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EXTRACTION OF EEG SIGNALS FROM POLYSMNOGRAPHIC RECORS BY APPLYING COMBINED CASCADED ADAPTIVE FILTERS

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ABSTRACT

Polysomnographic(PSG) is a technique used to diagnosethe various sleep disorders. PSG is also called as sleep study. Blood oxygen levels, brain waves, body positions, eye movements, heart rate (ECG) are some of the signals involved in PSG. Especially EEG signals are examined by doctor in order to identify neural oscillations during sleep.

Artefacts in EEG records are caused by various factors like Base interference(BE), muscle artefacts (EMG), Electrocardiogram (ECG) and power line noise. These noise sources increasethe difficulty inanalysingtheEEG signals andobtainingoriginalinformation. For this reason, it is necessary to design specific filtersto decrease such artefacts in EEGsignals.In this project a combined cascaded LMS & NLMS algorithm is proposed and measure the metrics like SNR, MSE, LSE, MAE.

Keywords:*EEGsignal,Artefacts,LMS&NLMS,SNR,MSE,LSE,MAE.*

1. INTRODUCTION

"Extraction of EEG signals from polysomnographic records by applying combined cascaded adaptive algorithm" involves the utilization of adaptive filtering algorithm to removal of EEG data from PSG studies.

A diagnostic procedure called polysomnography evaluates physiological aspects ofsleep,suchasbreathing,eyemovements,muscle activity, and brain waves (EEG). EEG signals are of special importance since they can be used to identify sleep problems and it is a visual representation of brain electrical activity that is obtainedfromscalprecordings.EEGsignalduring recordingtime,suchaseyeblink,eyemovements, muscle activity, and power line interference. As a result,EEGsignalsshouldbeprocessedtoremove these noises and obtain efficient EEG features. More standard methods are now employed to remove artefacts from EEG readings.one of the best method is applying adaptive algorithm like LMS & NLMS algorithms to remove the artefacts.

The objective of this paper is to provide a method for accurately and efficiently separating EEG signals from PSG data for use in clinical settings for the detection and treatment of sleep disorders. The project will have a big impact on diagnosingsleep disordersmore accurately, which willhelppatientsreceivebettercareandlivebetter lives.

2. ARTEFACTSINEEG

An electrical signal is indicated as a Artefact whicharelistedfromthescalp,butitisnotthepart ofcerebralorigin.AnyEEGsignalthatisunrelated to brain activity is considered an artefact. The artefacts in the EEG comesfromsourceslikemuscles,theeyes,outside noise or electrical noise. There are basically two primary categories of EEG artefacts.

Physiological artefacts and non-physiological artefacts it is also called as external artefacts.

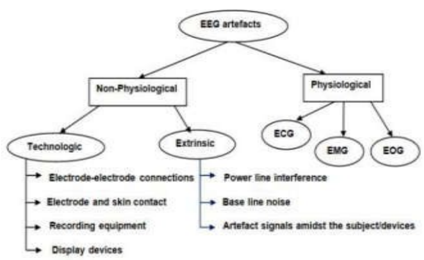

Figure2.1:Classificationofartefacts

An artefact is referred to as a physiological artefactifitssourceisthesubject'sbody.Asource thatisoutsideisreferredtoasan externalartefact.

3. METHODOLOGY

It is proposed that a cascading of 4 adaptive filterswhicharеusedtoremovetheartefactsfrom the EEG signals.

Now the fig 3.1 represents the block diagram of 4 adaptive filters which are in cascaded.

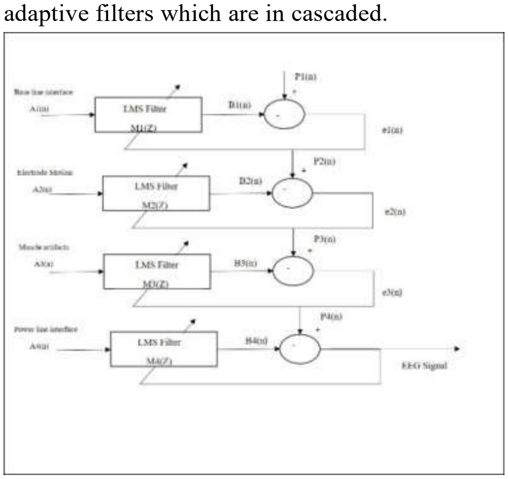

Figure3.1:Blockdiagram

The block diagram consists of 4 adaptive filters which are cascaded.

3.1 ADAPTIVEFILTER

Adaptive filters are a type of digital filter that continuously modifies its filter coefficients to enhance performance. They are frequently employed to eliminate undesirable noise or interference from a signal in signal processing applications. The fundamental concept underlying adaptive filters is to modify the filter coefficients according to the provided input signal and the desired output signal.

Thealgorithmmodifiesthefiltercoefficientsto reduce the contrast between the actual and desired outputsignalsusingamathematicalmodeltoassess therelationshipwithintheinputandoutputsignals.

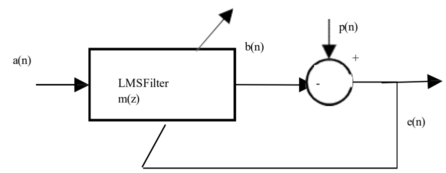

Figure3.2:Structureofadaptivefilter

From the structure of the adaptive filter a(n) represents the reference signal, b(n) represents the output of the LMS filter which is m(z), p(n) represents the corrupted signal, e(n) represents the error signal.

Thecapacityofadaptivefilterstotrack changes in the input signal over time is one of its keyfeatureswhichisused forthenoisecancellation

There are different types of algorithms used in the adaptive filter like LMS algorithm, NLMS algorithm, RLS algorithm.

Therearehugenumberofapplicationsaretherefor adaptive filters like echo cancellation, system identification, inverse modelling etc.

3.2 LMSALGORITHM

Least Mean Square algorithm is the simple adaptive algorithm. In digital signal processing applications, the least mean squares (LMS) algorithm is a well-liked adaptive algorithm for modifying the coefficients of a digital filter. The LMSalgorithmadjuststhefiltercoefficientsbased on the error between the filter output and the desired output. It is a stochastic gradient descent process.

$$e(n)=p(n)-b(n) \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

wherep(n)representsthedesiredoutputandb(n)is the filter output

The LMS method operates by gradually changing thefiltercoefficientsinthedirectionofthenegative gradient of the error

TheweightupdatedequationoftheLMSalgorithm is given by

$$w(n+1)=w(n)+2*\mu.a(n)*e(n) \quad \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

wherew(n)isthevectoroffiltercoefficientsattime n,µisthestepsizeor,e(n)istheerrorattimen,and a(n) is the input signal at time n.

The rate of convergence of the LMSalgorithm is determined by the important parameter called step size.

3.3 NLMSALGORITHM

Normalized Least Mean Square (NLMS) algorithmisoneoftheadaptivefilteringalgorithm. There are some disadvantages in the LMS algorithmthat isfixedstep sizeforevery iteration and there is no limit for the LMS algorithm to overcome the difficulty NLMS algorithm is developed.

IntheNLMSalgorithmthestepsizeisnormalized. TheextensionversionoftheLMSalgorithmisthe NLMS algorithm in which maximum step size is calculated.

$$\mu(n)=\frac{\beta}{|a(n)|^2} \quad (3)$$

Where β is the normalized step size (0 < β <2)

ThentheweightupdatedequationoftheLMSfilter is varied to the

$$w_i(n+1)=w_i(n)+\frac{\beta}{|a(n)|^2}e(n)x(n-k) \ldots(4)$$

Accordingtothefigure3.1thereareFouradaptive filters which are cascaded.

Inthefirststage,$a_1(n)$isthefirstreferencesignal i.e.,BaselinewhichisgiventothefirstLMSfilter i.e., $m_1(z)$. The filter produces the output as $b_1(z)$ which is the estimation of base line present in the EEG. $p_1(n)$ is the input signal which is corrupted with different artefacts like EEG, base line interference, electrode motion, EMG and the power line interface.

$$e_1(n)=p_1(n)-b_1(n)$$

now the $e_1(n)$ signal consists of all signals except thebaselineinterference.Nowthe$e_1(n)$isgivento corrupted signal $p_2(n)$ to the second stage.

In the second stage, $a_2(n)$ is the second reference signal i.e., electrode motion which is giventothesecondLMSfilteri.e.,$m_2(z)$.Thefilter producestheoutputas$b_2(z)$whichistheestimation ofartefactsofelectrodemotionpresentintheEEG. $P_2(n)$ is the input signal which is corrupted with different artefacts like EEG, electrode motion, EMG and the power line interface.

$$e_2(n)=p_2(n)–b_2(n)$$

now the $e_2(n)$ signal consists of all signals except theelectrode motion. Now the $e_2(n)$ is given to corrupted signal $p_3(n)$ to the third stage

In the third stage $a_3(n)$ is the third reference signal i.e., EMG(Muscle) artefacts which is given tothethirdLMSfilteri.e.,$m_3(z)$.thefilterproduces the output as $b_3(z)$ which is the estimation of artefacts of EMG present in the EEG. $p_1(n)$ is the input signal which is corrupted with different artefacts like EEG, EMG and the power line interface.

$$e_3(n)=p_3(n)–b_3(n)$$

now the $e_3(n)$ signal consists of all signals except the muscle artefacts. Now the $e_3(n)$ is given to corrupted signal $p_4(n)$ to the fourth stage.

In the fourth stage, $a_4(n)$ is the fourth reference signali.e.,powerlineinterferencewhichisgivento thefourthLMSfilteri.e.,$m_4(z)$.Thefilterproduces theoutputas$b_4(z)$whichistheestimationofpower line interfacepresentintheEEG.$P_4(n)$istheinput signal which is corrupted with different artefacts like EEG, the power line interface.

$$e_4(n)=p_4(n)–b_4(n)$$

Itisthefinaloutputoftheadaptivefilterwhich produces the clean EEG signal without any noise. ThedatabaseiscollectedfromtheMIT–BIH Polysomnographic physio bank.

4. SIMULATIONANDRESULTS

The simulation results are obtained in MATLAB andalsocomputedfidelityparameterslikeSignalto Noise Ratio (SNR), Mean Square Error (MSE), Mean Average Error(MAE), Least Square Error(LSE) with LMS & NLMS algorithm.

WaveformsforLMSalgorithm

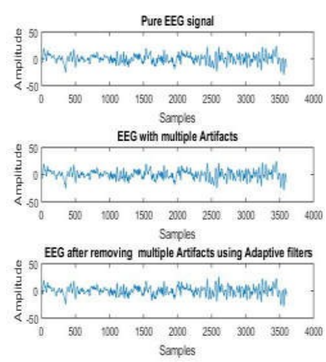

Figure4.1:ResultsofpureEEGsignalsusing LMS algorithm

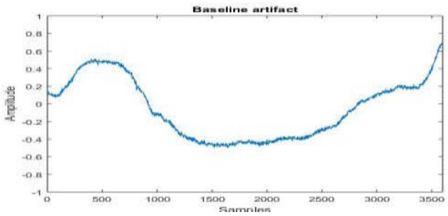

Figure4.2:Baselineartefact

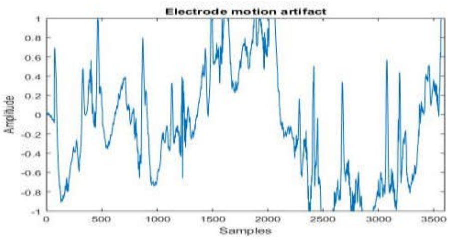

Figure4.3:Electrodemotionartefact

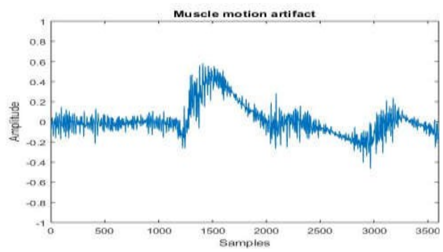

Figure4.4:Musclemotionartefact

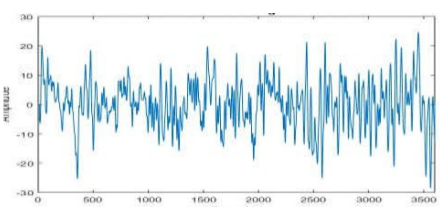

Figure4.5:NoisedEEGafterremoving baseline artefact

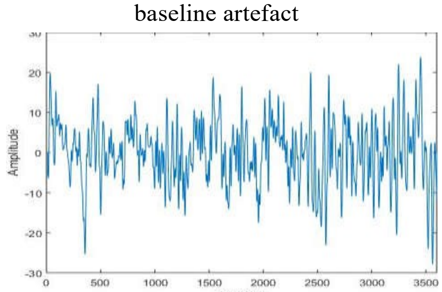

Figure4.6:NoisedEEGafterremovingbaseline noise and electrode motion

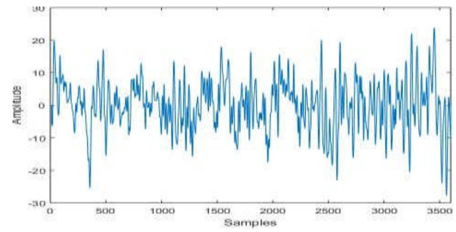

Figure4.7:NoisedEEGafterremovingbaseline noise, electrode motion and EMG artefacts

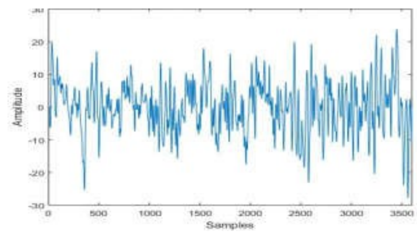

Figure4.8:PureEEGsignalafterremovingall artefacts

s.no	Step size	Input SNR	Output SNR	LSE	MAE	MSE
1	0.001	20.9097	93.1963	4.3506e-4	2.3945e-07	2.9780e-08
2	0.002	20.9097	86.8770	8.8114e-4	4.7515e-07	1.2231e-07
3	0.003	20.9097	83.1359	0.0013	6.9368e-07	2.7824e-07
4	0.004	20.9097	80.4351	0.0018	8.9128e-07	4.9853e-07
5	0.005	20.9097	78.2925	0.0023	1.0705e-07	7.8615e-07

Table4.1:ErrorparametersusingLMSalgorithm Wave forms for NLMS algorithm

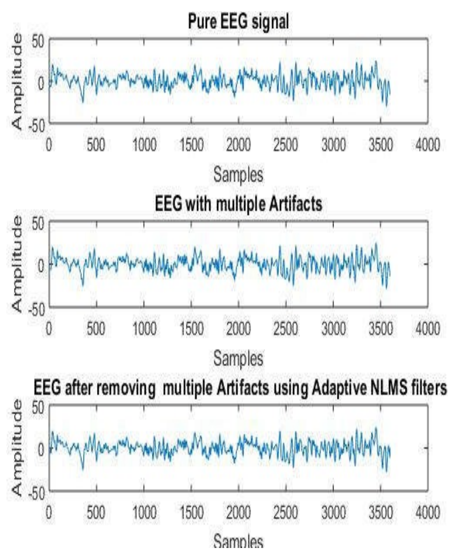

Figure4.9:ResultsofpureEEGsignalsusing NLMS algorithm

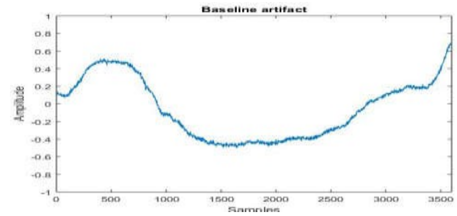

Figure4.10:Baselineartefact

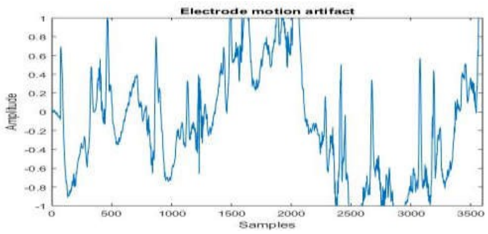

Figure4.11:Electrodemotionartefact

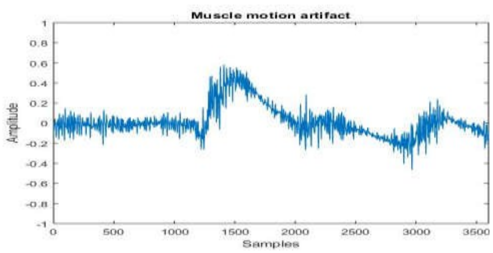

Figure4.12:Musclemotionartefact

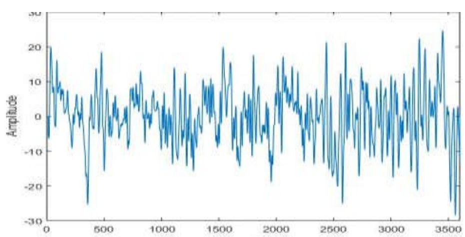

Figure4.13:NoisedEEGafterremovingbaseline artefact

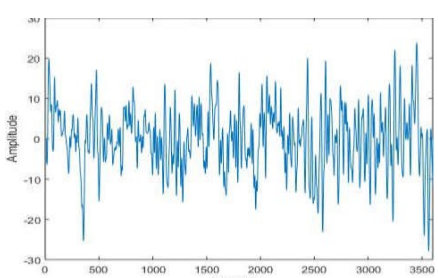

Figure4.14:NoisedEEGafterremovingbaseline noise and electrode motion

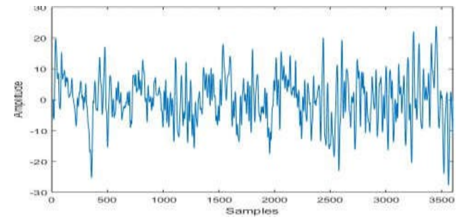

Figure4.15:NoisedEEGafterremovingbaseline noise, electrode motion and EMG artefacts

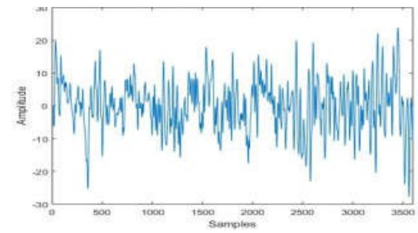

Figure4.16:PureEEGsignalafterremovingall artefacts

s.no	Step size	Input SNR	Output SNR	LSE	MAE	MSE
1	0.001	20.9097	100.1904	4.0878e-4	3.1778e-09	5.6244e-09
2	0.002	20.9097	94.1679	8.0058e-4	7.1838e-08	2.0646e-08
3	0.003	20.9097	90.6443	0.0012	1.2024e-07	4.2966e-08
4	0.004	20.9097	88.1441	0.0015	1.7937e-07	7.1124e-08
5	0.005	20.9097	86.2047	0.0018	2.5242e-07	1.0408e-07

Table4.2:ErrorparametersusingNLMS algorithm

5. CONCLUSION

The implementation of LMS & NLMS algorithmsofAdaptivefilteronnoisedEEGsignal wasperformed. The noisedEEGsignals isapplied tocombinedcascadedAdaptivefilterandobtained pureEEGsignals.TheresponsesofLMSalgorithm basedadaptivefilterareshowninthefigurefrom 4.1 to 4.8 and the responses of NLMS algorithm basedAdaptivefilterareshowninthefigurefrom 4.9to4.16.ThefidelityparameterslikeSNR,MSE, LSE, MAE are calculated and compared between the LMS & NLMS algorithm. From the table 4.1 and 4.2 we get that step size 0.001 is the best step sizebecausethestepsizesfrom0.002to0.005SNR ratiodecreasesandLSE,MAE,MSEareincreases so, 0.001 is best step size. The output SNR is increased in table 4.2 as compared to the table 4.1. So from the above discussions it is concluded that NLMS algorithm produces better responses in terms of SNR, MSE, MAE, LSE.

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