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Adaptive Optimal Dictionary Construction Scheme for Multi-Scale Joint Compression and Recovery of MECG Signals in WBAN

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Abstract

In tele-cardiac monitoring systems deployment of Compressive Sensing (CS) in Wireless Body Area Network (WBAN) needs to ensure true representation of ECG data for accurate prognosis and diagnosis. In this context data presentation strategy plays a critical role prior to sub-sampling phase in CS algorithms at codecs for designing energy efficient, least distortion based signal compression and recovery schemes. Most of the previous designed Adaptive CS algorithms used single dictionary only for the full length segment of Multi-channel ECG (MECG) signals. The objective of the present work is to perform simultaneous compression and recovery of MECG signals with least distortion .This MMV (Multiple Measurement Vector) problem was solved by applying the proposed low distortion based Adaptive Dictionary (AD) construction technique within the CS frame work to obtain clinically acceptable high fidelity data. An optimal dictionary is concurrently generated for each block of ECG data for every channel. Results illustrate that the proposed adaptive best mother wavelet-based optimal dictionary (ABMOD) construction scheme achieves least average PRD (Percentage Root Mean Square Difference) and WEDD (Wavelet Energy based Diagnostic Distortion) values of 4.03 and 3.59 compared to existing 6.60 and 6.07 for PTB database with 70 compressed measurements and PRD1 of 0.475 against 1.13 for MIT-BIH ECG database with 192 measurements respectively relative to that of landmark Sub-band weighted mixed norm minimization (SWMNM) algorithm. The CR was 90.06 % or 7.14 against 6.34 of SWMNM algorithm which clearly indicates higher compression ability of the proposed ABMOD algorithm and subsequent energy preservation. This demonstrates the superior performance of the proposed ABMOD algorithm in terms of Joint compression and reconstruction for MECG signals. Further same studies were performed using pan-tompkin's algorithm for filtering purposes and results reveal that SNR was enhanced for the proposed algorithm for both MECG data bases.

Keywords: *Multi-channel ECG Compression, Adaptive Dictionary, Adaptive Compressive Sensing, Joint Compression, WBAN.*

1. Introduction

Wearable bio-monitors driven by limited energy and memory require embedded compression algorithms which are capable of processing signals with least energy consumption and lesser on-board memory foot print. The emergent CS [1] is a data acquisition technique which captures signals at sub-nyquist rate and is still able to reconstruct data with high fidelity using very less compressed measurements. In [2] [15] CS theory affirms that information obtained by a few random linear projections of a sparse signal onto the sparse sampling matrix is sufficient for its accurate reconstruction.

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CS based dimension reduction technique is realized by simple matrix-vector product operation producing sparse compressed vector .However, the signal of interest like ECG, EEG being captured needs true representation of the data being generated at the source. Most of the works [3] [4] [5] focus on either design of sensing matrix or sparse recovery algorithms. In real-time medical experts require simultaneously recorded multi-channel information for analysis single channel information does not suffice for making any medical decision. Many prior multi-channel compression CS algorithms [6] [7] [8] [9] [10] [11] applied single basis matrix which used db4 mother wavelet only in DWT domain for signal decomposition and thus has resulted in higher distortion metrics. Recently proposed landmark work, SWMNM [12] algorithm achieved the least diagnostic distortion measures PRD and WEDD of 6.60 and 6.07 [12] respectively which could be further brought down by novel block-wise decomposition approach. Hence to meet the minimum error and sparsity requirement of CS algorithm, a block-wise adaptive decomposition method proposed in our previous work [13] has been extended for MECG signals. Typical scenario of CS-based MECG WBAN tele-cardiology monitoring system for block-wise dictionary construction is depicted in Fig.1. In E-health monitoring application like MECG the collected data forms compressed multiple measurement vector (MMV) at the data aggregator which is further transmitted to the medical server. The reconstruction process is performed on CS decoder so that it can be used for medical analysis or diagnostic purposes.

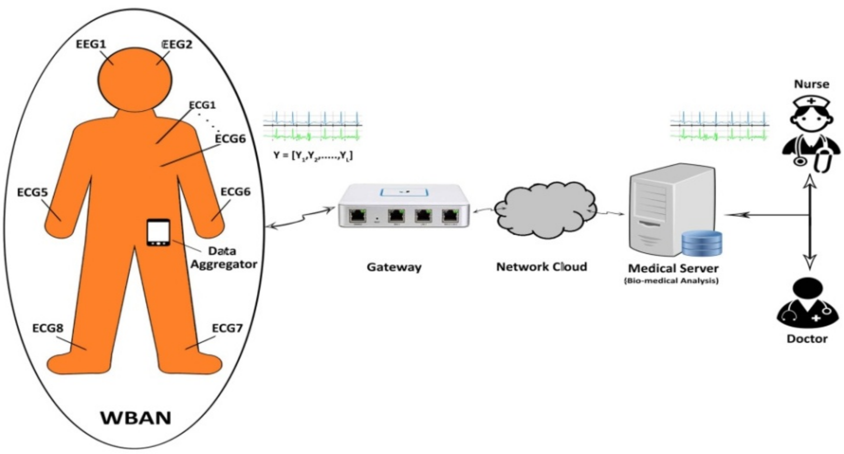

Fig.1. A typical CS-based MECG WBAN Tele-cardiology monitoring system.

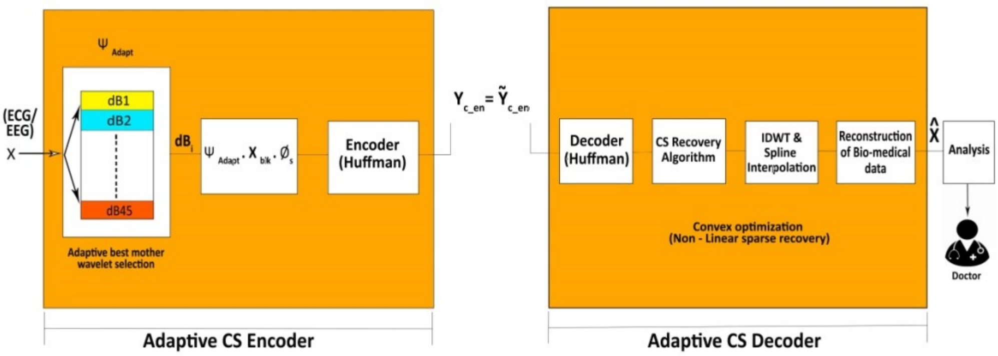

Fig.2. Block-wise adaptive dictionary construction scheme.

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The block-wise adaptive dictionary construction strategy for single channel ECG in a WBAN bio-node is illustrated in Fig.2. In Adaptive CS encoder, the best mother wavelet is determined by searching through wavelet space db '1- 45' based on the minimum PRD [13] value for the given ECG block of 512 samples from X. The adaptive dictionary decomposes the signal by applying ψ_{Adapt} ,sub-sampled by Φ_s, Huffman encoded and then compressed vector $Y_{c\_en\_mmv}$ is further transmitted. The same process is followed in each wireless ECG bio-node concurrently for all the MECG channels. In Adaptive CS decoder the received MMV vector $\hat{Y}_{c\_en\_mmv}$ is Huffman decoded, processed by CS recovery algorithm and converted to time-domain. The missing coefficients are generated by cubic-spline interpolation. $\widehat{X}$, the reconstructed vector obtained after solving the convex optimization problem needs to be very close to original ECG data X.

In this paper adaptive dictionary is found out for each block of every ECG channel to obtain sparser signal representation then mutual correlation among the channels is utilized for performing Joint Compressive Sensing (JCS) and synchronous MECG recovery. This accounts for lesser data acquisition, transmission and saves huge amount of energy contributing to extension of life time of the WBAN node.

The content of this article has been compiled in six sections. Section I justifies the need for Adaptive dictionary in CS framework. In section II recent works on MECG signals have been reviewed along with their limitations. Section III highlights the motivation of the current work. The algorithm and flow chart of the proposed solution are illustrated in section IV , experimental dataset used and performance measures have been briefed out in section V. In Section VI result analysis of the proposed work has been carried out.

2. Literature Survey

It is known that wavelet transform coding methods fair higher in terms of signal restoration quality compared to CS algorithms [8] but expend more energy during acquisition phase leading to quicker energy drain of battery in bio-sensors. To overcome this problem one of the solutions is sparse representation which causes low complexity approach data collection [18] in the bio-sensor thus leading to enhanced energy efficient CS algorithm.

In heart monitoring applications, ECG signal acquired in each channel is a projection of information generated from the same source, heart viewed from different perspective. Therefore a part of the information is shared among the multiple channels while recording simultaneously from a subject indicating a certain degree of similarity. It has been discovered that individual channel compression and reconstruction [8] is statistically sub-optimal. Hence to overcome this problem [8-12], [14-15] proposed dictionary- based multi-scale CS algorithms for joint compression to save energy and concurrently obtain sparse recovery of all the MECG signals. Recently proposed MECG signal CS compression techniques have been analyzed in this section.

The system level design issues of CS and adaptive sampling techniques, trade-off amongst the parameters have been discussed from time and frequency (TF) transform domain perspective in [2] where experimental study resulted in achieving CR of 16x for ECG and EMG signals at SNR of 60dB when 1-bit Bernoulli sensing matrix was used for sampling purpose under evaluation of different CS reconstruction algorithms with varying computational complexity. Study revealed that optimal trade-off can be achieved between sparsity control and accuracy by means of adaptive thresholding mechanism.

In [15] an adaptive approach for optimal signal representation was proposed where best basis selection strategy was carried out considering only two mother wavelets db3 and coiflet. The limitation is that minimal PRD achieved was 0.6 for CR of 50% and found to increase with CR but neither other mother wavelets nor block-wise approach were investigated. [3] Proposed JSM models and mathematical foundations of MMV model for Distributed compressive sensing (DCS) framework. DCS theory enables us to jointly compress and simultaneously reconstruct all the ECG signals using joint sparse representation but common sparsifiying basis. Initially efficient MECG compression and recovery by applying DCS over multi-signal ensemble was illustrated in [5]. MECG signal acquisition is a distributed data sensing problem. Distributed Compressive sensing (DCS) is a variant of single channel CS but designed for multiple correlated signals across different channels and is represented by MMV model. Joint sparsity was discovered through inter-channel correlation by using K-SVD algorithm [15] to learn basis vectors for sparser representation and performing joint compression.

Sparsified individual ECG channels were separately compressed and reconstructed together simultaneously using JSM-2 model. DCS-K-SVD based proposed algorithm achieved mean values of SNR of 28.53and CR of 8.35.Demerit of this work being higher WEDD, PRD of 2.60,3.74 respectively. The proposed algorithm does not exploit inter-channel correlation at compression end thus leading to faster energy drain. JSM-2 model proposed in exploits both structural and temporal dependency [6] for single channel ECG signal compression where precise partially known support (PKS) was built based on the statistical support information (SSI) for every classified ECG heartbeats. Improvement in the performance of joint reconstruction algorithm, weighted Simultaneous Orthogonal Matching Pursuit Algorithm (W-SOMP) [6] where sparsification was realized with 4th level decomposition in DWT domain, yielded PRD in the range of 6-15% .This illustrated that some of the ECG records could not be reconstructed within 0-9% PRD range and needs improvement. Authors claimed that proposed algorithm works correctly for low dimension measurement vector only and hence is not suitable for medium or higher dimension vector which may be present in ECG leads. Hence there is need for strategy to find a technique which could effectively compress all ECG records.

For real-time medical analysis a heart specialist relies on standard 12-channel information rather than single lead ECG data for making diagnostic decisions, hence multi-channel ECG (MCG) compression is a pre-requisite for accurate prediction or diagnostic purposes [6]. A power-aware two lead joint CS (JCS) ECG signal compression and recovery algorithm was proposed in [7]where common sparsity among channels was utilised for data reduction and recovery. Results quantified that JCS lead to enhancement in CR metric up to 72.7% and reduction in PRD compared to normal CS. Sparser representation is one of the prerequisites for design of energy efficient CS algorithm. One such attempt Adaptive Fourier decomposition (AFD) was proposed in [1] for lossless single channel ECG compression and high quality reconstruction. AFD achieved mean CR in the range of 17.6–44.5 and PRD between 0.8–2.0% when tested over MIT-BIH database. Even though PRD is of “Very Good” class, the CR values indicates very less compression capability and does not result in optimal trade-off between CR and PRD .Also AFD method has not been applied for MECG signal compression. Instead of applying single fixed dictionary, the signal feature- based dictionary or basis functions could be generated for effective representation of the data. [20] QinTan et.al, proposed Improved Simultaneous Orthogonal Matching Pursuit (ISMP) algorithm for simultaneous representation of multi-lead ECG signals with a hybrid dictionary made of Hermite and

Gabor functions based on the ECG features. The convergence rate of ISMP [9] achieved was much faster than its predecessor SMP at the second stage because of the adaptive basis, but CR improvement was observed in only certain channels and no information about PRD or WEDD metrics was mentioned.

Adaptive dictionary (AD) learning techniques play significant role in effective joint compression and restoration of multi-channel signals and one such technique Method of Optimal directions (MOD) was proposed in [10] to create dictionary at every sub-band. The derived sub-dictionaries exploited correlation at each sub-band for effective sparser ECG representation. Mother wavelet Daubechies db4 wavelet with decomposition level 3 was applied and results illustrated that almost all the records were reconstructed with PRD in range 0-9% for measurements of 115 or more. The CS algorithm based on multi-scale learned sub-dictionaries created at different sub-bands rather than traditional wavelet or single–scale dictionaries was used which proved that multi-scale dictionaries [10] were more effective in design of muti-channel ECG CS compression algorithms. Every patient's medical profile is distinct, hence subject specific data representation is needed. An attempt to build pathology specific dictionary was done in [15] where Singular Value Decomposition (SVD) based learning technique for joint sparse representation of the ECG channel information was proposed which exploited similarity between channels. JSM-2 model proposed by [15] has been applied for MECG signals recovery, DCS-SOMP algorithm simultaneously reconstructed all the signals by using distinct linear combinations of same set of bases. with the 60 columns in the learnt dictionary the DCS-SOMP achieved average PRD, WEDD, SNR and CR of 3.74, 2.60, 28.53 and 8.35 respectively. Wavelet coefficients at each sub-band possess different significance, thus weight assignment for sub-band coefficient was considered in design of CS algorithms by Dornoosh Zonoobi et al. [17] .The proposed weighted-CS (WCS) approach produced probability model which demonstrated that good reconstruction quality with considerably lesser computational complexity to suit the embedded applications in wearable ECG monitoring devices. Even though good CR of 10.63 was achieved but higher PRD1 of 9.03 was reported when the signal was decomposed over DCT domain compared to DWT domain. Hence recovered signal quality needs further improvement.

A DWT based HOSVD method was proposed to eliminate redundant data by exploiting intra and inter-beat correlation in ECG cycles, and inter-lead correlation [25] among all MECG (12-lead) signals where Daubechies 9/7 Biorthogonal wavelet filters was applied on the tensor matrix to perform 7-level decomposition .HOSVD algorithm [25] achieved maximum average CR and minimum PRD of 15.09 and 2.81 when tested over PTB ECG database. Other metrics like PRD1 and WEDD were not tested over MITT-BIH dataset. Since the method relies on presence of R-peaks which may not be available in all cases it may lead to failure of the scheme and also causes energy depletion for detection of peaks which is not preferable for a wearable WBAN node.

In most of the works the dictionaries are generated using Dictionary Learning (DL) techniques utilizing structured nature of ECG signals .It is well known that for basis vectors belonging to the same class of signals, sparse modelling using learned dictionary [15] fits more with data and gives effective representation. The degree of coherence between the columns of the dictionary is regulated and provides more flexibility to the preciseness of a sparsely decomposed signal. It was also noted that the error decreased with increase in number of columns in the dictionary but minimum size of the matrix is desirable for energy conservation in WBAN node.

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AD-Q6, a two stage dictionary learning (DL) [19] based CS reconstruction algorithm was proposed. The initial dictionary Ψ is replaced after finding more appropriate dictionary based on the ECG signal characteristics like QRS complex as against the Standard Dictionary (SD) algorithms which are based on sparsity alone. The technique performed better than lossy methods like SPIHT, MMB-IHT algorithm in terms of achieved CR values and the quality of the reconstructed signal was on-par with previous works when evaluated over MIT-BIH arrhythmia dataset. Result revealed that for PRD of 5.5%, the proposed AD-Q6 algorithm consumed least energy of 30.9μW while SPIHT and MMB-IHT took 50.65 μW and 49.4μW respectively for CR of 14.8. However, SPIHT yielded least power consumption for PRD less than 3% [19] but needs optimal trade-off between PRD and power consumption. More delay is introduced for searching among redundant dictionaries and needs to be eliminated. The dictionaries were created by applying the K-SVD algorithm and the sparse optimization problem was solved using the Basis Pursuit (BP) algorithm [19].The sparse vector with the minimum l_1 norm provided close approximation to the original signal.

Any MECG compression method should preserve critical information in vital signals required by the doctors for bio-signal analysis and detection of diseases or disorder while improving CR and restoration quality. In work by Sibasankar Padhyet al. [9], extended the technique of [6], [14] where low complexity multi-scale SVD (MSVD) technique was proposed for MECG signal compression capable of retaining all the morphological features of ECG data. Eight independent and fundamental leads were considered as MECG data namely leads I,II and precordial leads V1,V2,V3,V4,5,V6 in their work. Dimension reduction was achieved by exploiting intra and inter-channel similarity found amongst wavelet transformed coefficients after baseline wander removal and amplitude normalization. Wavelet decomposition was done by Daubechies 9/7Biorthogonal wavelet filters yielding a CR of 19there by reducing memory requirement by 19 times. The proposed MSVD technique [9] achieved an average CR and PRD values of 19.34:1 and 3.05%, respectively. WEDD diagnostic metric was not reported.

Multi-scale CS (MSCS) framework [8] was proposed where MECG signals from CSE database were decomposed by applying bi-orthogonal 9/7 wavelet filters till 6^{th} level in eigen space as sparsifiying basis. MSCS with PCA [8] exploits sub-band level correlation to further reduce the data. The signal reconstruction was performed deploying orthogonal matching pursuit (OMP) algorithm. Simulation results achieved lower PRD of 4.72% and WEDD of 3.28% at CR equal to 10.84 for lead AVF while PRD and WEDD values of all leads are not within the acceptable range.

Recently in 2016 a spatial correlation based multi-scale joint MECG CS framework was proposed by Anurag Singh et al. [12] which exploited energy, entropy and amplitude decay in each sub-band in DWT domain to identify diagnostically important coefficients. With an objective to improve the diagnostic accuracy of recovered ECG signals with minimum number of observations, sub-band energy based weighted MNM (SWMNM),an iterative re-weighted algorithm was proposed based on WMNM[17] concept. Weight assignment is carried out for each sub-band at each level of resolution and later concurrent restoration of all the MECG channels is performed. The average values of PRD, WEDD and SNR for PTB database achieved are 6.6, 6.07 and 23.67, PRD1 for MIT-BIH database is 1.13 respectively. Results illustrated that SWMNM is better than PWMNM in noisy scenarios as it achieved good quality reconstruction even when data is compressed up to 90% [12]. SWMNM technique achieved CR of 89.6% at few compressed observations, PRD of 6.60 and WEDD of 6.7% and PRD1 of 1.13 with 192 measurements.

Many reported CS algorithms are based on either temporal or spatial correlation which resulted in sub-optimal solution in restoration of multi-channel signals.

To tackle the above problems a novel spatio-temporal correlation based MECG compression technique [11] was proposed very recently in 2017. The reported spatio-temporal Bayesian learning (STBSL)-JCE algorithm utilizes block sparsity for encoding and parallel reconstruction of all the signals. This work also used db4 for sparsification of all the channels. The proposed algorithm STBSL-JCE by A. Singh et al., [11] has been evaluated over RAW MECG signals to test for its robustness in case of noisy signals. PRD and WEDD of 2.15 and 1.13 with CR of 6.58 were achieved for MIT-BIH database .Also PRD 1.67 for 192 measurements was achieved for PTB database. PRD and WEDD of 4.68 and 3.61 with CRR of 73.33% were achieved over PTB database. The sparse binary sensing matrix in STBSL-JCE algorithm has only two 1's in each column and contributes to the lesser on-chip computations.

As the pre-processing tasks like baseline wander, filtering, feature detection and adaptive thresholding operations consume heavy energy [11] hence our proposed algorithm (ABMOD) has avoided any of these pre-process tasks to save the limited energy budget of WBAN ECG node.

3. Motivation and Problem Statement

From the above literature survey it can be hypothetically stated that block-wise sparsification using different mother wavelets could lead to sparser representation in spatial domain leading to higher compression and least-error in the recovered MECG signals. For the spatially correlated ECG signals there is variation in each block of ECG data, so optimal sparsification is desired to enhance the performance of CS algorithms. From section II it is evident that all the previous works [8-12] applied single mother wavelet during data preparation or sparsification phase prior to selection of significant samples in each block of data. A detailed survey of existing CS sparse representation algorithms was conducted in [16], highlighted that developing an efficient and robust sparse representation remains as a main challenge. The authors stressed that designing a more effective dictionary will be beneficial for improving the performance of compression algorithms.

Recently our previous work [13] yielded excellent results in signal compression and restoration quality for single channel ECG signal. Hence the proposed work is built on concept in [13] and extended for MECG signal using spatial correlation. Finding an optimal dictionary for MECG channels is a challenge and much needed solution. The objective of this work is to determine optimal dictionary for simultaneous compression and decompression of MECG signals resulting in clinically acceptable high fidelity signal.

4. Proposed Solution

Most of the previous works [8-12] have attempted to solve the problem of Joint MECG compression and concurrent recovery in WBAN using a single mother wavelet for dictionary construction which leads to low quality signal at reconstruction end making it unsuitable for medical analytical purposes. To overcome this problem, the most suitable daubechies mother wavelet is determined by searching in db '1-45' wavelet space based on the minimum error strategy for each sub-band in each ECG block. Then dictionary is constructed for each block under consideration. This process is repeated for each ECG channel as each block of data holds unique temporal characteristics but is usually spatially correlated in MECG data. In this work only spatial correlation has been exploited as it is built on the idea of landmark work [12]. Each channel has been decomposed till level-7 (multi-scale) with block size of 512 samples. The concept of multi-channel multi-scale adaptive block-wise dictionary construction scheme is illustrated in Fig.3 and corresponding ABMOD algorithm in Fig.4.

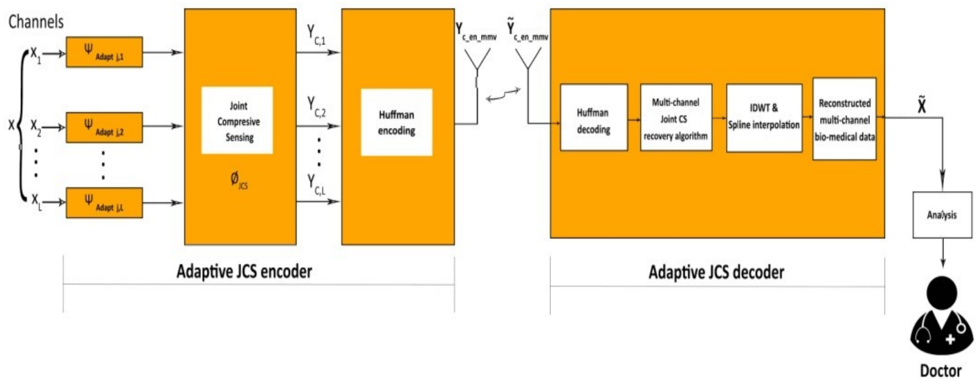

Fig.3. Multi-channel multi-scale adaptive block-wise dictionary construction scheme.

Adaptive Joint CS is performed on the all the ECG channels as in Fig.3. Matrix X comprises of MECG channel vectors. Initially Adaptive dictionary $\Psi_{\mathbf{Adapt\ j,\ i}}$ is generated for each block 'j' of Raw ECG signal vector X_i of channel 'i'. Then joint CS is performed on spatially correlated data simultaneously using sparse random binary sensing matrix $\square_{cs.}$ Generated compressed vectors $Y_{c,i}$ are then Huffman encoded to construct MMV, $Y_{\mathbf{c\_en\_mmv.}}$ This MMV is further packetized and communicated to the receiver by routing protocol in WBAN. In this study routing aspect has not be considered and is limited to Compression and recovery of MECG data.

In Adaptive Joint CS decoder the received MMV, $\tilde{Y}_{\mathbf{c\_en\_mmv}}$ is Huffman decoded and joint recovery of MECG signals is carried out. Then MECG signals are converted to time domain and the missing samples are generated using cubic spline interpolation technique. The reconstructed matrix of MECG $\tilde{X}$ needs to be having minimum difference with X to ensure clinical acceptance for diagnosis. Important notations used in this work are: e is noise tolerance, p means weight exponent, n is block size (512), ρ is convergence limit, t_{max} is maximum number of iterations**.**

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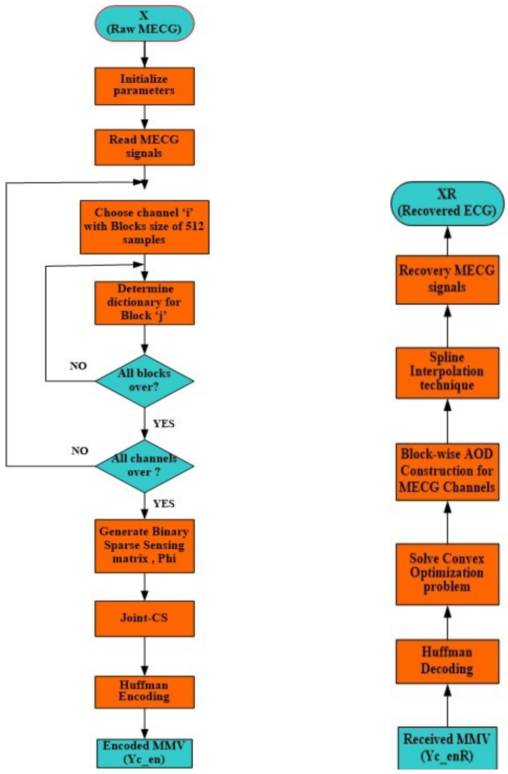

Fig. 4: ABMOD algorithm (a) Joint Compression (b) Joint Recovery.

Adaptive best mother wavelet based optimal dictionary (ABMOD) construction is generated as per flowchart in Fig 4. Joint Compressive sensing (JCS) of MECG data is done considering block-wise approach ,then Huffman encoded to generate compressed MMV vector Y_{c_en}, to be communicated over error-prone wireless medium as shown in Fig 4(a). The received MMV vector is decoded using Huffman technique and then convex optimization problem (COP) is solved to obtain unique and sparse solution. The signal is recovered based on block-by-block approach using corresponding dictionary Ψ applied at the encoder. The resulting block of ECG data is not the sparsest solution, varies slightly and thus does not have exact resemblance with the original coefficients. The missing samples are generated using cubic spline interpolation technique. Eventually the assembled coefficients in simultaneously formed multiple vectors constitute the recovered MECG data.

It is important to note that the proposed work has adopted benchmark Joint CS frame work for MECG compression [12] and SWMNM algorithm [12] is taken for comparing the performance of proposed ABMOD algorithm. Present work has incorporated adaptive dictionary construction technique within the CS frame work of SWMNM [12] algorithm to ensure least error and maximum possible data reduction which guarantees energy conservation of battery in wearable devices in WBAN.

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4.1 ABMOD algorithm

Input: X, e=0.3, p=0.5, ρ=10^{-2}, n=512, t_{max}=3, L=12, d=12

Procedure:

01. Read an L channel MECG record, X.
02. Choose first 4096 samples for each channel.
03. Find number of windows for sample size of n
04. for i=1:n:L // for i^{th} channel
05. for b=1:1:8 // for b^{th} block.
06. Divide and assign 'n' samples of i^{th} ECG channel to V{b}
07. for j=1:1:45 // find the best mother wavelet, dbj
08. [caj, cdj]=dwt(V{b},name) // single level decomposition
09. vj=rand;
10. caj=round(caj/vj,5)
11. cdj=round(cdj/vj,5)
12. rj=rj*vj;
13. // find PRD for b^{th} ECG block of i^{th} channel
14. //find minimum PRD and corresponding mother wavelet DBmin_j for each block.
15. // perform decomposition of ECG block V {b} till level-7.decompose(V{b}, DBminj_b)
16. if (b≤ 8) then repeat steps through 6 to 15 // check all blocks are over/not.
17. go to step 4 and repeat steps through 5 to 16 // take next ECG channel
18. end
19. Concatenate Wavelet Coefficients of channel '1 to L'
20. Generate Sensing matrix, Smat
21. Perform Joint CS compression of L channels
    B {1} = Smat * P1
    ⋮
    B {2} = Smat * P2
    B {8} = Smat * P8
22. Huffman encoding
    Comp {i} =…..encode (data (:)) // End of encoding process
23. // Beginning of decoding process and call Huffman Decoder
    Rec = decode (comp {i}….)
    B {i} = reshape (rec, [r, c]);
24. Initialize reconstruction of L channel ECG signals
25. //Solve convex optimization problem as in (10)
26. for i=1:length(B)
27. for k=1:tmax⁝
28. minimize (sum(norms(Packet.*W,2,2))
29. subject to
30. norm ((B{i}-Smat*Packet),'fro') ≤ e
31. end
32. if (Con < ρ) break;
33. end
34. // Recovery and transformation to time domain of channel ' i'
35. [car7,cdr7,……..,cdr1]= rec_s (RWC1)
36. R7=idwt(car7,cdr7,DBminj_b)

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37. R7_new=spline (t1,R7,t2)
⋮
R1_new=spline (t1,R1,t2)
38. X{1}=R1_new;
39. All ‘B’ Blocks recovered?
40. If yes repeat steps 31 to 33 for remaining ‘L-i’ channels
41. All ‘L’ channels recovered?
42. If yes then STOP and reconstruct X_R=[X_{R1}, X_{R2}, ……, X_{RL}]
43. Compute performance metrics.

OUTPUT: Y_c, X_R, CR, SNR, PRD, PRD1 and WEDD

4.2. Mathematical Model of MMV for ABMOD algorithm

In this work we have considered MECG as comprising of L equal to 12 channels (8 independent channels, rest of them can be derived using the former). The MMV model of the Adaptive JCS based codec is listed from (1) through (23).

4.2.1. Encoder Side

The raw MECG channels can be represented as

$$X = [X_1, X_2, \cdots, X_L] \tag{1}$$

where, X ϵ $\mathbb{R}^{NxL}$ denotes raw ECG matrix, L is number of ECG channels, X_i is data of one channel.

The ECG vector of i^{th} channel is given by

$$X_i = [X_{i1}, X_{i2}, \cdots, X_{iB}] \tag{2}$$

where, ‘i’ is the channel number and varies from ‘1 to L’, X_{i1} is the block ‘1’of i^{th} channel, B is the total number of blocks of a given ECG channel.

Individual channel vectors are given as below:

$$\left.\begin{array}{l} \text{ECG vector of Channel ‘1’, } X_1 = [X_{11}, X_{12}, \cdots, X_{1B}] \\ \text{ECG vector of Channel ‘2’, } X_2 = [X_{21}, X_{22}, \cdots, X_{2B}] \\ \vdots \\ \text{ECG vector of Channel ‘L’, } X_L = [X_{L1}, X_{L2}, \cdots, X_{LB}] \end{array}\right\} \tag{3}$$

Sparsification basis matrix or dictionary is denoted as

$$\Psi = [\Psi_1, \Psi_2, \cdots, \Psi_N] \tag{4}$$

Then K-sparse input signal Xis represented as

$$X = \sum_{i=1}^{K} \alpha_i \psi_i \tag{5}$$

where, A = [$\alpha_1 \alpha_2$, …. , α_N] $\epsilon\ \mathbb{R}^{NxL}$ is ECG wavelet coefficient vector ,

Compressed ECG vector of block 'j' of i^{th} ECG channel is given by

$$Y_{ij} = \Phi_{cs} \Psi_{i,j} X_{i,j} \tag{6}$$

where '**i**' is the channel number, '**j**' is the block number varying from1 to B, $\Psi_{i,j}$ is the adaptivebest mother wavelet (sub-dictionary) for **j**th block of i^{th} channel, $X_{i,j}$ is the j^{th} block of raw ECG data of the i^{th} channel.

Block-wise compressed ECG Vectors for channel 'i' are depicted as

$$\left.\begin{aligned} &\text{Block '1', } Y_{11} = \Phi_{cs1} \Psi_{1,1} X_{1,1} \\ &\text{Block '2', } Y_{12} = \Phi_{cs2} \Psi_{1,2} X_{1,2} \\ &\qquad\vdots \\ &\text{Block 'B', } Y_{1B} = \Phi_{csB} \Psi_{1,B} X_{1,B} \end{aligned}\right\} \tag{7}$$

Thus, compressed vector for block 'B' of i^{th} channel is given by

$$Y_{iB} = \Phi_{cs} \begin{bmatrix} \psi i,1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \psi i,B \end{bmatrix} \left[X_{i1}, X_{i2}, \cdots, X_{iB}\right] \tag{8}$$

In general SMV of channel 'i' is denoted as

$$Y_i = \left[Y_{i1}, Y_{i2}, \cdots, Y_{iB}\right] \tag{9}$$

Expanding equation (6b) Channel-wise SMV's are given as

$$\left.\begin{aligned} &\text{SMV of channel 1 is } Y_1 = \left[Y_{11}, Y_{12}, \cdots, Y_{1B}\right] \\ &\text{SMV of channel 2 is } Y_2 = \left[Y_{21}, Y_{22}, \cdots, Y_{2B}\right] \\ &\qquad\qquad\vdots \\ &\text{SMV of channel L is } Y_L = \left[Y_{L1}, Y_{L2}, \cdots, Y_{LB}\right] \end{aligned}\right\} \tag{10}$$

The compressed MMV vector of all 'L' channels of MECG is represented as

$$Y_j = \left[Y_{j1}, Y_{j2}, \cdots, Y_{jB}\right]$$

$$Y_j = \Phi_{cs} \begin{bmatrix} \psi i,1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \psi i,j \end{bmatrix} \left[X_1, X_2, \cdots, X_L\right] \tag{11}$$

MECG Information captured for all 'L' channels is a Compressed Multiple Measurement Vector (MMV) of dimension M x L and is given as

$$Y = \Phi_{Jcs} X \tag{12}$$

$$Y = \Phi_{Jcs} \Psi A = \Theta A \tag{13}$$

where $\Phi_{Jcs} \epsilon \mathbb{R}^{\mathbf{M \times N}}$, is random binary sparse sensing matrix.
$\Psi \epsilon \mathbb{R}^{\mathbf{N \times N}}$, is constructed adaptive dictionary matrix.
$\Theta \epsilon \mathbb{R}^{\mathbf{MxN}}$**,** is incoherent matrix which satisfies the Mutual Incoherence Property (MIP) for efficient reconstruction of MECG signals.

The objective of multi-scale multi-channel joint CS (MSMC-JCS) approach is to compress and retrieve all the ECG channels concurrently with minimum error.

Hence compressed MMV matrix obtained in (11) can also be written as

$$Y_{c\_mmv}=\left[Y_1, Y_2, \cdots, Y_L\right] \tag{14}$$

Y_{c_mmv} is further Huffman encoded to obtain matrix $Y_{c\_en\_mmv}$ which can be transmitted towards the destination.

$$Yc\_en\_mmv = \mathit{Huffman}\ (Yc\_mmv) \tag{15}$$

4.3.2 Decoder side

Received signals are estimated by solving convex optimization MMV problem. JSM1 and JSM2 have been together used for MECG ensemble signal recovery. In the hybrid approach all the signals have sparse representation in multi-scale dwt basis. All the signals have common support at coarse scales even though coefficients are different and support at each sensor will be different at finer scales.

The WMNM recovery algorithm used in [12] has been adopted for obtaining Sparse solution for MMV problem in (16). The recovery of MECG channels is based on sub-band energy based iterative WMNM algorithm [12]. The difference between recovery process in SWMNM[12] and proposed ABMOD algorithm is that block-wise inverse dwt using corresponding mother wavelet same as that used at encoder is applied in our work against same basis ,db4 used in [12].This facilitates minimum error based reconstruction of MECG channels and its suitability for medical diagnosis.

Row-sparsity based reconstruction of 'L' channel MECG data contaminated with noise, Y=ΘA+Z is treated as MMV problem based on (7), Z is additive noise vector .The sparse solution to (12) is obtained by solving standard MNM-based convex optimization problem[12]:

$$\underbrace{min}_{A} ||A||_{p,q} \text{s.t } \|Y - \Theta A\|_F \leq \varepsilon \tag{16}$$

where ε is upper bound of noise tolerance. $||.||_{\mathbf{F}}$ is the Frobenius norm,$||.||_{\mathbf{p,q}}$is the $l_{p,\,q}$ mixed-norm of vector A. In this work it is $l_{2,1}$ with inner norm-2 and outer norm-1 which induces final sparsity[12].

Solution in (16) extends to joint non-linear optimization for recovery of MECG by using weighted MNM (WMNM) technique is written as

$$\hat{A} = \underbrace{arg\ min}\ \frac{1}{2}\ ||Y - \Theta\hat{A}||_F^2 + \lambda \textstyle\sum_j w_j\ ||A^{\rightarrow j}||_2 \tag{17}$$

where weight vector $\boldsymbol{w} = \left[\frac{1}{\sigma_1^2}, \frac{1}{\sigma_2^2}, \ldots \ldots \frac{1}{\sigma_{1N}^2}\right]$, Y is compressed MECG matrix, Θ is reconstruction matrix, $\hat{A}$ is estimation of A, F is frobenious norm, w_j is complete weight for jth sub-band , $A^{\rightarrow j}$ is j^{th} row of A, λ is tuning parameter, σ_j is standard deviation and j varies as 1,2,….,N.

5. EXPERIMENTAL DATASET AND PERFORMANCE MEASURES

Simulation experiments were conducted on MATLAB 2018b platform with core i3 processor. Segment length of each ECG signal was taken as 4096 samples with fixed block size (N) of 512. Joint compression and recovery of multi-lead ECG signals was performed by the proposed ABMOD algorithm. The fundamental idea of least distortion has been used to determine the best mother wavelet Ψ prior to decomposition. The dimension of compressed measurements (M) was assumed to be70samples and 192as in [12] for PTB ECG and MIT-BIH Arrhythmia dataset respectively. M was chosen by design of random Binary Sparse sensing matrix (BSM) with d (=12), where d is the number of one's in the generated BSM per every column of joint sensing matrix, Φ_{Jcs}. The proposed ABMOD algorithm with level-7 decomposition as in [12] has been tested and validated over 2-lead ECG MIT-BIH arrhythmia [22] and 15-lead PTB database [21].

5.1 Performance Metrics

Any compression algorithm needs to reduce data so as to have minimum memory foot print, consume lesser bandwidth and least possible energy consumption. Efficiency of the proposed technique has been evaluated using measures such as Compression ratio (CR) , Signal to noise Ratio (SNR), Percentage root mean square difference (PRD) Normalized percentage root-mean-square difference (PRD1), Joint-PRD (JPRD) and Wavelet energy based diagnostic distortion (WEDD) [12].

$$\text{CR} = \frac{b_{orig} - b_{comp}}{b_{orig}} \text{ x } 100 \tag{18}$$

where,b_{orig} and b_{comp} are number of bits in raw and compressed ECG vectors.

$$\text{PRD (\%)} = \left(\frac{\|x-\hat{x}\|_2}{\|x\|_2}\right) \text{ x } 100 \tag{19}$$

where x and $\hat{x}$ represent raw and reconstructed ECG signal vectors.

$$\text{SNR} = -20\ log_{10}\,(0.01\ PRD)\ \text{dB} \tag{20}$$

PRD gives distortion level in recovered signal relative to the original signal but the demerit of PRD is that the average of the signal is not subtracted from the original ECG vector which causes a DC bias, leading to compromise in the accuracy [19] and therefore PRD1 is more commonly used. However in this work PRD is also included for comparison with CS algorithms in the literature.

$$\text{PRD1 (\%)} = \left(\frac{\|X-\hat{X}\|_2}{\|X-\bar{X}\|_2}\right) \text{ x } 100 \tag{21}$$

where $\bar{X}$ is the mean of vector X.

The PRD values between 0-2 % ("Very good"), 2-9% ("good") quality class and WEDD values less than 11.12% ("good") quality class respectively [12] are suitable for diagnostic purposes.

ISSN: 2233-7857 IJFGCN

$$\text{JPRD (\%)} = \frac{\|X-\hat{X}\|_F}{\|\hat{X}\|_F} \text{ x } 100 \quad (22)$$

where F is Frobenious norm.

$$\text{WEDD (\%)} = \sum_{j=1}^{S+1} \boldsymbol{w_j'} \, WPRD_j \quad (23)$$

where weight for j[th] sub-band is $w_j' = \frac{\sum_{k=1}^{N_j} w_{j,k}^2}{\sum_{j=1}^{S+1}\sum_{k=1}^{N_j} w_{j,k}^2}$, S is number of wavelet sub-bands or levels and $WPRD_j$ is the PRD value at j[th] sub-band.

6. RESULTS AND DISCUSSIONS

In our previous work, ABMWCS algorithm [13] was proposed for compression of single channel ECG signal, achieved an average PRD of 1.14 % and performed better than [5]. The present work is extension of [13] and based on concepts in [12] [5]. In the work sub-band energy based adaptive Joint Compression and recovery algorithm for MECG signal based on [12] has been proposed and evaluated. Minimum PRD based adaptive decomposition over different daubechies vanishing moments has been performed on all channels and a sparse random binary sensing matrix has been used for dimension reduction. Simulation studies have been carried out on two different databases PTB ECG database [21] and MIT-BIH Arrhythmia database [22].Results have been compared with SWMNM rather than PWMNM algorithm since PRD reduces with increase in block size [12]. The results of the experiments have been averaged over all the records of the databases.

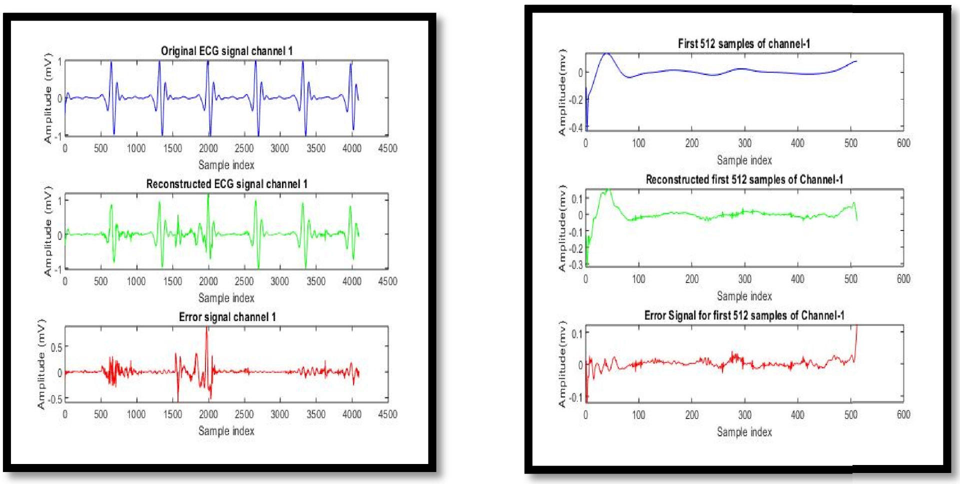
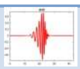
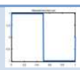
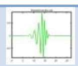
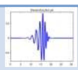
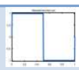
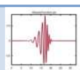
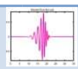
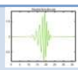


Fig.5. Plot of Lead I of S0058lrem .(a) Original, Reconstructed and Error signal (b) Block 1

Table 2: Block-wise chosen best mother wavelet for LEAD I of 4096 samples

Metric	Block1	Block2	Block3	Block4	Block5	Block6	Block7	Block8
DBmin	**db22**	**db1**	**db14**	**db16**	**db1**	**db17**	**db18**	**db19**
PRDmin	**5.26 e-09**	**4.66 e-04**	**2.43 e-08**	**2.40 e-08**	**4.12 e-04**	**2.41 e-08**	**2.41 e-08**	**2.47 e-08**
Wavelet function (Ψ)								

The results of Lead I are illustrated in Fig.5 and Table 2 as representation only. Lead I achieved the least WEDD (%) of 1.18 amongst 12 leads and graph illustrating original, recovered and difference signal is shown in Fig 5(a). Also block '1' of size 512 is plotted for visualization of original, reconstructed and error signal ,which used DBmin1 of db22 and has minimum PRD of 5.26e-09. The data presented in Table 2 above is for data packet (segment) size of X ϵ 512 x 8. The graphical illustration of other leads has been omitted for lack of space but the metrics for all the 12 leads have been represented in Table 4.Similarly for Noiseless MECG compression over PTB dataset best mother wavelets selected for one block of ECG of above said record is as shown below with corresponding PRD values.

DBmin = 'db6 db8 db20 db12 db5 db8 db7 db31'
PRDmV = 0.0002, 0.0002, 0.0004, 0.0002, 0.0010 ,0.0002, 0.0011,0.0002

6.1 Multi-lead ECG PTB database

The proposed ABMOD algorithm has been evaluated over universal PTB ECG standard database. Table 3 shows the values of different parameters set for experiments.

Table 3. Simulation Parameters

M (Measurements)	N (Raw ECG samples)	d (Number of 1's)	e (Error tolerance)	t_{max} (Max. iterations)
70 (192)	**512**	**12**	**0.3**	**3**

The lead-wise average statistical values are listed in Table 4. along with comparision to benchmark SWMNM algorithm.

Table 4. Performance comparison between SWMNM [12] and proposed ABMOD algorithm. The results are averaged over all the PTB data records for 12 channel information.

Algorithm	M	Metrics	Lead I	Lead II	Lead III	AVR	AVL	AVF	V1	V2	V3	V4	V5	V6	Avg	Database
SWMNM [12]	**70**	**PRD**	8.73	6.02	7.78	5.93	7.52	5.96	6.35	5.58	5.54	6.59	6.74	6.54	6.60	**PTB** (fs = 1000 Hz)
		SNR	21.18	24.41	22.18	24.54	22.47	24.49	23.95	25.07	25.13	23.62	23.43	23.68	23.67	
		WEDD	8.13	6.65	6.69	5.65	6.39	5.44	5.70	4.73	4.89	6.14	6.27	6.20	6.07	
Proposed (ABMOD) Noisy signals	**70**	**PRD**	3.078	5.44	1.29	10.66	2.66	1.13	1.70	4.05	19.9	6.23	1.91	2.37	**4.03**	
		SNR	15.24	8.80	23.17	3.90	16.30	24.49	19.87	11.28	5.81	8.58	18.80	18.20	**14.55**	
		WEDD	1.18	4.74	5.48	4.03	2.46	5.02	3.59	3.73	3.97	3.17	3.20	2.96	**3.59**	
Proposed (ABMOD) Noiseless signals	**70**	**PRD**	0.024	0.024	0.007	0.013	0.024	0.008	0.007	0.015	0.006	0.007	0.008	0.019	**0.006**	
		SNR	74.92	76.04	86.12	80.96	76.13	85.54	85.19	78.58	86.67	85.58	85.23	79.03	**86.67**	
		WEDD	5.358	7.521	2.671	3.35	5.57	2.93	2.55	6.01	2.47	2.63	2.50	4.43	**4.00**	
SWMNM [12]	**192**	**PRD1**	-	-	-	-	-	-	-	-	-	-	-	-	1.13	**MIT-BIH** (fs= 360 Hz)
Proposed (ABMOD) Noisy signals	**192**	**PRD1**	-	-	-	-	-	-	-	-	-	-	-	-	**0.47**	
Proposed (ABMOD) Noiseless signals	**192**	**PRD1**	-	-	-	-	-	-	-	-	-	-	-	-	**1.70 E-05**	
		SNR	-	-	-	-	-	-	-	-	-	-	-	-	**77.41 173**	
		WEDD	-	-	-	-	-	-	-	-	-	-	-	-	**6.608 4**	

ISSN: 2233-7857 IJFGCN

Table 5. Average values of Performance metrics for 12 channel PTB database.

Case	CR (%)	Output PRD	JPRD	SNR	WEDD (%)
Noisy signals	90.05	4.03	4.44	14.55	3.59
Noisless signals	90.05	0.006023	4.75	86.67	4.00

Remarks: The mean values of metrics for proposed ABMOD algorithm are enlisted in table 4 and 5 respectively. Experimental results illustrate that almost all the compression performance measures are within acceptable ranges [7] [12] [13].This demonstrates that the proposed method of adaptive dictionary generation in CS algorithm effectively reduces and restores that 12 channel MECG data which can be further used for diagnostic purposes. For one-to-one comparative study of proposed ABMOD and the SWMNM algorithm [12] experiments were carried out with same values of measurements (M), databases with same assumptions .

Following observations were noticed with respect to the proposed ABMOD algorithm. Average Output PRD of 4.03 is within 2-9% i.e., "very good" class, Average PRD1 (%) of 0.47 is much lesser than 1.13[12], Average JPRD(%) = 4.44, also average WEDD (%) of 3.59 is well within acceptable upper bound 11.12% [12]. However average SNR of 14.56 is less than 23.67dB[12] which may be due to presence of base-line wander and other noisy signal components along with MECG as filtering has not been implemented in pre-processing phase which needs further investigation. The average CR of 90.06 % is a very good figure of merit indicating reduced data during acquisition phase leading to lesser energy consumption, minimum storage and lesser bandwidth in wearable ECG sensors.

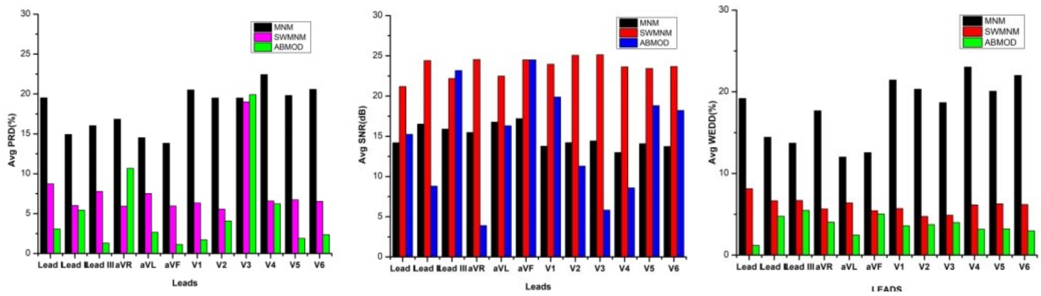


Fig.6. Comparision of SWMNM and ABMOD algorithm (a) AvgPRD (b) Avg SNR (c) Avg WEDD

Average CR (%) =N/M =512/70 =7.14

$$\mathbf{CR^1} = (1 - CR/100) \tag{24}$$

Thus CR^1= (1-7.14/100) x 100 = 0.9286 =92.86 %.

Fig.6. presents the performance comparision amongst classical MNM, SWMNM and proposed ABMOD algorithm. It can be inferred from Fig.6a and Fig.6b that both average PRD and WEDD have significant reduction compared to SWMNM in all the 12 leads of MECG when evaluated over PTB and MIT-BIH database. This is because of the adaptive sub-dictionary constructed for each block of ECG based on the minimum error strategy adopted at encoder and decoder side. Hence our proposed algorithm performs better compared to the average values in the metrics space. Performance evaluation has been carried out for the same value of M (70 & 192) for both PTB and MIT-BIH databases for

ISSN: 2233-7857 IJFGCN

comparative purposes. Fig.6c illustrates reduced SNR as against other techniques in noisy case and needs removal of noises using appropriate filtering techniques.

MECG signals filtered and subsequently processed through proposed ABMOD algorithm achieved tremendous improvement in the SNR values for all the channels. The impact of filtering increased the strength of signals against noise even though the PRD and WEDD metrics remained almost same for PTB dataset.

6.2 MIT-BIH Arrhythmia database

Case 1: Noisy ECG signals

The proposed ABMOD algorithm is compared with SWMNM for PRD1 metric over two-lead MIT-BIH database. The average PRD1 of0.47obtained for M (192) is less compared to 1.13 of SWMNM [12].This indicates relatively good performance of the proposed algorithm in restoration quality of the RAW MECG data.

Case 2: Noiseless ECG signals

Two-lead test MECG signals taken from MIT-BIT Arrhythmia dataset is fed to ABMOD algorithm. Here the signals are filtered using Pan-Tompkin algorithm [32] unlike above where RAW MECG are processed. The filtered signals are then normalized and mean subtracted and segmented by extracting first 4096 samples. Further segment of 4096 samples is divided into 8 blocks each consisting of 512 samples .The moving average filter is deployed. These MECG signals are compressed using the proposed ABMOD algorithm .

Table 6: Average Performance metricsof 2 channel ECG (MECG) from MIT-BIH database with N=512,d=12,m=192.

CR	PRD ch1	PRD ch2	PRD	PRD1 ch1	PRD1 ch2	AVG PRD1	Joint PRD	SNR1 (dB)	SNR2 (dB)	AVG SNR (dB)	WEDD ch1	WEDD ch2	AVG WEDD
72.72	0.00156	0.00202	0.00178	1.38E-05	1.91E-05	1.70E-05	3.82926	78.81518	76.00828	77.4117	5.14696	8.0698	6.6084

Remarks:

The response of the proposed ABMOD algorithm for noisy MIT-BIH dataset is illustrated in the table 6 above.

Average SNR of 77.4117 dB achieved post filtering and compression using ABMOD algorithm is much greater than23.67 [12].This illustrates signal strength is increased compared to noise and leads to enhancement of ABMOD algorithm performance due to elimination of noises. Relatively for MIT-BIH 2-lead dataset the algorithm responded positively with further reduction of PRD1 metric indicating lesser error compared to the compression of un-filtered signals. Also PRD1 of 0.47 has been reduced further in case of noiseless signal compression to1.70E-05 implying lesser difference between un-compressed and recovered signals

Further SNR and WEDD metrics have been included for reflecting the impact of filtering for noisy MIT-BIH ECG signals while these metrics have not been in the comparative works.The results press on the fact that filtering of the signals needs to be carried out prior to compression for obtaining highest performance.

ISSN: 2233-7857 IJFGCN

6.3 ENERGY CONSUMPTION ANALYSIS

6.3.1 On-node Sensing Energy Consumption

The WBAN sensor node acquires ECG signal on continuous basis and is battery powered whose life time varies from few hours to days. Hence it becomes very important to save this critical resource by consuming least energy. In this work WBAN node model [31] given in Table 6 has be incorporated to quantify the energy consumed by the underlying ABMWCS technique [13] executing on each node.

Table .7 WBAN node model [31]

Parameter	Value
Initial energy in WBAN node, E_0	2 J
CS energy consumption, Ec	0.005nJ/bit
CS Energy consumption/ channel , Ecs	Depends on sensing matrix dimension.

The mathematical expression used for computation of on-node energy consumption by proposed ABMOD algorithm per ECG channel is given by:

$$\text{Ecs} = 2NEc\sqrt{MN} + MNEc \tag{25}$$

where, N and Mare dimensions of raw ECG vector and measurement vectors. Since the length of M (70) and N (512) are fixed in this work for PTB dataset simulation results yielded **Ecs** =7.35e-05 J.

The total energy expenditure at the Adaptive JCS encoder (transmitter) due to ABMOD algorithm can be found out by

$$E_{TCS} = Ecs * L \tag{26}$$

For present work (L=8) independent ECG leads this accounts to E_{TCS} =5.8803e-04. This contributes to only 3.0000e-04 % of utilization of WBAN node battery energy for M equal to 70 and demonstrates the energy efficient sensor data acquisition capability of the proposed ABMOD algorithm.

6.3.2 Transmission Energy Consumption

The compressed data needs to be further communicated to the data aggregator or coordinator and requires energy. Transmission power consumption for 'L' channels in CS based transceiver is based on the formulae adopted from [12]

$$\mathbf{P_{tx}} = L * CR^1 * T * F_s * R \tag{27}$$

where L is the ensemble of MECG channels, T the transmission power expended per bit, Fs the sampling frequency (samples per second) of the ADC, R is the number of bits per sample (data resolution) and CR^1= (1-CR/100). CR of 90.06 % is obtained at 70 compressive measurements for the above experimental data. Thus for L (=8) independent elementary channels, CR^1=0.0994, T=5nJ/bit, f_{ess}=500sps and data bit-resolution, R=12. P_{tx}=23.85 µw .It can be observed that power consumption achieved by proposed

ISSN: 2233-7857 IJFGCN

algorithm is less than SWMNM (24.96 µW) and saved 4.44% battery energy of the multi-channel bio-monitors.

Table 7. illustrates that other algorithms have lower CR values and hence require more power to transmit and obtain the same reconstruction quality. It is evident that the proposed algorithm relatively demands lesser power budget of 23.85µW with much higher CR of 90.06, except PWMNM algorithm [12] which has least of 21.12µW as reported in the literature. Equation (19) has been utilized here for demonstration purpose only and may change with WBAN node.

Table 8.Comparision of Power Consumption profiles

Algorithm	Ptx (µW)
BP [4]	34.56
MNM [7]	34.56
IR-l1/l2 [24]	28.56
SOMP[14]	24.96
SWMNM [12]	24.96
PWMNM[12]	21.12
ABMOD(proposed)	**23.85**

7. CONCLUSIONS

In this article Adaptive optimal dictionary construction algorithm for joint compressive sensing and recovery has been proposed to solve the MMV problem of MECG signals. Adaptive Dictionary is determined in wavelet domain by exploiting sub-band level energy and spatial correlation between coefficients among the ECG channels to reduce data. The novelty being block-wise Adaptive sub-dictionary of all ECG channels was carried out concurrently prior to compressive sampling of MECG channels for both two lead MIT-BIH Arrhythmia and 12 lead PTB ECG database. Most appropriate mother wavelet is chosen for a particular ECG block. The proposed ABMOD algorithm achieved the average PRD%, SNR and WEDD% of 4.03,14.55 and 3.59 respectively as against 6.60, 23.67, and 6.07 for PTB ECG database of SWMNM technique .Also more significantly considered metric PRD1(%) of 0.475 is achieved against 1.13 [12] when validated over two lead MIT-BIH database. This indicates the higher degree of acceptability of ABMOD for further bio-medical signal analysis

Empirical results indicate that the proposed ABMOD algorithm performs superior compared to all the metrics of benchmark work [12] except that average SNR valueof 14.55is decreased against 23.67dB.The CR was 90.06 % against 89.60% of [12] which clearly indicates higher compression ability of proposed ABMOD algorithm and subsequent energy preservation. Also ABMOD relatively demands lesser power budget of 23.85 µW with much higher CR of 90.06 %, except PWMNM algorithm [12] which has least of 21.12 µW reported in literature. ABMOD algorithm saved 4.44% battery energy of the multi-channel bio-monitors at node transmission level .This indicates to enormous reduction in power consumption of wireless bio-monitors used in WBAN leading to enhancement of functional life time of the battery-driven devices.

Application of Pan-Tompkins algorithm for filtering the MECG signals followed by subsequent adaptive compression yielded tremendous improvement in the signal strength ,SNR metrics and further reduction in error metrics PRD and PRD1 for PTB and MIT-BIH datasets respectively. This increases quality of the reconstructed signal.

ISSN: 2233-7857 IJFGCN

Some of the directions are to apply machine learning techniques for determination of adaptive sparse dictionary, increase in SNR, study the impact of different filtering techniques, signal feature-based dictionary construction on the performance metrics of ABMOD algorithm from real-time perspective. All the work in this paper is simulation based and needs to be evaluated on commercial test bed WBAN hardware platform.

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