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A Novel Method For Seizure Prediction Based on Autoregressive Modelling and A Real-Time Error Correction Algorithm

Hari Prasad S. A.[1], Gowtham S.[1], Radhika R.[1], Arvind K. S.[1], Gowthami Renny[1], Pradeep Kumar K. A.[2*]

[1] Department of Electronics and Communication Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Coimbatore - 641112, India.

[2]Assistant Professor, Department of Electronics and Communication Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Coimbatore - 641112, India. Phone:+91-8056550176, e-mail: ka_pradeepkumar@cb.amrita.edu.*

**Corresponding author*

Abstract

Epilepsy is a chronic disorder of the central nervous system that causes individuals to experience recurrent seizures. Epilepsy is identified as the world's second most common brain disorder after stroke affecting nearly and over 40 million people worldwide. The work presented in this paper describes a novel method to predict the EEG (Electroencephalogram) signal with maximum possible accuracy. The feature used for the entire signal analysis and prediction is AR (Autoregression) Coefficients. The predicted signal was found to be highly accurate with least Root Mean Square Error. The classification and detection of seizure from the predicted signal is left for future implementation.

Keywords: Epileptic seizures, seizure prediction, autoregressive modelling, Burg's algorithm.

Introduction

Epileptic seizures are caused by excessive synchronized activity of a large group of neurons. It produces disruptive symptoms like lapse in attention, sensory hallucination or a whole body convulsion. The EEG is an important clinical tool for diagnosing, monitoring and managing neurological disorder associated with epilepsy [1]. The consequence of an epileptic seizure can be devastating depending upon the action in which the patient is involved, for instance a patient who is walking along the road might face an accident since the patient will have absolutely no control over the jerking movement of the body.

In such a situation, there is a need for a system or a device [2]–[4] that can predict the onset of an epileptic seizure well ahead and alert the user so that the user can take remedial measures. Such a device will have to have parameters such as minimum false detection rate, maximum sensitivity to epileptic seizures, longer period before which the seizure occurs, and the system could also be made portable.

In order to design systems with the above mentioned properties, several algorithms and methods have been proposed. The proposed methods include Autoregressive (AR) Modelling [5]–[9], Least Square Parameter Estimation [10], [11], Support Vector Machine (SVM) Classifiers [12], SVM Regularized By Kalman Filtering [12]–[15], EEG And EOG Monitoring [1], Artificial Neural Networks (ANN) [13], Correlation, Ictal Morphology Classification [1], Wavelet Analysis [16]–[18], Dynamic Wavelet Network [19], Adaptive Weiner Algorithm [3], Fractional Linear Prediction [20], Genetic Algorithms [21], [22]. Among these methods, autoregressive modelling is the most suitable method for prediction [7].

It is obvious that classification accuracy of prediction of a seizure increases if the prediction accuracy of the EEG signals is itself improved. This work focuses on improving the accuracy of prediction of the EEG signal. However, instead of using the raw EEG signals, autoregressive coefficients of EEG are used. Autoregressive coefficients are more suitable for the implementation of a real-time EEG prediction system [7]. To the best knowledge of the authors, devising of methods to improve the prediction accuracy of AR coefficients of corresponding EEG signal has not been made and claimed to be the novel contribution of this work. Thus the objectives of this work can be summarised as:

- To predict the variation of EEG signals indirectly by using the autoregressive (AR) coefficients as a measure of variation of the actual EEG signal.
- To improve the accuracy of the prediction by employing real-time corrective algorithms to ensure that the classifier can provide better classification without computational complexity.

System Architecture

The proposed system uses 5 EEG channels, selected as discussed, and determines the AR coefficients for a definite period of time for which the signal is known. Then, the variation of the AR coefficients is predicted. This method uses Burg's algorithm for calculating the AR coefficients. The process is divided into two stages, as shown in the figure 1.

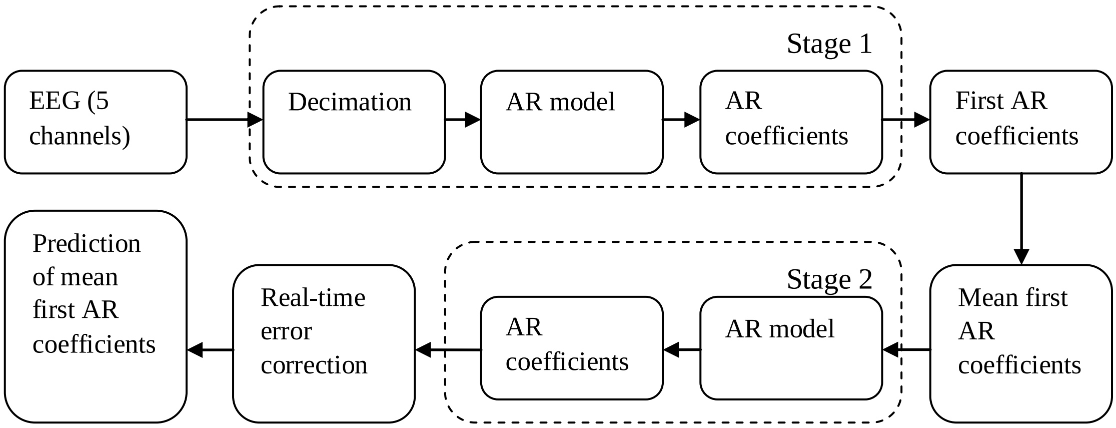


Figure 1: Block diagram of the process

Stage 1:
Five channels of the pre-processed EEG signals are given as input to stage 1. Decimation at the rate of N>>11 is carried out at this stage in order to decrease the computational complexity and to increase the period of prediction. Performing decimation at this high value is justified since the rate of change of AR coefficients is by order of magnitudes slower than EEG sampling rate[7]. The decimation factor is chosen in such that the final sampling period is lesser than the period of occurrence of an epileptic seizure. A bare minimum of at least 1 sample per second is preferable, as an epileptic seizure can exist for a minimum period of 1 second and seizures below 1 second have insignificant effects on the patients. The length of the input sample is chosen as discussed in forthcoming sections.

The AR coefficients for each of the channels for a definite known period are calculated and the first AR coefficients are then extracted to form a separate vector. This process is iterated by calculating the AR coefficients at each instant of time and then assigning the first AR coefficient obtained to that instant. The number of iterations is dependent upon the length of the input sample required to predict the desired period of signal. The ratio of the desired length of prediction to the length of the signal used to predict is chosen as 1:2, which provides a trade-off between accuracy and time taken for prediction as observed experimentally. Then the mean of the first AR coefficient vectors of all the channels is obtained and finally, a single vector is obtained. The order of the AR model is one, keeping in mind that our aim is to reduce mathematical complexity. The AR model employed uses the Burg's algorithm.

Stage 2:
In this stage, the variation of the mean first AR coefficient vector obtained in the first stage is predicted. The input to the second stage is the mean first AR coefficient vector. This block consists of an AR model of very high order in order to ensure high accuracy of the prediction. At the end of stage 2, the predicted variation of the mean first AR coefficient vector is obtained.

This process simplifies the prediction of EEG by predicting the variation of the AR coefficients rather than the EEG directly since the original signals are highly non-stationary which does not allow AR to be applied. The initial signal is assumed to be stationary and then the AR coefficients are calculated. The obtained mean first AR coefficients are not non-stationary unlike the original EEG signals. This allows the AR model to predict the variation of the mean first AR coefficient vector with relatively more certainty. The variation of the predicted mean AR coefficients is in direct correspondence with the original EEG signal. When an epileptic seizure occurs, the magnitude of the predicted mean AR coefficients increases and during the pre-ictal and inter-ictal periods, the magnitude of the predicted mean AR coefficients is relatively low. This two-staged approach also makes the process of prediction mathematically simpler so that there is least computational load on the system which in turn saves the time taken for predicting a given length of signal.

Autoregressive Modelling

In general, autoregressive modelling predicts the present value of a signal which is expressed as a weighted sum of the past values of the signal. The main aim of an autoregressive process is the determination of the AR coefficients, i.e. the weights, and then to use them for upcoming iterations to predict the forthcoming values of the signal. Chisci et al[7] have used autoregressive modelling for EEG signal prediction. Their methods use the autoregression coefficients directly to detect seizures. The model proposed by them determines the AR coefficients of the EEG channels, and then again the variation of the AR coefficients is predicted using least square parameter estimation. This idea forms the basis of this work, after incorporating modifications, improved results have been achieved. Yule-Walker method and Burg's algorithm are the two prominent algorithms available for calculating AR coefficients.

Yule-Walker AR method, also called the autocorrelation method, fits an autoregressive (AR) model to the windowed input data by minimizing the forward prediction error in the least squares sense. It calculates the AR coefficients by using the formula,

$$X_t = \sum_{j=1}^{p} \varphi_j x_{t-j} + \varepsilon_t \qquad \text{-(1)}$$

where X_t is the value of X at time instant t. φ_t are the coefficients in the autoregression. x_{t-j} is the previous values. ε_t is the forward error.

The Burg method fits an autoregressive (AR) model to the input data by minimizing (least squares) the forward and backward prediction errors while constraining the AR parameters to satisfy the Levinson-Durbin recursion. The Burg method avoids calculating the autocorrelation function, and instead estimates the reflection coefficients directly. Burg's algorithm ensures a stable AR model and is computationally efficient when compared to Yule-Walker method [23]. Hence the presented work employs Burg's algorithm in both the stages mentioned previously.

AR Order And Input Sample Length Selection:

The first stage in this process is an AR(1) process, i.e. an AR model of order 1. An AR(1) process is mathematically defined as:

$$x_n + ax_{n-1} = \varepsilon_n \qquad - \qquad (2)$$

Where x_n = value of the present sample at time n, the value which is to be determined, a = AR coefficient, x_{n-1} = value of the past sample at time n-1, ε_n = AR error

In equation (1), x_{n-1} can be substituted with its AR(1) model, and this can be repeated infinitely, as shown below.

$$x_n = \varepsilon_n - a\varepsilon_{n-1} + (-a)^2\varepsilon_{n-2} + \ \dots \ + (-a)^{n-1}(\varepsilon_1 - ax_0) \qquad - \qquad (3)$$

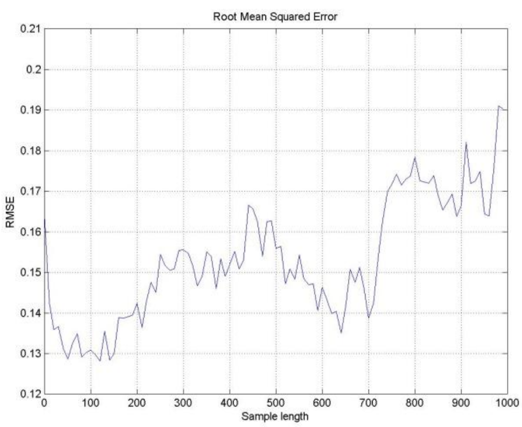
From equation (3), the expectation of x_n is determined as in equation 4.

$$E[x_n] = E[\varepsilon_n - a\varepsilon_{n-1} + (-a)^2\varepsilon_{n-2} + \ \dots \ + (-a)^{n-1}(\varepsilon_1 - ax_0)] \qquad - \qquad (4)$$

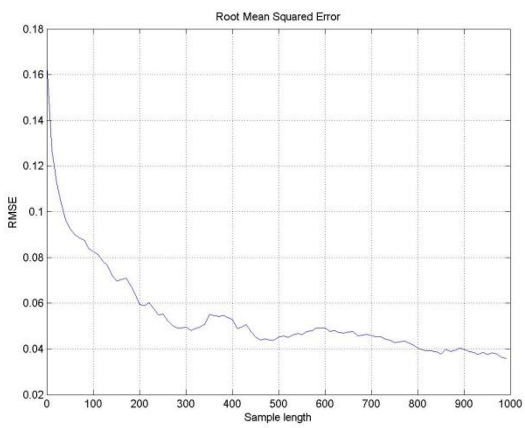
It is seen from equation 3 that the expectation of x at time n is dependent on all of the past values, up to t = 0. Hence it can be concluded that the higher the number of input samples for the AR(1) process, the closer is the value of x at the time n to the true value. This forms the basis of using more than two samples for the AR(1) process, though two values are sufficient.

Though it is allowed to use more than 2 samples (for an AR(1) process), it is not advisable to choose a very large number since this could slow down the system as the AR model becomes more computationally complex. Hence, to arrive at an optimal number for the input sample length, the following steps were carried out.

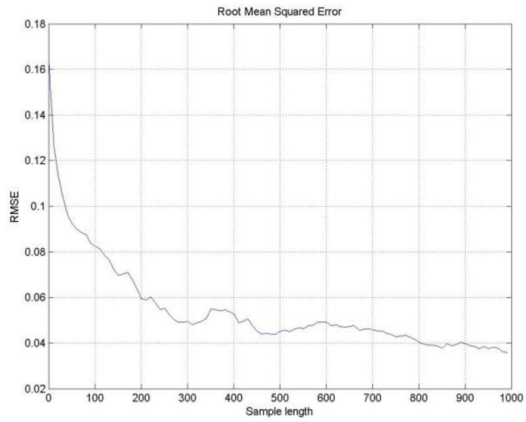
The first stage being an AR(1) process, it requires a minimum input length of 2 samples. The length of the sample given to the first stage was varied from 10 to 1000 and the Root Mean Square Error (RMSE) was determined for each length. The RMSE obtained for each sample length for different patients is shown in the figures 2 (a), (b) and (c).



(a)



(b)



(c)

Figure 2: Variation of RMS error against input sample length

It is observed that, for a length ranging from 600 to 700 samples, the RMSE is minimum/less for each of the cases. Hence, the length of the input sample given to the stage 1 was chosen to be 650, from the experimental study.

The comparison of the actual and predicted waveforms of the mean first AR coefficients vector for input sample lengths 10, 650, and 1000 are shown in figures 3, 4 and 5.

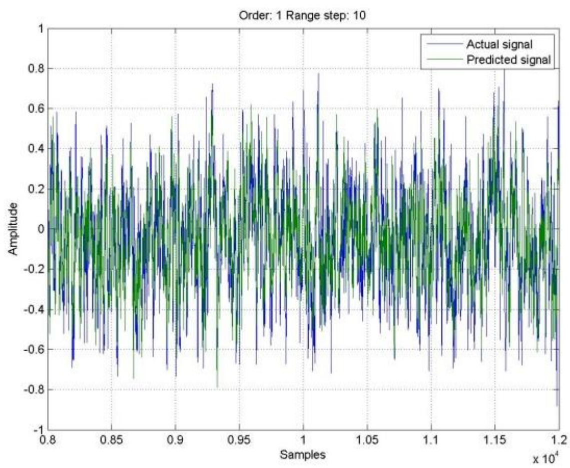


Figure 3: Actual and predicted waveforms for order = 1 and sample length = 10

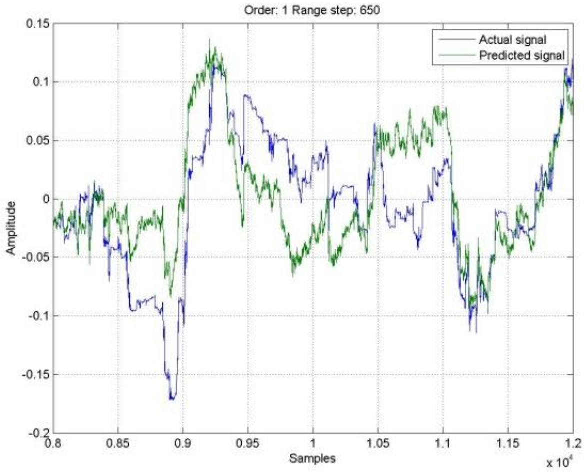


Figure 4: Actual and predicted waveforms for order = 1 and sample length = 650

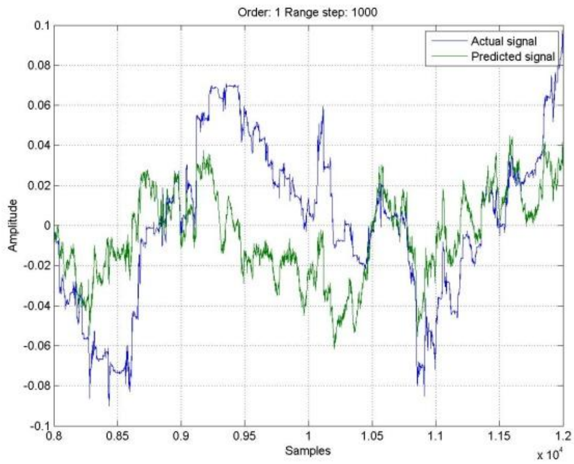


Figure 5: Actual and predicted waveforms for order = 1 and sample length = 1000

From figures 3, 4 and 5, it is seen that the actual waveform for a length of 10 samples is highly random, whereas for lengths of 650 and 1000 samples, the waveform is less random. Between the predictions for sample lengths 650 and 1000, the prediction with the sample length of 650 has a better correlation with the actual one when inspected visually as in figure 4, and also, the RMSE is lower for the length 650.

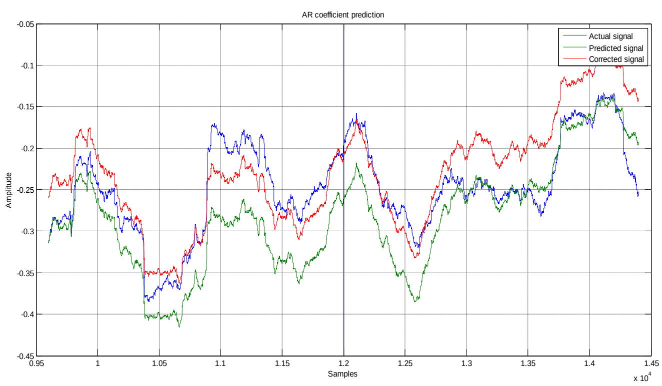
Real Time Error Correction

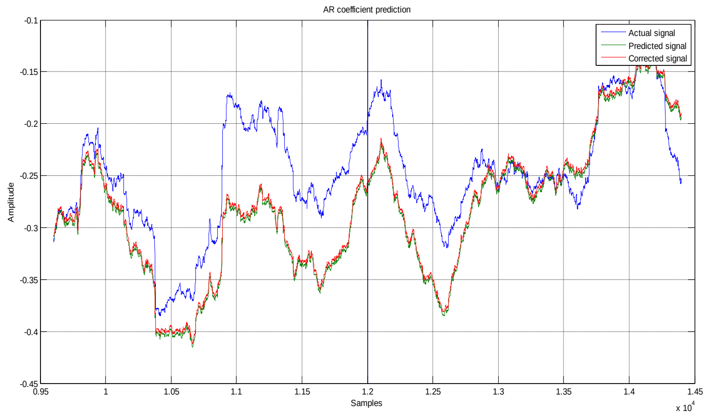
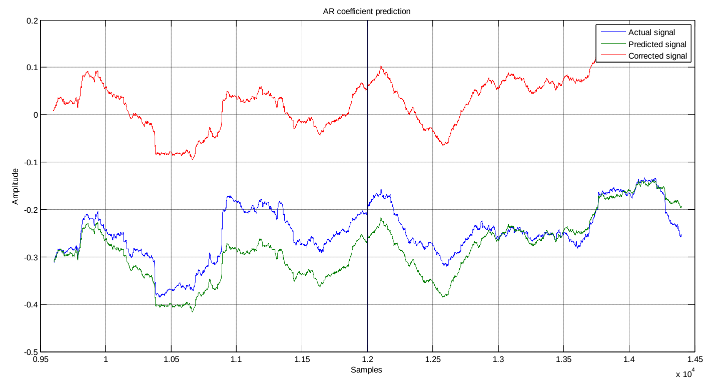
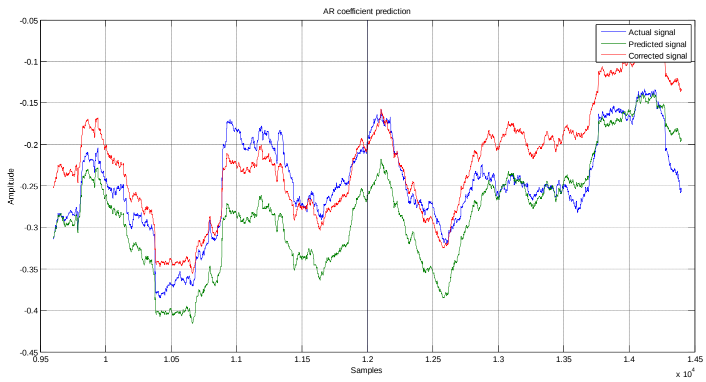
After acquiring the mean AR coefficients from various channels, the signal has been plotted and it has been found that there is a fair amount of RMS error of the predicted signal when compared to the original signal. In an attempt to minimise the RMS error of the predicted signal, various correction methods had been studied. Among those, the basic correction method seemed to be a suitable option as observed from the literature survey which supported this method for obtaining a better result in the process of error minimisation.

Initially, the algorithm for error correction method was kept simple. Using 20 minutes of the signal, the signal contents of the next 10 minutes have been predicted. Now, from the predicted 10 minutes of the signal, for an initial time frame of 5 minutes, the error is to be determined for every sample of the signal (in comparison with the original signal). Next for each sample in that time frame of 5 minutes, a value of error is to be calculated. From the matrix of error values for the 5 minute signal, a single mean error of all error values are computed. Now, with this mean error value, the last 5 minutes of the predicted signal is taken and each sample is corrected (addition/subtraction/multiplication). After correcting the last 5 minutes of the predicted signal, the corrected signal is plotted along with the actual signal and predicted signal. (Three plots have been shown in the same figure represented by different colours. (Actual signal - BLUE /Predicted signal - GREEN /Corrected signal - RED)**.**

For studying all possible errors that are to be calculated and used for correction, the following errors have been shortlisted: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Normalised Root Mean Square Error (NRMSE), Mean Error (ME). To find the best choice to be employed in the error correction method, all the four errors are implemented and the corrections are made. MSE, RMSE and ME, when used for correction, is added or subtracted (whichever yields the best result - trial and error) and when NRMSE is used, the value is multiplied with the predicted sample value to obtain the corrected value. The table below shows the output figure with all three signals - actual, predicted and corrected, where the correction is done using all 4 above mentioned errors, one-by-one. Table 1 illustrates the correction performed using each of the above mentioned error parameters.

Table 1: Implementation of error correction using Mean Error, MSE, RMSE and NRMSE

Error Used	**Result Plots**
Mean Error	

MSE	
NRMSE	
RMSE	

By comparing the figures in table 1, the one which used RMSE for correction was found to produce better results than the other three figures. Thus, from the static method of error correction, the best error that could be used for error correction method was determined. Also, the efficient span of correction is determined through detailed study of the plots. It has been inferred that, when the error of a 5 minute signal is calculated and used for correction of another part of predicted signal, the accuracy of correction is at its best for the first two minutes. This information will prove to be useful in the next process of error correction.

The next step for the correction mechanism is Real Time cumulative error correction method. In this method, a time window is set and the window is kept in motion and the error calculation cum correction is done simultaneously. A 57 minute signal is used for the entire process. The initial 40 minutes are used and the rest 17 minutes are predicted using AR coefficients and AR Burg's method. The first 5 minutes (40 - 45 minutes - Correction Window) is taken and RMSE is calculated and then the next 2 minutes (45 - 47 minutes - Corrected Window) of the predicted signal is corrected. After this, the correction window and corrected window is moved by a 2 minute time frame i.e., the samples of 42 - 47 minutes signal is taken and their RMSE is calculated and then the correction process is done to 47 - 49 minutes. An important point to be noted here is that the samples of 45 - 47 minutes signal used for the RMSE calculation in the above phase of correction, are taken from the samples corrected of the pen-ultimate phase. Similarly the correction window and corrected window are moved by a 2 minute time frame and the process is repeated. Like the last phase, for every phase up to 57 minutes, the corrected samples are used for the error correction processes.

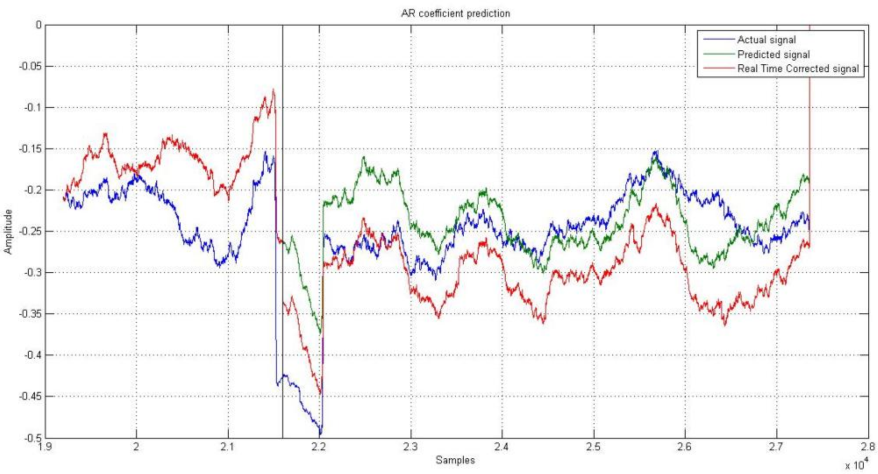


Figure 6: Real time error correction

The figure 6 has three plots - actual, predicted and corrected signals. Thus, by the process of cumulative error correction method, the error minimisation for the predicted signal is done successfully.

Results

This section explains in detail the results obtained from the proposed model as described in the previous chapters. A comparison is made with the results obtained in every step in the process.

Parameter For Measuring System Performance

The main aim of the work done is to make the system predict the mean AR coefficients as accurately as possible. Hence, the parameter chosen to measure the proposed system's performance was Root Mean Square Error (RMSE). Other parameters like Mean Squared Error (MSE), Normalised Mean Square Error (NRMSE), Standard deviation, Variance etc were not suitable for this process as their dimensions did not match with that of the obtained output. RMSE has the dimensions same as the predicted waveform and hence can be used as a reliable measure of accuracy.

Input to the system

The results were obtained from EEG data collected from 22 subjects consisting of 5 males of ages ranging from 3 years to 22 years and 17 females of ages ranging from 1.5 years to 19 years. The signals were obtained from the Physionet.org database. The EEG channels chosen were FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3.

Prediction without any correction scheme

This section describes the system working without proper AR order selection and length selection methods. The following figures show the inputs and outputs of the system. The input in figure 7 has a length of 200 samples after decimation by a factor of 32. The sample length of 200 samples translates to 25 seconds of original EEG data. Figure 8 shows the AR coefficients calculated for every 200 sample window. The process is as described in the previous section. The sample length of 12000 samples translates to 1500 seconds.

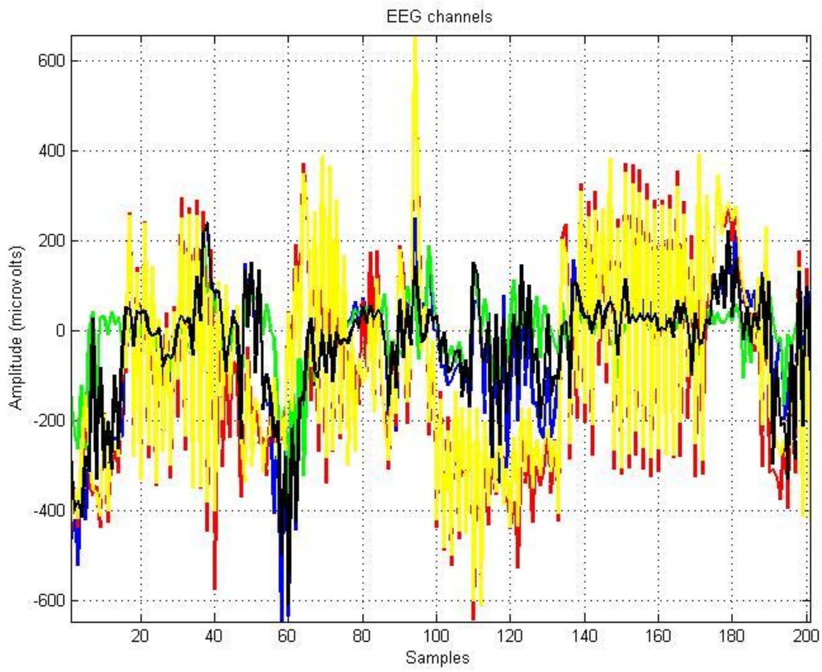


Figure 7: Pre-processed EEG channels

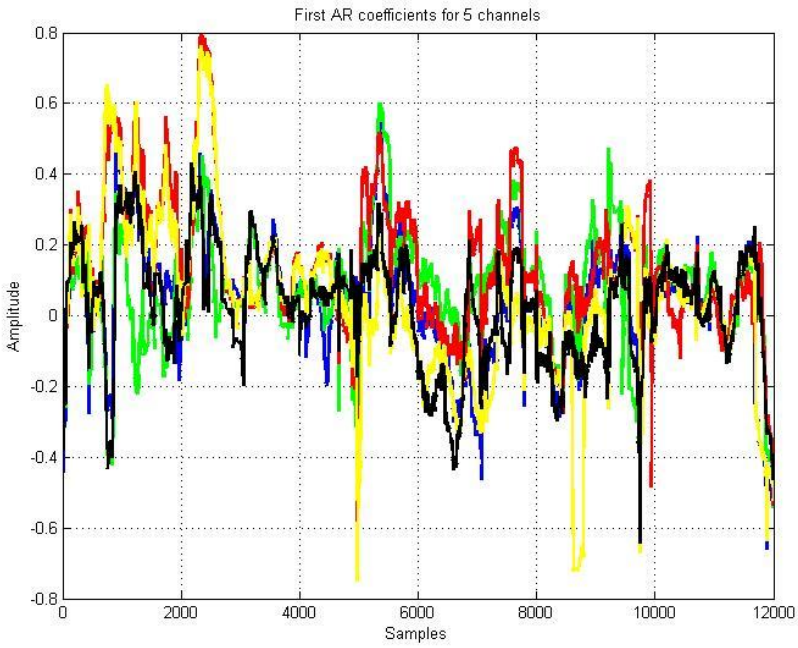


Figure 8: First AR coefficients for 5 EEG channels

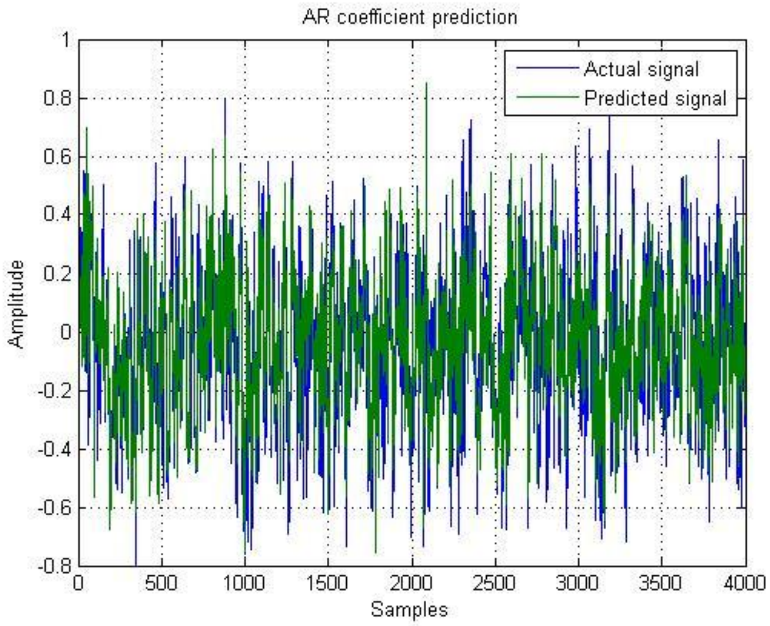


Figure 9: Mean first AR coefficient prediction, sample length = 10

The plot in figure 9 shows the comparison of the actual values of the mean first AR coefficients and its predicted values. The prediction is done with input sample length of 10 samples (chosen arbitrarily). The RMSE calculated for this trial is 0.16425, which is beyond the useful range for classification purposes.

Prediction with corrected order and sample length

This section explains the working of the system with order selected as per the process as discussed previously. The figure 10 illustrates the results. The order of the AR model in stage 1 was chosen as 1, since a minimum order had to be maintained in order to keep the computational complexity to a minimum. In stage 2, the order was chosen as 8000 in accordance with the criteria defined in the previous section.

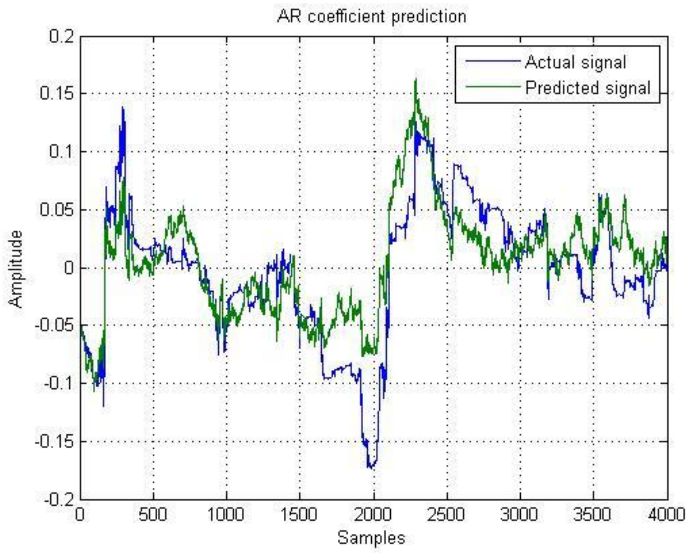


Figure 10: Mean first AR coefficient prediction, sample length = 650

The prediction obtained in figure 14 has a root mean squared error of 0.034222, which is lesser than that of the case in the previous section which had arbitrary order and input sample length selections.

Prediction with real-time error correction

This section describes about the error correction methods employed in the proposed system. The AR coefficients were predicted as described in section 6.4. The RMSE was obtained for 5 minutes (0 - 5 minutes) of the predicted signal and then a correction was applied to the prediction for the next 2 minutes (5 - 7 minutes). Then the RMSE was calculated for 5 minutes (for 2 - 7 minutes) and then the correction was applied to the next 2 minutes (7 - 9) minutes. Figure 11 shows the cumulative error correction applied to the predicted mean first AR coefficients.

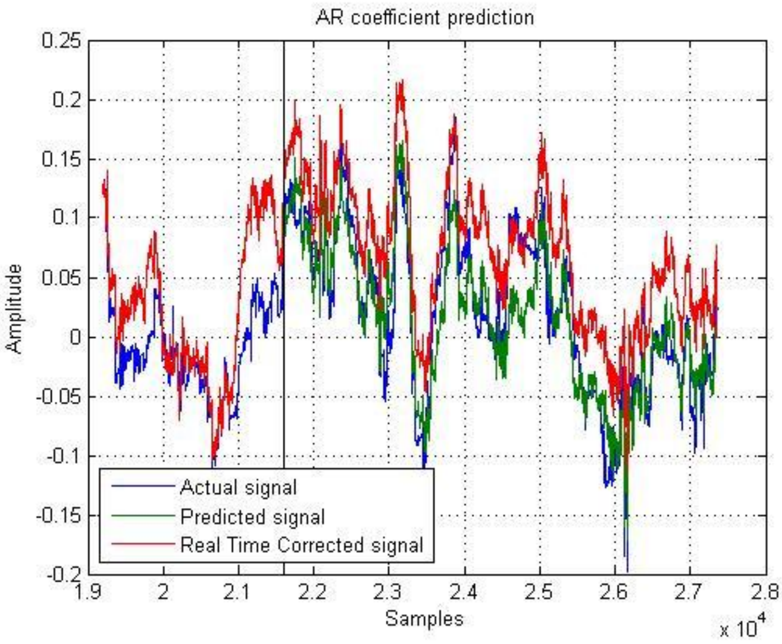


Figure 11: AR coefficient prediction with cumulative error correction

The blue waveform is the actual mean AR first coefficients that were already calculated. The green waveform is the predicted mean AR first coefficients. The red waveform is the corrected mean first AR coefficients. The correction was done in real time along with the prediction. The black vertical line marks the beginning of the real time error correction. The red waveform on the right is the corrected waveform. On the left of the black vertical line, the corrected and the predicted signal overlap and hence the green line is not visible. The RMSE of the corrected waveform is 0.028500, which is lesser than both the cases as described in the previous sections. Similar results were obtained for other cases. Table 2 shows a comparison of the RMSE for different cases with only prediction, prediction with corrected length and order and prediction with real time error correction.

Table 2: Comparison of RMSE of prediction without any correction, with corrected length and order, and with real-time error correction

	Root Mean Squared Error		
Case	**Prediction (without error correction scheme)**	**Prediction with corrected length and order**	**Prediction with real time error correction**
1	0.164250	0.034222	0.028500
2	0.164000	0.101000	0.083400
3	0.083282	0.024200	0.021500
4	0.109360	0.026956	0.029400
5	0.101780	0.023651	0.022100
6	0.162570	0.038728	0.027600
7	0.165230	0.033698	0.028800
8	0.075586	0.018574	0.014300

It is seen from table 2 that the RMSE for the real time prediction is very less compared to the other two. The less error makes it easier for the classifier to determine the decision boundary. The design of the classifier is, however, beyond the scope of this work.

By the above mentioned steps, the prediction of the mean first AR coefficients has been tuned in a manner to provide the least possible error so that classification can be done with better accuracy. Classification of the waveform for the presence or the absence of epileptic seizures has not been implemented in this current work since the aim was only to perfect the prediction of the mean first AR coefficients and classification was beyond the scope of the project.

Conclusion and Future Scope

The work presented in this paper is a system for predicting the waveforms of EEG indirectly by predicting the variation of the AR coefficients of the original EEG signal. The system has been designed with low computational needs in order to allow the system to be ported to a portable system which can predict seizures from the online analysis of EEG. In order to obtain a perfect classification of the EEG with 100% sensitivity and zero/minimum false prediction rate, the EEG signal has to be predicted with maximum possible accuracy. Hence only the prediction of the EEG signal using the variation of its AR coefficients was taken as the main objective of this work. In order to assess the working of the system, EEG databases from Physionet.org were used which are well known and widely used.

Scalp EEG signals have been used in this method, but the use of intracranial EEG signals would provide a more noise-free input for the system and reduce the need for the complex signal conditioning systems. Future work will be concentrating on the methods for classification of the features obtained by using the methods discussed in this method, and also concentrate on the signal conditioning methods which will help in providing a good quality EEG signal input to the system without affecting the portability of the system.

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