Classification of Electroencephalograph (EEG) Signals Using Quantum Neural Network

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Abstract

In this paper, quantum neural network (QNN), which is a class of feedforward neural networks (FFNN's), is used to recognize (EEG) signals. For this purpose ,independent component analysis (ICA), wavelet transform (WT) and Fourier transform (FT) are used as a feature extraction after normalization of these signals. The architecture of (QNN's) have inherently built in fuzzy. The hidden units of these networks develop quantized representations of the sample information provided by the training data set in various graded levels of certainty. Experimental results presented here show that (QNN's) are capable of recognizing structures in data, a property that conventional (FFNN's) with sigmoidal hidden units lack . Finally, (QNN) gave us kind of fast and realistic results compared with the (FFNN). Simulation results show that a total classification of 81.33% for (ICA), 76.67% for (WT) and 67.33% for (FT).

Keywords: Quantum Neural Network, EEG, ICA, Wavelet

1. INTRODUCTION

Brain is the center of central processing of Physical and mental activities, which is mostly affected by the Physical performance.

Neurons, or nerve cells, are electrically active cells which are primarily responsible for carrying out the brain's functions. Neurons create action potentials, which are discrete electrical signals that travel down axons and cause the release of chemical neurotransmitters at the synapse, which is an area of near contact between two neurons [1,2].

An electroencephalograph (EEG) is the measurement of electrical activity generated by the brain. First measured in humans by Hans Berger in 1929 [3].

In general, EEG is obtained using electrodes placed on the scalp with a conductive gel. In 1998, Rodrigo Q. Q. described and extended two new approaches that started to be applied to (EEG) signals (a) the time-frequency methods, and (b) the methods based on Chaos theory [4].

Quantum neural network (QNN's) is a promising area in the field of quantum computation and quantum information. In 1996, Lov K. Grover, proposed a method can speed up a range of search applications over unsorted data using Quantum mechanics [5]. Several models have been proposed in the literature but for most of them need a clear hardware requirements to implement such models. One of the most exciting emerging technologies is quantum computation, which attempts to overcome limitations of classical computers by employing phenomena unique to quantum-level events, such as nonlocal entanglement and superposition. It is therefore not surprising that many researchers have conjectured that quantum effects in the brain are crucial for explaining psychological phenomena, including consciousness [6]. Jarernsri. L. Mitrpanont, Ph. D. Ananta Srisuphab, presented the approach of the quantum complex-valued backpropagation neural network or QCBPN. The challenge of their research is the expected results from the development of the quantum neural network using complex-valued backpropagation learning algorithm to solve classification problems [7].

Independent component analysis (ICA) is essentially a method for extracting useful information from data. It separates a set of *signal mixtures* into a corresponding set of statistically independent component signals or *source signals*. ICA belongs to a class of *blind source separation* (BSS) methods for separating data into underlying informational components [8]. The mixtures can be sounds, electrical signals, e.g., electroencephalographic (EEG) signals, or images (e.g., faces, fMRI data). The defining feature of the extracted signals is that each extracted signal is statistically independent of all the other extracted signals[9].

The basis signal, or wavelet, used to decompose a signal does not produce information about “frequency” in the traditional sense, but rather a distribution of time and scale is created. A change in scale represents stretching or compressing the wavelet by a factor of two. It is therefore possible to reconstruct any signal using one wavelet as the basis and placing as many wavelets as are needed at different times with different amplitudes and scales[10].

Fourier Transform (FT) which transforms a signal (function) that exists in the time (or space) domain to the frequency domain. The FT accomplishes this task through a kernel composed by sine and cosine waveforms. This is the origin of the main disadvantage of FT for signal analysis [11].

The FFT (Fast Fourier Transform) can be computed relatively quickly, at or around real-time. The FFT does have its disadvantages, however. The frequencies used to decompose a signal are a function of the sampling frequency of the signal and the number of frequency bins desired. Without modifying these two parameters, these frequencies are not selectable. A simple sine wave whose frequency does not fall on one of the frequencies of the transform will produce a spectrum with energy spread to many frequencies[10].

2. METHODOLOGY

In (ICA), each signal is described as a scalar variable, and a set of signals as a vector of variables, and the process of obtaining signal mixtures from signal sources using a set of mixing coefficients [9]. ICA showing us how a set of source signals can be represented as a scattergram in which each point corresponds to the values of the signals at one time, and that a set of mixing coefficients can be used to implement a geometric transformation of each point.

$$x1 = as1 + bs2 \qquad (1)$$

$$x2 = cs1 + ds2 \qquad (2)$$

where (a, b, c, d), a set of mixing coefficients.

The resultant set of “mixture” points can be transformed back to the original set of “source signal” points using a set of unmixing coefficients, which reverse the effects of the original geometric transformation from source signals to signal mixtures.

s1 = αx1 + βx2 ....(3)

s2 = γ x1 + δx2...(4)

where (α, β, γ, δ), a set of unmixing coefficients and (s1, s2) are the original signals.

The desecrate wavelet (DWT) of a signal *x* is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response *g* resulting in a convolution of the two:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \quad ....(5)$$

The signal is also decomposed simultaneously using a high-pass filter *h*. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter. However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then subsampled by 2 (g- high pass and h- low pass):

$$y_{low}[n] = \sum_{k=-\infty}^{+\infty} x[k]g[2n-k] \quad ....(6)$$

$$y_{high}[n] = \sum_{k=-\infty}^{+\infty} x[k]h[2n+1-k] \quad ....(7)$$

This decomposition has halved the time resolution since only half of each filter output characterises the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled.

With the downsampling operator $\downarrow$

$$(y \downarrow k)[n] = y[kn] \quad ....(8)$$

the above summation can be written more concisely

$$y_{low} = (x * g) \downarrow 2 \quad ....(9)$$

$$y_{high} = (x * h) \downarrow 2 \quad ....(10)$$

However computing a complete convolution *x* * *g* with subsequent downsampling would waste computation time. The Lifting scheme is an optimization where these two computations are interleaved [12,13].

The fast Fourier transform (FFT) is a discrete Fourier transform algorithm which reduces the number of computations needed for Npoints from $2N^2$to $2N\lg N$, where lg is the base-2 logarithm. If the function to be transformed is not harmonically related to the sampling frequency, the response of an FFT looks like a sinc function. Discrete Fourier transform can be computed using an FFT by means of the Danielson-Lanczos lemma if the number of points $N$is a power of two. If the number of points $N$is not a power of two, a transform can be performed on sets of points corresponding to the prime factors of Nwhich is slightly degraded in speed. Prime factorization is slow when the factors are large, but discrete Fourier transforms can be made fast for $N=2$, 3, 4, 5, 7, 8, 11, 13, and 16 using the Winograd transform algorithm [14].

Fast Fourier transform algorithms generally fall into two classes: decimation in time, and decimation in frequency. The Cooley-Tukey FFT algorithm first rearranges the input elements in bit-reversed order, then builds the output transform (decimation in time). The basic idea is to break up a transform of length N into two transforms of length N/2 using the identity [15].

$$X(k)=\sum_{n=0}^{N-1} x(n)\omega_N^{nk}\,, \qquad k=0,\dots,N-1 \quad \text{..........................(11)}$$

$$x(n)=\frac{1}{N}\sum_{n=0}^{N-1} X(k)\omega_N^{-nk}\,, \qquad k=0,\dots,N-1 \quad \text{................(12)}$$

where,

$$\omega_N = \exp(\frac{-2\pi \quad j}{N}) \quad \text{...(13)}$$

x(n) is the signal in time domain.

X(k) is the signal in the frequency domain.

To selecting the best features from the signal which is dealt with (ICA), (WT) and (FFT), classification method was used for this purpose.

The individual within-class scatter matrix and the total within-class scatter matrix is defined by

$$S_i=\sum_{x\in\chi_i}(x-\mu_i)(x-\mu_i)^T \qquad i=1,2 \qquad \text{...................................(14)}$$

$$S_w = S_1 + S_2 \qquad \text{...(15)}$$

where, **μi** is the mean vector of the class **i** .

We can obtain the transform vector *w* with maximal between class distance and minimal within class variance by Fisher criterion function and Lagrange multiplier method: [16]

$$w = S_w^{-1}(\mu_1-\mu_2) \qquad \text{...(16)}$$

The QNN consists of n_i inputs, one hidden layer of n_h nodes, each hidden node represents a multilevel function (Eq. 17), and n_o output units. The output units are sigmoidal [17].

The equation of the output of hidden layer can be written as:

$$\tilde{h}_{j,k} = \frac{1}{n_s}\sum_{r=1}^{n_s} h^r_{j,k} = \frac{1}{n_s}\sum_{r=1}^{n_s} \mathrm{sgm}(\beta_h(\bar{h}_{j,k} - \theta^r_j)) \qquad \text{..........................(17)}$$

$$\mathrm{sgm}(\tau) = 1/(1+\exp(-\tau))$$

Where: βh is a slope factor, θ_j^r's define the jump positions in the transfer function, and n_s is the number of levels or sigmoids in the hidden unit.

3. RESULTS AND DISCUSSION

This section presents experimental classification results on the (EEG) data set which is used in (QNN). The results were obtained by using the (ICA), (WT) and (FFT) are from two different electrodes of the scalp hat, as in tables 1,2 and 3:

	(QNN) electrode no.1					(QNN) electrode no.5				
	TP	FN	FP	Se	PP	TP	FN	FP	Se	PP
CLASS 1 (baseline)	25	1	4	.96	.86	25	0	5	1	.83
CLASS 2 (rotation)	25	2	3	.926	.89	24	0	6	1	.8
CLASS 3 (multiplication)	24	2	4	.923	.857	26	0	4	1	.867
CLASS 4 (counting)	26	2	2	.929	.929	19	1	10	.95	.655
CLASS 5 (letter comp.)	22	4	4	.846	.846	22	0	8	1	.733
TCA	81.33%					77.33%				

TABLE 1: Classification Results With QNN By Using (ICA).

	(QNN) electrode no.1					(QNN) electrode no.5				
	TP	FN	FP	Se	PP	TP	FN	FP	Se	PP
CLASS 1 (baseline)	25	2	3	.926	.89	25	0	5	1	.833
CLASS 2 (rotation)	22	2	6	.916	.79	23	3	4	.8846	.85
CLASS 3 (multiplication)	23	3	4	.88	.85	22	7	1	.758	.956
CLASS 4 (counting)	24	2	4	.923	.86	22	5	3	.814	.88
CLASS 5 (letter comp.)	21	3	6	.875	.78	19	8	3	.703	.86
TCA	76.67%					74%				

TABLE 2: Classification Results With QNN By Using WT(db1).

	(QNN) electrode no.1					(QNN) electrode no.5				
	TP	FN	FP	Se	PP	TP	FN	FP	Se	PP
CLASS 1 (baseline)	21	6	3	.78	.875	20	2	8	.9	.714
CLASS 2 (rotation)	20	4	6	.83	.77	20	6	4	.769	.83
CLASS 3 (multiplication)	19	6	5	.76	.79	18	3	9	.857	.67
CLASS 4 (counting)	20	3	7	.87	.74	17	5	8	.77	.68
CLASS 5 (letter comp.)	21	4	5	.84	.807	22	0	8	1	.73
TCA	67.33%					64.67%				

TABLE 3: Classification Results With QNN By Using (FFT).

Where,

(TP_i) is (true positive) classification for class i.

(FN_i) is (false negative) classification for class i.

(FP_i) is (false positive) classification for class i.

$$Sensitivity(Se) = \frac{TP_i}{TP_i + FN_i} \qquad \text{...(18)}$$

$$Positive\ \ Predictivity(PP) = \frac{TP_i}{TP_i + FP_i} \qquad \text{..(19)}$$

From tables(1,2 and 3), we can notice that, different results were obtained from different electrodes and that means (EEG) signals are different from electrode to another according to mental tasks.

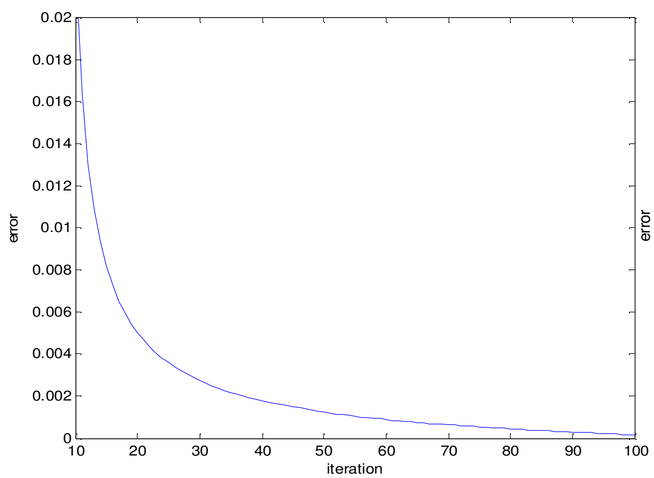

FIGURE 1: Error By Using ICA (1rst.electrode).

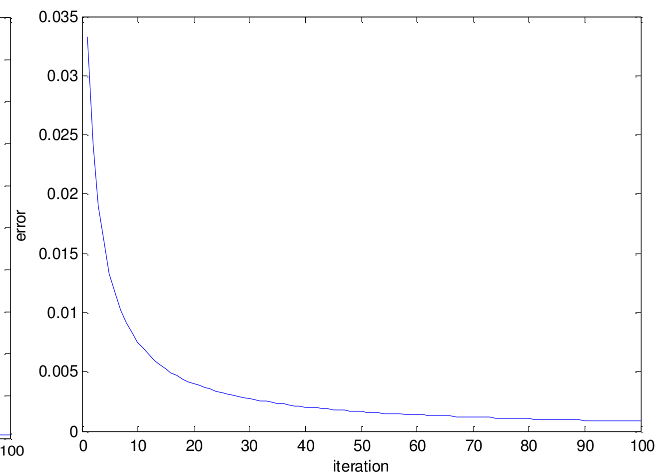

FIGURE 2: Error By Using ICA (5th.electrode).

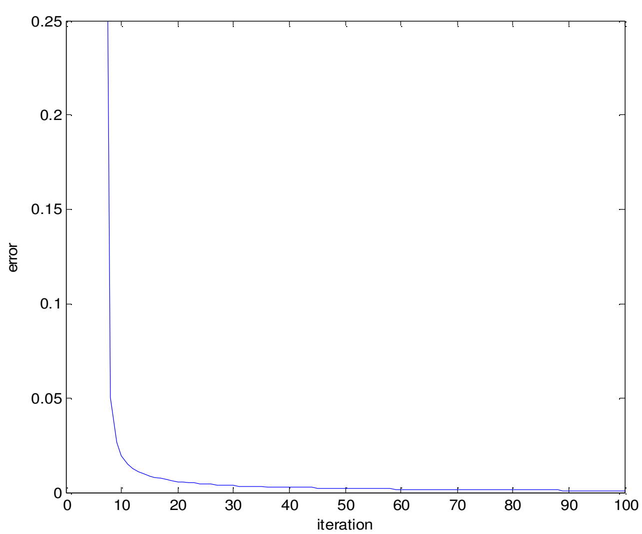

FIGURE 3: Error By Using WT(db1) (1rst.electrode).

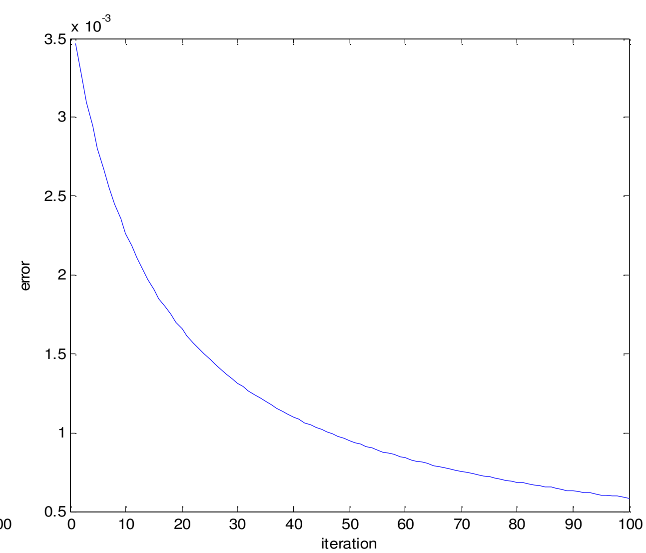

FIGURE 4: Error By Using WT(db1) (5th.electrode).

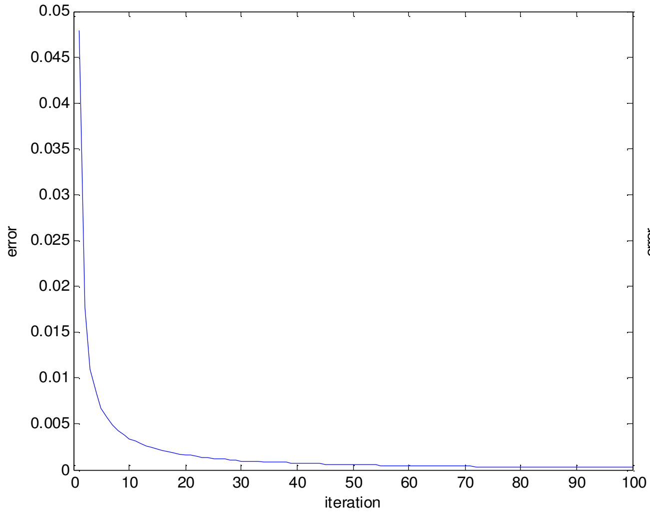

FIGURE 5: Error By Using FFT (1rst.electrode).

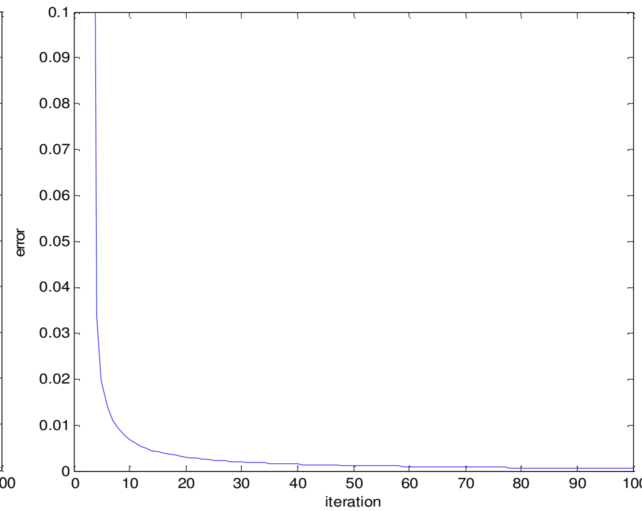

FIGURE 6: Error By Using FFT (5th.electrode).

The error diagrams for the first and fifth electrode, (Fig.1 to Fig.6), tell us that, the value of error is decrease whenever the training is progress until convenient weights and biases are obtained.

4. CONCLUSION

As resultant for this research, different results were obtained from different electrodes. Because of different mental tasks for different positions of brain.

Generally, the results were obtained from first electrode best than the fifth electrode's results. And the classification of (EEG) signals by using (ICA) best than by using (WT and FFT), and the classification by using (WT) best than by using (FFT). Besides, classification of class(4) from the first electrode is best than fifth electrode. It means the mental tasks which read from the first electrode as (EEG) signals ,may be they were specialist with routine actions (like counting) more than the others.

5. REFERENCES

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