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ON-NODE ADAPTIVE BLOCK SPARSE COMPRESSIVE SENSING APPROACH FOR EEG DATA REDUCTION IN WBAN

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Abstract: Electroencephalography (EEG) signal is vital for detection and analysis of brain related disorders. Brain waves are non-sparse in either in time or many other transform domains. In this paper the proposed algorithm applies optimal mother wavelet for each block rather than applying single mother wavelet for sparsification of entire EEG signal. Sparsification of individual blocks is done based on the least percentage difference metric in the work. Block adaptive decomposition has been performed for implementation of compressive sensing of single channel EEG signal and proposed method has been tested over different datasets. Results reveal that the average Percentage Root mean square Difference (PRD) value of 0.146625 and 0.0057 achieved are very close to 0% and fits into "excellent" reconstruction quality class of 0-2%. This demonstrates that the proposed algorithm has higher fidelity and is very apt for biomedical analysis for detection of epileptic disorder using the recovered signal.

Keywords: EEG, WBAN, Adaptive Dictionary, Adaptive compressive sensing.

I. INTRODUCTION

In recent years medical problems are increasing due to various factors, resulting in higher mortality rate. To tackle this ambulatory tele-monitoring of vital sign with wireless technology enabled wearable light-weight devices have to be deployed as multichannel devices are bulky. Also wearable nodes have multiple resource constraints like memory, bandwidth and energy source. A very small sensor network comprising of wearable wireless bio-monitors located in, on or near the body which are capable of recording medical signals non-invasively and communicating the data to remote location for further analysis is known as Wireless Body Area Networks (WBAN).

Electroencephalography (EEG) is an important vital sign and deploys non-invasive method of recording patients brain waves .It is widely used for detection of epilepsy, sleep-related and other disorders. EEG signal is derived by the potential difference between two electrodes and is of order of µv. Typical signals detected on the scalp are in the range 20–150 µv peak-to-peak over a 0.5–60 Hz bandwidth[3]. Conventional EEG recorders are bulky and not suitable for wearable ambulatory applications. The data generated for 24 h for single channel EEG recording amounts to approximately 1 GB .For low-power, easy to use, portable systems, the channel count should be minimized without affecting diagnostic accuracy[3].

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Hence in this work single EEG channel approach has been considered and tested for the designed block adaptive compressive sensing algorithm. .For continuous monitoring sensing EEG consumes significant energy from battery which stands as a critical resource for deciding the life time of the sensors.

Hence in order to enable EEG recordings in daily-life activities, tiny wearable EEG sensors need to be used , which means low-power operation and energy-efficient wireless data transmission [1]. Wearable EEG monitors are resource limited wireless enabled nodes capable of capturing brain waves and communicating to remote locations. Thus Low power consumption is the key requirement of any wearable EEG systems.For meeting low complexity operations in wearable EEG monitors data reduction at acquisition stage itself where selective sampling is done and thereby compression of EEG signal is performed. This technique of simultaneous sampling- compression is known as Compressive Sensing or **Compressive Sampling (CS)** algorithm[2].

As per [22] for a typical transmitter that consumes 50 nJ/b, transmitting each channel consumes approximately 120μW. With these figures, only a one-channel system is feasible hence single channel EEG channel has been taken for our study, major challenge is to realize high-quality wearable EEG systems with better performance. Decreasing the required power consumption by using emergent compressive sensing strategy is the method adopted in this work. The objective of the work is to achieve energy efficient EEG compression technique and recover high quality signal with very less measurements.

This paper is divided into seven sections. Section I contains introduction to WBAN,CS and EEG bio-monitors. Section II covers related works done in the area of CS algorithms for EEG signals .Section III Problem statement. Section IV demonstrates proposed solution and discusses the ABSCS algorithm with mathematical equations and flow chart. Experimental database and performance metrics have been listed in section V. In section VI Results and Discussions have been presented with tables.

II. LITERATURE SURVEY

Recent works based on CS algorithms for EEG signal compression have been studied below . The quantification of CS on resource constrained embedded WBAN ECG node for lower complex, energy-efficient ECG compression was carried out in [2] and achieved a 37.1% compare to its DWT counterpart. For a fixed mother wavelet based decomposition the PRD values achieved for most of the MIT-BIH records was between 2 to 9% , hence adaptive signal decomposition may be explored for further reduction of PRD and applied for EEG signal. Automatic sleep stage annotation method known as Sleep EEGNet was proposed in [5] using a single-channel EEG signal but no compression was done. In [6] Wearable EEG via lossless compression for multi channel EEG signal was proposed where the low-power platform is able to compress, by a factor between 2.3 and 3.6, up to 300sps from 64 channels with a power consumption of 176μW/channel. In [7] Sparsification is based on DCT for each EEG channel and the proposed STSBL algorithm based on spatio-temporal correlation ensured that the classification of BCI and the estimation of drowsiness was not disturbed even when compression was 80%, making it very suitable for 24 x 7 wireless tele-monitoring of multichannel signals. The proposed CS based encoder [8] for multiple EEG signal compression achieved CR of 4:1 and saved 75% of the transceiver energy consumption, but the quantification of the power consumption was not

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done. The EEG signals taken from the CHB-MIT database [14] had block size of 256.The average time taken was 0.06 second per epoch by the BSBL-BO algorithm.

CS often resorts to a dictionary matrix to recover a non-sparse signal and depends on the sparsity of its representation [20], but finding such a dictionary matrix for many physiological signals is a difficult task. In [9] DCT based BSBL-BO algorithm was proposed for EEG compression and yielded average NMSE of 0.078±0.046 and SSIM of 0.85±0.08. In the second study, dictionary was based on Daubechies-20 Wavelet Transform (WT) with sparse binary sensing matrix with entry of each column consisting of fifteen 1's and remaining elements 0 but sparsification was not block adaptive..A matrix completion based formulation for compressive sensing technique proposed in [11] for EEG tele-monitoring capable of reducing the energy consumption , achieved NMSE of mean and standard deviation of 0.066 and ± 0.028 respectively for CR of 2:1 and classification accuracy of 80% on BCI Competition III Dataset 1.SNR of 60.12 dB for 16-bit resolution EEG data. Inter-channel correlation of MEEG signals was exploited with Low-rank + row-sparse – analysis prior (Gabor) [10],CS based recovery method yielded MSE of 0.041 for 50% Compression and 0.088 for 25% compression respectively and classification accuracy of 80 % for compressed signal.

It was observed that best basis selection [17] strategy using parameter based mother wavelet optimization resulting in significant improvement of performance in compression with respect to DWT and random selection of the mother wavelet but was tested taking db3 and Coiflet only. For a CR of 2:1 least PRD achieved was 0.6 [17] and increased with CR but other mother wavelets were not inspected.

Benchmark work [18] for best mother wavelet selection in based on least PRD strategy to compress the ECG signal in DWT domain and achieved average values of PRD ,CR and SNR of 0.23, 15.2 and 66.96 respectively tested over single channel ECG 48-records of MIT-BIH arrhythmia database.. Trade-off for lower CR is the major limitation of this work for obtaining lower PRD values and energy consumption analysis was not done. Evaluation for EEG signal was not done.

Sparse representation is a critical requisite for CS-based compression of a signal. CS theory suggests that if a signal is sparse or compressive, the original signal can be reconstructed by using only a few measured values [16] at sub-nyquist sampling rate relative to conventional Shannon's theorem .

From the review, of literature it can be seen that least NMSE reported is 0.041 for EEG compression in WBAN and further reduction of this metric makes the recovered signal very close to the source signal. Major motivation for this work is that EEG wave in not sparse unlike EEG and further accurately reconstructed EEG signal results in avoiding false classification. This enables for medical diagnosis and analytical purposes.

III. PROBLEM STATEMENT

EEG is non-stationary signal with varying characteristics for every block and being non-sparse in time or any other transform domain like DCT, DWT domain, recovering high quality EEG signal is difficult to achieve using single mother wavelet based dictionary. EEG signal compression and recovery has to be done with least error using optimal dictionary. None of the above cited works in literature explored block adaptive sparsification approach to obtain optimal mother wavelet based dictionary to achieve lower distortion , energy efficient compression.

IV. PROPOSED SOLUTION

EEG signal compression in WBAN has been effectively carried out by many significant works. Compression and recovery problems both for single and multi-channel EEG signal using different [7-11] CS algorithms have been reported in literature. But the previous approach [10] obtained average NMSE of 0.041.To further reduce error in recovered EEG signal this work proposes Adaptive Block Sparse Compressive Sensing (ABSCS) approach .The scope of the proposed algorithm is limited to the digital CS domain.

In general CS theory implementation relies on three main requirements [3]:

(i) Sparse signal representation
(ii) Mutual Incoherence Property (MIP)
(iii) Non-linear reconstruction method.

The proposed method addresses the sparsification requirement (i) of the CS theory. Adaptive decomposition of the EEG signal has been performed in the proposed algorithm to give the sparsest representation. Least PRD based adaptive decomposition method has been incorporated to find the optimal mother wavelet for the producing block-wise sparsest version of EEG signal. Proposed method explores daubechies mother wavelet dbi, where 'i' varies in the range of 1 to 45 and mother wavelet dbi which generates least PRD has been chosen for sparsification as given by (1a).

Proposed ABSCS algorithm for compression and decompression of EEG signal is illustrated in Figure 1. Pre-recorded EEG signal of 4096 samples [13-15] is read and stored as EEG segment. Elimination of base-line wander and normalization of the EEG segment is done. Then divide the input EEG segment into 8 blocks of size ,N=512 samples. Since EEG is non-sparse in any domain ,sparsify each block of EEG segment by selecting best mother wavelet by using least PRD based wavelet choice criterion . In Sparsification stage threshold the DWT coefficients which are smaller than or equal to certain threshold value which gives significant or non-zero wavelet coefficients as per .This completes the Adaptive decomposition of each EEG block to obtain sparsest version as in (1).The sparse EEG block is further compressed by Gaussian random sensing matrix as in (2).The compressed Single Measurement Vector (SMV) is encoded using static-Huffman technique.

Block –wise signal recovery is performed by applying spgl1-solver toolbox[].BPDN algorithm has been applied to obtain the sparsest representation of the EEG block under consideration, then IDWT is applied on each block by using the same dbi that was used at the compression end .The time-series sequence is further processed by spline interpolation technique to gain back the missing samples .check whether all the EEG blocks have been processed ,if not repeat the steps for consecutive blocks till the end. Concatenate the outputs of spline interpolation phase and form reconstructed EEG segment of 4096 samples. Recovered EEG segment is passed through classifier which decides whether it is epileptic or not.

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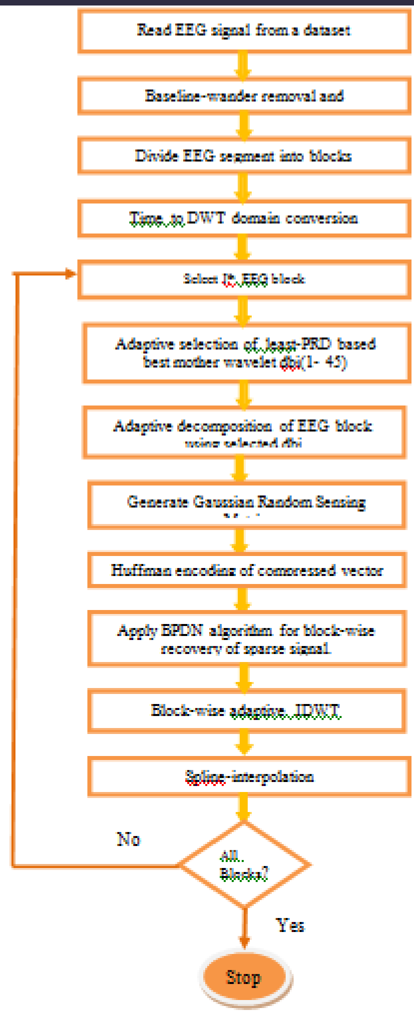

Figure 1 : **Proposed ABSCS algorithm**

Mathematical model of the proposed ABSCS algorithm

Compression Phase:

$$\mathbf{X_{EEG} = \Psi_{SP}\ A} \qquad (1\text{ a})$$

where,

Ψ_{SP} : Adaptive dictionary.

A : RAW EEG signal coefficient vector.

X_{EEG} :Sparse EEG vector.

Ψ_{SP} is chosen by changing DWT daubechies dbi with index 'i' varying between 1 to 45 and subsequently checking its PRD value for each 'i'. Ψ_{SP} which transforms raw EEG signal into least number of non-zero coefficients is chosen as best mother wavelet for the respective block.

Minimum PRD is computed for each EEG block of 512 samples and its corresponding dbi is used for generation of adaptive dictionary Ψsp and is then applied over EEG block under consideration. The wavelet coefficients which are smaller than the threshold (TH) are reduced to zero by using expression in (1b)

$$\mathbf{TH} = \frac{\sigma}{\sqrt{N}}\sqrt{2\log N} \qquad (1b)$$

where,

TH is the threshold,

N is the signal length

σ^2 is the noise variance of the signal.

$\phi_{MxN} \in R_{M\times N}$ is called the Sampling matrix. The number of observations M required to reconstruct the original signal depends on the incoherence between the matrices Ψ_{SP} and ϕ_{MxN}.. For two incoherent, matrices , CS demonstrates that a compressible signal with a sparsity K can be recovered with a higher probability while MIP property ensures that sparse signal reconstruction is possible.

The number of compressed measurements 'M' of each EEG block, block(j) is found as below.

$$\mathbf{M_j \leq K_j / C\log_{10}(N_j/K_j)}\ . \qquad (2)$$

The compressed EEG vector is obtained by

$$\mathbf{Y_{Mx1} = \Phi_S\ X_{EEG}} \qquad (3)$$

where, $\mathbf{\Phi_S}$: Gaussian random sensing matrix.

$\mathbf{Y}$: Compressed vector.

Decompression Phase:

EEG Signal is reconstructed by finding optimal solution applying (4) and BPDN algorithm with l_1-norm.

$$\underset{\mathbf{X_{EEG}}}{\mathbf{Minimize}}\ \|\mathbf{X_{EEG}}\| \quad \mathbf{s.t} \quad \|\boldsymbol{\phi}_s\mathbf{X_{EEG}} - \mathbf{b}\| \leq \boldsymbol{\varepsilon} \qquad (4)$$

where $\boldsymbol{\varepsilon}$ is the approximated noise level in the received data.

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EEG signal recovery is a convex optimization problem (4) and has been solved effectively by spgl1 solver toolbox[12] by taking l_1 norm. For each EEG block the missing samples are estimated using cubic spline interpolation method. Inverse DWT is applied for each of these block obtained above based on the adaptive dictionary constructed at compression side.

V . DATABASE AND METRICS

This section details about the database used for simulation studies and the performance metric equations.

A. EXPERIMENTAL DATABASE

ABSCS algorithm has been evaluated over select records from two different databases namely CHB-MIT Scalp EEG database[13] and EEG signal from RSVP task[14].

EEG signals are openly accessible for research purpose. Only one EEG channel is extracted from the input records and fed as input to ABSCS algorithm.

B. PERFORMANCE MEASURES

Performance of the proposed ABSCS algorithm has been noted using metrics namely execution time in (s), Percentage Root Mean Square Difference (PRD) ,Compression Ratio (CR), Signal to Noise Ratio (SNR), Measurements (M), Energy consumption (ECS), Root Means Square Error(RMSE) and Normalized PRD (PRDN).

$$\mathbf{CR} = \frac{b_{orig} - b_{comp}}{b_{orig}} \text{ x } 100 \qquad (5)$$

where, b_{orig} - bits in raw vector.
b_{comp} - bits in compressed vector.

$$\mathbf{PRD} = \frac{||XEEG - XEEG||}{||XEEG||} \text{ X } 100 \qquad (6)$$

$$\mathbf{SNR} = -20 \ log_{10} \ (0.01 \ PRD) \text{dB} \qquad (7)$$

Reconstruction quality of **"Very good"** class [2] is desirable for clinical acceptability. Table 1 shows the different recovery classes.

Table 1 : PRD and Quality Class [2]

Sl. NO	PRD	Reconstructed Signal Quality
1	0 - 2%	"Very good"
2	2 - 9%	"Very good" or "good"
3	≥ 9%	Not possible to determine the quality group

Energy consumption is computed by following expression:

$$Ecs = 2NEc\sqrt{MN} + MNEc \qquad (8)$$

Table 2: Energy consumption parameters [19].

Parameter	Value
Initial energy in WBAN node, E_0	2 J
Traditional energy consumption , Ee	50nJ/bit
Amplifier energy consumption Eamp	0.01nJ/bit
CS energy consumption, Ec	0.005nJ/bit

VI. RESULTS AND DISCUSSIONS

Simulation experiments have been carried out on MATLAB 2018b software platform over intel i3 processor. Single channel EEG signal from two different databases have been provided as test inputs. Results have been noted for compression and decompression of EEG segments of length 4096 samples and illustrated in table 3 and 4 respectively. The proposed **ABSCS** algorithm is tested for one channel EEG signal with segment length of 1024 samples with fixed window size ,N= 512,for both chbmit and EEG rsvp physionet dataset.Level-6 decomposition is done over each block of EEG data and sparse signal was recovered by solving non-linear convex optimization problem (4) by BPDN algorithm coupled with cubic spline interpolation . 100 rounds for each block has been conducted and then it's average values have been tabulated below.

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Table 3: Performance o f ABSCS algorithm for EEG RSVP physionet dataset.

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EEG record	Execution time(s)	CR	PRD	SNR	M	Ecs (J)	RMSE	PRDN
rsvp_10Hz_02b_edfm	1.750137	64.0803	6.0110e-04	104.421	2023	1.5934e-04	0.0104	8.8018e-04
rsvp_10Hz_03a_edfm	1.486102	63.7784	0.0028	91.0185	2040	1.6018e-04	0.0082	0.0050
rsvp_10Hz_02a_edfm	1.437801	64.0625	0.0023	92.6545	2024	1.5939e-04	0.0114	0.0027
rsvp_10Hz_03b_edfm	1.391137	61.6300	0.0172	75.2981	2161	1.6612e-04	0.0234	0.0173
Average	1.516294	63.3878	5.73E-03 (0.0057)	90.8480	2062	1.61E-04	0.01335	6.47E-03
Max	1.750137	64.0803	1.72E-02	104.421	2161	1.66E-04	0.0234	1.73E-02
Min	1.391137	61.63	6.01E-04	75.2981	2023	1.59E-04	0.0104	8.80E-04

Remark : The average PRD value of 0.0057 is achieved by the proposed algorithm. Record rsvp_10Hz_02b_edfm.mat produced minimum PRD of 6.0110e-04 (0.0006011) and consumes minimum energy by 2023/8= 253 measurements , RMSE and PRDN of 0.0104 and 8.8018e-04.Thus we conclude that proposed ABSCS algorithm is energy efficient.

Table 4: Performance o f ABSCS algorithm for chbmit database

Table 4: Performance o f ABSCS algorithm for chbmit database

EEG record	Execution time(s)	CR	PRD	SNR	M	Ecs (J)	RMSE	PRDN
chb01_01_edfm	3.861825	63.4233	0.2456	52.1963	2060	1.6117e-04	0.0313	0.2504
chb01_04_edfm	1.778199	62.9972	0.2533	51.9266	2084	1.6235e-04	0.0532	0.2535
chb01_07_edfm	1.683949	64.0625	0.2881	50.8091	2024	1.5939e-04	0.0613	0.2882
chb01_08_edfm	1.797291	62.6953	0.1311	57.6480	2101	1.6319e-04	0.0078	0.1313
chb01_09_edfm	2.013084	63.5476	0.1654	55.6311	2053	1.6082e-04	0.0236	0.1654
chb01_10_edfm	1.702924	63.2990	0.1237	58.1525	2067	1.6151e-04	0.0170	0.1246
chb01_11_edfm	1.768710	63.7784	0.1650	55.6498	2040	1.6018e-04	0.0134	0.1650
chb01_12_edfm	2.663144	62.9616	0.0504	65.9554	2086	1.6245e-04	0.0358	0.0508
chb01_13_edfm	1.713632	63.4766	0.1189	58.4955	2057	1.6102e-04	0.0268	0.1190
chb01_14_edfm	1.998070	64.0447	0.2863	50.8634	2025	1.5944e-04	0.0812	0.2868
chb01_15_edfm	1.651985	63.1214	0.0392	68.1384	2077	1.6201e-04	0.0339	0.0417
chb01_16_edfm	1.610350	63.3878	0.0776	62.1995	2062	1.6127e-04	0.0370	0.0785
chb01_17_edfm	2.507284	63.7962	0.1397	57.0958	2039	1.6013e-04	0.0212	0.1417
chb01_18_edfm	1.706307	63.4766	0.0836	61.5597	2057	1.6102e-04	0.0137	0.0843
chb01_19_edfm	1.819448	63.5653	0.0784	62.1134	2052	1.6077e-04	0.0148	0.0823
chb01_20_edfm	1.908118	63.3168	0.1075	59.3721	2066	1.6146e-04	0.0477	0.1078
Average	1.895703	63.48655	0.146625	58.0053	2057	1.61E-04	0.032481	0.148206
Max	2.663144	64.2578	0.2881	68.1384	2101	1.63E-04	0.0812	0.2882
Min	1.61035	62.6953	0.0392	50.8091	2013	1.59E-04	0.0078	0.0417

Compressed ,recovered and error for single channel EEG signal record chb01_15_edfm for segment of 4096 samples is shown in Figure 2 below .

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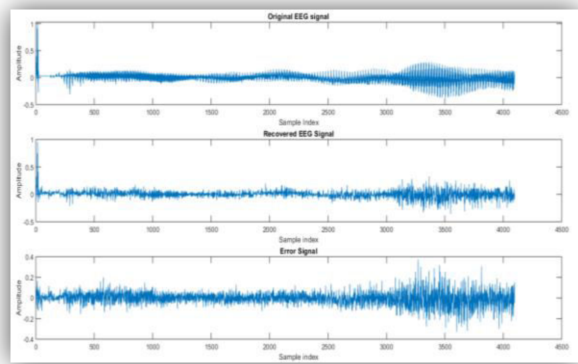
Fig 2: Response of EEG chb01_15_edfm record .



Remark: Simulations have been carried out on select records of chbmit database and experimental results in table 4 illustrates that average values for PRD achieved by proposed algorithm is 0.146625 % and is close to 0% .This indicates that reconstruction capability of the proposed algorithm fits in the range of [0-2%] and recovered signal can be easily used for diagnosis. The average number of measurements required for EEG compression is 2057 for input segment length of 4096 samples divided into 8 blocks each of 512 samples. The mean number of measurements is 2057/8 i.e., 257 which is around 50.19. Even the mean values of RMSE and PRDN values are 0.032481 and 0.148206 which also indicate that recovered EEG signal is of high quality. Minimum PRD value of 0.0339 is achieved for chb01_15_edfm.mat and highest CR was 68.1384 and NMSE computed yielded 0.0328 which is better than [10].

Proposed method, ABSCS compresses other 1-D biomedical signals like Respiratory, PPG effectively but results have been omitted for lack of space.

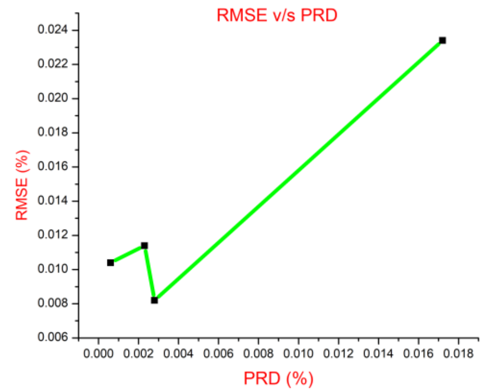


Fig 3: **RMSE v/s PRD**

RMSE increases with PRD values except in the PRD range [0.02 - 0.03].

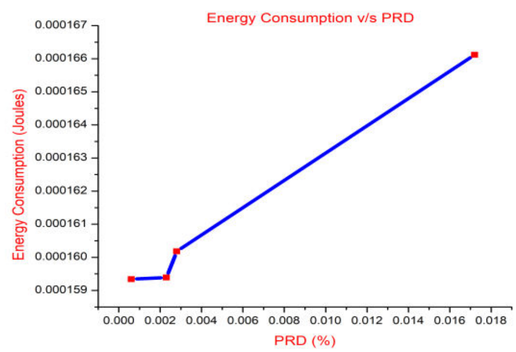


Fig 4: **Ecs v/s PRD**

Energy consumption by ABSCS algorithm increases with PRD .

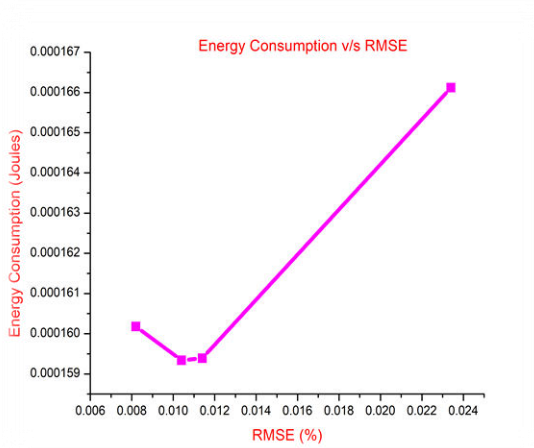


Fig 5: ECS v/s RMSE

Energy consumption increases with RMSE.

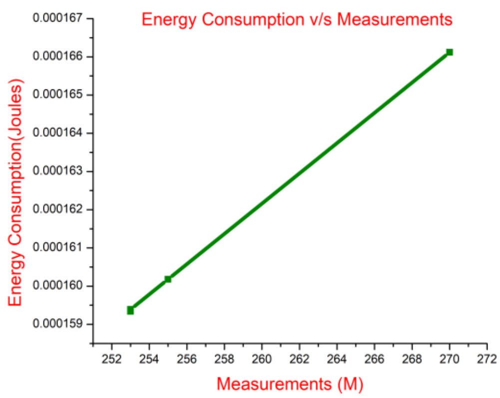


Fig 6: ECS v/s M

Energy consumption linearly increases with Above figures illustrate that Energy consumption for the proposed algorithm is low for lesser M and PRD values.

VII. CONCLUDING REMARKS

The proposed ABSCS algorithm performs block-wise sparsification by adaptively choosing appropriate daubechies wavelet based on minimal PRD value, computed over DWT domain for optimal EEG signal representation. The block-adaptive sparsification strategy in compressive sensing algorithm reduces dimension of single channel EEG signal by hard thresholding method and was tested with inputs from two different datasets. The average values of PRD, RMSE and PRDN metrics achieved by ABSCS algorithm are 0.146625, 0.032481 and 0.148206 for chbmit dataset and 0.0057, 0.01335 and 6.47E-03 for RSVP physionet dataset respectively. Results show that ABSCS algorithm yields least error and recovers signal with higher quality which is useful for medical analysis purposes. It is evident that the proposed ABSCS algorithm can efficiently compress and recover the EEG signals with high fidelity in embedded EEG bio-nodes. Further this work can be extended by improving CR, design of suitable sensing matrix and explore for the MEEG channel compression.

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