Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Elman neural networks for dynamic modeling of epileptic EEG

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Abstract - **In this paper, autoregressive modeling technique and neural network based modeling techniques are used to model and simulate electroencephalogram (EEG) signals. EEG signal modeling is used as a tool to identify pathophysiological EEG changes potentially useful in clinical diagnosis. The normal, background and epileptic EEG signals are modeled and the dynamical properties of the actual and modeled signals are compared. Chaotic invariants like correlation dimension (D_2), largest Lyapunov exponent (λ_1), Hurst exponent (*H*) and Kolmogorov entropy (*K*) are used to characterize the dynamical properties of the actual and modeled signals. Our study showed that the dynamical properties of the EEG signal modeled using neural network (NN) techniques are very similar to that of the signal.**

Keywords- **Autoregressive modeling, neural networks, EEG, epilepsy.**

I. INTRODUCTION

The study of human brain activity by means of the EEG has profited from recent advances in the field of nonlinear time series analysis. In the past, the EEG has been characterized by using indices initially derived for the study of deterministic dynamical systems [1]. This new approach has provided a better insight about the way in which the brain works. Nonlinear methods have shown their ability to excel the traditional spectral techniques, tracing changes in the signal that would have remained undisclosed otherwise. Most of the studies undertaken hitherto have been carried out in one single EEG channel, whose nonlinear characteristics were calculated to test for differences among groups of healthy and diseased subjects [2] or different sleep stages [3]. Researchers have applied certain nonlinear techniques for prediction of epileptic seizures [4,5], characterization of sleep phenomena [6] and monitoring of anaesthesia depth [7].

Nonlinear systems can exhibit a wide spectrum of dynamical behaviors, which include fascinating chaotic dynamics. A chaotic system is deterministic, but the system output is not predictable in the long run. Conventional signal modeling techniques assume that these signals are generated by some linear system driven by random noise, but they are not appropriate to model the underlying nonlinear dynamics. In experimental dynamical systems, a procedure to reconstruct a state-space trajectory from the output of a system was introduced by Packard et al. [8]. Later, Takens proved that the reconstruction preserves two important qualitative descriptors of the original system dynamics: the dimension and the Lyapunov exponents of the system attractor [9]. This reconstruction establishes a bridge between a time-domain signal and a state-space representation of the original system. In this modeling approach, the resulting model is required to be capable of producing a time series which possesses the same dynamical invariants as the original signal. In other words, the resulting model is required to capture the underlying dynamics of the signal.

Epilepsy is a pathological condition characterized by spiky patterns in continuous EEG and seizure at times. The aim of our study is to model the EEG signals of healthy and epileptic subjects.

II. DATA DESCRIPTION

The EEG data for analysis were obtained from the EEG database available with the University of Bonn, Germany. [10] Two sets each containing 30 single channel EEG segments of 23.6-sec duration, were composed for this study. These segments were selected and extracted from continuous multi-channel EEG recordings after visual inspection for artifacts. The control EEG dataset consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized electrode placement scheme. Volunteers were relaxed in an awake state with eyes open. Epileptic EEG dataset contains data recorded during seizure activity. All EEG signals were recorded with the same 128-channel amplifier system, digitized with a sampling rate of 173.61 Hz and 12 bit A/D resolution. All the datasets were preprocessed and tested for stationarity and nonlinearity before estimating the chaotic invariants.

III. METHODS

A. Auto Regressive Modeling Technique

Using Autoregressive modeling approach, the nth value of the signal considered as the output, y(n) is given by

$$y(n) = \sum_{k=1}^{p} a(k)\,y(n-k) + w(n) \qquad (1)$$

where p is the order of the AR model, w(n) is a white noise with zero mean and variance σ^2.

This linear prediction equation is characterized by p unknown parameters, a(k). Within each epoch, the series was assumed to be stationary. The a(k) parameters and σ^2 were, then, estimated with the Burg's method[11,12].

One of the most important aspect of the use of AR method is the selection of the order p. Much work has been done by various researchers on this problem and many experimental results have been given in literature such as the papers presented by Akaike [13]. The order of the model was chosen as the one that minimizes the Akaike information criterion (AIC) figure of merit,

$$AIC(p) = N.Ln\left(\hat{\sigma}^2\right) + 2p \quad (2)$$

Where N is the number of data samples and $\hat{\sigma}^2$ is the estimated white noise variance. In this work the order of the AR model is taken as: p=16.

B. Neural network Modeling Technique

Elman networks [14] are two-layer backpropagation neural networks, with the addition of a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman networks to learn to recognize and generate temporal patterns, as well as spatial patterns. The block diagram of the Elman network is given in Fig.1.

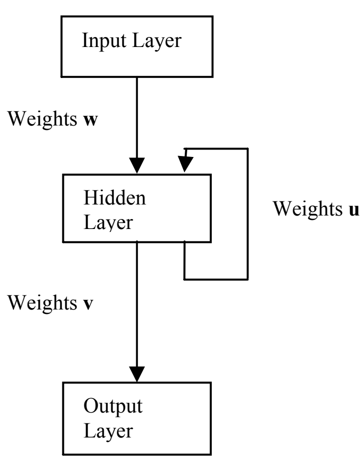

Fig.1. Block Diagram of the Elman neural network

The output of the hidden layer $y_j(t)$ is given by

$$y_j(t) = f(net_j) \quad (3)$$

$$net_j(t) = \sum_i w_{ji} x_i(t) + \sum_h u_{jh} y_h(t-1) + \vartheta_j \quad (4)$$

The final output $y_k(t)$ is given by

$$y_k(t) = g(net_k) \quad (5)$$

$$net_k(t) = \sum_j v_{kj} y_j(t) + \vartheta_k \quad (6)$$

V. Results and Discussion

In this work, two models – one using AR modeling technique and other using NN modeling technique are constructed to predict the EEG signals. The order of the AR model is 16. The neural network model is constructed with 24 inputs, one hidden layer with 24 hidden neurons and one output layer with one output neuron (24-24-1). The network is trained with 50 datasets each of normal, background and epileptic EEG and tested with 30 datasets each of normal, background and epileptic EEG. The results of the reconstructed signal and the chaotic invariants analysis of the reconstructed signal are presented in this section.

A. Reconstructed Signal

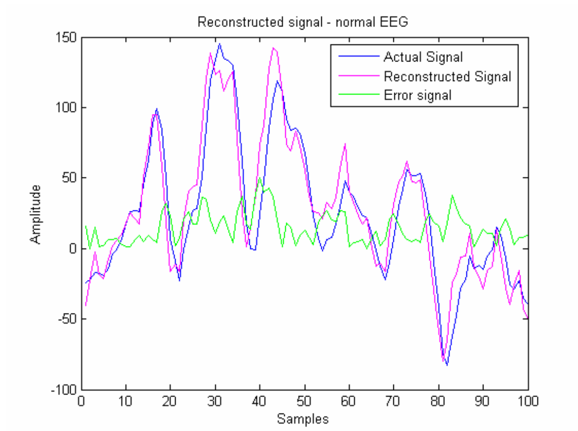

Fig.2. Normal EEG signal reconstructed using AR model

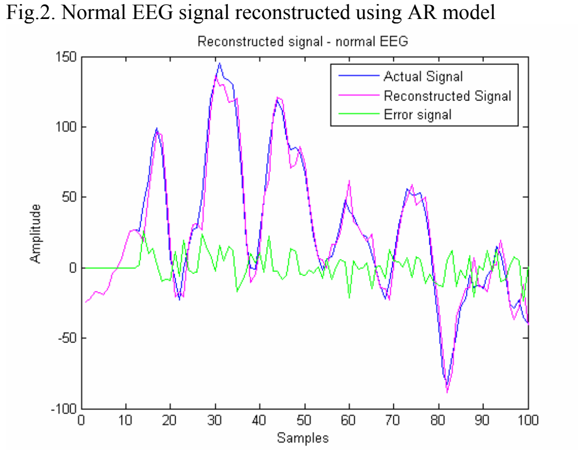

Fig.3. Normal EEG signal reconstructed using NN model

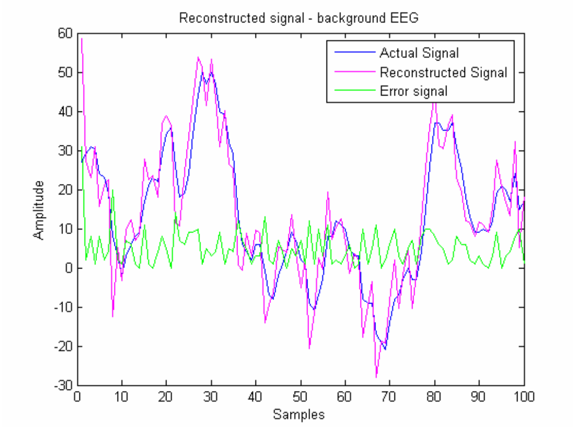

Fig.4. Background EEG signal reconstructed using AR model

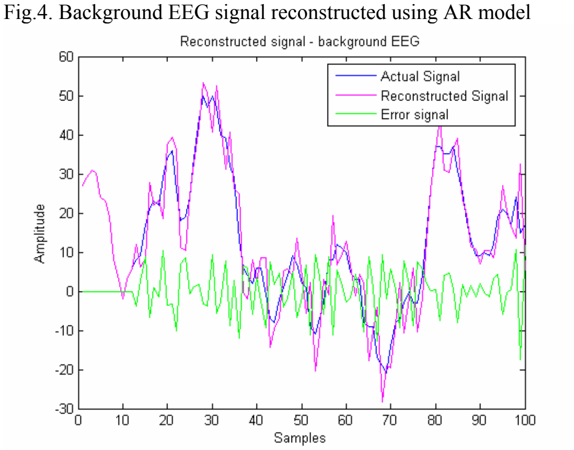

Fig.5. Background EEG signal reconstructed using NN model

The normal, epileptic and background EEG signals are reconstructed using the two models – AR model and NN model and the results are given in Figure 2 - 7. From the results it can be seen that the NN model can successfully approximate the EEG signal better than the AR model. To compare the performance of the two modeling techniques, the error signal is computed for the reconstructed signals and given in the figures (Fig.2 to Fig.7). The NN model initially models the signal with no error and eventually diverges but with a little error. This is expected from any chaotic signal and is denoted by the presence of positive Lyapunov exponent. The intention of the model is to generate the time series that preserves the nonlinear dynamical properties of the signal. The tests for the preservance of the dynamical properties in the modeled signals are discussed in the following section.

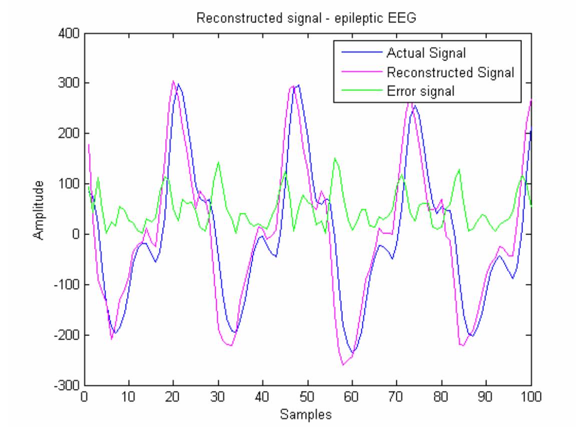

Fig.6. Epileptic EEG signal reconstructed using AR model

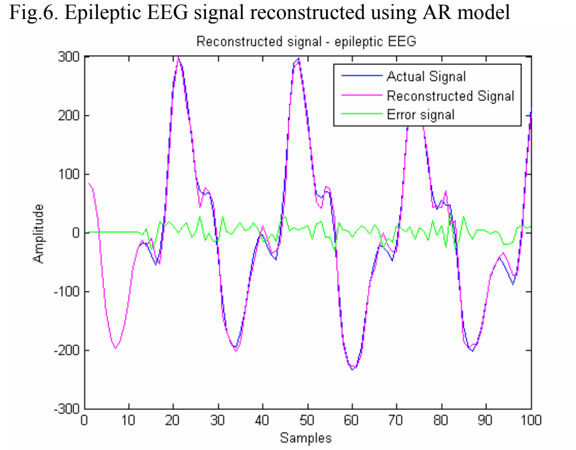

Fig.7. Epileptic EEG signal reconstructed using NN model

B. Chaotic Invariants Analysis

TABLE I
CHAOTIC MEASURES OF NORMAL EEG

Chaotic Invariants	**Original**	**AR**	**NN**
D_2	4.8768	4.5672	4.7731
λ_{max}	0.2036	0.1876	0.1903
H	0.3248	0.2974	0.3124
$KSEN$	0.6033	0.5788	0.5876
$APEN$	0.7096	0.6933	0.6932
SEN	-0.2215	-0.2341	-0.2333
REN	-0.1927	-0.2109	-0.2121
$D^{Higuchi}$	1.5132	1.4874	1.4972
D^{Katz}	1.8649	1.7991	1.8123

Table I to Table III show results of analysis of actual and the reconstructed normal, background, epileptic EEG signals using AR and NN modeling techniques. The chaotic invariants such as correlation dimension D_2, Lyapunov exponent $\lambda_{\max}$, Hurst exponent H, and entropy measures such as Kolmogorov Sinai entropy $KSEN$, approximate entropy $APEN$, spectral entropy SEN, Renyi's entropy REN and fractal dimension measures computed using Katz and Higuchi's algorithms ($D^{Higuchi}$ and D^{Katz}). The estimates of the largest Lyapunov exponents for reconstructed normal EEG signal of the NN model is 0.1903, while that for the AR model is 0.1876. The results are given in Table I. Again, it can be clearly seen that the results for the output of the NN model is very close to that of the original signal. The correlation dimension estimate for the normal EEG signal of both the models is given in Table I. From the correlation dimension estimate of the output of the NN model it can be seen that the NN model can preserve the characteristics of the original signal very well. Results of the chaotic analysis of the modeled signals of the background and epileptic EEG signals also indicate the NN model output is quite similar to that of the original signal. The dimension estimate of the output of the NN model is smaller than the original signal. This implies that the dynamics of the NN model is less complicated than the original system. The results are supported by the other estimates such as Hurst exponent and fractal dimension measures.

TABLE II
CHAOTIC MEASURES OF BACKGROUND EEG

Chaotic Invariants	Original	AR	NN
D_2	4.3451	4.1141	4.2311
$\lambda_{\max}$	0.1912	0.1832	0.1891
H	0.3411	0.3121	0.3265
$KSEN$	0.5391	0.5121	0.5198
$APEN$	0.6731	0.6534	0.6608
SEN	-0.4818	-0.5121	-0.4992
REN	-0.183	-0.2012	-0.1914
$D^{Higuchi}$	1.4051	1.2987	1.3528
D^{Katz}	1.5634	1.4521	1.5112

VI. CONCLUSION

The reconstructed signal from the output of the NN model is very similar to the original signal as compared to that of the AR model. To further quantify this similarity, the chaotic invariants of the reconstructed signals are estimated. The chaotic invariants represent the nonlinear dynamics of the signal. The chaotic invariants estimate of the actual, AR modeled signal and the NN modeled normal, background and epileptic EEG signals are compared. From the results it can be seen that the values of the NN modeled signal are closer to the original signal.

From all of these comparisons, it can be concluded that the NN model captures the underlying dynamics of the EEG signal very well compared to the AR model.

TABLE III
CHAOTIC MEASURES OF EPILEPTIC EEG

Chaotic Invariants	Original	AR	NN
D_2	3.9407	3.7534	3.8513
$\lambda_{\max}$	0.1845	0.1564	0.1734
H	0.3563	0.3231	0.3397
$KSEN$	0.4926	0.4571	0.4791
$APEN$	0.6484	0.6153	0.6278
SEN	-0.735	-0.7561	-0.7432
REN	-0.195	-0.2111	-0.1993
$D^{Higuchi}$	1.3546	1.2567	1.2983
D^{Katz}	1.5139	1.3967	1.4511

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