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Non- Linear Principal Component Analysis Neural Network for Blind Source Separation of EEG Signals

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Abstract: The complex system such as human brain generates electrical recording activity from thousands of neurons in the brain. This activity is given as electroencephalogram (EEG) waveforms. The EEG potentials represent the combined effect of potentials from a fairly wide region of the skull's skin (scalp). Mixing some underlying components of brain activity presumably generates these potentials. The mixing of brain fields at the scalp is basically linear mixture. The present study aims to design and implement an unsupervised neurocomputing model for separating the original components of brain activity waveforms from their linear mixture, without further knowledge about their probability distributions and mixing coefficients. This is called the problem of "Blind Source Separation "(BSS). It consists of the recovery of unobservable original independent sources from several observed (mixed) data masked by linear mixing of the sources, when nothing is known about the sources and the mixture structure. The current study used recently developed source separation method known as "Independent Component Analysis" (ICA) technique for solving blind EEG source separation problem. The ICA is used to decompose the observed data into components that are as statistically independent from each other as possible. The ICA algorithm that was used for linear BSS problem is the Nonlinear Principal Component Analysis (BSS) algorithm. The proposed ICA BSS model was implemented using the Matlab version6.1 package. The measured real EEG data signals obtained from normal and abnormal states from the (Neurosurgery Hospital) in Baghdad. The results of the present work show the good performance of the proposed model in separating the mixed signals. Since the present ICA model is a reliable, robust and effective unsupervised learning model which, enable us to separate the EEG signals from their linear observation records, and extract several specific brain source signals that are potentially interesting and contain useful information that help physician to diagnose the abnormality of the brain easily.

Key words: BSS, EEG, ECG Signals, neural networks, PCA

INTRODUCTION

The present problem is that the EEG signals result from the activity of neurons some significant distance a way from the sensor (electrode), which are using to take the measurement. Each electrode is a summation of the electrical neural activity of a large number of individual neurons in the vicinity, therefore because of the distance between the skull and brain, and their different resistivities, electroencephalographic data collected from any point on the human scalp includes linear mixture of activity generated within a large brain area (X-Yang and Yen-Wei, 1998). Mixing some underlying components of brain potential generates this activity, this is considering a blind EEG signals separation problem (Isaksson and Wennberg, 1998).

Literature Review: The importance of signal processing and analysis of EEG waveforms based on computer encouraged the scientists in their hard work:

(Maeig *et al.*, 1996) Applied the original infomax algorithm to electroencephalogram (EEG) and event-related potential (ERP) data showing that the algorithm can isolate EEG artifacts, since the result proved that this algorithm is able to linearly decompose EEG artifacts such as line noise, eye blinks, muscle activity, and cardiac noise (Jung and Makeig, 1998). Mckeown *et al.* (1998) has used the extended ICA algorithm to investigate task related human brain activity in fMRI data (Jack and James, 1997). Barros *et al.* (2000) have proposed a fixed-point algorithm, which utilizes in extraction sleep-spindles from the (EEG) and channel isolation of these sleep spindles from a multi-channel electroencephalograph. Mckeown and Makeig (1998) have proposed a method based on an extended version of ICA algorithm for severing contamination of (EEG) activity by eye movements, blinks, and muscle, heart and line noise presents a serious problem for EEG interpretation and analysis. The results show that ICA can effectively detect, separate and remove the activity of a wide variety of artifactual sources in EEG records, with results comparing favorably to those obtained using conventional methods (Carl *et al.*, 2000). After that (Leichter *et al.*, 2001) present a novel model for classification of EEG data based on ICA as a feature extraction technique, and on evolving fuzzy neural

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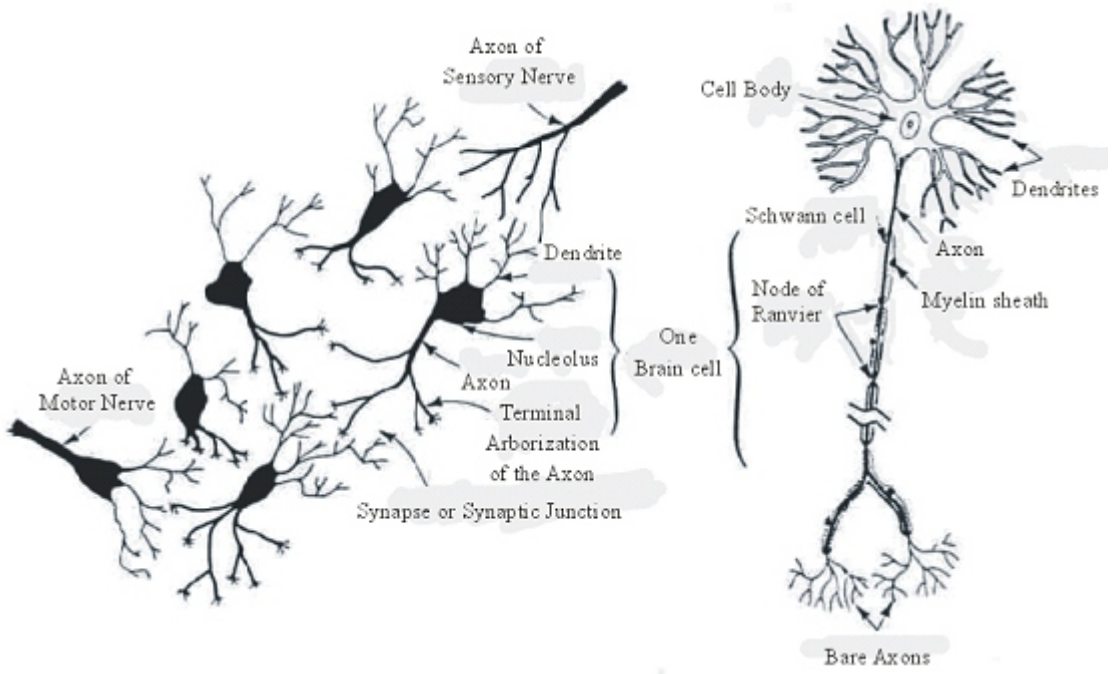

Fig. 1: Schematic structure of a biological neuron

networks as a classification modeling technique. This study demonstrates that ICA can dramatically improve the classification of (EEG) from various conditions (Kobayashi., 1999). Habl and *et al.* (2000) have studied ICA algorithm to separate EEG signals from tumor patients into independent source signals. The algorithm allows artifactual signals to be removed from the (EEG) and isolates brain related signals into single ICA components. Their results useful for a meaningful interpretation by the experienced physician (Briggs and Leslie, 1987) .

Aim of the research: The major objective of this work may be classified into the following:

- To study the nature of the electroencephalogram (EEG) signals.
- To study different methods used to analyse the EEG signals.
- To examine the relation between EEG signals and the Blind Source Separation (BSS).
- To study in deep the independent Component Analysis (ICA) technique and its relation with BSS.
- To implement an algorithm based on ICA to extract the underlying signal of the EEG signals.
- To examine the usefulness of the extracted EEG signals with the help of physician and doctor.

The basic theory:

The structure (anatomy) of the brain: The brain is a complex structure, comprised of very large numbers of nerve cells which are interconnected among them and which also receive data from the various sensory organs. A typical biological neuron has three major regions as shown in Fig. 1, Dendrites, Cell Body (Soma) and Axon (Al-Neami, 2001).

The axon-dendrite contact organ is called a "Synaptic Junction" or "Synapse", as in Fig 1. Synapses allow electrical impulses to flow throughout the brain and the central nervous system; one cell acting as a trigger to influence neighboring cells (James, 2002).

Organization of the brain: The brain is divided into four lobes, as illustrated in Fig. 2, these lobes are:

Frontal lobe: Located in front of the central sulcus of the brain as shown in Fig. 2. It concerns with reasoning, planning, parts of speech and movement (motor cortex), emotions, and problem solving.

Parietal lobe: Located behind central sulcus of the brain. It concerns with perception of stimulus related to touch, pressure, heat, cold, temperature and pain (Fig. 2).

Temporal lobe: Located just above the ears, as shown in Fig. 2. It concerns with perception and recognition of auditory stimuli (hearing) and memory (hippocampus).

Occipital lobe: Located at the back of the head, between the parietal lobe and temporal lobe and over the cerebellum. It concerns with many aspects of vision and contains the visual cortex (Eduardo and Carlos, 1996) (Fig. 2).

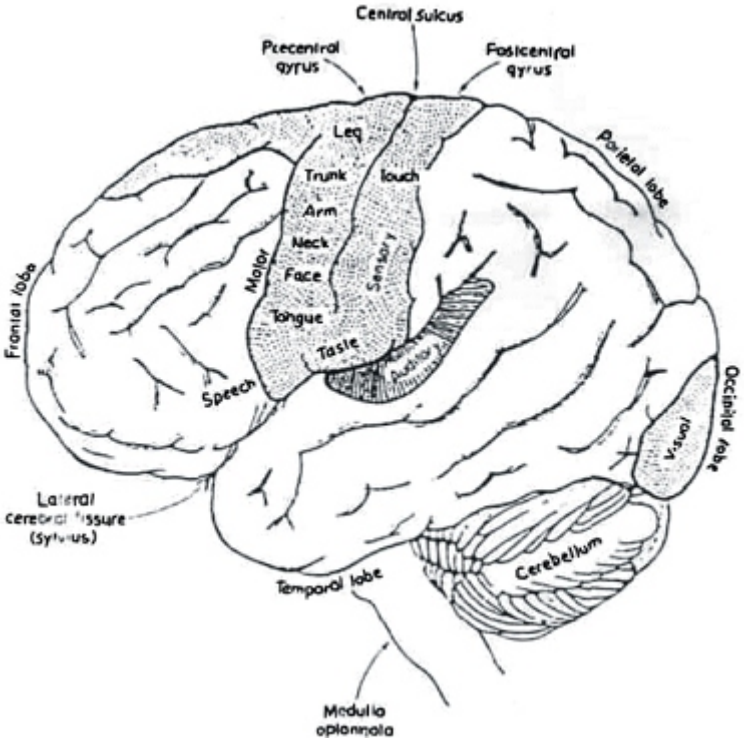

Fig. 2: Brain main lob

Table 1 : Location of present bipolar longitudinal montage

Fp2	F4	C4	P4	Fp2	F8	T4	T6	Fp1	F3	C3	P3	Fp1	F7	T3	T5
F4	C4	P4	02	F8	T4	T6	02	F3	C3	P3	01	F7	T3	T5	01
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16

EEC Recording modes: There are many modes of recording are used in the routine EEG, since the EEG equipment can be set up with different electrode combinations, the numbers of which depends on the number of electrodes placed on the scalp. The aim is to cover the entire surface of the scalp (Deltamed, 1997). The different combinations of electrodes are called the *montage.* For reading EEG signals there are two kinds of montages, since either the difference in potentials are recorded between two active electrodes (Bipolar Montage) or between an active electrode and a reference electrode (Unipolar Montage).

Bipolar montage: Bipolar montage type is divided into these cartologies:

- Longitudinal Montase (The Anterior-Posterior Montage):
- This explores the surface of the scalp from front to back and, simultaneously, from right to left, as in Fig. 3.

The transversal montage: This explores from right to leave and from front to back starting from FP2, F8, T4, T6, and 02 as in Fig. 4 the current work uses the two types

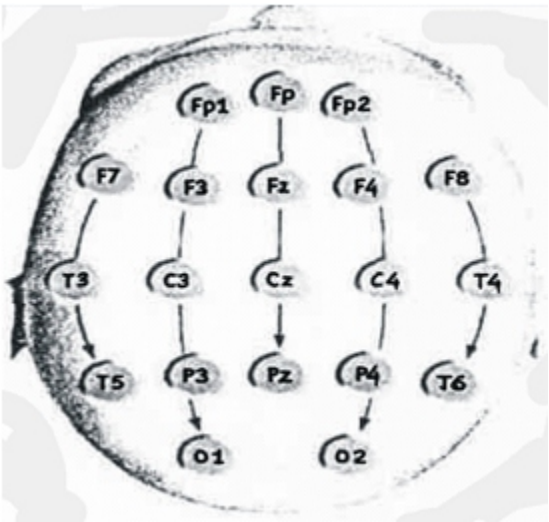

Fig. 3: Longitudinal bipolar montag

of montages for the measurement and each montages for different cases. First montage used bipolar longitudinal montage for EEG recording, and measures the EEG waveforms from (32) electrode, (16) channels as shown in Table 1 with Fig. 3. Second montage used bipolar

Table 2: Location of present bipolar transversal montage

Fp2	F8	F4	Fz	F3	T4	C4	Cz	C3	T6	P4	Pz	P3	02
Fp1	F4	Fz	F3	F7	C4	Cz	C3	T3	P4	Pz	P3	T5	01
1	2.	3	4	5	6	7	8	9	10	11	12	13	14

Table 3: Location of present uipolar mode montage

Fp1	Fp2	Fpz	F3	F4	F7	F8	Fz	C3	C4	T3	T4	Cz	P3	P4	T5	T6	Pz	01	02	Pz
G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2	G2
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21

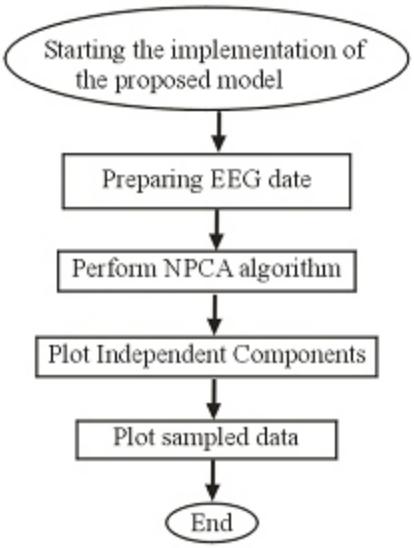

Fig. 4: The network of ICA algorithm

transversal montage for EEG recording and measures the EEG waveforms from (28) electrode, (14) channels as shown in Table 2 with Fig. 4.

Unipolar montage: The unipolar montage represent the successive connections for measuring the potentials from front to back and/or from left to right between one of the electrodes placed on the scalp and a reference electrode. This montage measures the EEG waveforms from (21) channels (Table 3 and Fig. 3).

The proposed ICA model: In this section, a model for implementing a complete ICA algorithm based on NPCA algorithm will be described. The input to this model is a file, which contains the sampled EEG data as a column vector. For more than one source of data, i.e. channels, the data must be of columns equal to the number of channels. The general flowchart of the proposed model is shown in Fig. 5.

The present ICA network model: The present model pertains to the neural network approach for blind source separation of EEG signals using ICA method. Fig. 6 shows the basic ICA neural network model. The model consists of a specific data acquisition system, which represents the computerized EEG device. Through this system one can obtain the observed EEG waveforms that contain the underlying source signals. The main goal is to extract the underlying EEG signals from the human brain. Since the observed data from biological systems is a superposition of some underlying unknown sources, the basic strategy suggested is to apply ICA network model to estimate the original brain sources from the observed data.

The present ICA algorithm: Nonlinear PCA Algorithm (NPCAA) Fig. 7 demonstrates the network of the present ICA algorithm. ICA of a random vector x consists of estimating the following generative model for the data:

$$x = As \tag{1}$$

where (he latent variables (components) s; in the vector $s = (S_1, S_2, ..., S_m)$ are assumed independent. The matrix A is a constant 'n x m' mixing matrix. The observed data are generated by a process of mixing the component *s*\. The independent components are latent variables, meaning that they cannot be directly observed. Also the mixing matrix A is assumed to be unknown. All observed is the random vector x, and one must estimate both A and s using it. This must be done under as general assumptions as possible. This algorithm consists of the following procedure:

Preprocessing: The success of ICA for a given data set may depend crucially on performing some preprocessing steps. This include:

- **Centering:** Prior to inputting the data vectors (observed signals) x to the ICA networks, they are made zero mean by subtracting the mean value, if necessary to assist in estimation ICA model.
- **Whitening:** The whitening process that precedes the separation step is a critical procedure. It was used to transform the data into an appropriate space and decrease the redundancy of the observed data (Kungana and Koontz, 1992). In the current study, PCA was used for whitening process, hence the input vectors x(k) are whitened by applying the transformation:

$$v(k) = Vx(k) \tag{2}$$

v(k): is the kth whitened vector; V: is the whitening matrix

The whitening matrix can be determined in two ways by using:

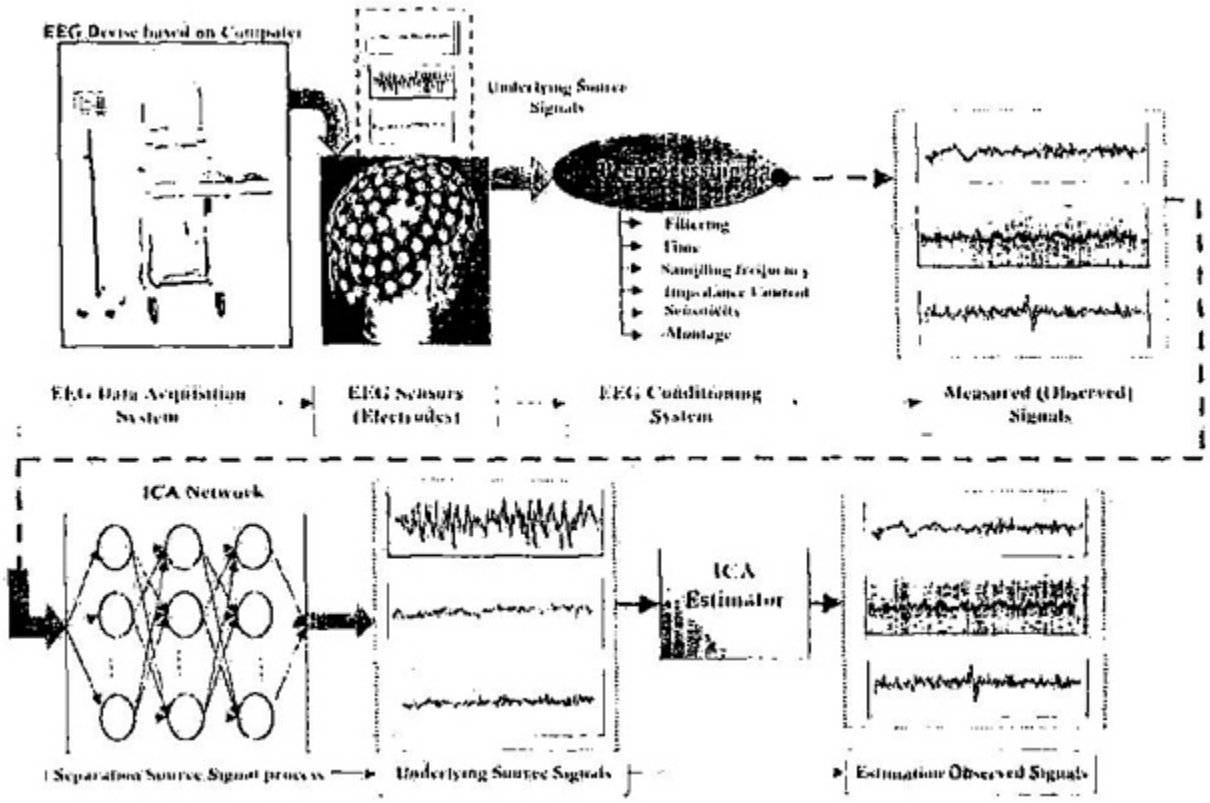

Fig. 5: Methodology of the proposed ICA mode

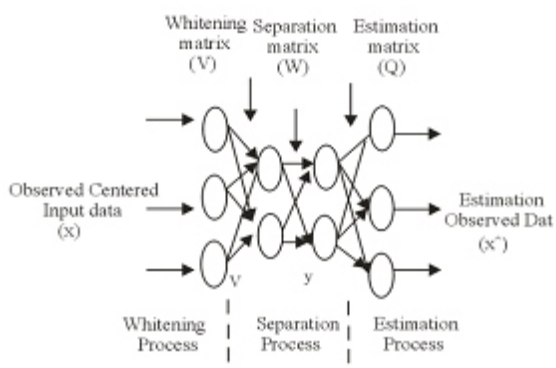

Fig. 6: The proposed ICA network mode

- Batch Approach
- Neural Learning Approach

For the "Batch Approach", standard PCA method was used to determine the whitening matrix, the PCA whitening matrix is given by:

$$V = D^{-1/2} H^T \quad (3)$$

V: is a whitening matrix, $V \hat{I} R^{mxn}$
D: diagonal matrix, D= dig $[\lambda_1, \lambda_2, \ldots, \lambda_n]$, $D \hat{I} R^{nxn}$ which represent eigen values of the covariance matrix Cx as:

$$C_x = E\{x(k)x^t(k)\} \quad (4)$$

H: associated (principle) eigenvectors.
$H = [c_1, c_2, \ldots\ldots, c_n]$, $H \hat{I} R^{nxn}$, with λ_i is the ith- largest eigenvalue of the covariance matrix C_x, ci for i=l,2,.....,n.
For the "Neural Learning Approach", an algorithm for learning the whitening matrix V neurally is a stochastic approximation algorithm to learn the whitening matrix is given by:

$$V(k+l)=V(k) - \mu(k) [v(k) v^T(k) - I] V(k) \quad (5)$$

v(k): is defined in Eq. (l)
I : identity matrix.
μ(k) : is a learning rate parameter, where it is recommended to adjust it according to the following equation:

$$\mu(k)=1/\{(y/(\mu(k\text{-}1))+\|v(k)\|^2_2\} \quad (6)$$

y : is the forgetting factor, since 0 < y< 1, μ(k) >0
When the whitening transformation V is applied to the inputs as in Eq. (2), then the resulting whitened outputs v(k) will posses the whiteness condition, that is :

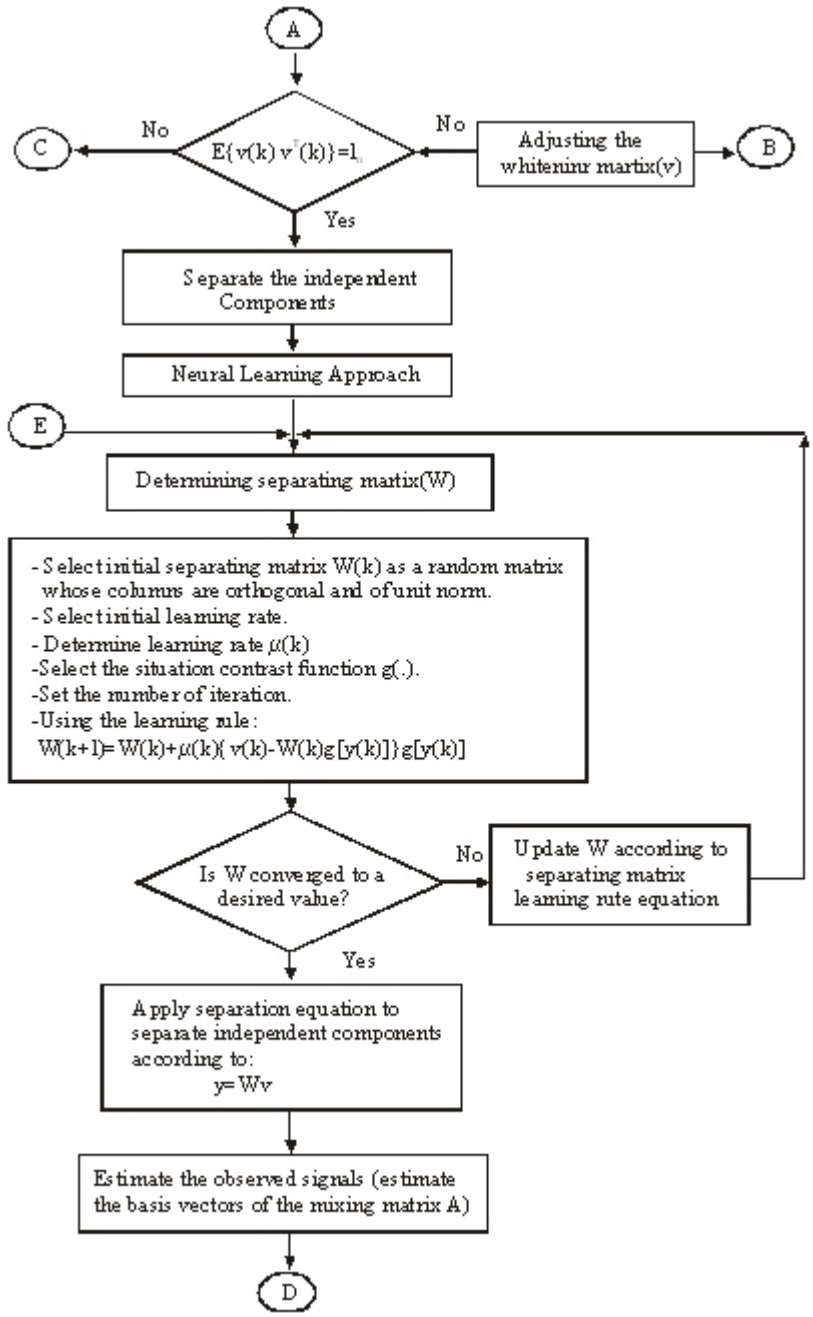

Fig. 7: Nonlinear PCA Algorithm (NPCAA)

$$E\{ v(k)\, v(k)^T \} = I_n \tag{7}$$

The whitening process normalizes the variances of the observed signals to unity. However, whitening the data can make the separation algorithms have better stability properties and converge faster. Hence whitening reduces the dimension of the data, and then the computational overhead of the subsequent processing stages is reduced

Separation: The separation of the whitened signals is the second stage of the ICA model architecture as shown in Fig. 7. Here proposed class of separation methods involves using neural networks to perform the separation of the source signals. This has done by applying nonlinear PCA subspace learning rule as shown below. The linear separation transformation is given by:

$$y(k)=W^T v(k) \tag{8}$$

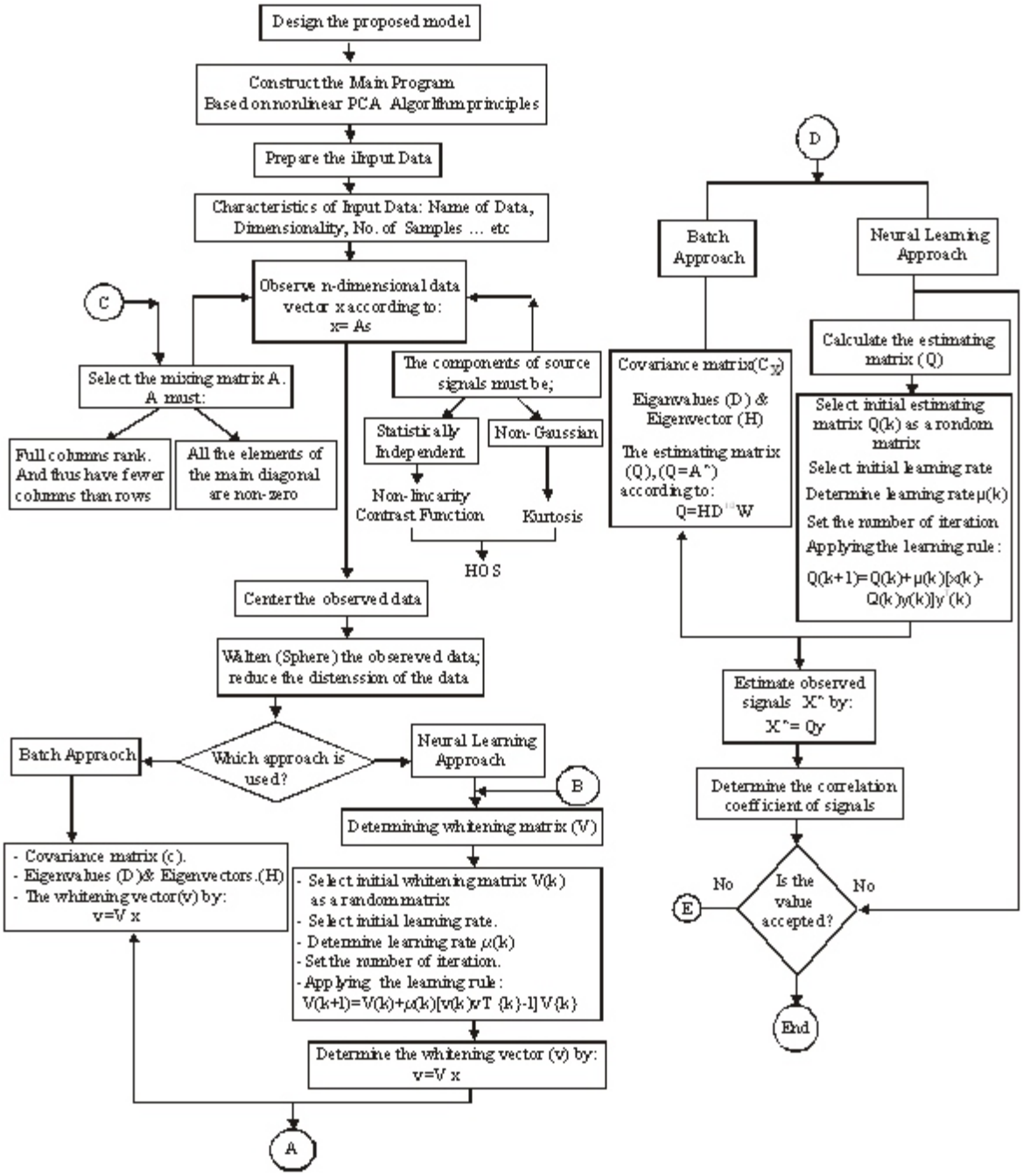

Fig 8: Procedure of Nonlinear PCA Algorithm

W: is the separation matrix. $W \hat{I} R^{nxm}$, ($W^T W = I_n$).
y(k): is the separated signals and the outputs of the second stage.
Since: s^(k) == y(k). s^(k) is estimated source signals s(k). Thus to obtain the separated signal y(k) in Eq. (8), it is important to apply neural learning method to determine the separation matrix W, this is based on the nonlinear PCA subspace learning rule given by:

$$W(k+1)=W(k)+\mu(k)\{v(k)-W(k)g[y(k)]\}g[y^T(k)] \quad (9)$$

v(k): is a whitened input vector given in Eq. (2)
μ (k): is a learning rate parameter, which be adjusted according to the scheme given as:

$$\mu(k)=1/\{(y/(\mu(k-1))+\| y(k) \|^2_2\} \quad (10)$$

g(.): is a suitably chosen nonlinear function, usually selected to be odd in order to ensure both stability and signal separation (Motoaki and Noboru, 1999). It turns out that non-linearities are central to the ICA decomposition. In turn, these non-linear functions imply the use of high-order statistics (HOS). Typically, the nonlinear function g(t)s chosen as:

$$g(t)= \beta \tanh(t/ \beta) \quad (11)$$

$$g(t)=df(t)/dt$$

$f(t)= \beta^2 \ln[\cosh(t/ \beta)]$, the logistic function, since $\beta = 1$. This is not an arbitrary use for the non-linearity in the learning rule of Eq. (9). It is motivated by the fact that when determining the ICA expansion, HOS are needed.

Estimation: This implies estimation of the ICA basis vectors, this is the last stage as in Fig. 7. Two methods are presented here to estimate the ICA basis vectors, or the column vectors of the mixing matrix A, they are:

- Batch Approach
- Neural Approach

The first method is a Batch Approach where the estimate of A, that is $\hat{A}$ is given by:

$$\hat{A}=H\, D^{1/2} W \quad (12)$$

D: is the eigen value matrix shown in Eq. (3)
H: has columns that are the associated eigenvectors shown in Eq. (3)
W: is the separation matrix

The second method is a *Neural Learning Approach* for estimating the ICA basis vectors. From Fig. 7, the last stage given an estimate of the observed data as:

$$\hat{x}=Q\, y \quad (13)$$

Comparing Eq. (13) with Eq. (l) (i.e., x =As), and since y = s^, then from this conclude that Q=A^. Therefore, the columns of the Q matrix are estimates of the columns of A, the ICA basis vectors. Since the Q is the estimation matrix as shown in Fig. 7. Thus the neural learning rule for estimating the ICA basis vectors is:

$$Q(k+l)=Q(k)+\mu(k)[x(k)-Q(k)y(k)]y^T(k) \quad (14)$$

$\mu(k)$: is the learning rate parameter that can be adapted during learning , it can be determined according to the following equation:

$$\mu(k)=1/\{(y/(\mu(k-1))+\| Q(k)\, y(k) \|^2_2\} \quad (15)$$

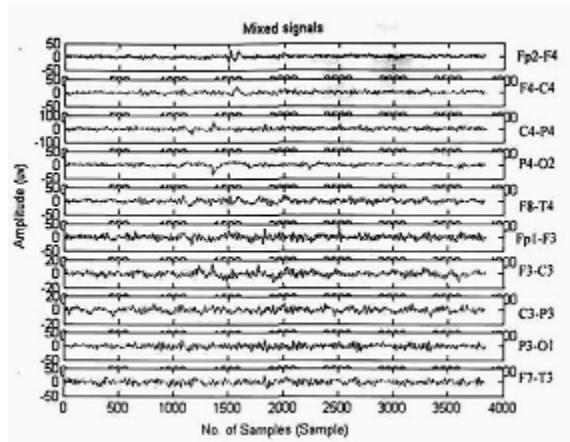

Fig. 9: The observed EEG signals.

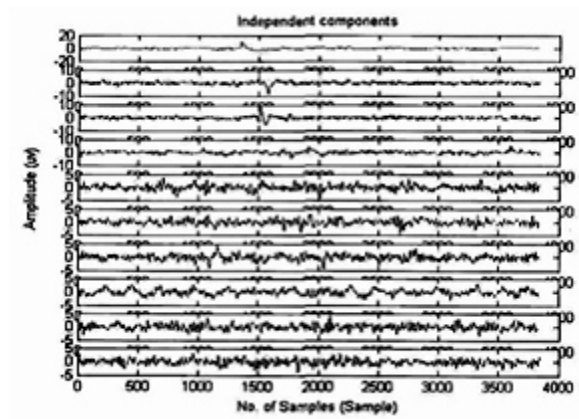

Fig. 10: The observed EEG signals for transversal montage test

Figure 8 shows the followed procedure of nonlinear PCA algorithm

EEG analysis results: In the following section, the separation of independent components for real EEG signals and for different cases will be presented. The results of the present work are obtained from different tests as shown below:

Bipolar EEG montage tests: The Bipolar montage tests, performed in this section, are divided into longitudinal and transversal montage tests.

Longitudinal montage test: Locations of electrodes and then the collected EEG signals are illustrated in Fig. 3.

These signals were filtered using a low pass filter with cutoff frequency of 1.2Hz and a high pass filter with cutoff frequency of l0Hz. The sampling rate of 384 sample/sec was used. Moreover, the test was collected from 10 channels and performed on a normal 32 years old person. The observed (recorded) signals are plotted in Fig. 9, 10.

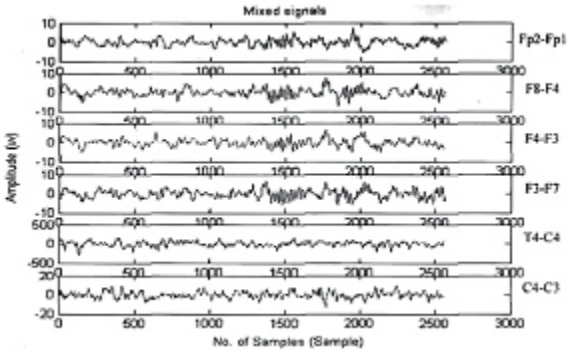

Fig. 11: THC Independent Components from Transversal Montage Test Using NPCA Algorithm

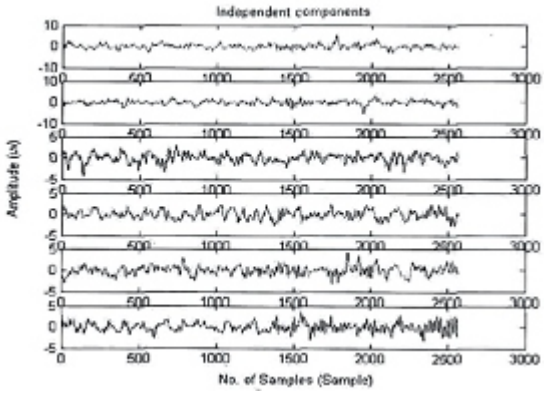

Fig. 12: Thc Independent Components fromTransversal Montage Test Using NPCA Algorithm

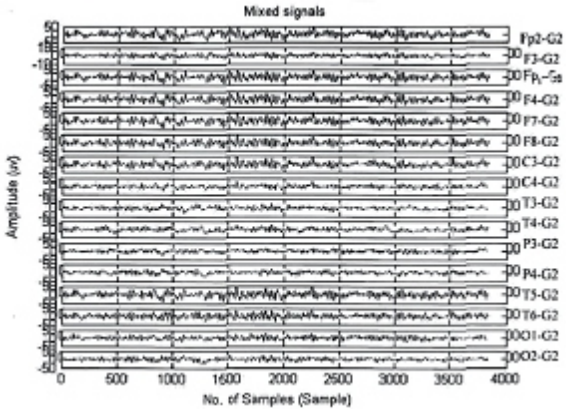

Fig. 13: The Observed EEG Signals for Unipolar Montage Test

Transversal Montage Test: The present bipolar transversal montage is shown the chaneel of montage were collected from 6 EEG channels, filtered using a low pass filter with cutoff frequency of 1.2Hz and a high pass filter with cutoff frequency of 101-lz. The signals are sampled at 256 sample/sec. The current patient is 27 years old with abnormal case. Separation of the observed signals into blind sources achieved by using NPCA algorithm, these observed signals are shown in Fig. l1.

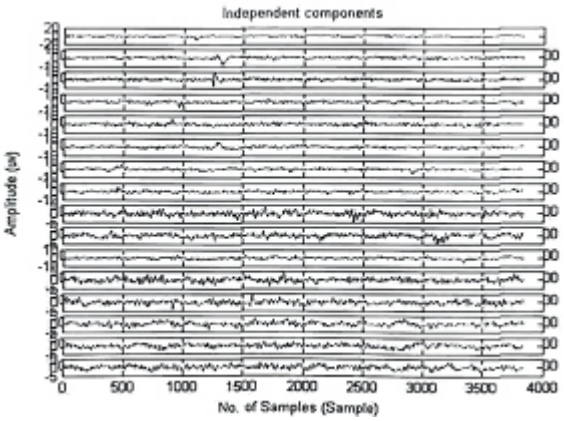

Fig. 14: The independent components from unipolar montage test using NPCA algorithm

Fig. 12 showed the underlying EEG signals (independent components) generated from separating process by using NPCA algorithm.

Unipolar EEG montage test: The present unipolar montage is illustrated in the current unipolar test involves separation of underlying EEG source signals from 36 years old and normal case, the number of channels in this test is 16 channels. The sampling rate is 384 sample/sec. The low pass filter is 1.2Hz; high pass filter is 10 Hz. The measured EEG signals during this test are shown in Fig. 13. For separation the independent components of this unipolar montage test, NPCA algorithm was used. These independent components that produced from the observed data of this test using NPCA algorithm are shown in Fig. 14.

CONCLUSION

The aim of this study is the design of an ICA neural network model, which can be used to analyze the complex EEG signals. The EEG signals were assumed to be blind signals. Therefore, the ICA neural network was used as a BSS of the EEG signals. This technique is very useful in applications for, which there are sets of data or observations, but little or no other information about specific parameter values of the system, which produced the observations. From EEG signal analysis, the following conclusions may be drawn:

1. The EEG signals are highly complex and generally non-Gaussian. Thus the conventional methods are limited to satisfy the present desire for extracting blind signals that help in diagnosis. One way of gaining further insights on the EEG signals is to introduce ICA and HOS techniques.
2. The present model of EEG analysis consists of three main stages: whitening, separation, and estimation.

(A) Whitening

- PCA used successfully in the whitening process as a preprocessing stage.
- The PCA option is provided as a principled though imperfect way to make the training tractable for large numbers of channels only not for separation of independent components because PCA based on 80S technique and on Gaussian data. While ICA is basically a way of separating and finding a special non-Gaussian data using HOS technique to perform a linear transform which makes the resulting variables as statistically independent for each other as possible.

(B) Separation

The NPCA algorithm is used for separation,

- NPCA learning rule is used for ICA estimation. Indeed, almost any nonlinear function can be used in the learning rule. Thus one has a large freedom in the choice of the nonlinearity in the NPCA learning rule. This result is important because practically all other ICA procedures use a fixed nonlinearity or a limited number of them.
- In this algorithm the inputs x(t) used in the algorithms at once, thus this enabling faster adaptation. The convergence depends on a good choice of the learning rate in the NPCA learning rule, hence a bad choice of the learning rate destroy the convergence.

(C) Estimation

- To estimate the ICA basis vectors (the column vectors of the mixing matrix A) both batch and neural approaches were used. Using the batch approach, by comparing these results with the actual mixing matrix, it found that the estimates of A column vectors is relatively close to the original mixing matrix A. The neural learning approach is used next to estimate the basis vectors of the ICA. The estimate of the mixing matrix is not exact; it is relatively close to the actual mixing matrix. The correlation coefficients between the observed signals x and the estimation signal x" is a very good values ranging from 0.98 to 0.999.
- From the extensive number of test performed using real EEG signal, the proposed model was found to be a very useful tool for doctor. This is due to the new signals, i.e. the independent components, which were presented.

Suggestions for future work: There are few points are suggested for future work:

- It would be interesting to extend the present model to diagnose the brain disorders by constructing a huge information and database based on physician experiences.
- Connect the ICA algorithms with the artificial intelligence techniques like fuzzy and genetic algorithms to extend their tasks to many other developed tasks such as, diagnosis, classification, and feature extraction of EEG waveforms.
- Apply other bioelectrical signals to the present model, like Electrocardiogram (ECG), Electrogastrogram (EGG) signals, and Electromyogram (EMG).

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