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Research Article

Softcomputing Techniques for Improved Electroencephalogram Signal Analysis

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Abstract

In clinical signal processing and computer aided diagnosis, noise and relativity of human judgment are two of the most critical challenges which researchers attempt to surmount using several softcomputing techniques. In this paper, the recent use of these techniques in application to the analysis of electroencephalogram (EEG) is explored. The trend and prospects of other softcomputing methods that could significantly improve signal processing of EEG are also presented. It was observed that disease diagnosis and decision making systems of medical experts on mental activities and modeling of electrical impulses of the human brain can be significantly improved using these techniques or a hybrid thereof.

Keywords: *electroencephalogram (EEG), Genetic Algorithm, Artificial Neural Network, Fuzzy systems, clinical diagnosis.*

1. Introduction

A. Softcomputing and general application in biomedical signal processing

The use of the term soft computing is increasingly becoming popular because of the growing areas of its application. Soft-computing could be defined as a group of computing techniques which functions synergistically and provides, in one form or another, flexible information processing capability for solving otherwise complex real life problems (Yardimci, 2009). These techniques which have been proven to possess the ability to greatly simplify ambiguous real life scenarios include Artificial Neural Network (ANN), which is a massive interconnection of artificial neurons functioning together to mimic the information processing technique of the human brain, Fuzzy Inference Systems (FIS) which employs a logic without a crisp boundary and expresses variables in terms of intelligible human linguistic terminologies, Genetic Algorithms (GA) (Taek *et al*., 2005), Particle Swarm Optimization (PSO), Artificial Fish Swarm Optimization (AFSO) (Neshat *et al*., 2012), Adaptive Neurofuzzy Inference System (ANFIS) and an increasing variety of hybrid methods. These techniques attempt to harness the power of parallel data processing and ability to handle non-crisp logic to proffer solution to a wide variety of day-to-day problems and applications. The advantages of these softcomputing techniques are numerous; efficient and easier optimization procedures, non-linear and parallel information processing, efficient input selection and feature extraction, cost-effectiveness, easier and accurate modeling of large datasets (Dehuri *et al*., 2012) and capability to simultaneously perform sensitivity analysis (Castillo & Guijarro-berdi, 2006). Other merits of softcomputing include possibility of training networks with large datasets simultaneously over multiple computing nodes, accurate predictive power, and ability to support clinical decision making (Bennett and Hauser, 2013; Endrerle & Bronzino, 2012; Papageorgiou *et al*., 2008). Other advantages of softcomputing techniques include their ability to inculcate human linguistic variables into computing, thereby making it more intelligible for programmers (Yardimci, 2009).

Due to their numerous advantages over classical programming techniques and wide range of possible applications, softcomputing techniques have found a wide range of applications in the medical domain. In the area of medical signal analysis, Artificial Neural Network has been applied for compression and filtering of biomedical signals with high accuracy (Chatterjee *et al*., 2013). In a similar research, user motion induced artifacts in Wearable-electrocardiogram (W-ECG) have been filtered to a degree of accuracy of 92% using Multi-layered

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Perceptron Neural Network (MLPNN) (Kher, 2013). Hybrid softcomputing techniques are also on the rise in medical applications. As much as these techniques are of good performance individually, they have been proven to perform even slightly better when combined in certain applications. This combination often helps programmers to usurp the different powers of the individual techniques to produce a more robust system. For example, a Hybrid Expert System (HES) was developed and employed in cardiology wherein the hidden layers and number of neurons of an Artificial Neural Network were optimized using Genetic Algorithm. Similarly on the use of hybrid systems, ECG signal was processed for abnormalities detection using a combination of multi-resolution wavelet transform and Artificial Neural Network (Rai, 2013).

B. Electroencephalogram

Electroencephalogram is a tool that shows the electrical representations of the neural activities of the human brain. With the aid of electrodes attached to the scalp, EEG helps to manage, isolate and diagnose several brain conditions in a nondestructive, noni-invasive manner. These include diagnosis and monitoring of coma, epilepsy, brain-death, damages or malfunctions that affect the structure or function of the brain, and other diseases. EEG is also useful in the analysis of the degree of mental alertness as well as locating brain tumour.

The first successful electroencephalogram (EEG) signals of the human scalp was first reported in the early 19th century when German scientist Hans Berger made a success at recording measurable traces of the electrical activities of the human brain (Majumdar, 2011). The knowledge base in EEG signal processing rapidly increased with deeper understanding of the functionality of the human brain.

Brain function is dependent on the circuitry of brain neurons which are either connected in divergent circuit or convergent circuits. In a divergent circuit, each branch in the axon of the presynaptic neuron connects with the dendrite of a different postsynaptic neuron. In a convergent circuit however, axons from several presynaptic neurons intersect at the dendrite(s) of just one postsynaptic neuron (Endrerle & Bronzino, 2012).

The human scalp electroencephalogram is formed when Excitatory Post-Synaptic Potentials (EPSPs) are generated at the apical dendritic trees of pyramidal neurons. This buildup in potential occurs when these neurons are stimulated in form of inputs at their apical dendrites thereby creating transient depolarization. The eventual current that flows through the volume conductor is obtained as a result of potential gradient from the soma membrane to the basal dendrites to the apical dendritic trees. The current which characterizes the EEG is classified as intracellular or extracellular currents depending on the current flow path (Majumdar, 2011).

This work therefore examines the overall impact of different softcomputing techniques on the accuracy and improvement of electroencephalogram and proffers possible modifications to the existing systems for better efficiency. A projected trend of the application of softcomputing and expert systems in the area of biomedical signal processing is also suggested.

2. Current challenges in EEG signal processing

Processing EEG data for exact localization of active neural signals is a complex task. It involves numerous steps: improvement of signal-to-noise ratio; segmenting various structures from anatomical MRIs; numerical solution of the electromagnetic forward problem; a solution to the difficult electromagnetic inverse problem; and appropriate control of multiple statistical comparisons spanning space, time, and frequency across experimental conditions and groups of subjects (Hämäläinen, 2013). EEG has no doubt been a very important tool for analysis of several brain conditions. However, this tool is not an exclusion from the problems encountered in typical electrical signal systems; noise. EEG is sensitive to voltage changes even in the order of microvolt. Therefore, in addition to the voltages from the human scalp, signals generated by the movements of several body parts which are non-indicative of the cerebral conditions are also recorded. These unwanted Electroencephalogram signals are called artifacts - ocular (EOG) or muscular (EMG) or a combination of both. Some very common forms of these are the signals generated as a result of eye movement or movement of associated muscles. These noises are often the sources of errors during interpretation of signals or during computer analysis (Priyadharsini & Rajan, 2012). Some artifacts spread across the scalp and may have a significant degree of spectral resemblance to pathological scalp EEG signals making conventional filtering techniques unsuitable (Figure 1 and Figure 2). This particularly poses serious challenge in the sense that accurate analysis becomes difficult

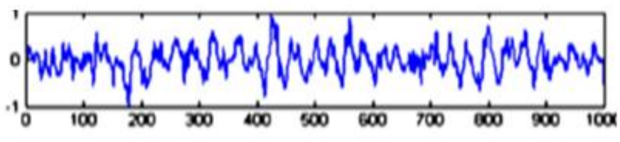

Figure 1 Standard EEG signal

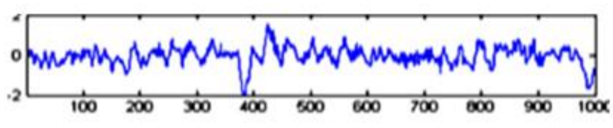

Figure 2 An EEG signal contaminated with artifacts

Removal of these artifacts is therefore necessary in the quest for enhanced signal representation and improved pathological diagnosis of brain states and conditions.

Additionally, Most reported predictive works on biological signal have relied on the implementation of logistic regression or discriminate function that classifies individuals into select groups based on linear combinations of the independent variables that increase the probability of maximal distinction of subjects into groups. In clinical studies many of the variables may be interconnected and the selection process used in logistic regression and discriminate function analyses often forces some variables out of the equation. This process may compromise the predictive power of the analysis and lead to less accurate case classification. To date, none of the published models have achieved the high degree of accuracy necessary for this purpose. Thus, the multivariate statistical models often lack the specificity needed for application in clinical decision making (Luki *et al*., 2012). The need for the development of more intelligent predictive models in biomedical signal analysis and computer aided diagnosis therefore remains crucial.

3. Artificial Neural Networks for Artifact removal

McCulloch and Pitts first described ANNs as a method of information processing using a network of binary decision elements or "neurons" (Luki *et al*., 2012). Over the last two decades, Artificial Neural Networks (ANN) have been employed as an alternative technique to classical statistical techniques (Adedayo, 2014)], an example of such application is the design and implementation of an ANN-based event classifier to analyze collected EEG signals in order to classify different neural events (Nawroj *et al.,* 2012). Neural networks are parallel, distributed, adaptive information- processing systems that develop their functionality in response to exposure to data (Luki *et al*., 2012). ANN models use artificial intelligent networks to perform excellently for classification, pattern recognition, and prediction in a way that mimics the information processing procedure of the human brain. These qualities have caused ANNs to enjoy wide range of applications in numerous fields.

Nodes in an ANN are connected by weights; the weights associated with the connections determine the strength of the connection. Therefore, the effective computational power in the network is a function of the density and complexity of the interconnections of neurons.

Artificial Neural Networks (ANNs) have powerful prediction capabilities because of their excellent pattern matching ability. Generally, ANNs consist of neurons connected through adaptable weights which are adjusted repeatedly during the training phase in order to obtain a set of network weights which most closely models the problem at hand. The predictive power of these networks has been investigated using a feed forward ANN and backpropagation learning algorithm for features extraction, combination and formation of new parameters and the results were impressive (Neurauter *et al.,* 2007).

Over the last few decades, a variety of algorithms and logical flows have been developed or modified which have significantly improved the overall performance of ANNs. One of the widely reported algorithms is Resilient Backpropagation (RP) algorithm. RP is an ANN training function that updates weight and bias values based on resilient backpropagation algorithm. In order to apply RP algorithm successfully, the network to be trained must fulfill the requirement of having a transfer function that has derivative functions. RP algorithm has the advantage of being faster than the Gradient Descent Algorithm (GDA) and requires only a modest amount of memory. This algorithm involves a direct adaptation of weights as informed by the local gradient trend. The distinguishing advantage of the RP algorithm is its ability to avoid the pitfall of being trapped by the gradient behaviour because it deals only with the direction of the partial derivative and not the size (Al-Naima & Al-Timemy, 2010). RP algorithm description is as follows:

For all weights and biases {

If $\left(\frac{\partial E}{\partial w_{ij}}(t-1) * \frac{\partial E}{\partial w_{ij}}(t) > 0\right)$ **then** {

$$\Delta_{ij}(t) = \textbf{minimum}\left(\Delta_{\text{ij}}(\text{t}-1) * \eta^{+}, \Delta_{max}\right)$$

$$\Delta w_{ij}(t) = -\boldsymbol{sign}\left(\frac{\partial E}{\partial w_{ij}}(t)\right) * \Delta_{ij}(t)$$

$$\text{w}_{\text{ij}}(\text{t}+1) = w_{ij}(t) + \Delta w_{ij}(t) \ \}$$

else if $\left(\frac{\partial E}{\partial w_{ij}}(t-1) * \frac{\partial E}{\partial w_{ij}}(t) < 0\right)$ **then** {

$$\Delta_{ij}(t) = \textbf{maximum}\left(\Delta_{\text{ij}}(\text{t}-1) * \eta^{-}, \Delta_{min}\right)$$

$$\text{w}_{\text{ij}}(\text{t}+1) = w_{ij}(t) - \Delta w_{ij}(t-1)$$

$$\frac{\partial E}{\partial w_{ij}}(t) = 0 \quad \}$$

else if $\left(\frac{\partial E}{\partial w_{ij}}(t-1) * \frac{\partial E}{\partial w_{ij}}(t) = 0\right)$ **then** {

$$\Delta w_{ij}(t) = -\boldsymbol{sign}\left(\frac{\partial E}{\partial w_{ij}}(t)\right) * \Delta_{ij}(t)$$

$$\text{w}_{\text{ij}}(\text{t}+1) = w_{ij}(t) + \Delta w_{ij}(t) \ \textbf{\}}$$

}

In other words, the adaptation procedure works in a way such that: if there is a change in the sign of the partial derivative of a weight w_{ij}, it implies that latest update has been too large and that the algorithm has leaped over a local minimum, therefore the weight-update value Δ_{ij} is reduced by a factor of η^{-}, where $0 < \eta^{-} < 1 < \eta^{+}$. If the sign of the derivative remains the same however, the weight-update is slightly incremented so as to speed up convergence of the algorithm over shallow regions. After the weight-update value has been determined, updating the weight follows the following rule: if there is a positive error (that is, a positive derivative), the weight is reduced by the value of the weight-update, if the error is negative, the weight is increased by the value of the weight-update (Riedmiller & Braun, 1993).

These improvements have been quite evident in the aspect of architecture optimization, training time reduction, training epoch optimization, improvement in sensitivity as well as overall performance of the networks. One of such architecture was reported by Luki et al., wherein Artificial neural networks based network was designed for the prediction of cerebral palsy in infants with central coordination disturbance (Luki *et al*., 2012).

In a similar research, artifact detection was improved significantly when radial basis function network (RBFN) was trained with various artifact features as training data (Goel *et al*., 2013).

The ability of ANNs to handle parallel processing of information has been put to use in the processing and analysis of biomedical signals. Features of interest in such signals could be extracted (Figure 3) and fed as inputs into the input layer of an ANN, depending on the weights, threshold and firing strength, these signals are propagated as inputs to other layers and the training could be repeated with the aid of the selected algorithm until the signal feature selection have been satisfactorily modeled.

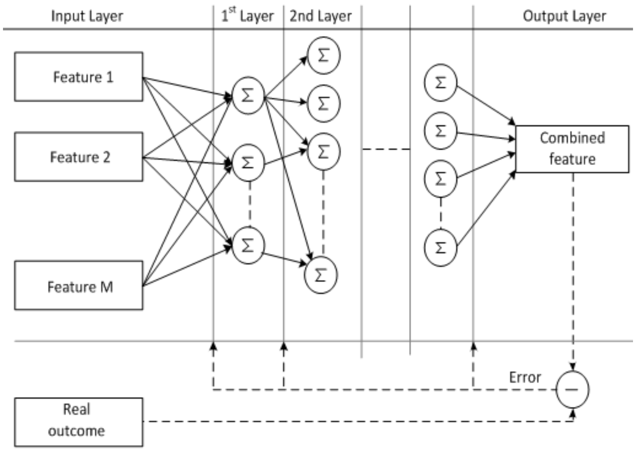

Figure 3 The Artificial Neural Network framework for feature selection of biomedical signals (Neurauter *et al.,* 2007)

Based on extensive literature review and in-depth understanding of the capabilities of ANNs, the ANN framework of Figure 4 has been proposed for the analysis of electroencephalogram signal. The entire acquired database is segmented into training and testing database.

The EEG training dataset is therefore statistically pre-processed for extraction of interested features. A feedforward ANN is designed, optimized and trained with the Layer Sensitivity Based (LSB) algorithm. The LSB ANN algorithm has the advantage of minimizing calculation overhead as well as reducing network training time by performing layer-by-layer sensitivity analysis of the network. The performance of the deployed network is then evaluated using appropriate performance index with respect to the separated testing dataset.

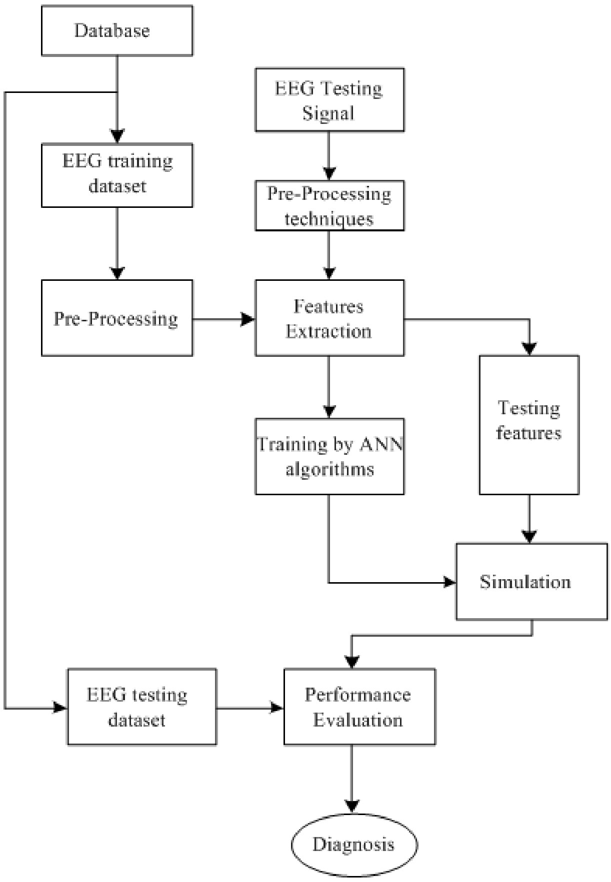

Figure 4 The proposed Artificial Network framework for EEG signal analysis

4. Fuzzy logic based systems for artifacts removal

The design and implementation of effective and efficient computerized processes for most medical systems remains a quite difficult task. The challenges encountered beam from the existence of uncertainties as a result of natural occurrence in modeling, measurement and instrumentation. Some of the helpful techniques for tackling these challenges are the Fuzzy Inference Systems (FIS) and other fuzzy-based hybrid systems. The current trend in the application of these techniques in medical systems is as a result of researchers taking full advantages offered by these techniques. These include the possibility of adequately representing medical systems and signals without explicit expression of the complete mathematical relationship between variables (Pandey & Mishra, 2009).

A new technique called Adaptive Noise Cancellation (ANC) has been reported (Priyadharsini & Rajan, 2012) for removal of artifact from EEG signals. This approach combines ANC with ANFIS. Adaptive Neurofuzzy Inference System is a hybrid softcomputing technique that combines the excellent pattern matching and learning capability of ANNs with Fuzzy Logic, segmenting its functions into five major levels. ANFIS could be readily programmed from MATLAB command prompt.

Available softcomputing techniques are however not limited to ANN and Fuzzy systems, other techniques that could be employed at different stages of the overall signal processing task include but not limited to Particle Swarm Optimization (PSO), Artificial Fish Swarm Optimization (AFSO) (Neshat *et al.*, 2012), and Artificial Bee Colony (ABC) (Yaghini, 2012), (Chen, *et al.*, 2011) optimization. These are processes which apply the natural principle of organism survival in providing global solutions to search and optimization problems. Genetic Algorithm (GA) and its hybrid techniques which employ the biological principles of generational offsprings and mutation are also applicable (Mitra *et al.,* 2006; Dhiman & Saini, 2014; Furtado et al., 2014; Gil, 2012).

The performances of some intelligent techniques, including some of the ones discussed thus far for artifact removal in terms of Signal-to-Noise Ratio (SNR) and EEG signal analysis are presented in Figure 5 and Figure 6. These include Adaptive Linear Neuron (ADALINE), Recursive Least Square (RLS) Wavelet transform and ANFIS.

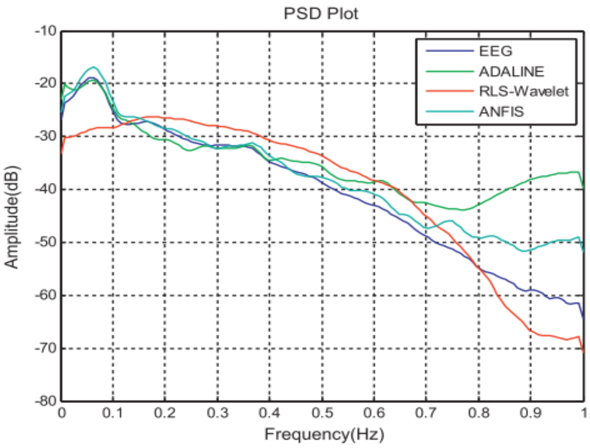

Figure 5 A comparison of the performances of the techniques for EOG artifact removal (Priyadharsini & Rajan, 2012)

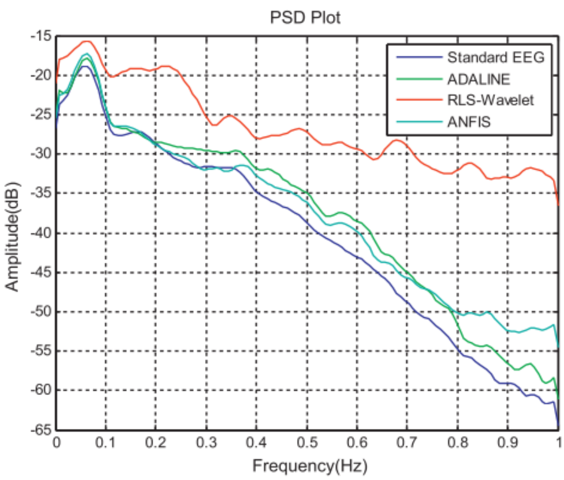

Figure 6 Comparison of the performances of different techniques for EOG and EMG artifact removal (Priyadharsini & Rajan, 2012)

It can be observed that the ADALINE and the Adaptive Neurofuzzy Inference System (ANFIS) were able to demonstrate their excellent pattern matching capability in the removal of different types of artifacts as shown by the Power Spectrum Density (PSD) plot. The RLS-Wavelet however has a relatively poor performance with respect to the ADALINE and ANFIS techniques.

The advantages of these systems make sure they remain of good interest to researchers. They help in eliminating several human factors in interpretation of results, in addition to the relative ease of re-trainability of many of these softcomputing techniques.

Conclusion

As direct responses to the observed challenges of electrical signal analysis, there have been wide reports on the growing impacts of softcomputing techniques in signal modeling, filtering and analysis. Analysis of electroencephalogram is not an exception to this trend and in this work, we have been able to evaluate some of these techniques and design different stages of a proposed neural network for EEG artifact removal. Even though it is evident that softcomputing techniques still have a long way to go especially in the aspect of EEG signal analysis and removal of unwanted signals, the positive prospects that these approaches offer remain interesting.

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