy and less power. A number of traditional ECG reconstruction techniques have been proposed to recover the clean ECG data. However because of some specific behavior and characteristics of raw ECG data like non sparsity and heavy contamination of noise the traditional methods do not succeed in this application. This paper proposes an effective reconstruction method followed by Independent Component Analysis (ICA) in an intention to obtain the clean ECG data. The proposed framework includes context based learning adopted reconstruction method. Experimental results along with simulation results show that this framework is able to reconstruct the raw ECG recordings with high accuracy and high quality. Context based learning learns the existing context in the signal and reacts to changing context, which uses k-means clustering via singular value decomposition i.e. KSVD algorithm to recover raw ECG signal. In this paper, the proposed method shows better reconstruction performance than the traditional compressed sensing method retaining the sparsity of the ECG signal intact.**

**Keywords:- Telemonitoring, telemedicine, compressed sensing, non sparsity, independent component analysis,context based learning .**

## I. Introduction

In sparse representations all or sometimes most of the informations of a signal are represented in a linear combination of smaller number of elementary signals otherwise called as atoms. These atoms are selected from a dictionary which is termed as over-complete dictionary. An over-complete dictionary is formed due to accumulation of number of atoms in which the number of atoms is more than the actual dimension of the signal space. As a result any signal can be delineated by more than one combination of several atoms. The specificness of sparseness leads to the extensive employment of popular transform based methods such as the Discrete Fourier Transform (FT), the wavelet transform (WT) and the Singular Value Decomposition (SVD). Hence sparse representations have gained widespread popularity for providing exceedingly better performance in case of applications like noise reduction, compression, features extraction, pattern classification and blind source separation.

Monitoring of ECG in noninvasive way is an essential approach to check the cardiac condition of patients. Various parameters like heart beat rate, morphology and dynamic behaviors are taken into consideration to determine the anomaly in cardiac condition of patients. Out of all the parameters heart beat rate is the main determining factor for monitoring the cardiac health [1]. However it is very strenuous task to extract clean ECG from the raw ECG recordings as ECG signals are contaminated with strong noises like ambient noise, muscle artifacts and instrumental noise [2]. Previously patients need to go to healthcare professionals frequently to monitor the cardiac condition. Now-a-days by the help of wireless telemonitoring patients get the tele assistance being in their home. Such telemonitoring system consists of a wireless body area network (WBAN) associated with a number of sensors which are placed on patients skin. A wireless body area network (WBAN) comprises of a number of body sensor units (BSUs) along with a single body central unit (BCU). A BAN is made up of different bio-signal and motion sensors along with ultra-low power short-haul radios. As illustrated in Fig. 1 real-time biomedical physiological signal is first transfered to a BAN personal base station (may be a smart phone or personal computer) and then communicated to a healthcare provider through the Internet. The amount of data transfered to the base station increases with addition of more sensors to the BAN. This system uses very low power radios like bluetooth in conjunction with devices like smartphones or desktops to communicate through the internet with the remote terminal health care provider. Such system helps the mankind in reducing frequent medical visit and also saves time and medical expenses.

While reconstructing the ECG signal, energy constraint is the strict constraint to be considered. Energy consumption can be minimized only if signal is compressed efficiently before transmission. Thus sparse representation is very important in ECG telemonitoring. By sparse representation noise in raw ECG signal can be removed, signal can be compressed efficiently which will automatically produce efficient reconstructed ECG signal [3]. ECG data compression schemes are divided mainly into two categories. First one is time domain or (direct) method and second one is transform method. In direct method, compression technique is applied directly on the ECG

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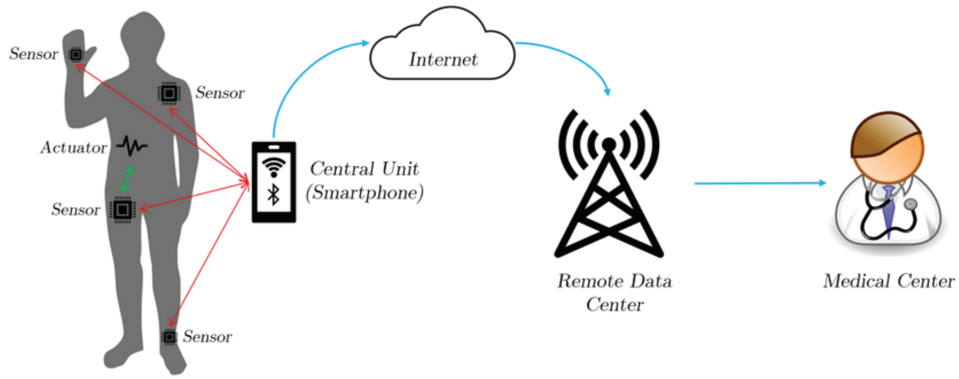


Fig. 1: Bio signal sensors communicate with a smart phone in a BAN to access a healthcare professional via the Internet.

data but in transform method ECG signal is transformed in to another domain in which the signal is sparsely represented. The ECG signals are neither sparse in time domain nor sparse in any transformed domain.

Till now, several techniques are proposed for exact detection of the pure ECG signal from the raw ECG signal. First untriggered averaging of ECG signal is done to know the average heart rate (HR) [4]. For detection of HR, mainly two fundamental methods are considered. First one is the peak detection method and the second one is the transform method [5]. In peak detection, generally a minute segment of ECG signal is taken at one time. Then the R wave of ECG is searched. The outcome of the search is dependent on the algorithm and the local signal to noise ratio (SNR) in the ECG signal segment [6]. When the ECG signal is distorted via noise with the surplus signals and the peak detection algorithm does not proceed in detection, a transform method may be able to still detect the HR [7]. Due to the non-invasive nature of measurement procedure of the ECG signal, the majority of the algorithms are able to detect the R waves and P waves. T waves generally remain unseen. Some algorithm such as adaptive filtering [8], [9], linear decomposition [10], non-linear decomposition, wavelet transform [11], independent component analysis (ICA), and blind source separation has been used here in the area of QRS peak extraction [12], [13]. ICA is considered to be an efficient method for extraction of the particular ECG waves from the composite electrocardiogram signals. Semi-blind source separation algorithm requires *a priori* information about the autocorrelation function of the primary sources, for extraction of the desired ECG signal [14].

In this paper, the focus is towards the reconstruction of ECG signal from the raw ECG signal. A new reconstruction technique is developed to obtain the clear ECG signal using context based learning, which uses KSVD algorithm.ICA decomposition method is used upon the reconstructed ECG signal and the original ECG recording to visualize the reconstruction performance. The rest of the paper is organized in following manner. Section 2 outlines the existing methodology for ECG reconstruction. The proposed scheme is presented in Section 3. Simulation results and performance analysis of the proposed method are depicted in section 4. Conclusions are presented in section 5.

## II. Related Work

Compressed Sensing is one of the promising tool to overcome the energy constraint in WBAN system for ECG telemonitoring.

### A. Compressed Sensing:

Compressed Sensing is a signal compression technique which depends upon the sparsity of signals to be compressed [15]. We can express the noisy model as

$$y = \phi x + v \tag{1}$$

where, $X \in R^{(N*1)}$ is the original signal to be compressed with length N. $\Phi \in R^{(M*N)} \quad (M << N)$ is the sensing matrix. $v$ is the noise in the CS system. x is the raw ECG signal, y is the compressed signal to be communicated through WBAN and we can ignore v. Thus, the model now becomes a noiseless model and is expressed as

$$y = \phi x \tag{2}$$

The signal x may not be sparse or may be sparse in some transformed domain. Thus we can express x as $x = \psi\theta$, where $\psi \in R^{(N*N)}$ is an orthonormal basis function of the transformed domain and $\theta$ is the representation coefficient vector which is generally sparse. Thus, the model (2) can be expressed as

$$y = \phi\psi\theta = \Omega\theta \tag{3}$$

where $\Omega = \phi\psi$. As $\theta$ is sparse, the CS algorithm first reconstructs $\theta$ using y and $\Omega$, and then reconstructs x by $x = \psi\theta$. At times, the signal x contains noise .That is, $x = u + n$, where u is the clean signal and n is the signal noise. Thus, the model (2) can be expressed as

$$y = \phi x = (u + n) = \phi u + \phi n = \phi u + w \tag{4}$$

## III. Proposed method

Despite so many ECG reconstruction techniques, we cannot obtain clean ECG signal after reconstruction process. Although a lot of research works have been done in this field, scope of improvement is still present. All these techniques satisfy the reconstruction up to some extent but do not give satisfactory result. Getting clean and clear ECG signal after recovery is still in its infancy. The QRS peaks are distorted after transmission and it is not recovered with accuracy. To address the above problem we propose a reconstruction technique aiming ECG output with high quality and high accuracy. The Context based learning learns the existing context in the signal and reacts to changing context. Context based learning uses KSVD algorithm to recover raw ECG signal. The block diagram of the proposed framework is shown in Fig. 2.

*1) Context based Learning:* Context based learning is a method that examines and reacts to an individuals changing context. It is also called as context aware learning. It is aware of its inputs state and surroundings and helps it adapt its behavior. It is generally used in rain removal from images as well as video [16]. This method first decomposes the signal into two parts such as the low-frequency and high-frequency components employing a bilateral filter. Then the high-frequency component is subjected to decomposition into a rain component and a non-rain component by adopting dictionary learning and sparse coding method. After this, the rain component is removed from the original signal successfully without distorting the original signal's diagnostic details [17].In this application this mathod adapts to the distortion made in the ECG during transmission and learning the changing context reconstructs the distorted signal.The input ECG recording is first converted into a number of patches as low frequency and high frequency patches . Then by dictionary learning and sparse coding the patches are decomposed into rain component and non rain component and the non rain component is removed from the original signal.

*2) The K-SVD Algorithm:* The K-SVD algorithm accepts an initial over complete dictionary $D_0$, a number of iterations k and a set of training signals arranged as the columns of the matrix X [18]. This algorithm intends to improve the dictionary iteratively so as to converge at sparser representations of the signals in X, by solving the optimization problem,

$$Min\ ||X - D\partial||_F^2\ \ subject\ to\ \|\gamma_i\| \leq K \tag{5}$$

The K-SVD algorithm consists of two basic steps, which together constitute the algorithm iteration.

- The signals in X are sparse-coded given the current dictionary estimate, producing the sparse representations matrix $\delta$.
- The atoms of dictionary are updated according to the current sparse representations.

Here the sparse-coding is incorporated using orthogonal matching persuit (OMP). The updation of dictionary is performed one atom at a time, optimizing the target function for each atom individually while keeping the rest atoms fixed.

**Algorithm 1** KSVD

**Input:** Signal set X, initial dictionary $D_0$, target sparsity $K$, number of iterations $k$.
**Output:** Dictionary $D$ and sparse matrix  such that X $\approx D\partial$

```
Initialize D = D_0
for n = 1 .. k  do
    ∀_i : ∂_i = Argmin ||x_i − D_γ||_2^2 subject to ||γ||_0 < K
    for j = 1 L  do
        Dj = 0
        I = indices of the signals in X whose representations use d_j
        E = X_I − D∂_I
        {d, g} = Argmin ||E − d_g^T||_F^2 subject to ||d||_2 = 1
        Dj = d
        ∂_{j,I} = g^T
    end for
end for
```

The key innovation of this algorithm is the atom update step, which is accomplished while taking care of the constraint in (1). To achieve this, the update step uses only the signals in X whose sparse representations use the current atom [19], [20]. Assuming $I$ denotes the indices of the signals in X which uses the jth atom, then the update is obtained by optimizing the target function

$$||X_I - D_I||_F^2 \tag{6}$$

over both the atom and its associated coefficient row in $\delta_I$. Then the resulting problem is a simple rank-1 approximation task.

### A. ICA Decomposition:

In signal processing domain, independent component analysis (ICA) method is used to separate a multivariate signal into its additive subcomponents. It is assumed that, the subcomponents are non-Gaussian in nature and are statistically independent from each other The data are represented by the random vector $x = (x_1, .....x_m)^T$and the signal subcomponents as the random vector $S = S_1, ...., S_N$. The motive is to transform the observed data by help of a linear static transformation W as $S = Wx$ into maximally independent sub-components given by some function $F(S_1, ...., S_N)$. In most of the applications such as ECG telemonitoring system, reconstruction performance is generally evaluated by comparing reconstructed recordings with original recordings considering mean square error (MSE) to be the leading performance modality. However, in our application, reconstruction of raw ECG recordings is not the ultimate goal; but the reconstructed signals undergo further processing in an intention of extraction of clean ECG by ICA . Since infidelity of MSE is common in case of structured signals, it is quite hard to find out by how much the final ECG extraction is affected by errors in reconstructed signals given by MSE. Thence, a more direct approach is to compare the extracted ECG from the recon-

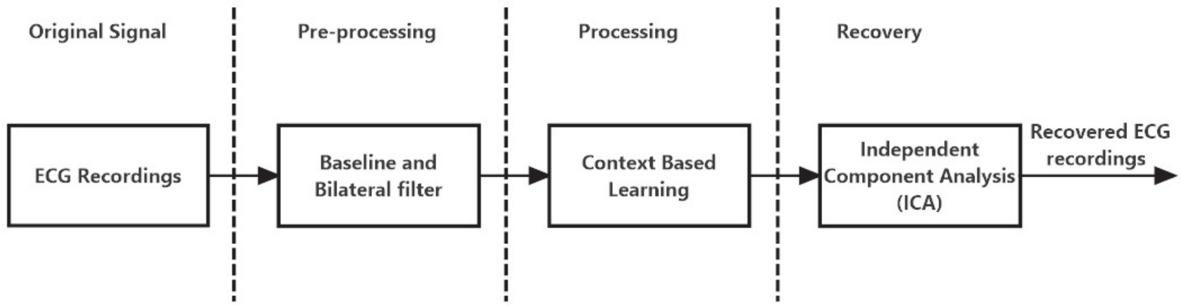


Fig. 2: Block diagram of proposed framework

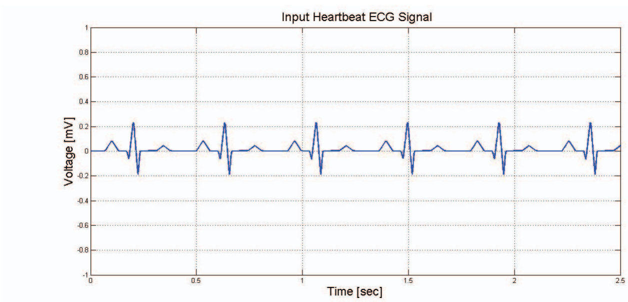


Fig. 3: Input ECG signal in KSVD


Fig. 4: Noisy ECG signal in KSVD

structed recordings with the extracted one from the original recordings.

## IV. Simulation results and discussion

### A. Result using Context based Learning

We use KSVD algorithm for context based analysis of ECG signal. To learn a particular context of ECG in this algorithm we first set patches in the ECG signal. Here patch of size n*n is taken, where n is 5. Then parameters for dictionary are set. Number of dictionary atom is twice the patch dimension. Number of patch for training is taken N=2000. First the ECG is loaded which is shown in Fig. 3. Then noise is added to it and the noisy ECG is shown in Fig. 4. After noise is added to the ECG patches are extracted. Then training data is created. Then signal is reconstructed using training data. Here we take a ECG data consisting of six number of PQRST complexes which is the input signal here. After this KSVD algorithm is adopted to reconstruct the ECG signal. The reconstructed ECG is shown in Fig. 5.

### B. Result using ICA Decomposition

In this experiment setup the open source electro physiological toolbox (OSET) data base is taken. This database consists of 8 channel recordings which is sampled at 1000 Hz. Then the dataset is down sampled into 250 Hz. Then the dataset is compressed and recovered using context learning algorithm. The original recording followed by reconstructed recording are shown in Fig. 6 and Fig.7. Next ICA decomposition

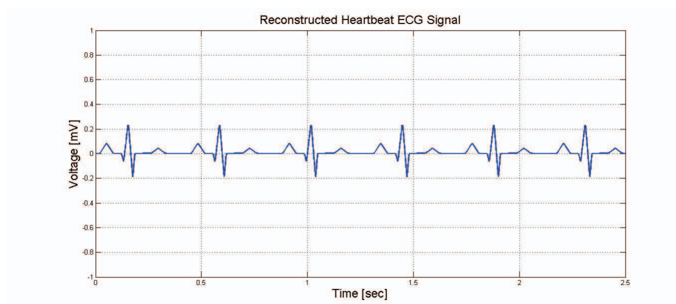


Fig. 5: Recovered ECG using KSVD

is performed over the original and reconstructed recordings and they are compared. The experimental parameters are chosen taking block length 24. Sensing matrix is taken of size 256*512 with each column containing 12 entries of 1s. Down sampling frequency is of 250 Hz. ICA decomposition of original recording of the 8 channels is shown in Fig. 8 and ICA decomposition of reconstructed recordings is shown in Fig. 9.

### C. Result using compressed sensing:

The signal taken here to recover is a real-world ECG data, which consists two peaks of fetal ECG and one peak of maternal ECG. The aim is to recover the signal without distorting the two peaks of fetal ECG (the two peaks locate

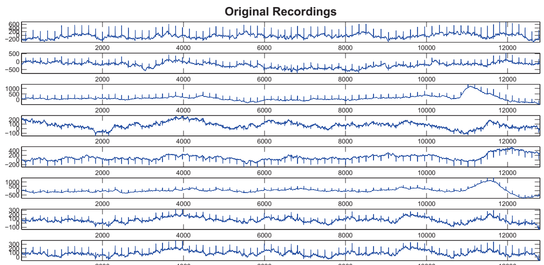


Fig. 6: original recordings

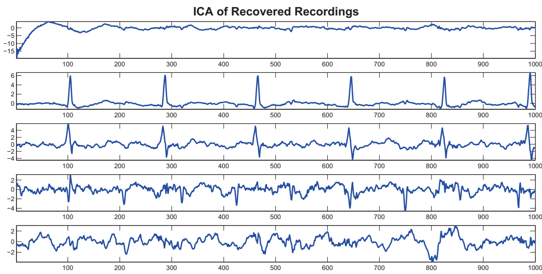


Fig. 9: ICA decomposition of reconstructed recordings

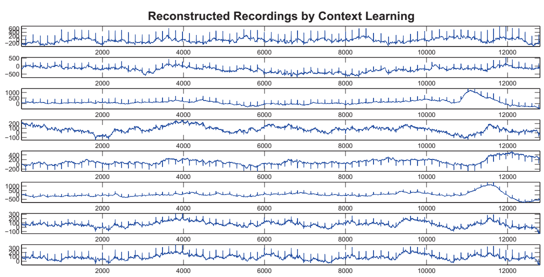


Fig. 7: reconstructed recordings by Context based learning

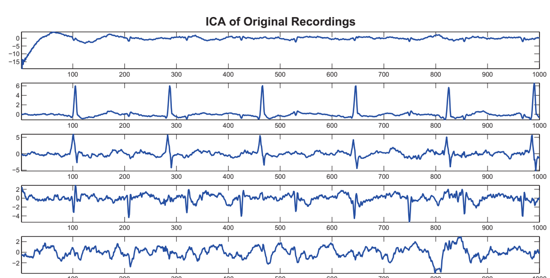


Fig. 8: ICA decomposition of original recordings

TABLE I: Co-sparsity and error calculation of KSVD

| Iteration | Error | Avg. co-sparsity | Denoising Error |
|---|---|---|---|
| 1 | 19.268 | 21.000 | 19.533 |
| 2 | 15.928 | 21.000 | 16.224 |
| 3 | 14.188 | 21.000 | 14.514 |
| 4 | 13.775 | 21.000 | 14.154 |
| 5 | 15.367 | 21.000 | 15.713 |

around at 65 and 180) and also the adult ECG QRS Peak. In the experiment a sparse binary matrix having size 125*250 is loaded first. The matrix is randomly generated, each column of which has only 15 entries of 1. First compressed sensing method is adopted to reconstruct the ECG data. The simulation result is shown in Fig. 10, where the reconstructed result of context based learning method is also shown.

From above two used method simulation results it is clear that in compressed sensing method the fetal peaks which are at points 65 and 180 are not visible. These fetal peaks are buried inside maternal ECG signal and they are not recovered efficiently. In context based learning method the fetal peaks are clearly visible as they are efficiently recovered and reconstructed. The adult ECG peak is efficiently reconstructed in context based learning method which is not recovered in CS method.

Then we perform 75 iterations to find the error, average co-sparsity and denoising error in context learning method which is mentioned in Table I. From the iterations it is clear that error and denoising error are almost equal. Throughout the iterations the co-sparsity is maintained without being destroyed. This specifies that the used KSVD algorithm efficiently reconstructs the ECG signal. PSNR of the two methods are calculated. The calculated PSNR of recovered ECG in context based learning is satisfactory and it is represented in Table II. This means that ECG reconstruction through context based method using KSVD is robust than thecompressed sensing schemes.

TABLE II: PSNR Comparision of used Methods

| Method | PSNR [dB] |
|---|---|
| Compressed Sensing | 20.2629 |
| Context Learning | 54.173 |

## V. Conclusions and Future scope

ECG signal telemonitoring using wireless body area network with low energy constraint is a challenge for emerging ECG reconstruction techniques. Thus this paper addresses an ECG reconstruction scheme . In this scheme we reconstruct

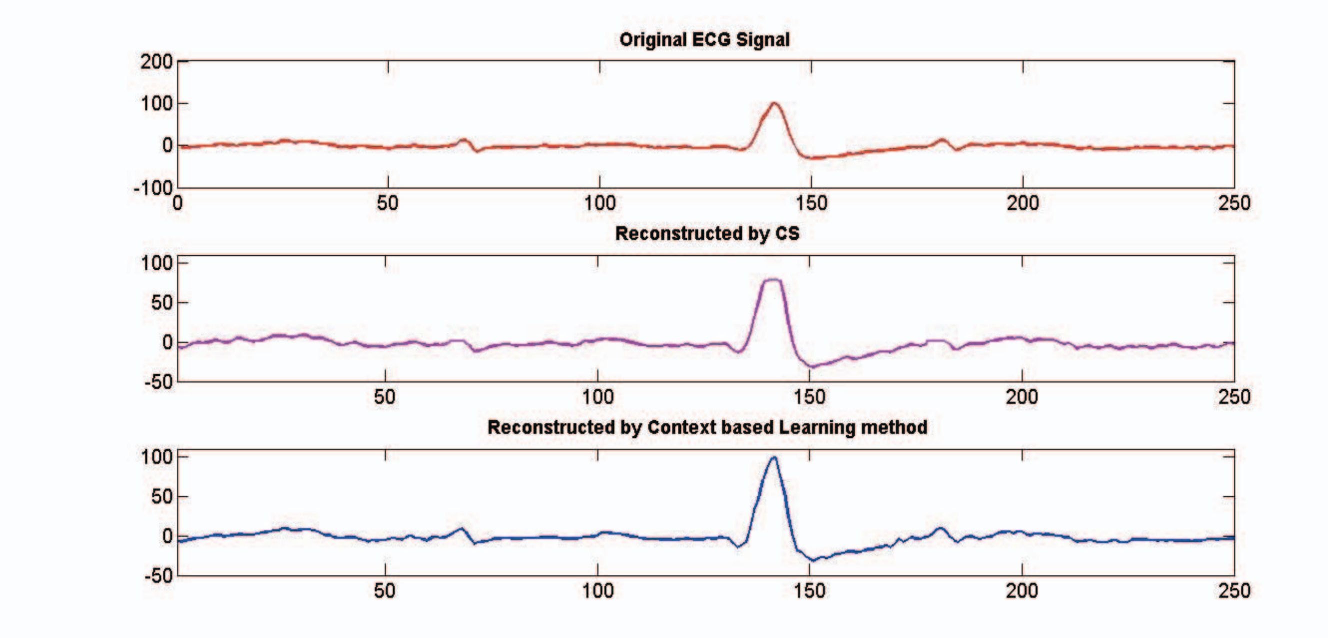


Fig. 10: Reconstructed ECG by compressed sensing and Context based Learning

the ECG signal using Context based Learning technique using KSVD algorithm. In this method the raw ECG is accurately recovered and the noise is efficiently removed showing enhanced PSNR value among traditional compressed sensing methods. It is observed that their construction methods do not destroy interdependence relation that exists between the multichannel recordings.Thus this proposed scheme is robust enough to reconstruct the ECG signal with better accuracy and improved quality. Further study may concentrate on some other robust reconstruction techniques which will give more improved performance result than our proposed method.

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