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Improved energy efficient design in software defined wireless electroencephalography sensor networks (WESN) using distributed architecture to remove artifact

M. Manojprabu, V.R. Sarma Dhulipala

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IMPROVED ENERGY EFFICIENT DESIGN IN SOFTWARE DEFINED WIRELESS ELECTROENCEPHALOGRAPHY SENSOR NETWORKS (WESN) USING DISTRIBUTED ARCHITECTURE TO REMOVE ARTIFACT

[*1]M.Manojprabu and [2]V.R.Sarma Dhulipala

[*1]Assistant Professor, Electronics and Communication Engineering, Angel College of Engineering and Technology, Tirupur. E-mail: manojprabumanoharan@gmail.com

[2]Assistant Professor, Physics, Anna University BIT Campus, Tiruchirappalli. E-mail: dvrsarma@gmail.com

Abstract:

Software Defined Networking (SDN) has focused enormous attractiveness in changing conventional network by means of offering flexible and dynamic network management. It has drawn important concentration of the researchers from together academia and industries. Mainly, integrating SDN in Wireless Body Area Network (WBAN) applications specifies capable results in terms of handling with the issues like traffic management, security, energy efficiency etc. Recent improvements in miniaturization and energy efficient physiological sensor designs in SDN based Wireless Body Area Networks (WBANs) paved the way for health monitoring systems for collection and processing the real-time physiological data. The collection of signals from different sensor allows reliable diagnosis in heterogeneous than in homogeneous WBANs. Inspired by the evolutions of heterogeneous WBANs, a study on Wireless Electroencephalography Sensor Networks (WESNs) is carried out under distributed signal processing. The distributed WESNs are designed under two different hierarchy i.e. Hierarchical Fully-Connected Topology (HFCT) and Ad-Hoc Nearest-Neighbor Topology (ANNT) to improve the energy-efficiency using distributed Multi-channel Weighted Weiner Filter design (MW2F). Here, each module transmits linear combination of local channels with other modules. The power efficiency is improved in MW2F signal processing algorithm by avoiding centralization of EEG data. A case study is carried out to test the reduced energy consumption after the removal of eye blink artifacts and it is tested with centralized counterparts. The MW2F is evaluated in both topologies against centralized environments and significant reduction of eye blink artifacts improves the energy efficiency in HFCT than other topologies.

Keywords: WBANs, WESNs, ANNT, HFCT, MW2F and centralized topology

1. Introduction

The energy efficient and miniaturization is the most hot research area in health monitoring systems, where the body is placed with several sensor nodes. These nodes can collect the EEG data and process it in real time and measures are considered to improve the energy efficiency. This system is called as Wireless Body Area Networks (WBANs) [1], and it offers higher demand in the area of physiological monitoring in hospital environment. The WBAN system is composed of several nodes with physiological sensors, wireless communication devices and a signal processing unit. These nodes can communicate with other sensor nodes placed over the body or it can be connected to a fusion center or a storage device. The signals collected from various resources are analyzed jointly in heterogeneous WBANs in real time environment for medical diagnosis.

The mini-scale sensor network in WBANs acquired its recent attention in many monitoring applications. It offers low power consumption with extreme miniaturization and it facilitates minor for a longer-term. Despite miniaturization, the monitoring the physical activity using sensor nodes increases steadily with per node density, thus allowing for robust miniaturized recording with high temporal resolution and spatial coverage. This tends to generate larger amount of data that makes the system to necessitate huge time interval and power for transmitting and processing the raw EEG signal in real time. Hence, it requires some novel signal processing algorithms [2], where some of which includes wavelet based [3], Bayesian [4], Neural Networks [5], Set Partitioning in Hierarchical Trees (SPIHT) [6] etc. to improve the energy efficacy.

Though, many algorithm exist to improve the energy efficiency in WESN, a very few studies reported to analyse the activity of brain signals. The analysis on brain signal is not an easier task, since the signals are of non-stationary, multichannel and contaminated with by eye blinks, eye movements, heartbeats, muscle activity and power line noise [7]. This ocular artifact poses severe constraints on interpreting the EEG data. The manual segmentation of these artifacts requires a technician and it is considered as time consuming to fragment the segments. Also, it leads to severe data loss and in recent past, the removal of artifacts is a major study [8] [9] in WESN. The present study considers eyeblink involuntary behavior in EEG signal. Certain approaches lies on reducing the ocular artifacts using regression analysis[8] [9][10], Principal component analysis (PCA) [11],Independent Component Analysis (ICA)[12], DANSE filtering [13] and other related approaches [14] – [20].We evaluated PCA and ICA according to only one criterion, recognition rate, even though other criteria such as computational cost may also apply. Most significantly, although we measured the effects of different ICA algorithms and PCA distance metrics, we cannot explain these differences in terms of the underlying data distributions. As a result, it is difficult to predict the best technique for a novel domain. In order to overcome the disadvantages of existing algorithms, a new algorithm is proposed in this work.

In this paper, a multichannel Weighted Weiner filter is used to find the neural activity of EEG signal and it effectively removes the eye blink artifacts. It uses two different architectures and the filtering is tested on HFCT and ANNT to improve the energy-efficiency.

The outline of the paper is presented as follows: Section 2 provides the data model, section 3 discusses the proposed system. Section 4 evaluates the present research and finally section 5 concludes the paper.

2. Data model and notation

The proposed study uses a 75 electrodes set and the data collected out from the electrodes in each sensor is divided into L frames. The k^{th} frame of n^{th} sensor is expressed in terms of vector-matrix notation combined with linear mixing model, which is given as below:

$$y_n(k) = x_n(k) + v_n(k)(1)$$

where n = 1, 2,..., N,$x_n(k)$ is the original eye-blink component of size L and $v_n(k)$is the pure EEG vector of size L.

In order to obtain a completeness using Eq.(1), a cross-correlation matrix is obtained using arbitrary column vectors $a(k)$ and $b(k)$ as

$$R_{ab} = E[a(k)b^T(k)](2)$$

where $E\{.\}$ is represented as the expectation operator, and $(.)^T$ represents the transpose of a matrix. The Eq.(2) stands true for chosen arbitrarily point.

3. Proposed Method

This section provides the details of implementing the Multi-channel Weighted Weiner Filter in removing the eye blink artifacts under Hierarchical Fully-Connected Topology (HFCT) and Ad-Hoc Nearest-Neighbor Topology (ANNT) topologies. Both the topologies act in a distributed fashion and it adopts low dimensional features to eliminate the sources of eye blink artifacts. The details of both the topologies adoption the Multi-channel Weighted Weiner Filter is given below is shown in the figure 1:

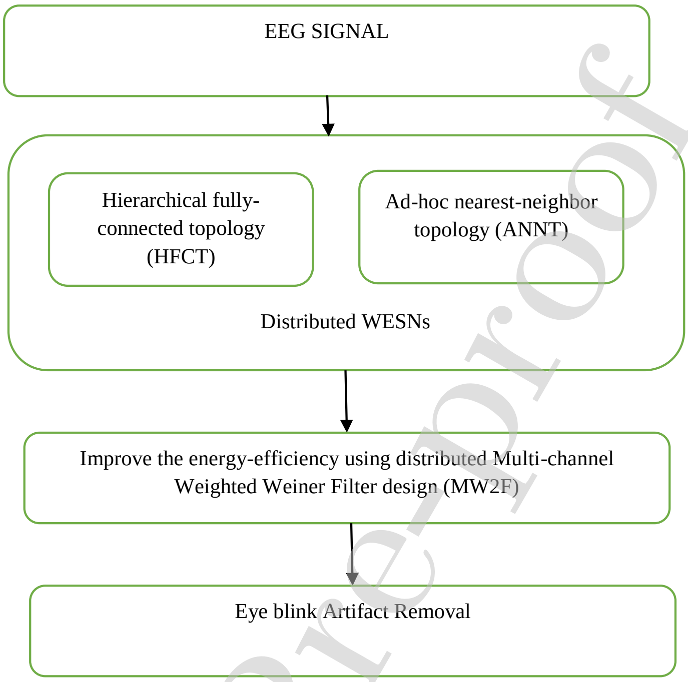


Figure 1: Proposed Methodology Diagram

a. Topologies used to Improve Energy Efficiency

i. HFCT

The distributed hierarchical topologies HFCT and ANNT use various electrodes that are clustered into 11 zones. This is represented as an 11-zone structured WESN, where each zone has an electrode array with 64 slave nodes are connected via short range wireless connection any one of the zones called Master. The Master zone ensures that it is highly powerful and has longer transmission range than slave nodes. The entire setup of HFCT is shown in Figure 2.

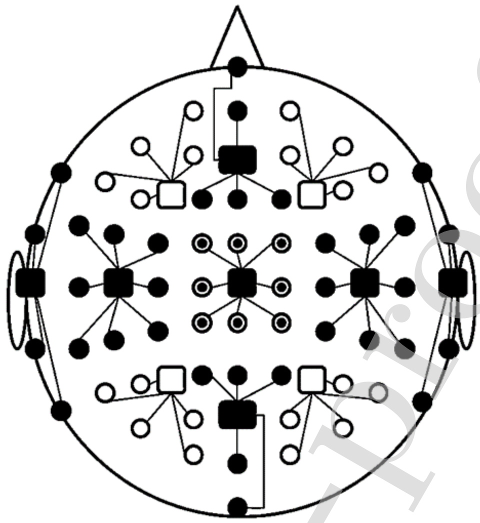


Figure 2: 75 electrodes with HFCT over WESN

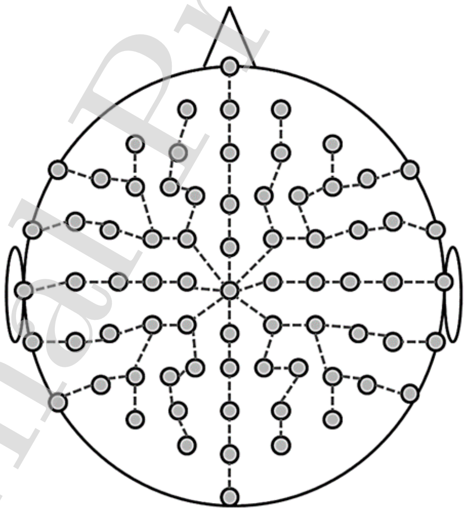


Figure 3: 75 electrodes in the form of tree topology over WESN

Such a mode of connectivity helps in providing full connectivity across all sensor nodes within zones. This accounts for faster data diffusion and eliminates feedback paths, whenever there is a flow in data between the nodes. Hence, it is very necessary to utilize distributed signal process and estimation algorithm.

The fully connected distributed topology often suffers from power usage due to longer transmission range. Since, the data transmission between the nodes placed on head requires larger power for transmission. This leads to increased attenuation of EM waves. Hence, it is very necessary for the master node to use a tree type topology (see Figure 3) for interconnection between the sensor nodes, which often reduces the power required for transmission.

Further, the adoption of distributed topologies for signal processing in WESN distributed architecture allows massive parallelization and it maps directly with the modular WESN architecture using low-power processors. It also reduces the communication cost between any two nodes, since the data is sent in a compressed manner. The nearest neighbor communication between the electrodes further reduces the attenuation of EM waves. This ensures that the distributed data compression algorithm makes the WESN highly scalable compared with centralized algorithm that operates on multi-hop fashion. The distributed process also reduces the cost associated with high-density wired electrode grids and finally the data rate is reduced i.e. between the data bus and this is reduces using data compression algorithm.

The availability of multi-channel in WESN requires centralization of data during the adoption of correlation between the nodes. This is considered challenging while design a distributed algorithm and this is resolved using a distributed realization on multi-channel signal processing task. Such distributed realization in multi-channels EEG processing is carried out through both the distributed topologies, namely, HFCT and ANNT. Further, a case study on removing the eye blink artifact is considered and this is removed using a multi-channel Weighted Wiener filter. The discussion on improving the transmission power efficiency is discussed in following sub-sections.

ii. ANNT

The proposed method uses ANNT with a set of 75-node electrodes (shown in Figure 4) that communicates with its nearest neighboring sensor node. Due to the availability of larger number of links, the ANNT can diffuse the information more quickly even if the communication is of a short distance type. The system gets more robust as the redundancy increases between the communication links. This is prominently due to the breakdown of links prior the division of network into two parts, which are not linked with each other.

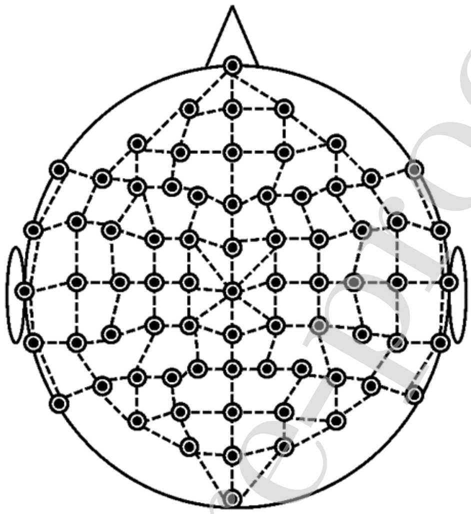


Figure 4: 75 electrodes with ANNT over WESN

Multi-Channel Weighted Weiner Filter

In filtering, we tend to estimate the presence of artifact component rather than estimating the clean EEG signal and finally subtracting it from the observation EEG signal vector. The eye-blink component is found by the application of linear transformation on the observation EEG signal vector:

$$\begin{aligned} x_n'(k) &= H_n y(k) \\ x_n'(k) &= H_n\left[x(k)+v(k)\right] \end{aligned} \qquad (3)$$

and H_n is regarded as the filtering matrix of $L \times LN$. Thus the error is given by:

$$e_n(k) = x_n'(k) - x_n(k) \qquad (4)$$

The filtering matrix is thus minimized using a mean square error (MSE):

$$J(H_n) = tr\left[e_n(k)e_n^T(k)\right] (5)$$

$$\frac{dJ\left(H_n\right)}{dH_n}=0 \quad (6)$$

$$H_n = R_{x_n y} R_{yy}^{-1} \quad (7)$$

The matrix $R_{x_n y}$ cannot be directly estimated as the $x_n(k)$ is not observable.

Thus considering the artifact and clean EEG signal as uncorrelated, stationary and zero-mean processes, the correlation matrix for an observation EEG signal is given by,

$$R_{yy} = R_{xx} + R_{vv} \quad (8)$$

And $R_{x_n y}$ can be verified using following expression,

$$R_{x_n y} = U_n(R_{yy} - R_{vv}) \quad (9)$$

Finally, by substituting (9) into (7) we obtain:

$$H_n = U_n\left[I_{NL\times NL} - R_{vv}R_{vv}^{-1}\right] \quad (10)$$

It is observed that the estimation of artifacts can lead to better estimation of observation signal.

Finally, if eye-blink artifact is $v_n(k)$ for estimating the EEG signal $x_n(k)$), then R_{vv} is estimated using

$$R_{vv} = R_{yy} - R_{xx} \quad (11)$$

Eye blink Artifact Removal

The most common artifact is the eye blink artifacts that occurs prominently in EEG recordings. To achieve effective data compression on EEG signals, the removal of artifacts should be considered first. This can be eliminated using proper filtering techniques, however, the design and analysis in removing the eye blink artifacts in distributed topology is considered challenging, since some of the EEG data is of centralized one.

To resolve the challenges associated with eye blink artifact removal, distributed algorithms are to be carried out to analyse and remove the presence of artifacts in EEG signal. The proposed method uses a multi-channel Weighted Weiner (MW2) Filter to find the artifact. The MW2 filter creates of linear combination of the signals obtained from the sensors. The MW2 filter operates entirely on a linear data model and it is applicable on signal enhancement problem.

Considering Eq.(1), the total number of EEG electrodes, N = 75 and hence the pure EEG signal is estimated at n^{th} electrode is given as follows:

$$v_n(k) \approx y_n(k) - x'_n(k) \qquad (12)$$

$$v_n(k) = y_n(k) - H_n y(k) \ (13)$$

The signal-to-noise ratio (SNR) improves the effectiveness of Weighted Wiener filtering. If the average estimated signal power is lesser than the observation signal power, then the effectiveness of filter is reduced. To improve the effectiveness of filter, Eq.(12) is not used directly, rather the MW2 filter based eye-blink components are estimated only on frontal electrodes. Here, regression analysis [21] is used for finding the pure EEG signals, which is represented as follows:

$$v_m(k) = y_m(k) - \alpha_m z(k), \ (14)$$

where m = 1, 2,..., M, $z(k)$ is the clean EEG signal, $\alpha_m$is attenuation factor, which is a time independent one. Hence, the correlation between EEG signal and $y_m(k)$ is given as:

$$\mathrm{tr}E\{y_m(k)z^T(k)\} = \alpha_m \mathrm{tr}E\{z(k)z^T(k)\} + \mathrm{tr}E\{v_m(k)z^T(k)\} \ (15)$$

Assuming, EEG signal as uncorrelated with zero mean, i.e. E$\{v_m(k)z^T(k)\}$ is 0 and then solving α_m, the following expression is obtained,

$$m = \mathrm{tr}[R_{ym}z] \,/\, \mathrm{tr}[R_{zz}] \ (16)$$

where, $R_{ym}z$ and $R_{zz}$is the correlation matrix and it is calculated by averaging the products of the observation EEG signal and EEG signal vector, respectively.

It is seen from [21] that the voltages of eye-blinks propagates very contrarily than the potentials in relation with the movements of eyes. However, the regression analysis as in Eq.(13) can be applied for the eye-blink correction. Upon the removal of some interferences from EEG signal, the differences in the propagation factors of blink and non-blink artifacts should also be eliminated from EEG signal.

Further, the presence of additional electrodes are not considered and the corrections are subjected to the correction of artifacts. Hence, the following substitution is used in this process, which is given below:

$$z(k) = x'_r(k) = H_r y(k), \text{ where } 1 \leq r \leq N, \quad (17)$$

where r is the index and this defines the reference electrode.

As per the model of Eq.(1) and Eq.(13), it can be inferred that a signal $x_m(k) = \alpha_m z(k)$ is an attenuated eyeblink signal. Thus $z(k)$ in Eq.(14) is replaced with$z'(k) = Bz(k)$, then $\alpha_m = \alpha_m/B$. Meanwhile the expression $\alpha_m z(k) = \alpha'_m z(k)$, an equivalent is obtained by replacing $x'_r(k) \approx x_r(k)$ in Eq.(13) and Eq.(14) instead of $z(k)$ and B is a bias factor.

The MW2 filtering estimates the eye-blink components easily and estimates in a faster way and this is possible using its weighted function on eye-blinks components,

$$z(k) = \frac{1}{\|w\|} \sum_{n=1}^{N} w_n x'_n(k) \quad (18)$$

where w_n is referred as a weighting factor and ||.||is the squared L2 norm.

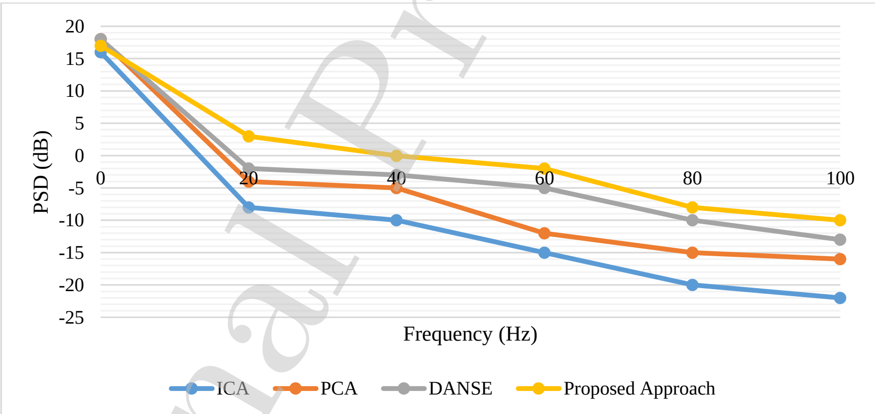
These factors can be set as constant values, which shows the influence of the artifacts on a sensor. However, in MW2 filter, the noise estimation is dependent on SNR, hence it is assumed that,

$$w_n = SNR_n = \frac{tr\left[R_{x_n x_n}\right]}{tr\left[R_{v_n v_n}\right]} = \frac{tr\left[R_{y_n y_n}\right]}{tr\left[R_{v_n v_n}\right]} - 1 \quad (19)$$

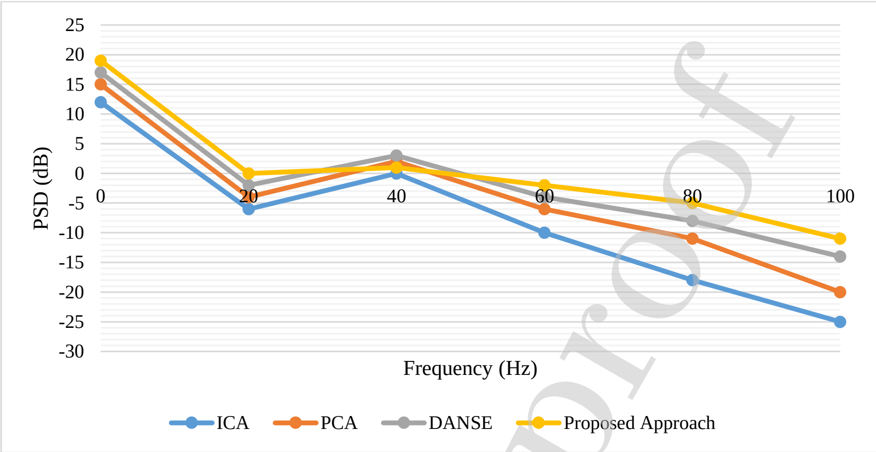
Thus the impact of the EEG electrodes are maximized with high SNR. Also, the eye-blink artifact is considered as a signal and the neural activity of brain as a noise. These assumptions helps in finding out the eye blink artifacts in EEG signal.

4. Results and Discussions

The present research addresses the issues associated with larger electrodes. The observation signals from the electrodes are filtered (band pass filtering) to average reference of range 0.1 to 100 Hz. The measuring index is expressed using signal distortion and attenuation of eye blink artifacts. A log-spectral distance between clean and filtered eye-blink artifact free segment is used to measure the signal distortion. A log-spectral distance between clean and filtered eye-blink artifact segment is used to measure the attenuation.



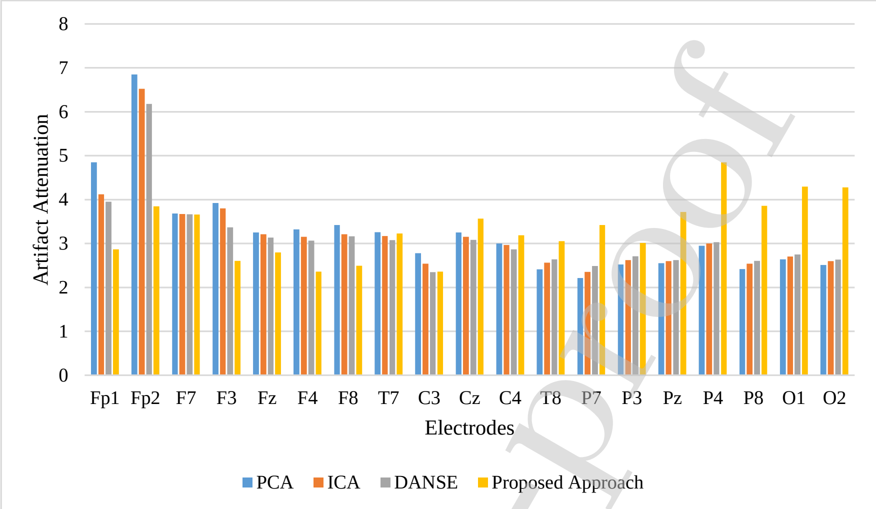
(a)



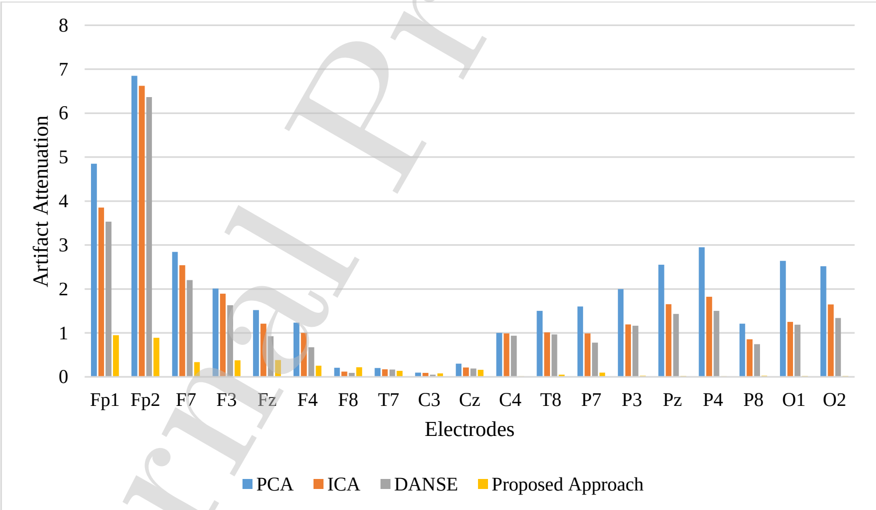
(b)

Fig. 6. PSD of EEG segments and filtered segments obtained using DANSE and MW2 filtering (for N = 3 and L = 15): (a) eye-blink artifact segment, and (b) eye blink artifact free segment.

The power spectral density (PSD) of the obtained segments are given in Figure 6. The PSD of eye blink artifact segment and the filtered segment is found to high than the PSD of clean and filtered segment. Also, the difference is very negligible using the proposed filtering approach. The proposed approach provides better results of PSD when compared with the other existing approaches like PCA, ICA and DANSE. The proposed approach shows 5% performance improvement when compared with the other existing approaches.



(a)



(b)

Figure 7 Quality measures for all EEG electrodes between the proposed and existing methods (a) eye-blink artifact attenuation (b) signal distortion

Figure 7 provides the results of Eq.(22) and Eq.(23) of proposed and existing DANSE approach on all electrodes. The proposed method outperforms the existing approach with regards to signal distortion. In terms of eye blink artifact attenuation, the existing method performs better than the proposed one for the backward and central electrodes. The proposed method however performs optimal for frontal electrodes. The proposed approach provides better results of artifacts attenuation when compared with the other existing approaches like PCA, ICA and DANSE.

5. Conclusions

In this paper, HFCT based distributed Multi-channel Weighted Weiner Filter and ANNT based distributed Multi-channel Weighted Weiner Filter are proposed for reducing the consumption of energy in WESN based on SDN. The results of distributed MW2 filtering under two topologies shows that there exist an average improvement in energy consumption by the proposed system than other centralized or distributed architectures. The case study on removing the eye blink artifacts is carried out effectively to improve the energy consumption in distributed environment. This effectively improves the energy utilization in both the topologies, which is possibly reduced using distributed MW2 filtering. Considerably, the communication cost is reduced to a greater extent than the existing methods. Further, the proposed system can be improved with high correlation techniques to eliminate the noises formed during eye blink artifacts in EEG signal.From the simulation result the proposed approach provides 5% better results of artifacts attenuation when compared with the other existing approaches like PCA, ICA and DANSE.

Future work will include the implementation of the proposed solutions in real medical devices, as well as repeating these tests on a larger scale testbed. Overall, we believe that the intelligent implementation of the solutions proposed in a self-organized WSN will pave the way for a pervasive healthcare system that is free of economic burdens and is able to focus on the real needs of patients regardless of their age span.

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AUTHOR DECLARATION

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

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Signed by all authors as follows:

Mr.M.Manojprabu

Dr.V.R.Sarma Dhulipala

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IMPROVED ENERGY EFFICIENT DESIGN IN SOFTWARE DEFINED WIRELESS ELECTROENCEPHALOGRAPHY SENSOR NETWORKS (WESN) USING DISTRIBUTED ARCHITECTURE TO REMOVE ARTIFACT

M.Manojprabu - Conceptualization, Methodology, Data curation, Writing- Original draft preparation, Visualization, Investigation.

V.R.Sarma Dhulipala- Validation, Reviewing and Editing