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System Modelling and Identification for EEG Monitoring using Random Vector Functional Link Network

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ABSTRACT- Brain signal research occupies a special position in recent biomedical research in recent times. In this work, the authors try to develop a model for monitoring the EEG signal of the patient. It is the extrinsic application of the system identification problem. The Random Vector functional link network (RVFLN) model as the variant of Neural Network, is proposed for the dynamic modeling of a practical system. RVFLN is a fast-learning feed-forward network and does not need iterative tuning that reduces the model's computational complexity and faster training performance. The model is verified with Electroencephalogram (EEG) signal for identification so that it is well suitable for tracking and monitoring systems for patients. The performance of RVFLN is compared with existing models. From the result analysis, it is found that the performance of the proposed RVFLN is most impressive with an efficiency of 99.86%.

Keywords: System Modelling, Identification, EEG, ELM, Random Vector functional link network.

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1. INTRODUCTION

The human brain is an extremely intricate organ and system. Understanding the behaviour and dynamics of billions of interconnected neurons from the signal coming from the brain involves understanding of numerous signal-processing techniques, from both the linear and non-linear domains, as well as their link to the physiological events.

Electroencephalography, sometimes known as EEG, is a popular method that is used to measure patterns in electrical brain wave responses to external stimuli. This approach is non-invasive. Monitoring these data might aid in determining the source of the problem or assessing brain activity after a severe head injury. The electroencephalogram (EEG) is a signal that contains information about the brain's state. The shape of the wave may include valuable information about the brain's condition. However, it is impossible for a human observer to directly observe these features. The shape of the wave may include valuable information about the brain's condition. However, it is impossible for a human observer to directly perceive these fine features.

System identification of brain activity and building an approximate mathematical model of the human nervous system from the relationship between sensory input and behaviour control improves our understanding of how the brain processes stimulus and response measurements, predicts infant seizures, etc. EEG signals are used in a variety of brain activity applications, which are modelled using system identification techniques.

2. LITERATURE SURVEY

System identification is a method of mathematically representing an equivalent model by studying a practical system (complex nonlinear). The system identification technique is based on minimizing the difference between the actual and predicted models [1]. Artificial Neural network (ANNs) methods getting more popular in near future and have successfully been applied in the field of black box and grey box nonlinear system identification [2-3]. Apart from the advantage of complex non-linear mapping, it carries some disadvantages like more time-consuming due to gradient-based algorithms like the backpropagation learning algorithm [4]. Huang, Zhu, and Siew (2004) suggested an exceedingly fast non-interactive, and data-driven learning method called an Extreme learning machine to circumvent the aforementioned constraint (ELM). Which is a feed-forward neural network with a single hidden layer (SLFNs). The major advantage of ELM is, it is a very fast learning algorithm. A sustainable development is required in the field of robustness to noise, deep features should be in the auto-learning process, numerical stability, sparsity of weights [5]. Furthermore, ELM has been improved to overcome these limitations, and a new approach called Random vector functional link network has been proposed (RVFLN) [6].

RVFLN has the same structure as ELM. The main difference between them is the direct link between the input to the output layer [7]. The proper selection of the number of hidden neurons and hidden layers has improved the performance of RVFLN. The following are some of the advantages of RVFLN over traditional models: it has better generalization performance, a simple architecture design, and a faster learning algorithm. Similarly, some other system identification techniques like Additive algorithms such as Least mean square (LMS) for identification and noise separation [8-12]. Various Nonlinear system identification and control related models are presented in [13-22].

2.1 Motivation for the model Development

The abnormalities condition of brain waves or in other words electrical flows activity of a brain is analysed through EEG. Epilepsy is a chronic condition characterized by unprovoked, recurrent seizures. A seizure is a condition in which the brain experiences a sudden surge of electrical activity. Epilepsy is diagnosed through EEG monitoring or observation of patients' daily behaviour through films, which can put a patient's life at risk and even cause death. In such a case machine learning is an essential tool for the identification and classification of EEG signals from the brain [23,24]. Before the classification of EEG signals, a perfect identification of the signal is essential. Taking motivation from the above discussions this paper proposes the RVFLN method as a machine learning approach for EEG signal identification. An NSC-ND dataset is used in work. The dataset contains EEG signals for three cases. Case 1 for ictal, case 2 for inter-ictal, and case three for pre-ictal. For the data set, the signal is sampled at 200HZ with a 5.12 duration. From these data sets training and testing, sets are divided into a 70:30 ratios.

2.2 Contributions

Consequently, the major contributions of this study might be characterized as follows:

1 The basic RVFLN method is chosen to make a perfect model because it is easy to learn and gives accurate results.
2 The superiority of the model is analysed with a biomedical EEG signal.
3 An NSC-ND dataset is used as EEG samples which contains three categories of the EEG signal.
4 Further, Performance analysis of the Proposed model is done with EEG signals.

The *Section 2* presents literature survey of different nonlinear model used for identification. *Section 3* presents a brief discussion on the proposed RVFLN architecture along with EEG monitoring also demonstrated. *Section 4* presents Simulation Results & comparisons with different models and their analysis. *Section 5* concludes the paper.

3. PROPOSED METHOD

In this section the Random vector functional link network (RVFLN) algorithm is formulated. The aim is to design a perfect nonlinear model, that should have the ability to map the output data with the input, hence the input -output relationship of the model is analyzed. In the *Section 3.1* the mathematical formulation of the architecture is discussed & the architecture of the proposed algorithm is depicted in *figure 1*.

3.1 RVFLN based Model Design

The Random Vector functional link network is proposed as a uni-layer feed-forward neural network. In general, Single Layer Feedforward neuron network's connection between nodes starts from the input node to hidden nodes and hidden nodes to output nodes, there is no direct connection between the input node to output node. The direct connection between the input and output nodes is the significance of RVFLN. When the weights and biases between the input nodes and hidden nodes are initialized randomly as fixed-parameters, it becomes more effective. Further tuning of weight is not required during the training stage. The advantage of direct link is it protects the RVFLN network from overfitting. *Figure 1* depicts the proposed RVFLN method's design. The Moore-Penrose pseudoinverse least square approach is used to calculate the output weights, while the input weights are chosen at random. Output can be calculated from the following formula:

$$\hat{T}_i = \sum_{j=1}^{N} \beta_j\, g\left(w_j^T X + B_j\right) + \sum_{j=N+1}^{N+P} \beta_j X_j \qquad (1)$$

Where the input matrix is represented as X= $[X_1, X_2 \dots\dots X_P]$, the node in the hidden layer is represented as P, w_j is weight vector, in equation $g(.)$ is used as nonlinear activation function, $b_j$is denoted as the bias of the network. The sigmoid function is calculated by:

$$g(w_j, b_j, X_j) = \frac{1}{1 + \exp(-w_j X_i - b_j)} \qquad (2)$$

The total number of nodes in the network is computed using the formula D=N+P. for each node, and the total input sample is A. So, the output of RVFLN is formulated as

$$H\beta = \hat{T}_i \qquad (3)$$

Where the hidden layer matrix can be calculated by H. $H = [H_1\ H_2]$

$$H = \begin{bmatrix} H(X_1) \\ H(X_A) \end{bmatrix} = \begin{bmatrix} X_1 & H_1(X_1) \dots\dots & H_N(X_1) \\ X_A & H_1(X_A) \dots\dots & H_1(X_A) \end{bmatrix}_{P\times D} \qquad (4)$$

Where, $H_1 = \begin{bmatrix} H(X_1) \\ H(X_A) \end{bmatrix}$ and $H_2 = \begin{bmatrix} H_1(X_1) & H_N(X_1) \\ H_1(X_A)\dots & H_1(X_A) \end{bmatrix}$

Output put weight β formulated as

$$\beta = [\beta_1, \beta_2, \dots\dots, \beta_N, \beta_{N+1}, \dots\dots \beta_D]^T \qquad (5)$$

The Target of the network can be formulated as

$$Y = [Y_1, Y_2, \dots\dots, Y_A]^T \qquad (6)$$

The error vector ξ can be formulated as

$$e = [e_1, e_2, \dots e_{A,}]^T \qquad (7)$$

Where $e_j = Y_j - T_i$

The β can be formulated as

$$\beta = H^T H^{-1} H^T Y \ \ or\ H^T [H H^T]^{-1} Y \qquad (8)$$

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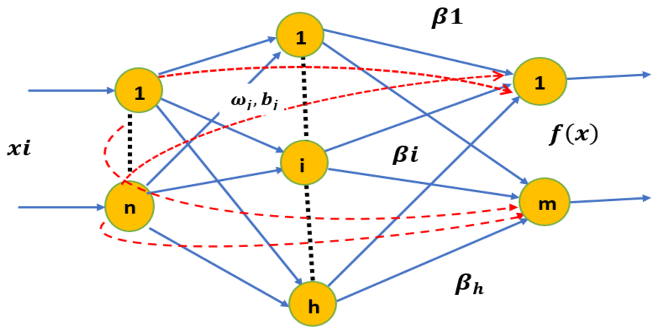

Figure 1: The architecture of the proposed RVFNL Network

4. SIMULATION RESULTS & DISCUSSION

In this section, the EEG model is applied to the proposed RVFLN model to evaluate its performance and efficiency.

4.1 Design of EEG Model

The Fourier EEG wave equation is given as:

$$A_x(\mathrm{P},\mathrm{M}) = \sum_{i=0}^{\infty}\sum_{t=0}^{\infty} L_{itj}\sin(y_{Pi}P + \emptyset_{Pi})\sin(y_{Mt}M + \emptyset_{Mt}) \qquad (11)$$

Where P and M are the no of waves with different spatial wavelengths made up by the frequency component of EEG. After analyzing the performance of the proposed model to evaluate the EEG signal, it is passed through the model for training and testing.

***Case 1*- Preictal signal**

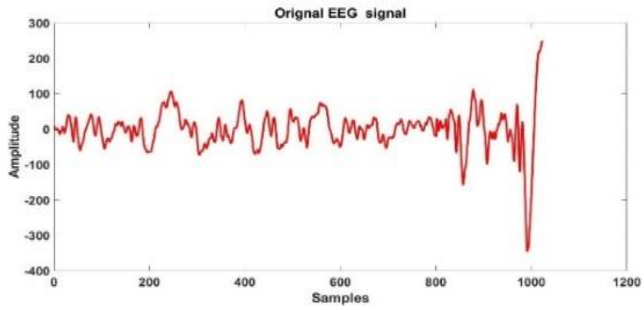

Figure 2: Original Pre-ictal signal

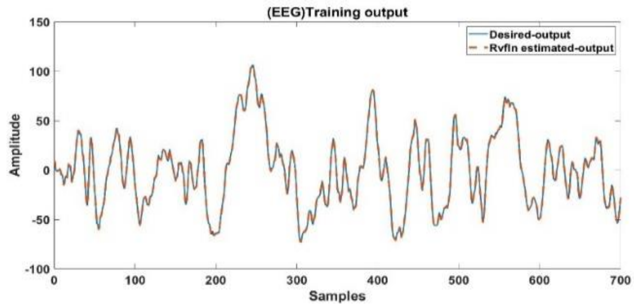

Figure 3: Pre-ictal signal identification of training

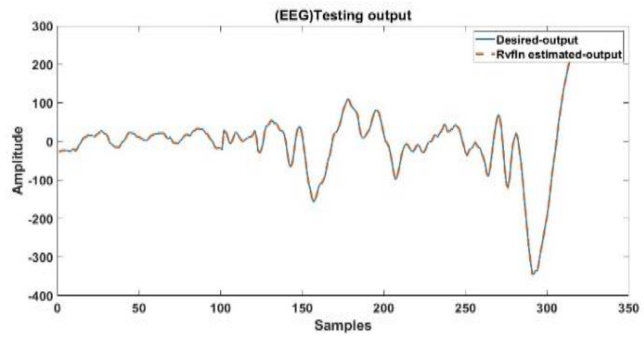

Figure 4: Pre-ictal signal identification of testing

Figure 2, 3, 4 represent the *Case 1* pre-ictal signal of EEG. In *figure 2* the original pre-ictal is depicted, *figure 3* represents the actual vs predicted and training output of the pre-ictal signal and in *figure 4* the actual vs predicted and testing output of the pre-ictal signal is depicted.

***Case 2*- pre-ictal signal**

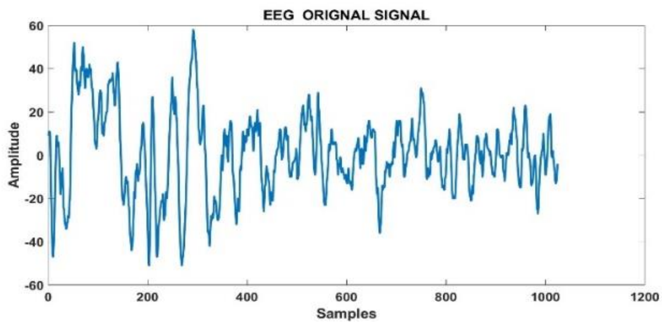

Figure 5: Original Inter-ictal signal

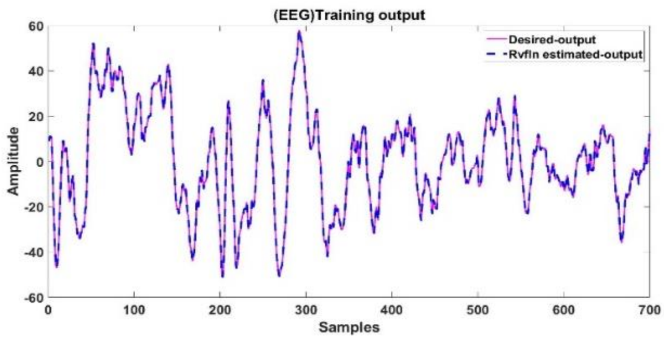

Figure 6: Inter-ictal signal identification of training

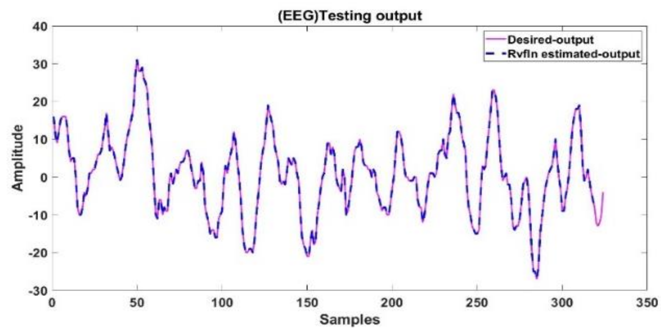

Figure 7: Inter-ictal signal identification of testing

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Figure 5,6,7 represent the case 2 Inter -ictal signal of EEG. In *figure 5* the original Inter -ictal is depicted, *figure 6* represents the actual vs predicted and training output of the Inter -ictal signal and in *figure 7* the actual vs predicted and testing output of the Inter -ictal signal is depicted.

***Case 3*- ictal signal**

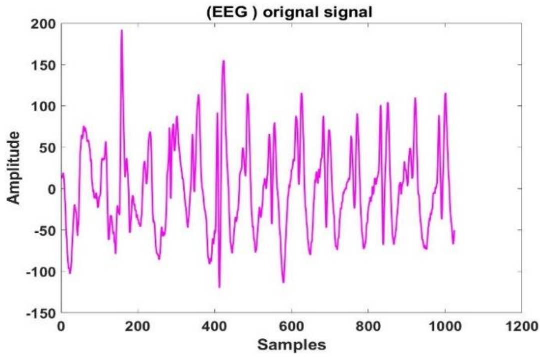

Figure 8: Original ictal signal

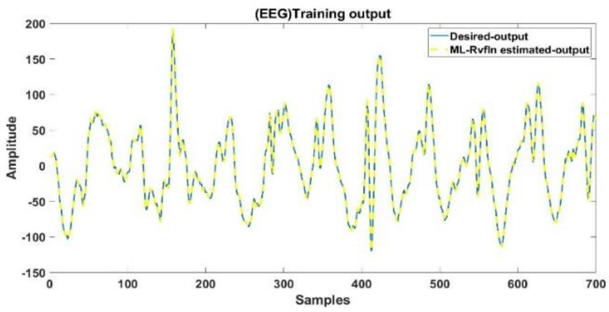

Figure 9: ictal signal identification of training

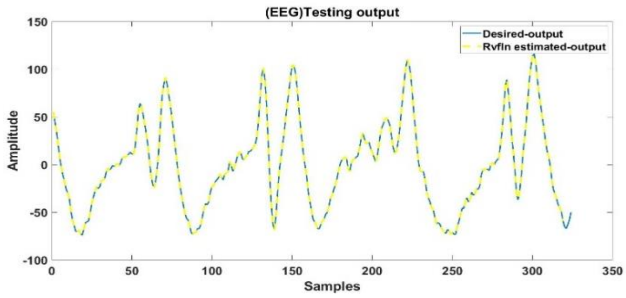

Figure 10: ictal signal identification of training

Table 1: Performance analysis of the Proposed model with different cases of EEG signals

No	EEG Signals	RMSE (Training)	RMSE (testing)
1	Preictal	0.0159	0.1542
2	Inter-ictal	0.0326	0.2920
3	ictal	0.0254	0.2822

Figures 8,9,10 represent the case 3 ictal signal of EEG. In figure *8* the original Inter -ictal is depicted, *figure 9* represents the actual vs predicted and training output of the ictal signal and in *figure 10* the actual vs predicted and testing output of the ictal signal is depicted. From the above results, it can be analyzed that, the proposed model is a good EEG identification model as the EEG signals were tracked perfectly and accurately**.** From *table 1* the performance of the model is analyzed. The training of the model starts with Preictal signal, where the model archives 0.0159 of training MSE and testing MSE is 0. 1542.The model is trained for Inter-ictal signal and achieve 0.0326 MSE for training and 0.2920 MSE for testing. Finally, the model is train for ictal signal and archives 0.0254 training MSE and 0.2822 testing MSE. From the above analysis it is observed that the model is accurate (it has perfect tracking) and need less training time to learn.

5. CONCLUSION

A Random Vector Functional Link Network (RVFLN) model is proposed in this paper. Further, an EEG signal with different cases of signals is taken for its accurate identification. The suggested RVFLN model differs from ELM and other neural network as it can provide a direct link from input to output, which improve the model's performance. The advantages of RVFLN includes a simple structural design, faster learning speed, better generalization performance, iterative tunning is not required for a faster network. The proposed model is mathematical model which represents the EEG signal. The model can be utilized for other dynamic systems where the non-linear and non-stationary signals can be utilized in future. Further the weight of the models can be optimized using recent optimization algorithm and kept for future work. The result is analyzed from the tables and figures, found that RVFNL has better performance with an efficiency of 99.86%.

Author Contributions: Rakesh Kumar Pattanaik is the research scholar pursuing his Ph. D. work. He is working in the area of Signal Processing and Machine Learning. His contribution in this paper is to execute the program and experiments with the guide. Dr Binod Kumar Pattanayak has verified the manuscript. Dr. Mihir Narayan Mohanty has given the concept and finalized the programs executed.

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