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Neural Network for Recognition of Brain Wave Signals

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ABSTRACT

Improving life quality for disabled patients and overall improvement of human thought concentration especially individuals suffering from Autism and Alzheimer can be accomplished with the aid of Brainwave Computer Interface (BCI). In this paper, a Radial Basis Functions (RBF) Artificial Neural Network (ANN) is constructed and a BCI is implemented using NeuroSkyS EEG biosensor for the recognition of brain signals. The analysis is presented through the consideration of a noisy environment to simulate a BCI in real world applications. A total of 256 data points are acquired in each thought. The data are transmitted via Bluetooth for MATLAB documentation and recognition rates in the highest 70 percent are recorded.

Keywords: Neural Network, BCI, NeuroSky, Feature Extraction, Noisy environment.

INTRODUCTION

Human to machine interaction is crucial for many human activities that require application of robots, computer devices, whose success in industry, military, and life highly relies on the way they communicate and interact with human. In medical research, Brain Computer Interface (BCI) had been implemented to allow people with disabilities to guide wheelchairs [1]. The intention of moving something is generally known as cognitive thought in BCI, it becomes useful for severely paralyzed people to move things around them. This technology is used to detect driver fatigue [2] and driver sleepiness [3]. The Electroencephalography (EEG) is a well-known term in BCI research community. It allows the user to interact with a system through mental actions alone unlike traditional control procedures such as physical manipulation or verbal commands [4]. There are basically two techniques that are used to monitor the users' brain activities and these include invasive (cortically-implanted electrodes) and non-invasive (EEG type) techniques. Invasive techniques usually provide more precise and accurate measurements.

Neural activity from cerebral cortex is extracted and used to control prosthetic limb [5]]. Non-invasive technique comes with an advantage of relieving the subject from the difficulties of operation as the subject can easily measure the neural activity through simple wearable items. After the recording of the stream of data, the data are usually processed by detailed algorithm to decode the subjects' intentions. An EEG signal is a measurement of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. The signal cannot register the activity of each neuron but it is a measurement of many neurons. Electrodes are used to record the signals. The positions of the electrodes are important because they describe the different parts of the brain. The brain owns three main layers and each layer can be simulated as impedance for EEG signals. The skull is the layer with the highest resistivity [6] and this is the reason why the electrodes position is well described in the conventional electrode setting called 10-20 system An EEG signal have a lot of information in the frequency domain as well as the time domain.

The brain operates at low frequencies that range from 1-50Hz, which is usually divided into six frequency bands: Delta: 1Hz - 4Hz. Theta: 4Hz - 8Hz, Alpha: 8Hz - 12Hz, Beta-Low: 12Hz 20Hz, Beta-High: 20Hz - 30Hz, Gamma: 30Hz - 50Hz [7]. One method to acquire brain wave signals is the Steady State Visual Evoked Potentials (SSVEP). It is a response to a visual stimulus modulated at a specific frequency. Another application of the BCI system is used to control Lego Mindstorms [11]. The performance of a Principal Component Analysis (PCA) ensemble classifier is used for P300-based spellers. Typically, the visual stimulus is generated using white fluorescent tubes modulated at around 13.25 Hz or by another kind of strobe light [12].

BRAIN WAVE COMPUTER INTERFACE DEVICE

A prototype of two wheeler robot is implemented and experimented controlled by a thought of a human being [8]. The eye-blink and ocular movement components could be decomposed by independent component analysis (ICA) using the 14-channel signals measured by the headset [9]. Emoitv EEG Neuroheadset is utilized to sense and capture users EEG and EMG data, and Emotiv Control Panel Software is employed to interpret the facial expressions and mind states and also to convert it into its corresponding text acronym. Both visualization and motor control methods were carried out and analyzed in order to accurately control the robot [10]. Wolpaw and his colleagues train individuals to control their -wave amplitude for cursor control [12]. The recent studies on BCI and Neurofeedback have applied different stimulus and cognitive tasks. It includes imagination of 3D cube, imagination movement of both the hands and rest to move the cursor to their respective targets, playing snake gameplay, performing oddball task session, and word eye blink flashes images of Wheres Waldo. Brain wave acquisition were also collected from moving the cursor to their respective targets, watching video clips and doing video games.

The commonly used algorithm for feature extractions and analysis are Neural Network, FFT, ICA, Bilinear Discriminant Component Analysis, Power Spectral Density (PSD), PCA, (LDA) and Fisher, Linear Discriminant (FLD), Correlation coefficient, Fast ICA algorithm, empirical mode decom position (EMD) and adaptive filtering. The NeuroSky platform provides a powerful foundation for developing applications that promote improved focus, concentration, working memory, and mind acuity. The raw EEG signals are obtained from one sensor with sample frequency Fs = 128Hz. It is the absolute minimum requirement in order to record EEG signals. It runs with a 5V battery and records 8 bits of data through a serial port on the used computer. The recorded samples are in the V range [13]. In [14] we acquired brain wave signals using NeuroSkys EEG biosensor, then transmitted them via Bluetooth connection to a laptop. We accounted for the noise from the environment such as music and presence people in the surroundings and we used statistical tools to analyze the brain wave signal in each task. In this paper we aim at recognizing the transmitted brain signal by using Neural Network [17] [18] trained and tested by energy based vectors.

Electrode Placement

The 10-20 system is used to describe the placement of electrodes on a human scalp. The scalp is divided into a grid that covers the top of the head relative to physical landmarks such as the nasion and inion. In our experiment, the electrode is placed in scalp location Fp1 (Frontal Pole) [14].

CONSTRUCTING FEATURE VECTORS

To extract energy parameters, we apply the Fourier analysis to brain signal selected for the testing phase. The frequency bands are chosen according to the scale of frequency bands covering 0 - 50 HZ. The next step is to compute the average absolute values of the Fourier coefficients over the corresponding bands of the scale to obtain the energy values [15]. Once the feature vectors were constructed, a Radial Basis Functions Neural Network is employed for recognition. The brain signal is analyzed with 256-point FFT. A 6channel band filter bank is simulated by averaging spectrum coefficients in each frequency band to cover a range of 0 50Hz. All energy parameters are transformed into a decibel scale of 0-60dB. Preference is made for the 6-element vector of energy values.

Artificial Neural Networks

A neuron is defined as the fundamental processing unit of the human brain. Figure 1 shows a model of a neuron that has N inputs (the X's), N weights (the W's), a bias b and an output Y [18]. This output is calculated by the formula:

$$Y = f\left(\sum_{i=0}^{N-1}(W_i X_i - b)\right). \qquad (1)$$

where b is an internal threshold or offset, and f is a nonlinear function chosen from one of the ones below:

(1)Hard limiter, where

$$f(x) = \begin{cases} +1 & \text{if } x > 0 \\ -1 & \text{if } x < 0 \end{cases}$$

or,

(2)Sigmoid functions, where

$$f(x) = \begin{cases} \tanh(\beta x) & \text{if } \beta > 0 \\ or & \\ 1/1 + e^{-\beta x} & \text{if } \beta > 0. \end{cases}$$

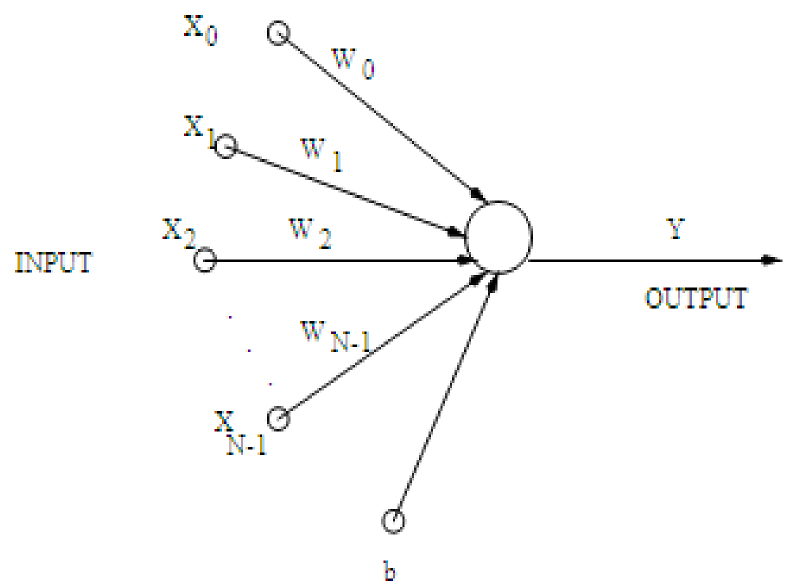

Figure 1: A computational node of a neural network

The Sigmoid nonlinearities are used often since they are continuous and differentiable. In general, an ANN is a network of several simple computational units. It has a great potential for parallel computation since the processing of the units is done independently and are widely used in pattern classification, matching and completion [17].

Radial Basis Neural Networks

The core of a recognition system is the recognition engine. The one chosen in the paper is the Radial Basis Functions Neural Network (RBF). This is a static two neuron layers feed forward network with the first layer, L_1, called the hidden layer and the second layer, L_2, called the output layer Figure 2. L_1 consists of kernel nodes that compute a localized and radially symmetric basis functions Figure 3. The pattern recognition approach avoids explicit segmentation and labelling of the speech signals. Instead, the recognizer uses the patterns directly. It is based on comparing a given pattern with previously stored ones. The way patterns are formulated in the reference database affects the performance of the recognizer. In general, there are two common representations [17].

The output y of an input vector x to a (RBF) neural network with H nodes in the hidden layer is governed by:

$$y = \sum_{h=0}^{H-1} w_h \varphi_h(x). \qquad (2)$$

where w_h are linear weights and φ_h are the radial symmetric basis functions. Each one of these functions is characterized
Input Layer Hidden Layer Output Layer (L 1) (L 2)

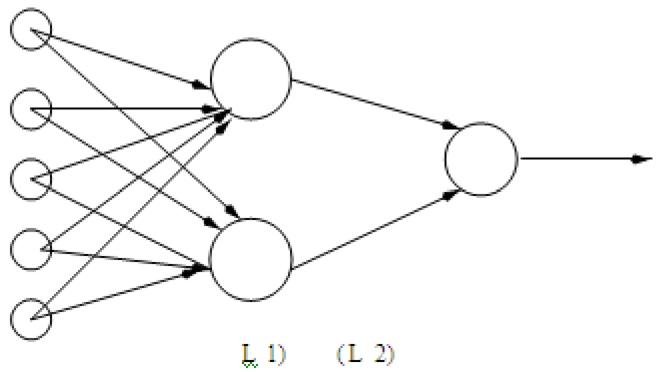

Figure 2: A multi-layer neural network

By its centre c_h and by its spread or width σ_h. The range of each of these functions is [0,1]. Once the input vector x is presented to the network, each neuron in the layer L_1 will output a value according to how close the input vector is to its weight vector. The more similar the input is to the neuron's weight vector, the closer to 1 is the neuron's output and vice versa. If a neuron has an output 1, then its output weights in the second layer L_2 pass their values to the neurons of L_2. The similarity between the input and the weights is usually measured by a basis function in the hidden nodes. One popular such function is the Gaussian function that uses the Euclidean norm. It measures the distance between the input vector x and the node centre c_h. It is defined as:

$$\varphi_h = \exp(\|x - c_h\|/2\sigma_h^2). \qquad (3)$$

Once the frequency bands are selected, we compute the

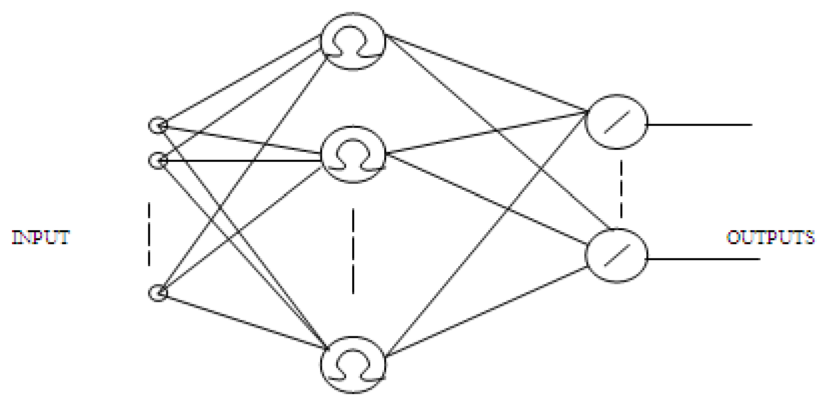

Figure 3: Radial Basis Function Neural Network

average absolute values of Fourier coefficients over the corresponding bands of the scale to obtain the energy values. These values are then scaled to a decibel scale of 0-60 dB.

$$E_{max} = \max(E(p)) \qquad 0 \le p \le P - 1 \qquad (4)$$

$$ES(p) = 20 * \log10(E(p)/E_{max}) \qquad 0 \le p \le P - 1 \ (5)$$

$$^{ES0}(p) = ES(p) - E_{max} \qquad 0 \le p \le P - 1 \qquad (6)$$

$$ES^{00}(p) = \max(ES^0(p), -60dB) + 60dB \qquad 0 \le p \le P-1 \qquad (7)$$

Since there are 6 bands, then P = 6. The second step after selecting the persons in the training set is to train the RBF network with the energy vectors constructed.

SIGNAL RECOGNITION

In this section, the RBF network built to train and recognize the brain signals of the test sets are constructed. The network contains two procedures, a training phase and a test phase.

Network Training Phase

The RBF network implemented in this paper is trained initially with the Matlab [16] Neural Network toolbox function newrb() which takes two input matrices: a goal

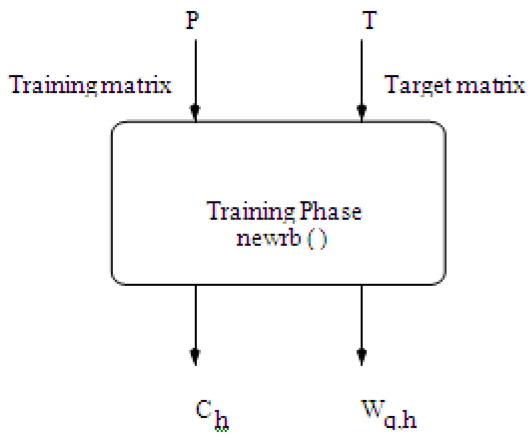

Figure 4: Training Phase of RBF Neural Network

Matrix and a spread matrix. It returns a trained radial basis network. The first input matrix P is a 6 ∗ Q matrix that contains a training set of Q vectors. The 6 correspond to the coefficients per trained signal. If the network is being trained with 2 persons then Q = 18 since every person is repeating each thought three times. The second input is a Q ∗ 3 matrix of targets T Figure 4. The rows of this matrix are targets vectors T_i that contain '1' in the targeted signal position and '0' otherwise. The output of the training function newrb() consists of the centres and the weights C_h and $W_{q,h}$ for the hidden and output layers respectively.

$$P = [v_1,v_2,...,v_Q] \quad (8)$$

$$T_i = [t_1,t_2,t_3] \quad (9)$$

$$T = [T_1,T_2,...,T_Q]^T \quad (10)$$

Network Recognition Phase

The Matlab [16] Neural Network toolbox function is used to perform the recognition phase. This function accepts a Figure 4: Training phase of the RBF network

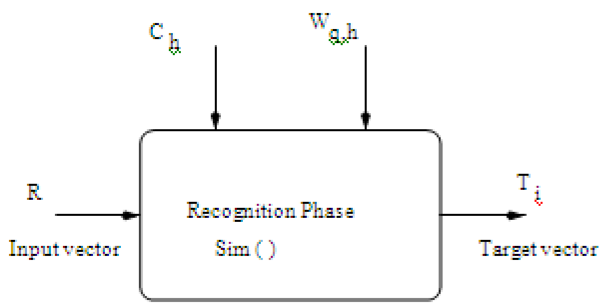

Figure 5: Recognition phase of the RBF network

Matrix R (similar to P of the training phase) of unknown brain signal vectors as an input along with the weights and bias vectors generated by the training phase Figure 5. Its output is a a unit diagonal matrix where '1' is placed in the recognized signals index.

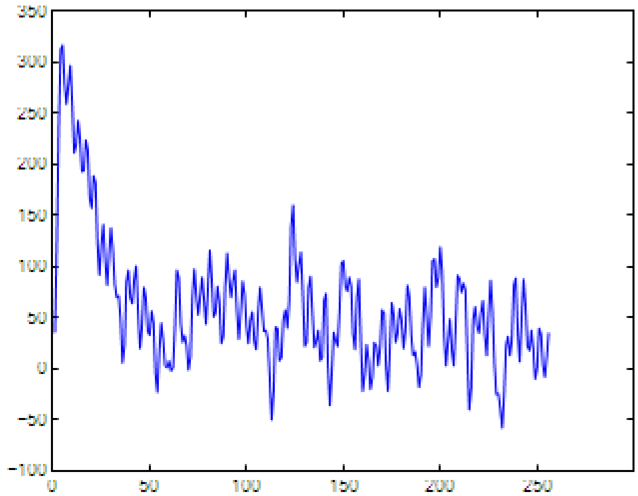

Figure 6: Person 1 "Backward" Signal

RESULTS

The database used in this work is the same one employed in our earlier work in [14]. As a sample, trial 1 "Backward" signal generated from person 1, is displayed in Figure 6. A total of 6 persons thinking six thoughts of back, forward, left, right, stop, move. Validation of the system were performed with perfect recognition rate resulting in testing with the same training set of thoughts from the same persons. The maximum recognition rate was recorded for" backward" and "stop" with 74 % and 77 % respectively. Basically, this work can lead to enhance machine performance by initially recognizing the signal ahead of sending it as a command to the machine.

CONCLUSION

A Radial Basis Functions (RBF) Artificial Neural Network (ANN) is constructed in this work to recognize brain signals. The database was populated with the implementation of a BCI using NeuroSkyS EEG biosensor. A total of 256 data points were acquired in each thought. The data were then transmitted via Bluetooth for MATLAB documentation. Validation of the NN were performed by testing with the same training set of thoughts from the same persons. Recognition rates in the highest 70 percent were recorded.

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