On-node Adaptive Block Sparse Compressive Sensing approach for EEG data reduction in WBAN

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**Abstract*:* *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 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.***

1. **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 micro-volts. Typical signals detected on the scalp are in the range 20–150 lV 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 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]. 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 [] 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 ASBCS 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.

1. **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 done in [2] and achieved a 37.1% compare to its DWT counter part. 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 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 proposed for best mother wavelet selection in [18] 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.

1. **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.

1. **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 (ASBCS) 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 (1).

Proposed ASBCS 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.

Spline-interpolation

Read EEG signal from a dataset

Baseline-wander removal and Normalization

Divide EEG segment into blocks

Time to DWT domain conversion

Adaptive selection of least-PRD based best mother wavelet dbi(1- 45)

Adaptive decomposition of EEG block using selected dbi

Generate Gaussian Random Sensing Matrix

Apply BPDN algorithm for block-wise recovery of sparse signal.

Block-wise adaptive IDWT

Huffman encoding of compressed vector

All Blocks?

Select Jth  EEGblock

NO

YES

Yes

No

Figure 1 : **Proposed ASBCS algorithm**

***Mathematical model of the proposed ASBCS algorithm***

**Compression Phase:**

**XEEG = ΨSP A** (1 a)

where,

**ΨSP** : Adaptive dictionary.

A : RAW EEG signal coefficient vector.

X **EEG** :Sparse EEG vector.

ΨSP is chosen by changing DWT daubechies dbi with index ‘i’ varying between 1 to 45 and subsequently checking its PRD value for each ‘i’. ΨSP 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 zeroed by using expression in (1b)

(1b)

where, TH is the threshold, N is the signal length and  is the noise variance of the signal.

ϕMxN ϵ RM×N is called the Sampling matrix. The number of observations M required to reconstruct the original signal depends on the incoherence between the matrices ΨSP and ϕMxN..  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.

**Mj ≤ Kj / C log10 (Nj /Kj) ,** (2)

The compressed EEG vector is obtained by

**YMx1 = ϕS XEEG** (3)

where, **ϕS** : Gaussian random sensing matrix.

**Y** : Compressed vector.

**Decompression Phase:**

**EEG Signal is reconstructed**  by finding optimal solution applying (4) and BPDN algorithm with Ɩ1-norm.

(4)

where is the approximated noise level in the received data.

EEG signal recovery is a convex optimization problem (4) and has been solved effectively by spgl1 solver toolbox [12] by taking l1 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 database used for simulation studies and the performance metric equations.

1. **EXPERIMENTAL DATABASE**

ASBCS 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 ASBCS algorithm.

1. **PERFORMANCE MEASURES**

Proposed ASBCS algorithm has been noted using metrics execution time in (s), Percentage root namelymean square difference (PRD) ,Compression Ratio (CR), Signal to Noise Ratio (SNR), Measurements (M), Energy consumption (ECS),RMSE and PRDN .

**CR = ** (5)

where, - bits in raw vector.

**-**  bits in compressed vector.

**PRD =** (6)

**SNR =** dB (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:

(8)

**Table 2:** Energy consumption settings [19].

|  |  |
| --- | --- |
| **Parameter** | **Value** |
| **Initial energy in WBAN node, E0** | 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 **ASBCS** algorithm was tested for one channel EEG signal with segment length of 1024 samples with fixed window size ,N= 512,for both EEG datasets namely chbmit and EEG rsvp physionet dataset.

Level-6 decomposition was 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 average values have been tabulated below.

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

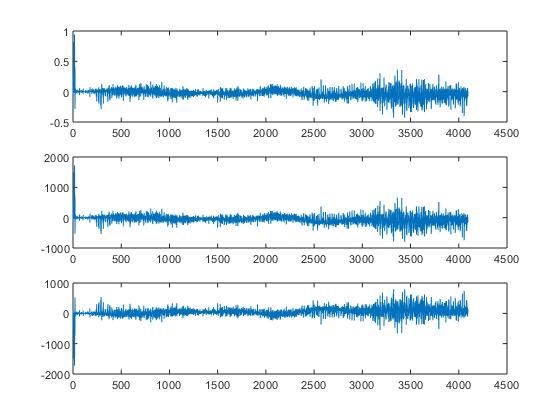
|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **EEG record** | **Execution time(s)** | **CR** | **PRD** | **SNR** | **M** | **Ecs (J)** | **RMSE** | **PRDN** |
| **rsvp\_10Hz\_02b\_edfm** | **1.750137** | **64.0803** | **6.0110e-04** | **104.421** | **2023** | **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 was 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 proposed compressive sensing algorithm is energy efficient.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **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** |

**Table 4: Performance o f ASBCS algorithm for chbmit database**

Compressed ,recovered and error for single channel EEG signal record chb01\_15\_edfm for segment of 4096 samples is shown in Figure 2below .

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**Fig 2: Response of EEG chb01\_15\_edfm record .**

**Remark:** Simulations were 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 was 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 compresses other 1-D biomedical signals like Resp,PPG but have been omitted for lack of space.

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

RMSE increase with PRD values.

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

Energy consumption by ABSCS algorithm increases with PRD .

Fig 5: **ECS v/s RMSE**

CS Energy consumption increases with RMSE .

1. **CONCLUDING REMARKS**

The proposed ASBCS 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 ASBCS algorithm are 0.146625, 0.032481 and 0.148206 for chbmit dataset and 0.0057, 0.01335 and 6.47E-03 for EEG RSVP physionet dataset respectively. Results show that ASBCS algorithm yields least error and recovers signal with higher quality which is useful for medical analysis purposes. It is evident that the proposed ASBCS 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.

**REFERENCES**

[1] V. Mihajlovi, B. Grundlehner, R. Vullers, and J. Penders, “Wearable,wireless EEG solutions in daily life applications: What are we missing? ”, *IEEE Journal of Biomedical and Health Informatics*, vol. 19,no. 1, pp. 6–21, Jan 2015.

[2] Mamaghanian et al.,“Compressed Sensing For Real-Time Energy-Efficient EEG Compression On Wbsn”,

*IEEE transactions on biomedical engineering*, vol. 58, no. 9, september 2011.

[3]. Jun Zhang, Liang Yuand Yuanqing Li, “Energy-Efficient EEG Compression on Wireless Biosensors via Minimal Coherence Sensing and Weighted l1 Minimization Reconstruction”, *IEEE Journal Of Biomedical And Health Informatics*, vol. 19,issue 2, march 2015.

[4] J. Gotman, ‘‘Automatic detection of seizures and spikes,’’ *J. Clin. Neurophysiol.*,vol. 16, no. 2, pp. 130–140, 1999.

[5] Mousavi S, Afghah F, Acharya UR (2019, “SleepEEGNet: Automated sleep stage scoring with sequence to sequence deep learning approach.”, PLoSONE 14(5): e0216456.

[6] Guillermo Dufort, Federico Favaro, Federico Lecumberry, “Wearable EEG via lossless compression”, IEEE,2016

[7] Zhilin Zhang,Tzyy-Ping Jung,, Scott Makeig, Zhouyue Pi,Bhaskar D. Rao,“ Applications to Compressed Sensing of Multichannel Physiological Signals”, *IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING*, 2014. DOI: 10.1109/TNSRE.2014.2319334

[8] Andrianiaina Ravelomanantsoa, Hassan Rabah, and Amar Rouane, “Simple and Efficient Compressed Sensing Encoder for Wireless Body Area Network”, *IEEE Transactions On Instrumentation And Measurement*, VOL. 63, NO. 12, DECEMBER 2014

[9] Zhilin Zhang, Tzyy-Ping Jung, Scott Makeig, and Bhaskar D. Rao, “Compressed Sensing of EEG for Wireless Telemonitoring With Low Energy Consumption and Inexpensive Hardware”, *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, VOL. 60, NO. 1, JANUARY 2013.

[10] A. Shukla, A. Majumdarm, “ Exploiting inter-channel correlation in EEG signal reconstruction”, *Elsevier, Biomedical Signal Processing and Control* ,(2015),pp 49–55.

[11] WazirSingh, AnkitaShukla, SujayDebn, Angshul Majumdar, “Energy efficient EEG acquisition and reconstruction for a Wireless Body Area Network ”,*Elsevier,INTEGRATION,theVLSIjournal* (2017), pp 295–302.

[12]<http://www.cs.ubc.ca/labs/scl/spgl1>[online]. E.vanden Berg and M. P. Friedlander, “SPGL1: A solver for large-scale sparse reconstruction,” April 2015.

[13]MIT-BIH arrhythmia database [online], [www.physionet.org/mitdb/-](http://www.physionet.org/mitdb/-) last accessed on 14/09/2017.

[14] CHB-MIT Scalp EEG database [online], <https://archive.physionet.org/physiobank/database/chbmit/> -last accessed on 07/08/2019

[15] EEG signal from RSVP task[online] : Matran-Fernandez A, Polo R (2017), “Towards the automated localisation of targets in rapid image-sifting by collaborative brain-computer interfaces”, PLoSONE,vol12,issue5,e0178498.

[16] Emmanuel J. Candès, Michael B. Wakin, “An Introduction to Compressive Sampling”, *IEEE signal processing magazine*, March 2008, pp:21-30

[17].Laurent Brechet, Marie-Françoise Lucas, Christian Doncarli, and Dario Farina, “Compression of Biomedical Signals With Mother Wavelet Optimization and Best-Basis Wavelet Packet Selection”, *IEEE*

*Transactions On Biomedical Engineering*, vol. 54, issue 12, December 2007.

[18] Veer Amol Motinath, Chandan Kumar Jha, Maheshkumar H. Kolekar, “A Novel EEG Data Compression Algorithm using Best Mother Wavelet Selection”, *IEEE Intl. Conference on Advances in*

*Computing, Communications and Informatics (ICACCI),* Sept. 21-24, 2016, Jaipur, India.

[19].Dapeng Wu,Boran Yang,Honggang Wang,Dalei Wu And Ruyan Wang, “An Energy-Efficient Data

Forwarding Strategy for Heterogeneous WBANs”, *IEEE access*, Volume 4, 2016.

[20] Zhijun Pei, Yaxin Wang. "Energy Efficient

Compressed Sensing of Bio-Signals with Sparse

Binary Matrix",4th International Conference on Information Science and Control Engineering (ICISCE), 2017.

[21] A. H. Beg, Md Zahidul Islam, “A novel genetic

algorithm-based clustering technique and its

suitability for knowledge discovery from a brain

data set", 2016 IEEE Congress on Evolutionary

Computation (CEC), 2016.