Chaotic Time Series Prediction using Correlation Dimension and Adaptive Neuro-Fuzzy Inference System

Pravin Kshirsagar
Department of Electronics Engineering
S.B.Jain Institute of Technology, Management and Research
Nagpur, Maharashtra, India
pravinrk88@yahoo.com

Dr. Sudhir G. Akojwar
Department of Electronics Engineering
Rajiv Gandhi College of Engineering, Research & Technology Chandrapur, Maharashtra, India
sudhirakojwar@rediffmail.com

Abstract — Nonlinear dynamic signal processing is attracting several researchers owing to its complex behavior which may be deterministic at macro level and may be in order but unruly behavior with respect to time is difficult to understand and interpret. EEG signals fall under such categories. Prediction of seizure in EEG is a challenging task. For this several prediction methodologies have been in use from time to time. But the complexity of signals which differ from person to person makes it complicated. . Keeping this view in mind, we propose to have better prediction of chaotic time series through this paper. Though there have been several attempts in the past, our research is related to use of ANFIS for chaotic time series prediction. Correlation dimension are the factors based on which convergent or divergent or chaotic nature of signal is predicted. In this paper we use correlation dimension for feature extraction providing to ANFIS model for giving précised result.

KEYWORDS - EEG SIGNALS, CORRELATION DIMENSION,ANFIS

INTRODUCTION

EEG signal is a spontaneous bioelectricity activity that is produced by the central nervous system. It includes abundant information about the state and change of the neural system; therefore it is widely used in clinic and neural-electricity physiological research.

An electroencephalograph is a record of the electrical activity generated by a large number of neurons in the brain. It is recorded using surface electrodes attached to the scalp or subdural or in the cerebral cortex. The amplitude of a human surface EEG signal is in the range of 10 to 100 μV. The frequency range of the EEG has a fuzzy lower and upper limit, but the most important frequencies from the physiological viewpoint lie in the range of 0.1 to 30 Hz. The standard EEG clinical bands are the delta (0.1 to 3.5 Hz), theta (4 to 7.5 Hz), alpha (8 to 13 Hz), and beta (14 to 30 Hz) bands. EEG signal analysis is helpful in various clinical applications including predicting epileptic seizures, classifying sleep stages, measuring depth of anesthesia, detection and monitoring of brain injury, and detecting abnormal brain states. Visual analysis of EEG signals in the time domain is an empirical science and requires a considerable amount of clinical and neurological knowledge. Many brain abnormalities are diagnosed by a doctor or an electroencephalographer after visual inspection of brain rhythms in the EEG signals. However, long-term monitoring and visual interpretation is very subjective and does not lend itself to statistical analysis. Therefore, alternative methods have been used to quantify information carried by an EEG signals.

Predicting future behavior of chaotic time series is a challenging area in nonlinear prediction. The prediction accuracy of chaotic time series is extremely dependent on the model and learning algorithm. In addition, the generalization property of the proposed models trained by limited observations is of great importance.

In the past decades, neural networks and related neuro fuzzy models as general function approximations have been the subjects of interest due to their many practical applications in modeling complex phenomena but when the number of observations for training is limited they can neither reconstruct the dynamics nor can learn the shape of attractor.

They may present the most accurate one step ahead predictions, but in larger prediction horizon their performance dramatically falls down. The uncertainty of EEG has repelled human to make efforts for determining predicted EEG signals before time so that feature critical condition of patient will be tackled and managed prior to any vast spread demolition. If we predict real time EEG signals which will help to save the life of patient.

In recent years, many modeling has gained significant importance through Artificial Intelligence (AI) techniques for their ability to learn hidden patterns from historical data and predict highly non-linear systems. The hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) are commonly used AI techniques which have been applied in variety of domains for such modeling.

Various feature extraction method such as correlation dimension, lyapunov exponent are the factors based on which convergent or divergent or chaotic nature of signal is predicted. This can be suitably applied to a neuro-fuzzy or simply an ANN system application in real time databases such as solar energy production and relative data are pre-processed using Fuzzy Logic techniques.

This paper aims at neuro fuzzy approach to the modeling on EEG signals data in which presence of chaos if any. The paper also throws light over the ANFIS model with feature extracting techniques through which analysis of real time prediction can be done effectively.

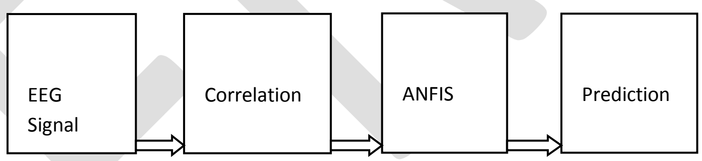

Figure 1.block diagram of system

Figure 1 shows the block diagram of the system.It consist large number of EEG signals which extracted its feature by Correlation Dimension,ANFIS model used for prediction of the neurological disorder from predicted output.

CORRELATION DIMENSION

Using the Grassberger-Procaccia (1983a, 1983b) algorithm to determine the correlation dimension D2, one defines the correlation integral:

$$C(r) = \lim_{n\to\infty} \frac{1}{N^2} \sum_{i\neq j} \theta(r - |\overrightarrow{v_m}(t_i) - \overrightarrow{v_m}(\overrightarrow{t_j})|)$$

where, θ(x) = 1 if x $\geq$ 0,θ (x) = 0 if x < 0, and N is the number of points in the time series. Cm(r) measures the fraction of pairs of points in space that are closer than r. If the system is chaotic one has that for sufficiently large m, m>m*, the correlation integral takes the following scaling form, independent of m,

$$C(r) \approx r^{D_2}$$

with the exponent giving the correlation dimension D2 of the attractor corresponding to the measured signal. Hence D2 can be obtained from the slope of In C(r) vs In r. The quantity m* is the minimal embedding dimension as it is the lowest integer dimension containing the whole attractor; m* gives information on the number of independent variables governing the dynamics of the system.

$$\mathrm{d} = \lim_{\mathrm{r}\to 0, \mathrm{n}\to\infty} \frac{\log \mathrm{Cm}(\mathrm{r})}{\log \mathrm{r}}$$

Plotting log Cm(r) against log r yields a curved line that can usually be subdivided into three parts: (i) the depopulation range (an irregular pattern) for small values of log r , (ii) the scaling range (a linear part) for intermediate values of log r , (iii) the saturation range (slope approaches zero) for large values of log r . The correlation exponent value is estimated from the slope of the scaling range. It must be noted that the exact delineation of the scaling region can be difficult and often requires visual inspection. Moreover, the scaling region becomes smaller and smaller with increasing of m , and eventually vanishes for large m (e.g. Ding et al., 1993; Husain and Siva Kumar, 2006). Hence the estimation of the correlation exponent partly is an empirical exercise. The correlation exponent is identified from the scaling range of log Cm(r) against log r plot for different embedding dimensions. Then the values of the embedding dimension m are plotted versus the correlation exponent d(m) . The estimated CD value typically increases with m and reaches a plateau on which the dimension estimate is relatively constant for a range of large enough m . This saturation value is the estimated CD of the analyzed signal, while the embedding dimension corresponding to the plateau onset is sufficient to estimate the dimension of the attractor. That is to say, the nearest integer above the CD provides the minimum dimension of the phase space essential to embed the attractor, while the value of the embedding dimension at which the saturation of the correlation exponent occurs provides an upper bound on the dimension of the phase space sufficient to describe the motion of the attractor (Fraedrich, 1986). If there is no plateau in the $d(m)$ curve, it indicates that the data could be stochastic in nature or severely affected by noise. In that case the CD value cannot be estimated. Therefore, the CD method is able to distinguish chaotic motion from a simple system and stochastic motion (Theiler, 1986).

For sufficiently large number of observations and the embedding dimension obtain above equation, from above equation we calculate CD of EEG signals.

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

ANFIS topology and the learning method that used for this Neuro-fuzzy network are presented. Both neural network and fuzzy logic are model-free estimators and share the mutual ability to deal with uncertainties and noise. The ANFIS combines two approaches: neural networks and fuzzy systems. If both these two intelligent approaches are combined, good reasoning will be achieved in quality and quantity. In other words, both fuzzy reasoning and network calculation will be available simultaneously. The ANFIS is composed of two parts. The first is the antecedent part and the second is the conclusion part, which are connected to each other with the fuzzy rules base in network form. As shown in this figure, it is a five layer network that can be described as a multi-layered neural network.

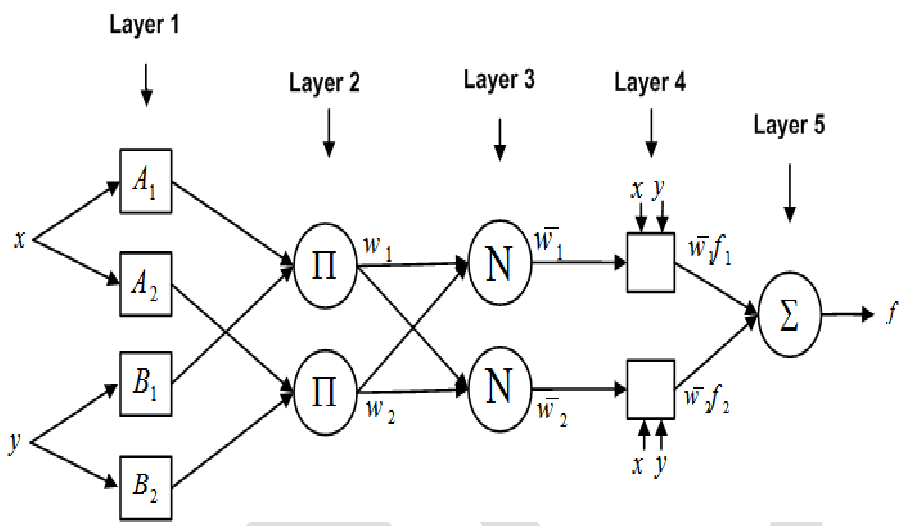

Figure 2. Basic structure of ANFIS

Each layer involves several nodes described by node function. The output signals from nodes in the previous layers will be accepted as the input signals in the present layer. After manipulation by the node function in the present layer will be served as input signals for the next layer. Here square nodes, named adaptive nodes, are adopted to represent that the parameter sets in these nodes are adjustable. Whereas, circle nodes, named fixed nodes, are adopted to represent that the parameter sets are fixed in the system. For simplicity to explain the procedure of the ANFIS, we consider two inputs *x*, *y* and one output *f* in the fuzzy inference system. And one degree of Sugeno's function is adopted to depict the fuzzy rule. Hence, the rule base will contain two fuzzy *if–then* rules as shown in rule 1 and rule 2 equations:

Rule 1: if x is $A1$ and y is $B1$ then $f = p1x + q1y + r1$.
Rule 2: if x is $A2$ and y is $B2$ then $f = p2x + q2y + r2$.

The terms p,q,r denote parameters of the output function whereas A,B are membership functions for inputs x,y respectively. The then-part of the rule is defined as consequent and the if-part of the rule is represented as premise. As shown in Fig.2 there are five layers in ANFIS architecture. Each layers functionality is illustrated below.

Layer 1**:** Every node i in this layer is a square node with node function as:

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4`$$

Where x is the input to node i, and i A (or B_{i-2}) is a linguistic label (such as “small” or “large”) associated with this node. In other words, 0l,i is the membership grade of a fuzzy set A and it specifies the degree to which the given input x satisfies the quantifier A. The membership function for A can be any appropriate membership function, such as the Triangular or Gaussian. When the parameters of membership function changes, chosen membership function varies accordingly, thus exhibiting various forms of membership functions for a fuzzy set A . Parameters in this layer are referred to as “premise parameters”.

Layer 2**:** Every node in this layer is a fixed node labeled as, whose output is the product of all incoming signals:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \qquad i = 1,2$$

Each node output represents the firing strength of a fuzzy rule.

Layer 3**:** Every node in this layer is a fixed node labeled N. The i th node calculates the ratio of the rule’s firing strength to the sum of all rules’ firing strengths:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}$$

Outputs of this layer are called “normalized firing strengths”.

Layer 4**:** Every node i in this layer is an adaptive node with a node function as:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

Where *wi* is a normalized firing strength from layer 3 and (p_i, q_i, r_i) is the parameter set of this node. Parameters in this layer are referred to as "consequent parameters".

Layer 5**:** The single node in this layer is a fixed node labeled Σ that computes the overall output as the summation of all incoming signals:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

This then is how, typically, the input vector is fed through the network layer by layer. We now consider how the ANFIS learns the premise and consequent parameters for the membership functions and the rules.

ANFIS has high ability of approximation that will depend on the resolution of the input space partitioning, which is determined by the number of MFs in the antecedent part for each input. In this paper, the MFs are used as Gaussian MF that *m* represents the center and □□determines the width of the MF respectively.

RESULTS

The correlation dimension of EEG signals of 2000 data packets each is calculated. In which enormous information of patients, it helps to analysis the data of patients. The output of correlation dimension is shown below.

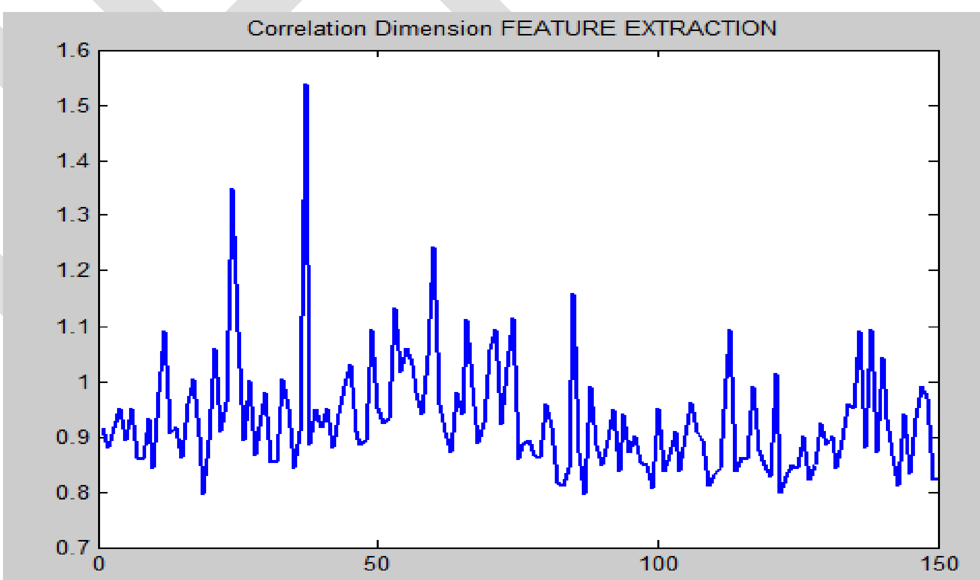

Figure 3. Output of correlation dimension

The figure 3 shows waveform contains the plot of all the features extracted from the EEG signals. Correlation dimension of EEG signals is then trained by anfis model for precise output.

The results obtained by the ANFIS model for EEG signals prediction was noted. After the model was trained using initial data set for 30 epochs, it was tested by using a random input.

The ANFIS is then training the data for 50% input data and checking data for rest of 50% data. The model was then tested over another time slot of the same time series. The results were obtained as shown below.

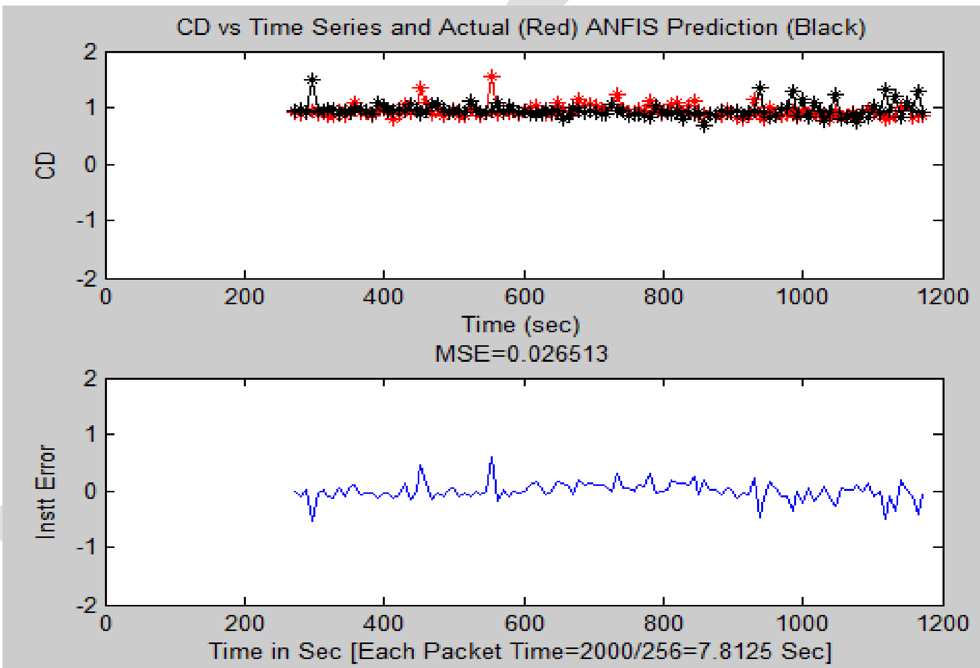

Figure 4. Prediction errors on testing ANFIS for chaotic time Series

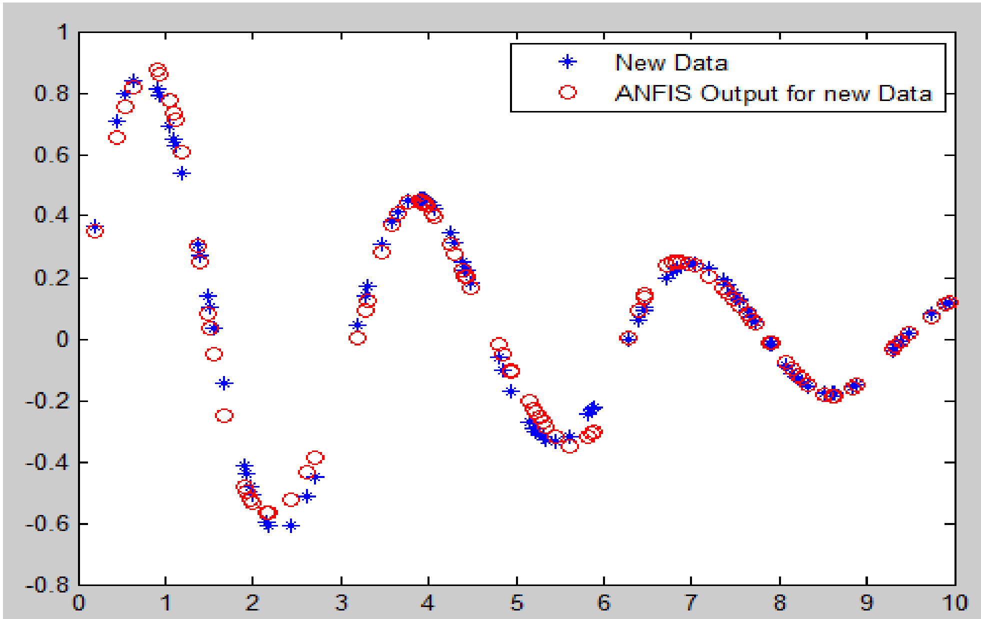

Figure 5. ANFIS Prediction

Fig. 4 shows ANFIS predicted output in which actual signals in red and predicted output in black and error calculate between actual and predicted output.

Thus the root mean square error (RMSE) in the above case was 0.0265 which is acceptable. RMSE in any case is calculated by,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y\_predicted_i - Y\_actual_i)^2}$$

CONCLUSON

Prediction of seizure in EEG is a challenging task. For this several prediction methodologies have been in use from time to time. But the complexity of signals which differ from person to person makes it complicated. This work is helps to overcome this problem and also work will to explore the prediction potential of chaos for seizure prediction. This work tries to build the bridge between the real time data and the future prediction in presence of chaos. The predicted data results indicate that the ANFIS module itself into any data set in any chaotic conditions and enormous latent on the EEG signal prediction in future helps to save life of patient.

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