Estimation and Artifact Removal in EEG signals with ARMA and Fast ICA

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Abstract. Recording of electroencephalogram (EEG) signals usually contaminate with artifacts like eye blinks and eye movements called as ocular artifacts. Even though, works related to artifact removal faces some difficulties to get rid of the challenges without loss of original signal as the both have similar frequency ranges. Our proposed system has introduced a model based on Autoregressive Moving Average (ARMA) and Fast ICA for the correction of ocular artifacts in EEG signals.. For the purpose of predicting the time series gap so as to obtain a futuristic prediction valued autoregressive moving average (ARMA) model for the estimation of statistical parameters and to use the Fast ICA for the better accuracy is proposed. The results after comparing with the existing methods say that the proposed model give the better results

Keywords: ARMA, EEG, EOG, adaptive filters, SNR and MSE

1 Introduction

The EEG bands delta, thete, alpha and beta are as shown in Fig.1. The EEG signal when collected from human scalp usually contaminate with other physiological signals like electrocardiogram (ECG), electromiogram (EMG) and electrooculogram (EOG) which are unwanted signals in the analysis of human brain activity.

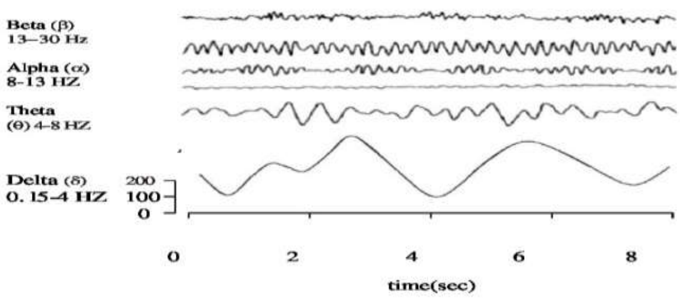

Fig.1. Four typical dominant brain normal rhythms, from high to low

A novel method for the removal of ocular artifacts is introduced and the sequence of paper is as follows; Section.2 describes about autoregressive moving average (ARMA) model, Section describe steps for Fast ICA algorithm, Section 4 analyses about the results with the existing methods, section 5. Gives conclusion

2 Autoregressive Moving Average (ARMA) model

The ARMA is a popular model used in parameter estimation and the output is modeled as a linear difference equation of present and previous inputs as stated in equation (1) and past outputs as

$$y((k) = \sum_{j=1}^{n} a_j y(k-j) + \sum_{i=0}^{m} b_i u(k-i) \tag{1}$$

here u (k) and y (k) are inputs and outputs at discrete-time k, a_j and b_i are the ARMA parameters. The ARMA equation in vector form is,

$$y(k) = \theta^T \theta(k) \tag{2}$$

here θ^T=[a, b_0,…,b_m] is the parameter vector and Φ^T(k)=[y(k-1),…,y(k-n,u(k),….u(k-m)] is the measurements vector.

In most of the recursive methods the gradient is applied to search for a vector to minimize the error between the model and system. Selection of proper fitting function is crucial for successful system identification. In this work, the Sum Square Error (SSE) Criterion function was used

$$SSE = \sum_{k=1}^{N} (\hat{y}(k) - y(k))^2 \tag{3}$$

$$H(z) = \frac{Y(Z)}{U(Z)} = \frac{b_0 + b_1 z^{-1} + \dots + b_m z^{-m}}{1 - a_1 z^{-1}, - \dots - a_n z^{-n}} \tag{4}$$

here N is number of measurements

3.Fast ICA algorithm

The gaussianity can be maximized with projection wT x [7]-[8]. Nongaussianity is here measured by the approximation of negentropy J(wTx). As discussed the variance of wTx is unity. For whitened data this is equivalent to constraining the norm of w to be unity.Denote by g the derivative of the non quadratic function G used in (4); for example the derivatives of the functions in (5) are:

$$g_1(u) = \tanh(a_1 u)\ ,\ g_2(u) = u\exp(-u^2/2) \quad (5)$$

Where 1≤a1≤2 is a suitable constant, often taken as a1=1. The basic Fast IC analysis algorithm is as below:

Step1. Choose an initial weight(random) vector w.

Step2. Let $w^+ = E\{xg(w^T x)\} - E\{g'(w^T x)\}w$

Step3. Let $w = w^+ / \left\| w^+ \right\|$

Step4. If not converged go back to step2.

4. Feature extraction

Figure 3 shows below the mixture signals and Fast ICA components.

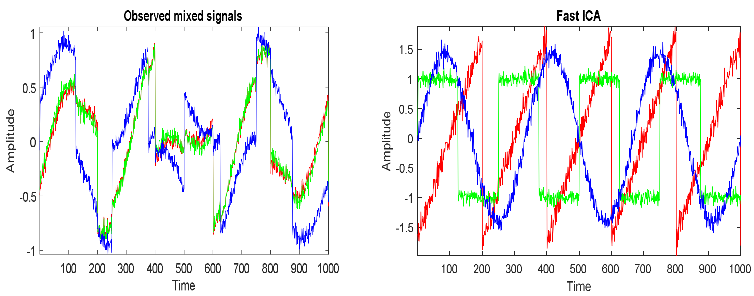

Fig.3.Observed mixture signals(left) and Fast ICA components(Right)

performance analysis

The performance metric that are used to analyze the performance of our proposed work is as follows:

Accuracy

Classification Rate or Accuracy is given by the relation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

TP: True Positive TN: True Negative

FP: False Positive FN: False Negative

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Sensitivity

Sensitivity measures the proportion of actual positives that are correctly identified

$$Sensitivity = \frac{TP}{TP+}$$

Specificity

Specificity measures the proportion of actual negatives that are correctly identified as such

$$Specificity = \frac{TN}{TN+}$$

Precision

Information retrieval (IR) is the activity of obtaining information system resources relevant to an information need from a collection.

$$Precision = \frac{TP}{TP+}$$

Recall

It is the ratio of total number of correctly classified positive points to the total number of positive examples.

$$Re\,call = \frac{TP}{TP+FN}$$

F-measure:

The F-Measure is nearer to the smaller value of Precision or Recall.

$$f - measure = \frac{2 * recall * precision}{recall + precision}$$

Mean Square Error (MSE)

$$MSE = \frac{1}{n}\sum(Y_i - \hat{Y}_i)^2$$

Signal noise Ratio (SNR)

$$SNR = \frac{P_{SIGNAL}}{P_{NOISE}}$$

PSNR

$$PSNR = 20.log_{10}(MAX_I) - 10.log_{10}(MSE)$$

Noise

$$Noise = Re\,ceived\ signal - sent\ signal$$

Bit rate

$$bitrate = \frac{no\ of\ bits}{time}$$

Table 1: Proposed Model

Parameters/reference	Proposed system
Accuracy	98.6098
Sensitivity	27.6364
Specificity	99.3585
Precision	73.8412
Recall	43.2558
F-measure	61.6471
MSE	24.1852
SNR	11.9482
PSNR	15.5482
Noise(dB)	0.6781
BitRate(bit / sec)	230
Execution Time(per hour)	55.2486
Simularity Structure	230

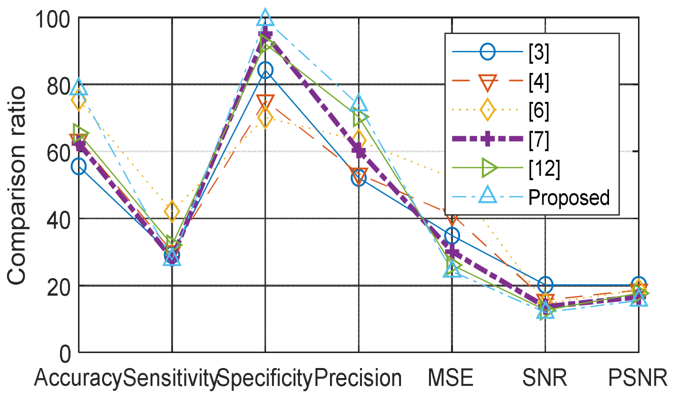

Fig.3.Overall performance criteria

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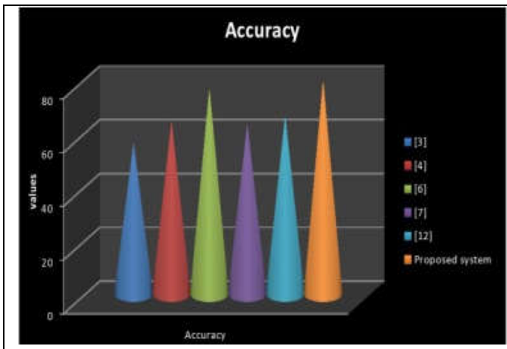
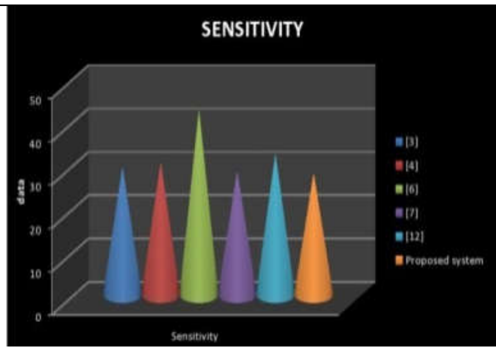
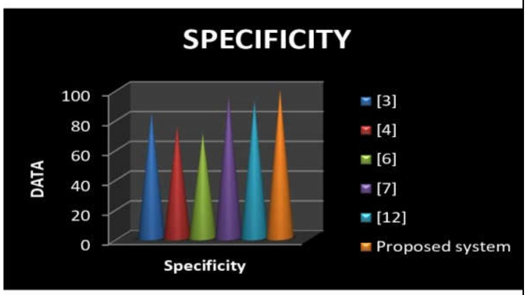
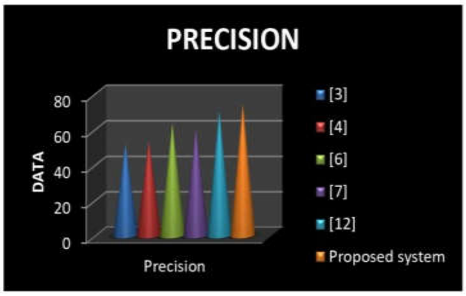
3. Results comparison:

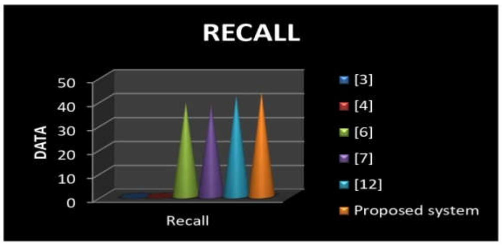
In this section, the proposed system is compared with :[3], [4], [6], [7], [12] based on artifacts removal in EEG in order to evaluate the different parameters undergone over the process. The parameters are stated in table 1.

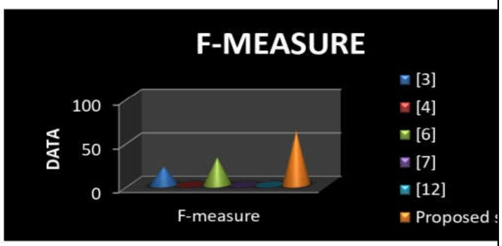












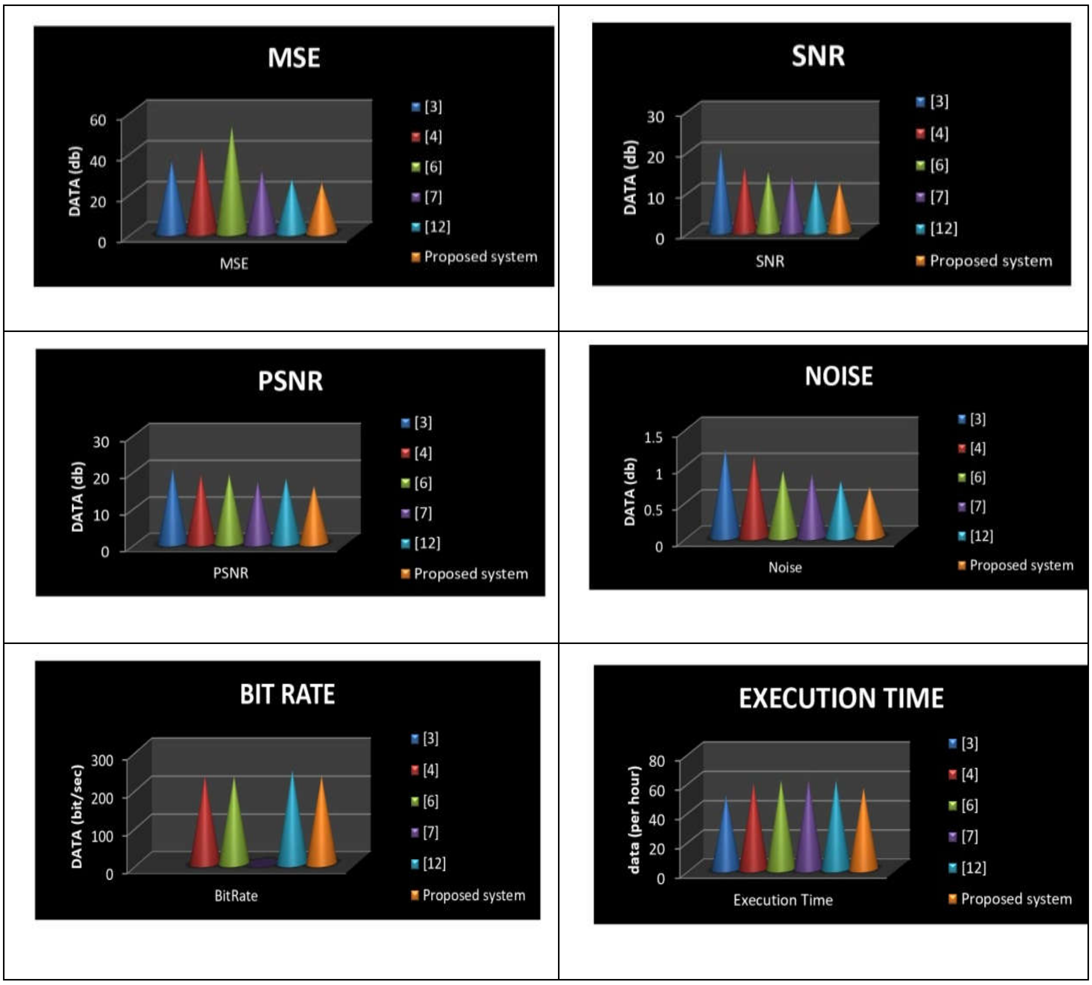


Fig.4. comparison of existing model with proposed model

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