MULTIVARIATE EMD AND DEEP LEARNING BASED ARTIFACTS REMOVAL FROM EEG SIGNAL

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***Abstract*: The main aim of this project is to design and develop a technique for the removal of artifacts that occur while performing the EEG experiments on human brain. Initially, the EEG signal will be subjected to Pre-processing in order to improve the quality of the signal and to make it suitable for the successive step of feature extraction. Feature extraction process will be done using the Multivariate EMD, and hence the features are extracted from the pre-processed signal. The presence of artifacts will be removed using the Deep Learning Algorithm (DLA) with the Long Short Term System (LSTM) on the extracted feature. Training of deep learning will be done using the empirical mode decomposition signal. The implementation will be done using MATLAB and the performance of the proposed method will be compared with the existing works, such as ICA, WICA, FICA based on Mean Squared Error (MSE), Root Mean Square Error (RMSE), and signal to Noise Ratio (SNR).**

***Keywords*-Multivariate EMD, deep learning algorithm, long short term memory.**

I. INTRODUCTION

Electroencephalography is an electrophysiological monitoring method to record electrical activity of the brain. It is typically noninvasive with the electrodes place along the scalp, although invasive electrodes are sometimes used such as in electrocardiography. EEG measures voltage fluctuation resulting from ionic current in the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus either on event-related potentials or on the spectral content of EEG. EEG is most often used to diagnose epilepsy, which causes abnormalities in EEG readings. It is also used to diagnose sleep disorders, depth of anesthesia, coma, encephalopathies, and brain death. EEG used to be a first-line method of diagnosis for tumors, stroke and other focal brain disorders. But this use has decreased with the advantage of high-resolution anatomical imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). Despite limited spatial resolution, EEG continues to be a valuable tool for research and diagnosis. It is one of the few mobile techniques available and offers millisecond-range temporal resolution which is not possible with CT, PET or MRI. Derivatives of the EEG technique include evoked potentials (EP), which involves averaging the EEG activity time-locked to the presentation of a stimulus of some sort (visual, somatosensory, or auditory). Event-related potentials (ERPs) refer to averaged EEG responses that are time locked to more complex processing of stimuli; this technique is used in cognitive science, cognitive psychology, and psychophysiological research.

Mechanim

The brain's electrical charge is maintained by billions of neurons. Neurons are electrically charged (or "polarized") by membrane transport proteins that pump ions across their membranes. Neurons are constantly exchanging ions with the extracellular milieu, for example to maintain resting potential and to propagate action potentials. Ions of similar charge repel each other, and when many ions are Mechanisms pushed out of many neurons at the same time, they can push their neighbors, who push their neighbors, and so on, in a wave. This process is known as volume conduction. When the wave of ions reaches the electrodes on the scalp, they can push or pull electrons on the metal in the electrodes. Since metal conducts the push and pull of electrons easily, the difference in push or pull voltages between any two electrodes can be measured by a voltmeter. Recording these voltages over time gives us the EEG.

The electric Potential generated by an individual neuron is far too small to be picked up by EEG or MEG. EEG activity therefore always reflects the summation of the synchronous activity of thousands or millions of neurons that have similar spatial orientation. If the cells do not have similar spatial orientation, their ions do not line up and create waves to be detected. Pyramidal neurons of the cortex are thought to produce the most EEG signal because they are well-aligned and fire together. Because voltage field gradients fall off with the square of distance, activity from deep sources is more difficult to detect than currents near the skull.

Scalp EEG activity shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges, spatial distributions and are associated with different states of brain functioning (e.g., waking and the various sleep stages). These oscillations represent synchronized activity over another work of neurons. The neuronal networks underlying some of these oscillations are understood (e.g., the thalamo cortical resonance underlying sleep spindles), while many others are not (e.g., the system that generates the posterior basic rhythm). Research that measures both EEG and neuron spiking finds the relationship between the two is complex, with a combination of EEG power in the gamma band and phase in the delta band relating most strongly to neuron spike activity.

Biological artifacts:

EEG data is almost always contaminated by such artifacts. The amplitude of artifacts can be quite large relative to the size of amplitude of the cortical signals of interest. This is one of the reasons why it takes considerable experience to correctly interpret EEGs clinically. Some of the most common types of biological artifacts include:

1. Eye-induced artifacts (includes eye blinks, eye movements and extraocular muscle activity)
2. ECG (cardiac) artifacts
3. EMG (muscle activation)-induced artifacts
4. Gloss kinetic artifacts

The most prominent eye-induced artifacts are caused by the potential difference between the cornea and retina, which is quite large compared to cerebral potentials. When the eyes and eyelids are completely still, this cornea-retinal dipole does not affect EEG. However, blinks occur several times per minute, the eyes movements occur several times per second. Eyelid movements, occurring mostly during blinking or vertical eye movements, elicit a large potential seen mostly in the difference between the EOG channels above and below the eyes. An established explanation of this potential regards the eyelids as sliding electrodes that short-circuit the positively charged cornea to the extra-ocular skin. Rotation of the eyeballs, and consequently of the cornea-retinal dipole, increases the potential in electrodes towards which the eyes are rotated, and decrease the potentials in the opposing electrodes. Eye movements called saccades also generate transient EMG potentials, known as saccadic spike potentials (SPs).

The spectrum of these SPs overlaps the gamma-band, and seriously confounds analysis of induced gamma-band responses, requiring tailored artifact correction approaches. Purposeful or reflexive eye blinking also generates EMG potentials, but more importantly there is reflexive movement of the eyeball during blinking that gives a characteristic artifactual appearance of the EEG. Eyelid fluttering artifacts of a characteristic type were previously called Kappa rhythm. It is usually seen in the prefrontal leads, that is, just over the eyes. Sometimes they are seen with mental activity. They are usually in the Theta (4–7 Hz) or Alpha (7–14 Hz) range. They were named because they were believed to originate from the brain. Later study revealed they were generated by rapid fluttering of the eyelids, sometimes so minute that it was difficult to see. They are in fact noise in the EEG reading, and should not technically be called a rhythm or wave. Therefore, current usage in electroencephalography refers to the phenomenon as an eyelid fluttering artifact, rather than a Kappa rhythm. Some of these artifacts can be useful in various applications. The EOG signals, for instance, can be used to detect and track eye-movements, which are very important in polysomnography, and is also in conventional EEG for assessing possible changes in alertness, drowsiness or sleep. ECG artifacts are quite common and can be mistaken for spike activity. Because of this, modern EEG acquisition commonly includes a one-channel ECG from the extremities. This also allows the EEG to identify cardiac arrhythmias that are an important differential diagnosis to syncope or other episodic/attack disorders. Glossokinetic artifacts are caused by the potential difference between the base and the tip of the tongue. Minor tongue movements can contaminate the EEG, especially in parkinsonian and tremor disorders.

Environmental artifacts:

In addition to artifacts generated by the body, many artifacts originate from outside the body. Movement by the patient, or even just settling of the electrodes, may cause electrode pops, spikes originating from a momentary change in the impedance of a given electrode. Poor grounding of the EEG electrodes can cause significant 50 or 60 Hz artifact, depending on the local power system's frequency. A third source of possible interference can be the presence of an IV drip; such devices can cause rhythmic, fast, low-voltage bursts, which may be confused for spikes. Motion artifacts introduce signal noise that can mask the neural signal of interest. Therefore, effective signal noise processing measures were of great interest in the scientific community. An EEG equipped phantom head can be placed on a motion platform and move din a sinusoidal fashion. This contraption enabled researchers to study the effectiveness of motion artifact removal algorithms. Using the same model of phantom head and motion platform, it was determined that cables way was a major attributor to motion artifacts.

The electroencephalogram (EEG) is a measurement modality for recording electrical activity generated by the cerebral cortex. The electrical activity in the brain is recorded via measurement electrodes attached to the surface of the scalp. Due to its convenient acquisition, noninvasive access, and high temporal resolution, EEG signals play an increasingly important role in the field of neurologic instrumentation and measurement, cognitive research, disease diagnosis, and rehabilitation engineering. These signals have small amplitudes and strong randomness, so they can be very easily contaminated with various muscle artifacts. Artifacts are divided into two. They are physiological artifacts and extra physiological artifacts. Physiological artifacts are generated from body other than brain. Extra physiological artifacts are generated from outside of body such as equipment and environment.

The EEG signals detected will vary, depending on the location of the electrodes on the scalp. A number of well-characterized artifacts can corrupt EEG recordings, such as electromyogram (EMG), electrocardiogram (ECG), and electrooculogram (EOG) signals caused by head muscle contraction, heart beats, and eye movements, respectively. One of the most common artifacts influencing the quality of EEG signals are the electrooculography (EOG) activities whose magnitude is usually much higher than that of EEG signals. EOG has a burst of high-energy in low-frequency, which seriously affects the EEG basic rhythm waves. EOG artifacts (EOAs) can make the analysis and interpretation of EEG signals difficult and will also affect the diagnosis of doctors.

In order to reduce the interference of EOAs, subjects are asked not to blink for a long time or to blink as infrequently as possible, which causes eyes uncomfortable. Especially for some specific patients, such as children with attention deficit hyperactivity disorder (ADHD), it is difficult to obey it. Hence, many EOAs often appear in EEG signals. The common clinical practice is to directly reject EEG segments with eye artifacts. However, it may lead to some loss of important EEG information. Therefore, it is very essential to effectively remove EOAs from EEG signals and preserve underlying brain activity signals with little distortion in the pre-processing of EEG signals. In the existing method MEMD-CCA, first utilizes MEMD to jointly decompose the few-channel EEG recordings into multivariate intrinsic mode functions (IMFs). Then, CCA is applied to further decompose the reorganized multivariate IMFs into the underlying sources. Reconstructing the data using only artifact-free sources leads to artifact- attenuated EEG. We evaluated the performance of the proposed method through simulated, semi simulated, and real data. The results demonstrate that the proposed method is a promising tool for muscle artifact removal in the few-channel setting. ICA linearly unmixes multichannel EEG recordings into maximally statistically independent components (ICs) by exploiting higher order statistics (HOS). The derived ICs represent the underlying sources generating the measured multichannel EEG, and removing artifact-related ICs in reconstruction can lead to relatively artifact-free EEG. While ICA is fairly successful the effectiveness of ICA has been challenged in several recent studies. By exploiting HOS, ICA is capable of isolating the artifacts with stereotyped scalp topographies into individual ICs. However, muscle artifacts usually have variable scalp topographies, since the shape and amplitude of the artifacts depend on the degree of muscle contraction, the type of muscles contracted, and the number of muscles involved. CCA has been recently proposed as an alternative BSS technique to solve muscle artifact problems in the EEG. By using the original EEG as the first data set and its time-delayed version as the second data set, CCA, based on second-order statistics (SOS), aims to find sources maximally auto correlated and mutually uncorrelated. Muscle artifacts have a relatively low autocorrelation due to their broad frequency spectrum compared with background EEG signals, and thus CCA utilizes this distinguishable feature to isolate muscle artifacts from ongoing EEG. The limitation of the existing method is that, while fast EEMD has been developed and we used it in the test, there is no fast algorithm for MEMD, but can be expected in the future. Currently, the heavy computational cost limits MEMD-CCA to be used in the offline situation. If the number of dimension of data is relatively high and there are not enough observations, the result of covariance matrix may be inaccurate and the covariance matrix is close to an ill-posed matrix. In the few- channel situation, the maximum number of dimension (channels) is far less than the number of the observations, compared with high-density multichannel situation.

II. METHODOLOGY

The main aim of this project is to design and develop a technique for the removal of artifacts that occur while performing the EEG experiments on human brain. Initially, the EEG signal will be subjected to Pre-processing in order to improve the quality of the signal and to make it suitable for the successive step of feature extraction. Feature extraction process will be done using the Multivariate EMD, and hence the features are extracted from the pre-processed signal. The presence of artifacts will be removed using the Deep Learning Algorithm (DLA) with the Long Short Term System (LSTM) on the extracted feature. Training of deep learning will be done using the multivariate empirical mode decomposition signal. The block diagram of the proposed system is shown in figure. The implementation will be done using MATLAB and the performance of the proposed method will be compared with the existing works, such as ICA, WICA, FICA based on Mean Squared Error (MSE), Root Mean Square Error (RMSE), and signal to Noise Ratio (SNR). LSTM is an artificial recurrent neural network architecture used in the field of deep learning. LSTM has feedback connection that make it a general purpose computer. It cannot only process single data points, but also entire sequence of data.

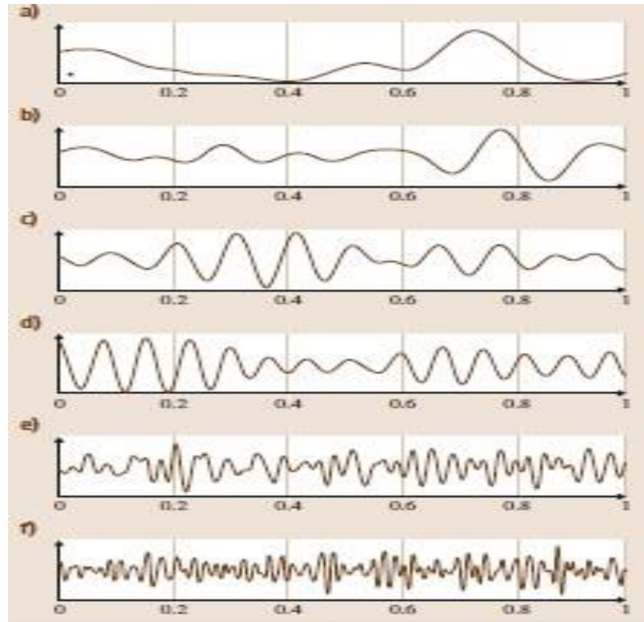

Fig 1: EEG waves a) delta band b) Theta band, c) Alpha band, d) mu-rhythm, e) Beta band, f) Gamma band

EEG signal

EEG is a measurement for recording electrical activity of a brain. During recording the electrodes are placed on the surface of the scalp. The recorded waveforms reflect the cortical electrical activity. EEG activity is quite small measured in microvolt. The signal frequencies of human EEG waves are

1. Alpha
2. Beta
3. Theta
4. Delta

Preprocessing

EEG signal required special processing for using them a part of application. So initially EEG signal need preprocessing to enable brain computer interface. Preprocessing technique helps to remove unwanted components such as distortion, noise, nonlinearities and crosstalk from the EEG signal and hence improve the signal to noise ratio. A preprocessing block aids to in improving the performance of the system by separating the noise from the actual signal. The preprocessing filter named notch filter is applied to remove 50hz to 60hz low frequency noises.

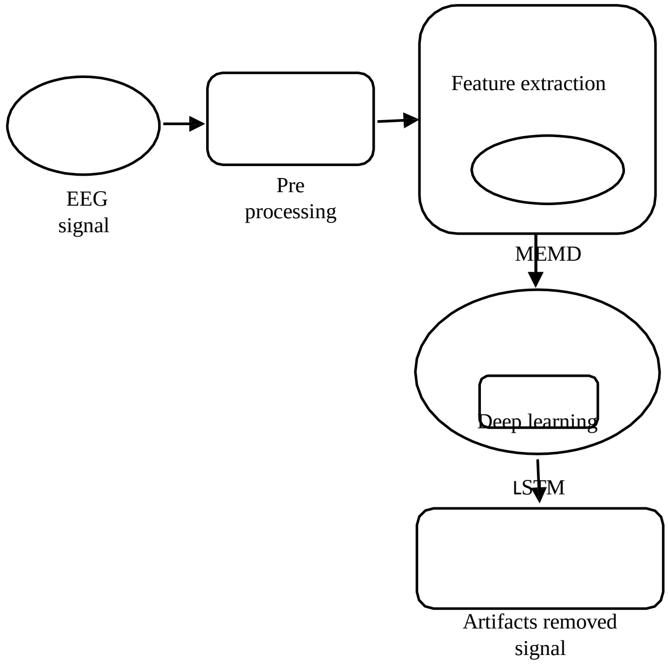

Fig 2: Block diagram

Empirical mode decomposition

Empirical Mode Decomposition (EMD) in conjunction with Hilbert spectral analysis is called Hilbert - Huang Transform (HHT). It adaptively and locally decomposes any non-stationary time series in a sum of Intrinsic Mode Functions (IMF) which represent zero-mean amplitude and frequency modulated components. The EMD represents a fully data-driven, unsupervised signal decomposition and does not need any a priori defined basis system. EMD also satisfies the perfect reconstruction property, i.e. superimposing all extracted IMFs together with the residual slow trend reconstructs the original signal without information loss or distortion. The method is thus similar to the traditional Fourier or wavelet decompositions but the interpretation of IMFs is not similarly transparent. The empirical nature of EMD offers the advantage over other empirical signal decomposition techniques like empirical matrix factorization (EMF) of not being constrained by conditions which often only apply approximately. Especially with biomedical signals one often has only a rough idea about the underlying modes and mostly their number is unknown. The EMD method was developed from the assumption that any non-stationary and non-linear time series consists of different simple intrinsic modes of oscillation. The essence of the method is to empirically identify these intrinsic oscillatory modes by their characteristic time scales in the data, and then

decompose the data accordingly. Through a process called

sifting, most of the riding waves. The EMD algorithm thus considers signal oscillations at a very local level and separates the data into locally non-overlapping time scale components. It breaks down a signal x(t) into its component IMFs obeying two properties:

1) An IMF has only one extremum between two subsequent zero crossings, i.e. the number of local minima and maxima differs at most by one.

2) An IMF has a mean value of zero.

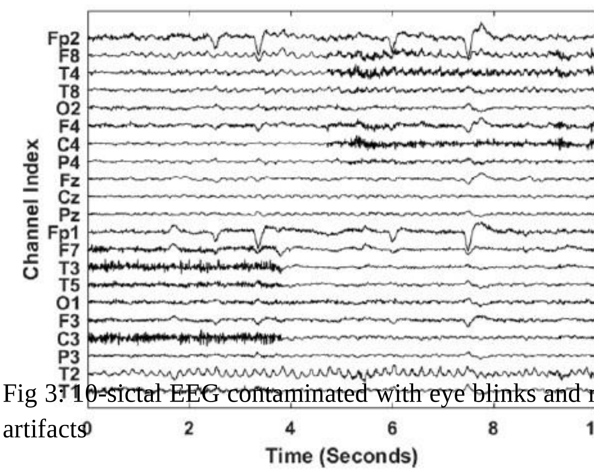

Fig 3: 10-sictal EEG contaminated with eye blinks and muscle artifacts

Ensemble EMD:

Empirical mode decomposition (EMD), is a fully data-driven decomposition technique for nonlinear and nonstationary signals. EMD decomposes a given time series signal x, into a finite set of AM/FM components (IMFs), which represent fast to slow oscillations. An IMF is a function that satisfies the following two conditions: 1) the number of extrema and that of zero-crossings must either be equal or differ at most by one and 2) at any point the mean value of the envelope defined by the local maxima and local minima should be zero. There are a few steps taken to obtain IMFs from a recorded signal x(t). First, all the local maxima and minima of x(t)the time series should be found. A smooth upper envelope u(t) of the signal is calculated from the local maxima through interpolation. Additionally, a lower envelope b(t) is similarly calculated from the local minima. The next step involves computing the mean m(t) of the two envelopes as

$$m(t) = (u(t)+b(t))/2 \quad (1)$$

Subtracting this mean from the recorded signal results in a new signal

$$h(t) = x(t) - m(t) \quad (2)$$

In the second-sifting process, the signal h(t) is treated as the new signal and the above-mentioned steps are repeated until h(t) satisfies the two aforementioned conditions. Once this is achieved, the signal h(t) is referred to be the first IMF$c_1(t)$. Then, the residual signal is,

$$r_1(t) = x(t) - c_1(t) \quad (3)$$

It is treated as a new signal and the aforementioned steps are repeated to obtain the subsequent IMFs until the residual signal $r_n(t)$becomes a monotonic function. Finally, the signal x(t) is decomposed as a linear combination of n IMFs $c_j{}'$s and a residual r_n

$$x(t) = \sum_{j=1}^{n} c_j + r_n \quad (4)$$

The standard EMD algorithm is highly sensitive to noise and may lead to the phenomenon of mode-mixing, whereby similar frequencies appear across different IMFs. The noise-assisted EEMD algorithm defines the IMF components as the mean of an ensemble of IMFs acquired by applying standard EMD on individual signal trials corrupted by independently added white noise of finite amplitude. Since the noise in each trial is assumed to be generated independently, the noise tends to cancel out in the ensemble mean of sufficient trials.

Feature extraction

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is a dimensionality reduction process, where an initial set of raw variables is reduced to more manageable groups (features) for processing, while still accurately and completely describing the original data set. When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data. Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to over fit to training samples and generalize poorly to General new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Many machine learning practitioners believe that properly optimized feature extraction is the key to effective model construction. Results can be improved using constructed sets of application dependent features, typically built by an expert. One such process is called feature engineering.

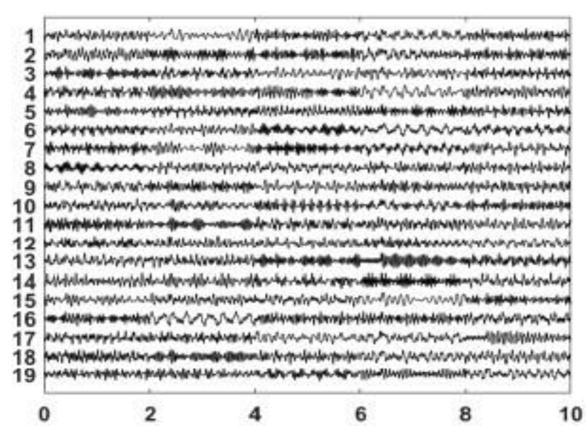

Fig 4: Cleaned simulated EEG signal

Multivariate EMD:

One drawback of univariate EMD is the problem of uniqueness. Due to the random nature of EEG signals and artifact, the IMFs acquired for distinct EEG channels may be different in number and/or frequency, largely compromising subsequent joint analysis of multicomponent signals obtained in a channel-by-channel manner. To address this issue, a multivariate extension of EMD, MEMD, has been proposed to simultaneously decompose multivariate signals into multivariate IMFs. Unlike defining the local mean using the average of upper and lower envelopes in standard EMD, MEMD generates multiple N-dimensional envelopes by projecting the N-dimensional signal along different directions in N-dimensional spaces and then the local mean is obtained by averaging all N-dimensional envelopes. MEMD calculates all the multivariate IMFs in a similar manner to the EMD method. Subtracting the local mean from the original signal results in a new signal. If the new signal fulfills the stop page criteria, it is identified to be the first multivariate IMF. After subtracting the first multivariate IMF from the original signal, the residual signal is defined as a new signal for extracting the second multivariate IMF and so on. The whole decomposition process can be stopped when all the projected signals meet any of the stoppage criteria. To further alleviate the problem of mode-mixing still existing in standard MEMD, quasi-dyadic filter bank properties of MEMD on white Gaussian noise (WGN) has been proposed as a noise-assisted MEMD decomposition method for multivariate signals. Unlike EEMD, where several realizations of white noise are directly added to the signal, this method is implemented by adding extra WGN channels to the original multivariate data channels to generate a dimensionality increased composite signal and then processing the created composite signal via MEMD. The multivariate IMFs corresponding to the recordings are retained by dropping the IMFs associated with multidimensional WGN. MEMD enables the alignment of similar modes present across multiple channels in the same-index IMFs, which is difficult when employing EMD in channel wise fashion. By simultaneously analyzing the intrinsic modes across multiple data channels instead of channel-by-channel, MEMD has the ability to generate a more accurate estimate of the signal envelope and thus identify the common activity between multiple data channels more robustly, especially for EEG where muscle artifacts are broadband and the useful information narrowband, both exhibiting various degrees of non-stationarity with spatial and temporal dependence. Thus, in this paper, the noise assisted MEMD algorithm will be adopted.

III. RESULTS

The electrical activity of a human brain which is recorded by using EEG. Brain wave contains mainly 4 types of wave. Alpha, Beta, Theta and Gamma waves. Alpha wave ranges from 8 to 13Hz. This wave found in normal person when they are awake in quiet or resting state. Frequency of beta wave ranges from 13 to 30Hz. Theta wave have the frequency range 4 to 8Hz. The frequency ranges of delta wave ranges from 0.5 t0 4 Hz. The presence of artifacts will be removed using the Deep Learning Algorithm (DLA) with the Long Short Term System (LSTM) on the extracted feature. Training of deep learning will be done using the multivariate empirical mode decomposition signal. The implementation is done by using MATLAB and the performance of the proposed method will be compared with the existing works, such as ICA, WICA, FICA based on Mean Squared Error (MSE), Root Mean Square Error (RMSE), and signal to Noise Ratio (SNR). EOG, EMG and ECG artifacts the EEG signal. ECG artifacts is identified by its fixed period and morphology and is limited to T3-A1 channel. It also shows ipsilateral ear referential montage. EMG artifacts represent the motor unit potential as typically observed on needle electrode examination during electromyogram with a frequency of 20-100 Hz.

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