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Brain Computer Interface for paralyzed people

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Abstract

A Brain-Computer Interface (BCI) is a communication system designed to allow the users who has suffer of totally paralysis to send messages or commands without sending them through the brains normal output pathway. The overall objective of this project is to design and implement an algorithm that could separate and classify task-related Electroencephalography (EEG) signals which is the movement of right or left index finger from ongoing EEG signals by using the Independent Component Analysis (ICA). This separation would effectively speed the classification of EEG patterns. The task-related EEG signals were taken and classified using adaptive pattern classifier which is consist of combing the Kohonen Self-Organizing Map (SOM) with Learning Vector Quantization (LVQ). The algorithm was trained and tested using offline EEG signals measured according to ten-twenty International system obtained from a computerized EEG system in Ibn-Rushd Hospital.

Keywords: communication system paralyzed for people.

ربط الدماغ بالحاسـوب للأشخاص العاجزين عن الحركـة

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الخلاصة :

ربط الدماغ بالحاسوب (BCI) هو نظام اتصال مصمم للمستخدمين الذين يعانون من الشلل الكلي لإرسال الرسائل او الأوامر دون إرسالها عن طريق مخارج الدماغ الطبيعية. ويتمثل الهدف الرئيسي للمشروع من تصميم وتنفيذ خوارزمية ذكية قادرة على فصل وتصنيف إشارات الدماغ (EEG) الخاصة بالحركة والتي تتمثل في حركة إصبع السبابة لليد اليمنى واليسرى. تم فصل إشارات الدماغ الخاصة بالحركة عن غيرها باستخدام خوارزمية تحليل العنصر المستقل (ICA) التي تزيد من سرعة تصنيف إشارات الدماغ الخاصة بالحركة. تم تصنيف إشارات الحركة باستخدام مصنف الأنماط المتكيف والذي يتألف من دمج مصنف خريطة التنظيم الذاتي (SOM) مع مصنف تكميم المتجهات المتعلم (LVQ). تم تدريب الخوارزمية واختبارها باستخدام إشارات الدماغ (EEG) والمقاسة حسب النظام الدولي 10-20في مستشفى ابن رشد للطب النفسي.

Section I: Introduction

One of the most important and distinguishing aspects of humans is the ability to communicate. Communication between peoples is richer and more complex than any other form of communication because thoughts, emotion, or concepts cannot directly convey before it translated into verbal or written statements, gesticulations, facial gestures, drawing or other recognizable expressions. The brain is responsible for such translations. [1]

Some peoples who suffer from some diseases related to the nervous system such as Amyotrophic Lateral Sclerosis (ALS), are excluded from the outside world because the neural pathway that control the voluntary muscles are impaired. Thus for this reason a new pathway was founded to communicate with the outside world by using the electrophysiological signal resulting from the brain. These signals are measured by using EEG device. Such systems are called BCI. [2][3]

There are two types of BCI based on the acquisition of neurophysiologic signals; the first type is the direct BCI which involves invasive procedure to implant electrodes in the brain, thus the signals acquired from single or small groups of neurons used to control the BCI, whereas the second type is the noninvasive BCI that based on the analysis of EEG phenomena associated with various aspects of brain functions. [4][5]

A BCI system built on the guiding principle: "think and make it happen without any physical effort". Indeed the "think" part of this principle involves the human brain, "make it happen" implies that an executor is need (here a computer), and "without any physical effort" means that a direct interface between the brain and the computer is required. [6]

The Artificial Neural Network (ANN) such as Independent Component Analysis (ICA), and Self-Organizing Map (SOM) play a big role in the proposed BCI system, it is used to process the EEG signal and to classify the processed signal to obtain the output command (left or right index finger movement). The relationship between the input and the output determine the network behavior. The ANN models attempt to use some organizational principles believed to be used in the human brain [7][8][9].

This work aims to design and implement an algorithm that processes the EEG signals and extracts the type of mental tasks whether if it is right or left finger movement. These mental tasks could be converted to commands that control some devices such as a wheelchair or mouse cursor.

This paper is organized as follows; Section II presents an EEG signal database. Section III describes the theoretical background of BCI, Digital Filters, ICA, SOM, and LVQ. Section IV presents the proposed system, and finally the result and discussion are described in sections V and VI respectively.

Literature Review

Many researchers deal with EEG signal and try to separate and classify the movement-related patterns from the ongoing EEG signal; the power of movement-related EEG patterns can be increase or decrease in a specific frequency within that patterns.

In[10] detected the event-related Desynchronization (ERD) of the ongoing EEG signal during the imagination of hand and foot movements. EEG signals were acquired using three bipolar channels located2.5cm anterior and posterior to the electrodes C3, Cz, and C4 of the international 10-20 system. These EEG signals are classified using learning vector quantization (LVQ) neural network.

In[11,12] used the ICA for processing EEG signal and extract feature vector which is used to train a LVQ neural network in order to discriminate the left and right actual and imagery hand movements.

Whereas[13] separated the imagination of left and right finger movement by ICA of 64 electrodes placed according to the 10-20international system. Then two reliable neural features term contra lateral and psilateral rebound map were extracted. Four classifier (fisher linear discriminate (FLD), back-propagation neural network (BP-NN), radial-basis function neural network (RBF-NN), and support vector machine (SVM)) were used to investigate the efficiency of rebound maps.

And[14] separated the movement and non-movement related human EEG by using Independent Component Analysis (ICA)method. Two kinds of movement were performed: distal right index finger flexion/extension and proximal right shoulder elevation. The EEG was recorded using 64 electrodes according to 10-20 international system.

Section II: EEG signal Database

The EEG signals were measured using a computerized EEG device located in Ibn-Rushd Hospital. These signals are saved as a database for further processing. The whole scalp was covered with 19 electrodes according to the 10-20 international system, and referenced against forehead as shown in **Figure. (1)**, the recorded signals were digitized at256 Hz according to the specification of the computerized EEG device. The recording procedure consists of two sessions without feedback, each session divided into two parts, one part for the left index finger movement and the other one for right index finger movement, each part contains several trials as shown in **Figure. (2)**.

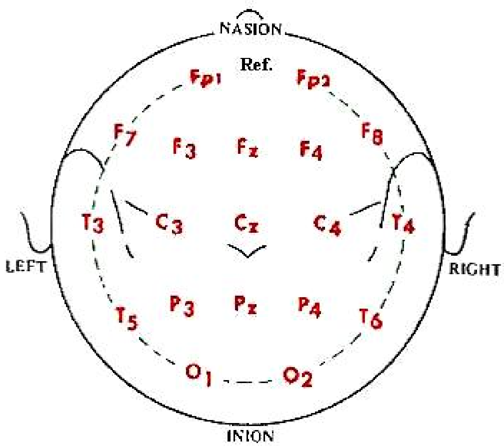


Fig. (1): The configuration of scalp electrodes based on the international 10-20 system.

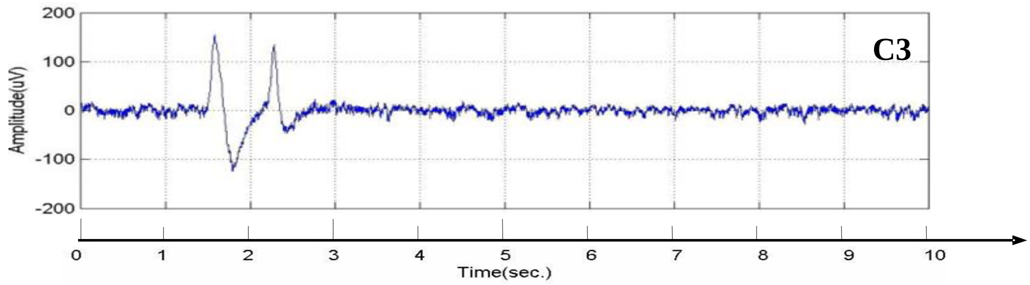


Fig. (2): One trial recorded at electrode C3 of a right index finger movement.

Section III: Theoretical background

1. BCI

The common structure of the BCI system is shown in **Figure. (3)**, and it consists of [15][16][17]:

- ***EEG signals acquisition unit:*** The EEG signals are obtained from the brain through micro or macro electrodes in invasive or non-invasive methods respectively, after that the signals are amplified and sampled.
- ***Processing unit:*** It consists of
- Signal pre-processing unit: once the signals are acquired, it is necessary to clean them from the noise and the artifacts.
- Signal classification: the signal should be classified using ANN to find out which kind of mental task the subject performing.
- ***Output unit:*** once the signals are classified, it translated into device commands or orders to perform a certain application such as operate a simple word processing program or control a wheelchair.

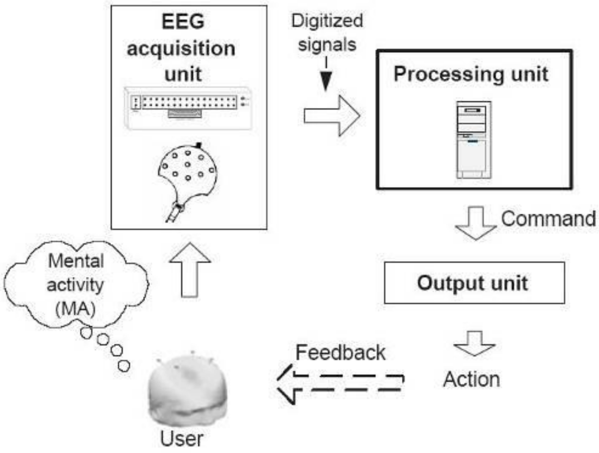


Fig .(3): The BCI Architecture

1.1. Electroencephalography (EEG)

The (EEG) is a medical technique that measures the electrical activity of the brain. This activity is generated by billions of neurons, and each one is connected to thousands of other neurons [18].

The EEG signals are complex spatiotemporal signals. The statistical properties of which depend on the state of the subject and on external factors, even when the subject behavioral state is almost constant. The duration of epochs that have the same statistical properties (i.e. that are stationary) is limited. Therefore EEG signals present essential non-stationary properties [19]. The temporal resolution of EEG signals is very good, in millisecond or even better. While the spatial resolution is poor, it depends on the number of electrodes, about in centimeter range [6].

A. EEG Artifacts

Contamination of EEG data can occur at many points during the recording. The artifact sources both biologically or technically generated such as line noise, eyes blink and movement, muscles and cardio artifact as shown in **Figure. (4)**[6][21].

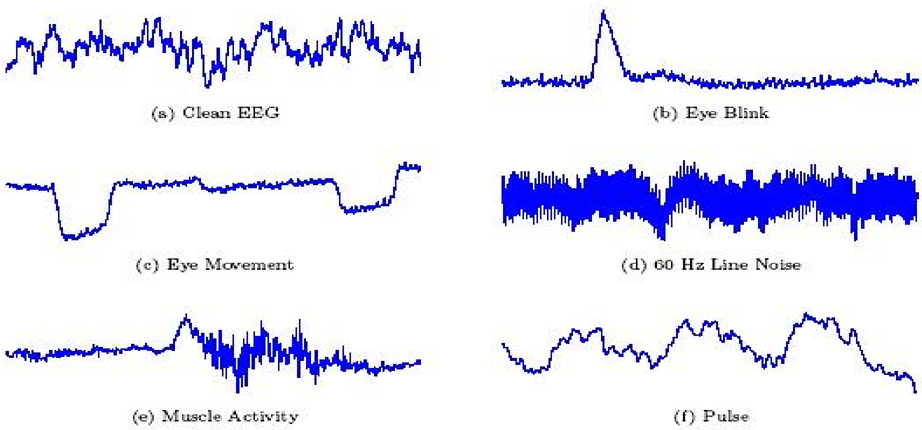


Fig. (4): EEG artifact waveforms

B. Rhythmic Brain Activity

The normal people's brain waves show different rhythmic activity depending on the level of consciousness. Also these rhythms are affected by different actions and thoughts [6]. Therefore the rhythms can be characterized by their amplitude, frequency, duration, and the brain areas in which that rhythms are generated, and they are divided into: [20][22]

- **Delta Rhythm:** this rhythm lies within the frequency range 0.5-4 Hz, and with variable amplitude. It associated with deep sleep.
- **Theta Rhythm:** this rhythm lies within the range of (4-7) Hz, with a variable amplitude. Theta arises from emotional stress, and it also associated with creative inspiration and deep meditation.
- **Alpha Rhythm:** this rhythm is at (8-13) Hz and occurring during wakefulness over the posterior regions of the head with variable amplitude but is mostly below 50 μV in adults. Best seen with eyes closed and under conditions of physical relaxation and relative mental inactivity.
- **Mu Rhythm:** it is an (8-12) Hz, with amplitude below 50 μV, and it is associated with motor activity and it maximally recorded over motor cortex. Mu Rhythm is blocked by movement. This blocking appears before actual movement of the muscles, therefore it seems related to conceptual planning of the movement.
- **Beta Rhythm:** this rhythm lies within the frequency range of (13-30) Hz, beta rhythm can mainly found over the frontal and central reign. A central beta rhythm is related to the mu rhythm. It can be blocked by motor activity, and also it associated with active thinking, active attention, focus on the outside world, or solving concrete problems.
- **Gamma Rhythm:** this rhythm lies within a frequency range of about 35 Hz and above, it is thought that this band reflects the mechanism of consciousness.

1.2. Sensorimotor Cortex, Event-Related Synchronization (ERS) and, Event-Related Desynchronization (ERD)

The sensor motor cortex also known as Rolandic cortex, consists of both the motor cortex and the somatosensory cortex. The motor cortex plays the greatest role in control of very fine, discrete muscle movements that is located anterior of the central sulks [5][23][24].

The primary motor cortex is organized somatotopically so that different parts of it control different parts of the body. Each part of the body is represented in the brain in proportion to its relative importance in motor behavior. Body parts that are used for complicated movements such as the hands are represented by larger areas in the primary motor cortex, as shown in **Figure. (5)** [24].

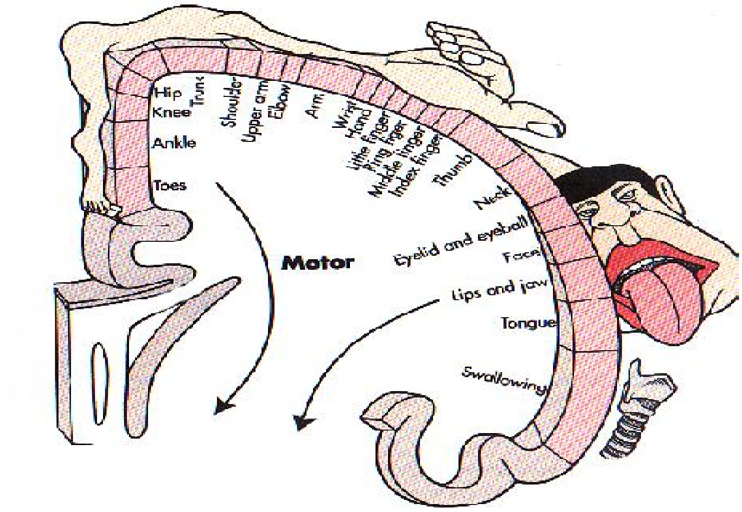


Fig. (5): The somatotopic organization of the motor cortex

The voluntary movement is composed of three phases: planning, execution, and recovery [25]. The planning and execution phases can be viewed as an EEG correlated of an activated cortical motor network, resulting in alpha and lower beta bands amplitude attenuation namely ERD. The recovery phases may reflect deactivation in the underlying cortical network, producing amplitude enhancement, namely ERS [5][13][26].

The post-movement beta ERS are founded in the first second after termination of a voluntary movement when the mu rhythm still displays a desynchronization pattern of low amplitude. The post-movement beta ERS shown in **Figure. (6)** has these features[7]:

- The beta ERS has a somatotopic organization.
- The beta ERS is significantly larger with hand as compared to finger movement.
- The beta ERS is found not only after a really executed but also after an imagined movement.

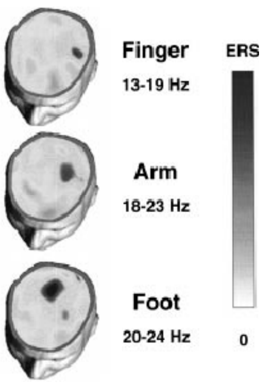


Fig. (6) Movement-specific location of the beta ERS in one subject after finger, arm and foot movement.

The post-movement beta ERS is a relatively robust phenomenon and is found in nearly every subject after finger, hand, arm and foot movement. It is dominant over the contra lateral primary sensor motor area and has a maximum around 1000 ms after movement-offset [7].

2. Digital Filters

The digital filters are used for two general purposes which is either for signal separation or signal restoration [27]. Basically, there are two types of digital filters:

- **Finite Impulse Response (FIR):**it is implemented using convolution method, by convolving the input signal with the digital filter's impulse response.
- **Infinite Impulse Response (IIR):**it is implemented using recursion method, by combining previously calculated values from the output besides points from the input

The output of FIR filters are more accurate than the output of IIR, but it requires much processing time than IIR. Anyway, the implementation of FIR filters are much easier than IIR filters, this led the FIR filters to be used most of the applications where accuracy is necessary.

2.1. Windowed-Sinc FIR Filters

Windowed-sinc FIR filters are used to separate one band of frequencies from another. They are very stable, produce few surprises and can pushed to incredible performance levels. The pass-band is perfectly flat, the attenuation in the stop-band is infinite, and the transition between the two is infinitesimally small. The idea of the windowed-sinc filter is to convolving the input signal with the filter kernel (impulse response of the filter). The filter kernel is obtained by taking the inverse Fourier transform of the ideal frequency response of the low-pass filter, which produces the ideal filter kernel as shown in **Figure. (7)**, the form of this kernel is called sinc function, given by

$$\boldsymbol{h}[\boldsymbol{i}] = \frac{\sin(2\pi f_c i)}{i\pi} \qquad (1)$$

Where ***h[i]*** is the filter kernel, f_c is the cutoff frequency as a ration to the sampling rate, and ***i*** is the index

The Sinc function continues to both negative and positive infinity without dropping to zero amplitude, so to overcome this problem the sinc function will be modified by truncated the kernel of the filter to M+1 point symmetrically around the main lobe, and to multiply the truncated sinc function by a smoothly tapered curve called Blackman or Hamming windows resulting the windowed-sinc filter kernel, and these windows are gives respectively by:

$$w[i] = 0.54 - 0.46\cos(2pi/M) \qquad \textbf{(2)}$$

$$w[i] = 0.42 - 0.5\cos(2pi/M) + 0.08\cos(4pi/M) \qquad \textbf{(3)}$$

Where ***w[i]*** is window kernel, ***M*** is the length of the filter kernel, and ***i*** is the index.

The idea of improving the frequency response is by reducing the abruptness of the truncated ends of the filter kernel as shown in **Figure . (8)**

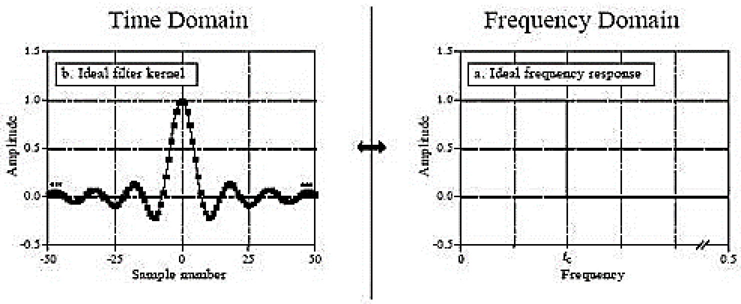


Fig. (7): The frequency and impulse response of the ideal low-pass filter

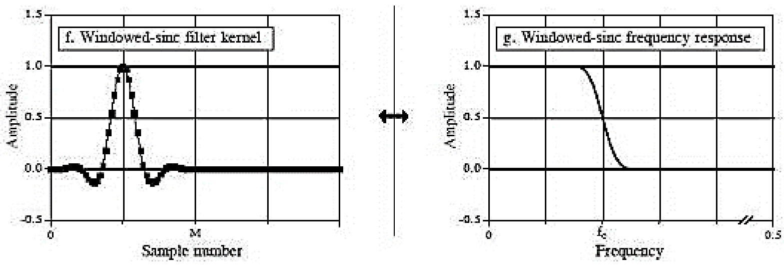


Fig. (8): The frequency and impulse response of the windowed-sinc low-pass filter.

High-pass, band-pass and band-reject filters are designed by starting with a low-pass filter, and then converting it into the desired response, using spectral inversion. The High-pass filter is achieved from Low-pass filter by change the sign of each sample in the filter kernel and then, add one to the sample at the center of symmetry as shown in **Figure. (9).**

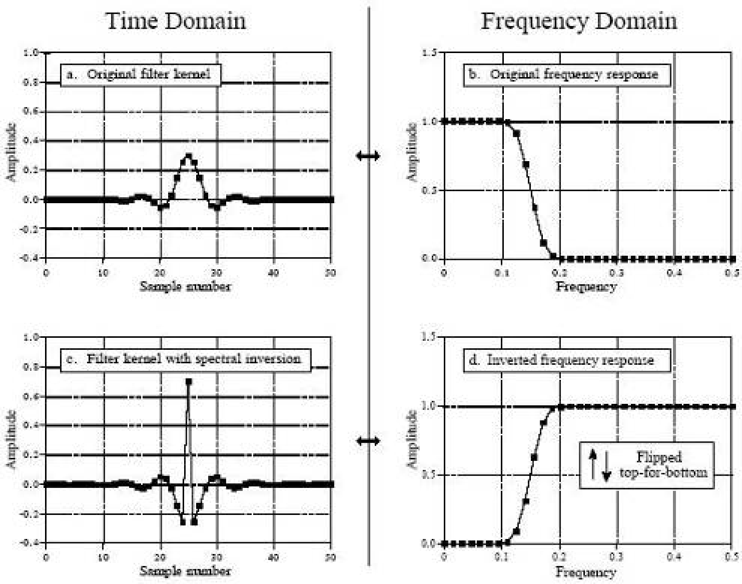


Fig. (9): Example of converting a low-pass filter to a high-pass filter using spectral inversion

Band-reject filter is achieved by adding the filter kernels of the Low-pass and High-pass filters, while the Band-pass filter is achieved by convolving the kernels of the Low-pass and High-pass filters.

2.2. Moving Average Filter

The moving average filter is most common filter, because it is easiest digital filter to understand and use. It is optimal for reducing random noise while retaining a sharp step response; this makes it the primer filter for time domain encoded signals. This filter is given by:

$$y[i]=\frac{1}{M}\sum_{j=-(M-1)/2}^{(M-1)/2} x[i+j] \qquad \textbf{(4)}$$

Where $x[\bullet]$ is the input signal, $y[i]$ is the output signal, and, M is the number of points in the average, and should be odd.

3. Artificial Neural Network (ANN)

The (ANN) is a general mathematical computing paradigm that models the operation of biological neural system such as ICA, SOM, and LVQ [28].

3-1 Independent Component Analysis [8][29][30][31]

The independent component analysis (ICA) is a linear transform of multivariate (multidimensional) data designed to make the resulting vectors as statistically independent as possible. ICA is used to primarily to separate unknown source signals from their linear mixture, and also it can be used for feature extraction.

Assuming that there are m observed linear mixtures $x_1(k)$, $x_2(k)$, ..,$x_m(k)$ of n independent components (source signals) $s_1(k)$, $s_2(k)$, ..,$s_n(k)$

$$x_j(k)=a_{j1}s_1(k)+a_{j2}s_2(k)+.....+a_{jn}s_n(k) \qquad \textbf{(5)}$$

for j=1, 2, …, m

Or in vector notation

$$\mathbf{x}(\boldsymbol{k})=\boldsymbol{A}\mathbf{s}(\boldsymbol{k}) \qquad \textbf{(6)}$$

Where $\mathbf{x}(k)=[x_1(k), x_2(k), .., x_m(k)]^T$, $\mathbf{x}\in R^{m\times 1}$, is the observed signals ,$\mathbf{s}(k)=[s_1(k), s_2(k), .., s_n(k)]^T$, $\mathbf{s}\in R^{n\times 1}$, is the source signals (independent components),$\boldsymbol{A}$ is the mixing matrix, $\boldsymbol{A}\in R^{m\times n}$, where $m\geq n$, and k is the time index.

Without loss of generality, the observed signals and the independent component assumed to have zero mean. The basic idea of ICA is to estimate the inverse of mixing matrix (***W***) and obtain the independent component by

$$\boldsymbol{s}(\boldsymbol{k})=\boldsymbol{W}\boldsymbol{x}(\boldsymbol{k}) \tag{7}$$

Where ***W*** is the separation matrix, and equal to $\boldsymbol{W}=\boldsymbol{A}^{-1}$.

The independent components are assumed to be statistically independent, that is the joint probability density of source signals (independent component) is equal to the product of the marginal probability densities of the individual signals:

$$\boldsymbol{p}[\boldsymbol{s}_1(\boldsymbol{k})\boldsymbol{s}_2(\boldsymbol{k})\ldots\boldsymbol{s}_n(\boldsymbol{k})]=\boldsymbol{p}[\boldsymbol{s}_1(\boldsymbol{k})]\times\boldsymbol{p}[\boldsymbol{s}_2(\boldsymbol{k})]\times\ldots\times\boldsymbol{p}[\boldsymbol{s}_n(\boldsymbol{k})]=\prod_{i=1}^{n} p[s_i(k)] \tag{8}$$

There are two modes of ICA, on-line mode and batch mode. In the on-line case, the algorithms are obtain by stochastic gradient methods, whereas the batch (off-line) mode has much more efficient algorithms such as Fast ICA. The convergence of Fast ICA is cubic (or at least quadratic) than the gradient-based algorithms. Also in the Fast ICA there is no step size parameter, and it is parallel, distributed, computationally simple, and required little memory space.

3-2 Kohonen Self-Organizing Map (SOM)

The SOM is unsupervised, competitive learning, clustering network, in which only one neuron is “on” at a time. It is an effective tool for visualization of high-dimensional data, in other words, the SOM transforms input patterns of arbitrary dimension to a one or two dimensional map of feature in a topological ordered fashion[29][32].The winning neuron is determine from[29]

$$q(k)=\min_{\forall i}\|x-w_i\|_2 \quad \boldsymbol{i}\mathbf{=1,\ 2,\ \ldots,\ m} \tag{9}$$

Where $q(k)$ is the index of the winning neuron, $\|\bullet\|_2$ is the Euclidean norm, x is the input vector, w_i is the synaptic weight vector of neuron i in the two-dimensional array, and m is the total number of output neuron.

And the synaptic weight vectors that associated with the winning neuron and the neuron within a defined neighborhood of the winning neuron are updated according to: [29]

$$\boldsymbol{w_i(k+1)}=\begin{cases}\boldsymbol{w_i(k)+\mu(k)[x(k)-w_i(k)]} & \boldsymbol{if\ i\in N_q(k)}\\ \boldsymbol{w_i(k)} & \boldsymbol{if\ i\notin N_q(k)}\end{cases} \tag{10}$$

Where $0 < m(k) < 1$ (the learning rate parameter).

3-3 Learning Vector Quantization (LVQ)

It is a supervised learning technique that can classify input vectors based on vector quantization. LVQ1 is very similar to Kohonen SOM even though LVQ1 is a supervised network and Kohonen SOM is unsupervised. The winning neuron of LVQ1 is determined by[29]

$$q(k) = \min_{\forall j} \|x_i - w_j\|_2^2 \quad \textbf{(11)}$$

Where $q(k)$ is the index of the winning neuron, $\|\bullet\|_2^2$ is the square of Euclidean norm, $\boldsymbol{x}_i$, for i=1, 2, …, N is the set of input vectors, and $\boldsymbol{w}_j$, j=1, 2, …, m is the weight vectors.

The weight vectors can be initialized by taking the first m (total number of classes) vectors from the set of training vectors. The updating rule for modifying a weight vectors is that: the weight vector $\boldsymbol{w_j}$ is moved in the direction of the input $\boldsymbol{x_i}$ if the class labels of the input vector (C_{xi}) and of the weight vector (C_{wq}) of the winning neuron is agree according to:

$$\boldsymbol{w_q(k+1)=w_q(k)+m(k)[x_i(k)-w_q(k)]} \quad \textbf{(12)}$$

Otherwise the weight vector is moving in the opposite direction away from the input vector if the class labels do not agree as follows[29]:

$$\boldsymbol{w_q(k+1)=w_q(k)-m(k)[x_i(k)-w_q(k)]} \quad \textbf{(13)}$$

Section IV: The proposed system

The block diagram of the proposed BCI system is shown in Fig. (10) that based on ERS detection of beta band.

Fig. (10): The proposed structure of BCI system

The recorded EEG signals are processed by temporal filter using FIR filter and then by spatial filter using ICA. The ICA decomposed the EEG signals into task-related and task-unrelated components. The task-related components were used for subsequent signal reconstruction. After filtering the reconstructed signal with the reactive frequency of beta band, envelops of this signal are extracted. These envelops are classified using an adaptive classifier, which consists of Kohonen SOM and LVQ1. Finally after determining the type of movements, the computer converts these movements into commands that might use to derive a wheelchair or control a mouse cursor.

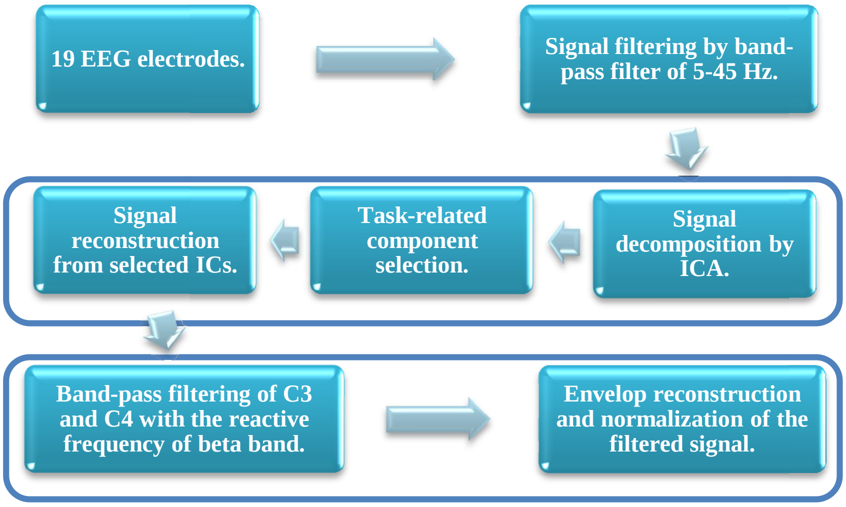


Fig. (11): The block diagram of EEG signal processing

1. EEG Signals Processing

The EEG signal must be prepared in such a way that the classifier can recognize it. This preparation is made off-line. The block diagram of the signal processing is shown in **Figure. (11)** and following steps demonstrate the Pre-processing session:

A. Band-Pass filter of 5-45 Hz

The first step of processing the EEG signal is band-pass filtered at 5-45 Hz to remove the DC. Drift, eyes artifacts, and power line noise of 50 Hz.

A 5-45 Hz band-pass filter is implemented using a Windowed-Sinc FIR filter with a Blackman window; therefore the filter kernel of the low-pass filter is calculated by combining Equations (2), and (4) as illustrated below:

$$h[i] = K\frac{\sin(2pf_c(i-M/2))}{i-M/2}\left[0.42-0.5\cos\left(\frac{2pi}{M}\right)+0.08\cos\left(\frac{4pi}{M}\right)\right] \quad \textbf{(14)}$$

Where $h[i]$ is the filter kernel, $K=1$is the filter gain, $M=1025$ is the length of filter kernel,$f_c = f_c/256$ is the cutoff frequency as a ratio to the sampling rate, and$i$ is the index.

The algorithm of calculating the filter kernel of band-pass filter with cutoff frequencies of f_{c1}=5 Hz and f_{c2}=45 Hz is shown below

1. ***Let M=1025, srate =256, f_1= f_{c1}/srate, f_2= f_{c2}/srate.***
2. ***Calculating the low-pass filter kernel at f_1***

for $i=1$ *to* M *step* 1
if $(i-(M+1)/2)=0$ *Then*
$hl[i] = 2\times\pi\times f_1$
else
$hl[i] = (\sin(2\times\pi\times f_1\times(1-(M+1)/2))/(1-(M+1)/2))\times$
$(0.42-0.5\times\cos(2\times\pi\times i/M)+0.08\times\cos(4\times\pi\times i/M))$
end if
end for

3. *Calculating the low-pass filter kernel at f_2*

for $i=1$ *to* M *step* 1
if $(i-(M+1)/2)=0$ *Then*
$hh[i] = 2\times\pi\times f_2$
else
$hh[i] = (\sin(2\times\pi\times f_2\times(1-(M+1)/2))/(1-(M+1)/2))\times$
$(0.42-0.5\times\cos(2\times\pi\times i/M)+0.08\times\cos(4\times\pi\times i/M))$
end if
end for

4. *Normalize both filter kernels*

$hl = hl/sum(hl)$
$hh = hh/sum(hh)$

5. *Change the low-pass filter kernel of hh to high-pass filter using spectral inversion*

$hh= -1\times hh$
$hh((M+1)/2) = hh((M+1)/2)+1$

6. *Add the low-pass filter kernel hl to the high filter kernel hh to obtain a band-reject filter kernel*

$hb=hl+hh$

7. *Change the band-reject filter kernel to a band-pass filter using spectral inversion*

$hb = -1\times hb$
$hb((M+1)/2) = hb((M+1)/2)+1$

The filtered signal is obtain by using (***conv***) command that convolve the input signal with the filter kernel.

B. Signal Decomposition by ICA and task related component selection and reconstruction

The calculation of independent components is carried out by Fast ICA algorithm. The input matrix ***X*** is arrange into $19\times n$ matrix, where 19 represents the number of electrodes, and n is the number of sample points. The Fast ICA first remove the mean of each row vector of the ***X*** matrix and then uses a whitening procedure to transform the covariance matrix of zero-mean data into an identity matrix. The Fast ICA algorithm search for the matrix that transform the whitened data into a set of components as mutually independent as possible. According to equation (23), the matrix ***X*** is transformed to matrix ***S*** via a separation matrix ***W*** where the rows in matrix ***S*** are mutually independent.

$$\boldsymbol{S}=\boldsymbol{W}\boldsymbol{X} \tag{15}$$

Where ***S*** is an $m\times n$ matrix of independent components, ***W*** is the separation matrix, and ***X*** is an $m\times n$ matrix of input signal.

The algorithm of Fast ICA is describe as below:

- **Step 1**. Center the data using Equation (11) to make its mean equal to zero.
- **Step 2**.Whitening the data using Equations (14), (15) and (16) to give $\boldsymbol{z}$.
- **Step 3**.Choose $m=19$, the number of independent components to estimate
- **Step 4**.Choose initial values for the $\boldsymbol{w_i}$, i= 1,…,19, each of unit norm. Orthogonalization the matrix ***W*** as in step 6.
- **Step 5**. For every i= 1,…,19 , let $\boldsymbol{w} \leftarrow E\{\boldsymbol{z}g(\boldsymbol{w}^{T}\boldsymbol{z})\} - E\{g'(\boldsymbol{w}^{T}\boldsymbol{z})\}\boldsymbol{w}$

  Where g and g' is defined as below, with a_1=1:

$$g_1(y) = \tanh(a_1 y) \tag{16}$$

$$g_1'(y) = a_1(1-\tanh^2(a_1 y)) \tag{17}$$

- **Step 6**. Do a symmetric orthogonalization of the matrix $\boldsymbol{W} =(\boldsymbol{w_1},\ldots,\boldsymbol{w_m})^{T}$ by using Equation (26).

$$\boldsymbol{W} = (\boldsymbol{W}\boldsymbol{W}^{T})^{-1/2}\boldsymbol{W} \tag{18}$$

- **Step 7**. If not converge, go back to step 5, else exit.

Each column of the mixing matrix ***A***, which is a $\boldsymbol{W}^{-1}$, represents a spatial map describing the relative projection weight of the corresponding components at each EEG electrode. Therefore, according to the spatial maps, the components that show a large projection at electrodes C3, Cz, and C4 which are related to motor region, are categorized as task-related components and the rest of components are categorized as task-unrelated components as shown in **Figure. (12)** and **(13).**

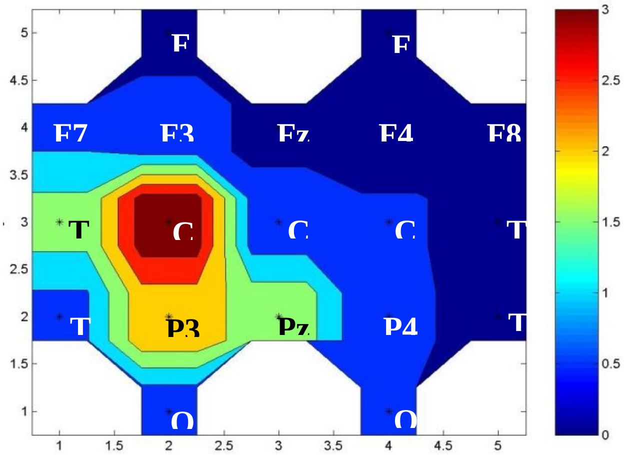
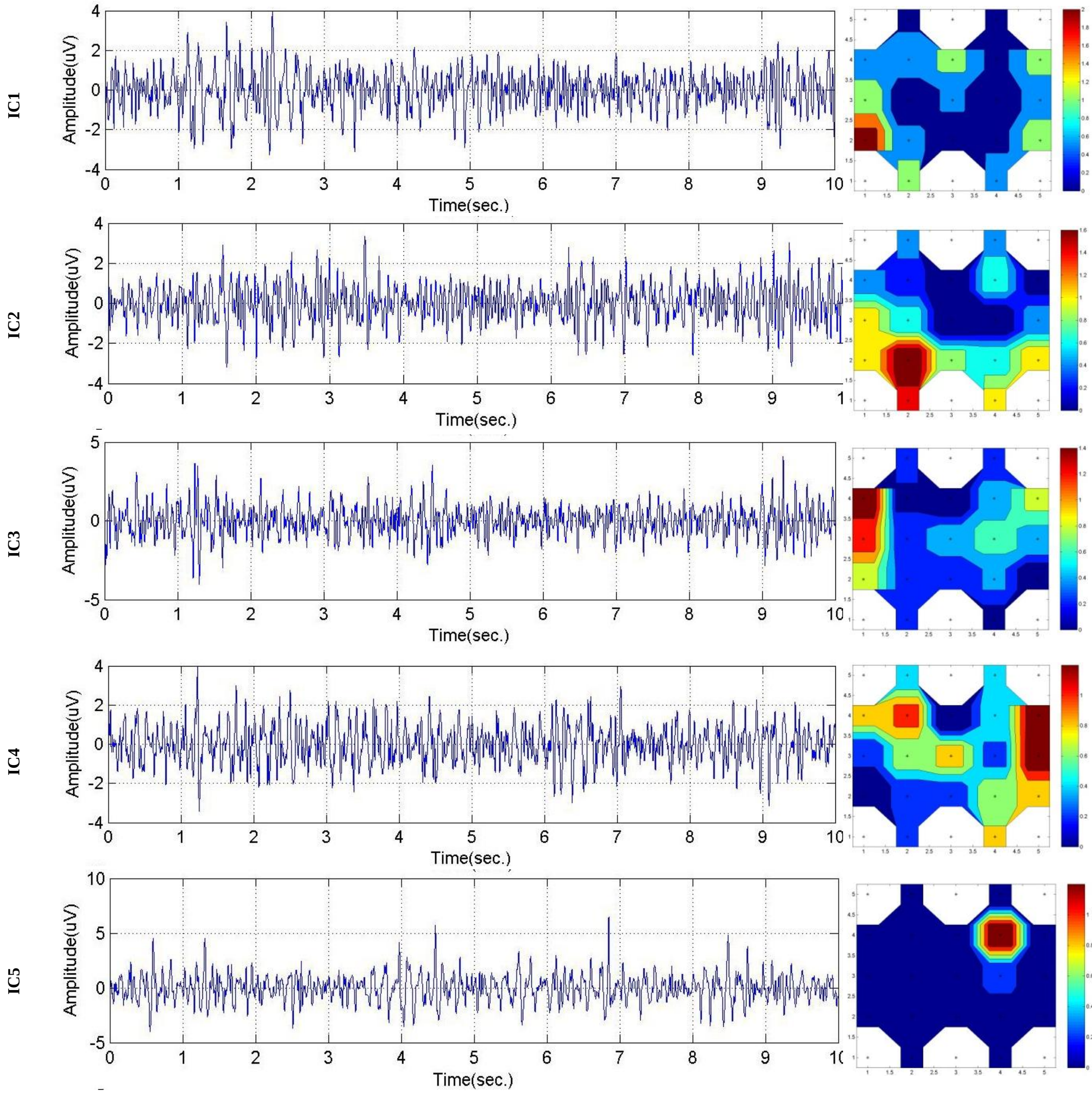
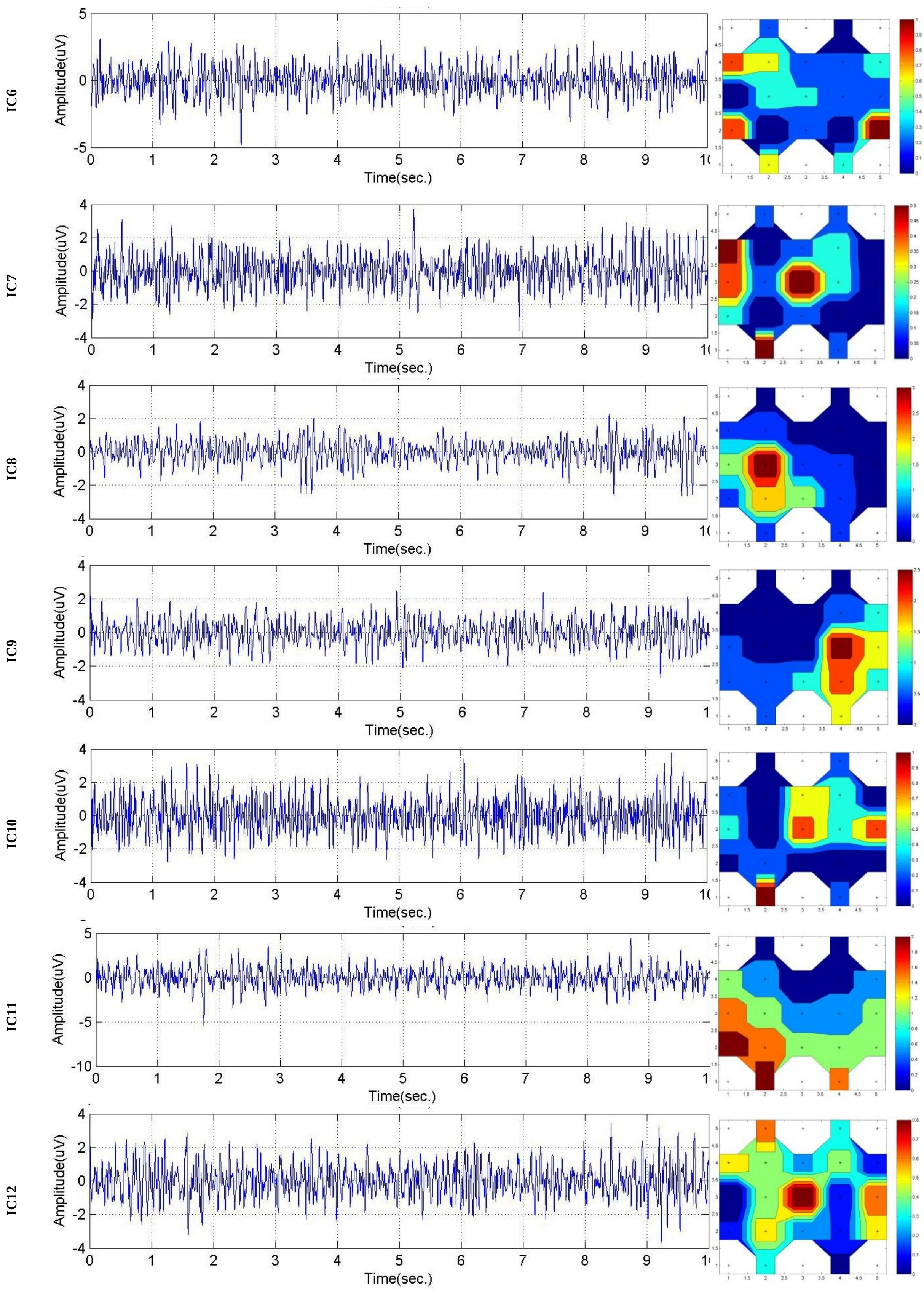


Fig. (12): The location of one scalp electrode that shows the strength (factor value) of the independent component at each electrode.




IC6
IC7
IC8
IC9
IC10
IC11
IC12
Amplitude(uV)
Time(sec.)

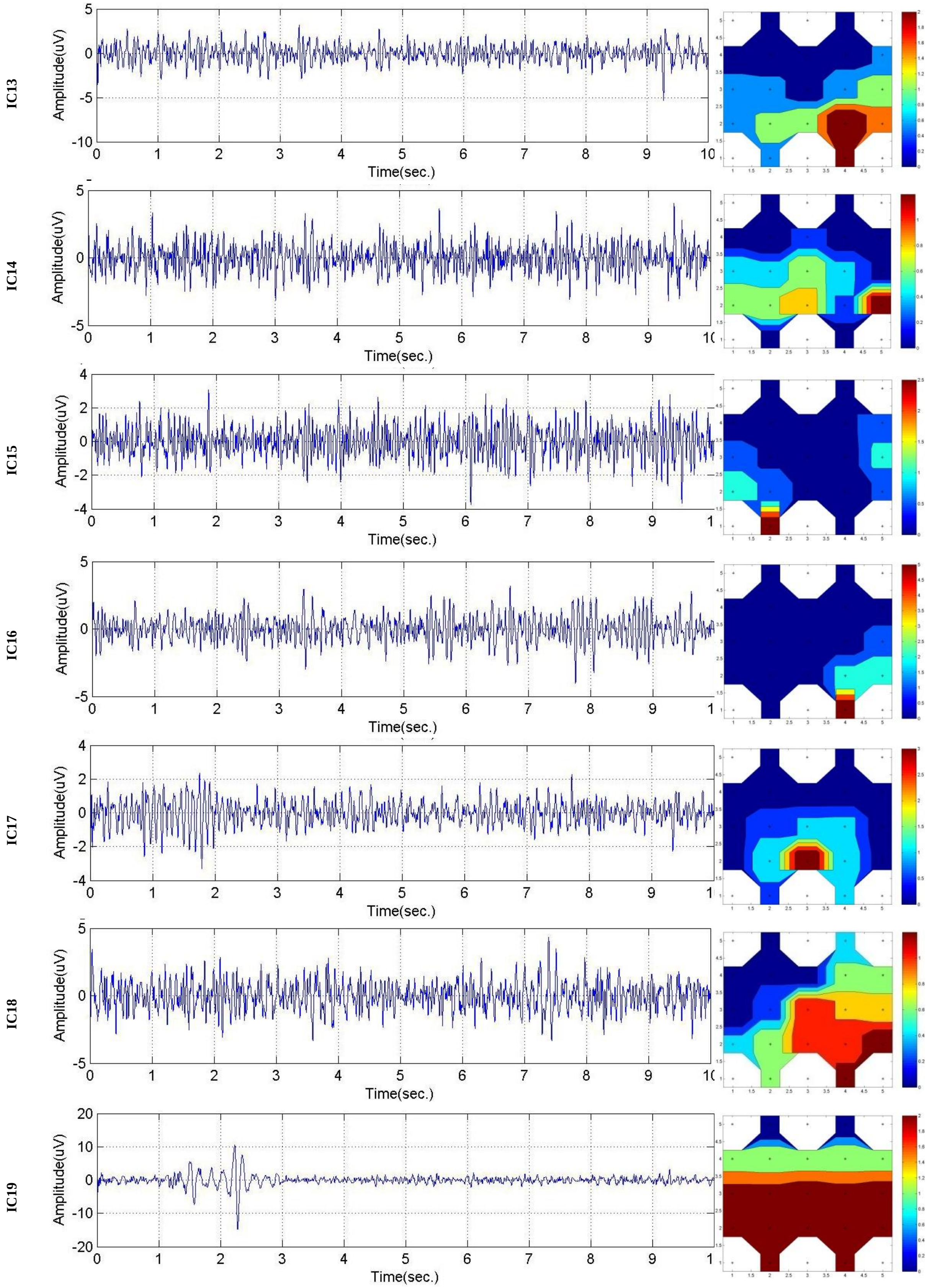


Fig. (13): The 19 independent components corresponding with their spatial maps of a right index finger movement trial for (male, 24years old).

Maps IC8, IC9, and IC12 are related to the motor region and it categorized as task-related components, while the others are task-unrelated components. Zeroing the columns of $\boldsymbol{A}$ corresponding to the task-unrelated components, the task-related components are reconstructed as equation(19):

$$\boldsymbol{X_{rec}}=\boldsymbol{AS} \qquad \textbf{(19)}$$

Where $\boldsymbol{X_{rec}}$ is an $m \times n$ matrix of reconstructed signal, $\boldsymbol{A}$ is the mixing matrix, and $\boldsymbol{S}$is an $m \times n$ matrix of independent components.

C. Envelop reconstruction

The signals of electrodes C3 and C4 of the reconstructed signal are filtered using windowed-Sinc FIR filter with the reactive frequency of beta band as shown in **Figure. (14).**

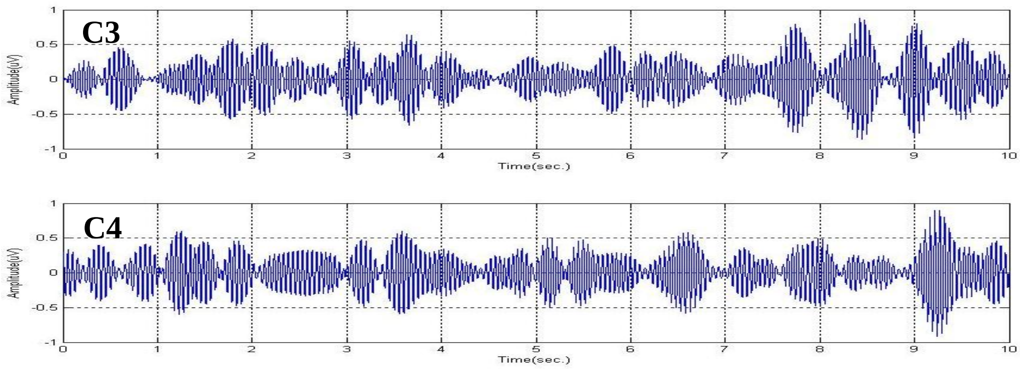


Fig. (14): One trial of right index finger movement filtered with the reactive frequency band for (male, 24years old).

After that, the envelopes of the filtered C3, and C4 signals are computed and smoothed using moving average filter of 33 points in Eq. (6), as shown in **Figure. (15).**

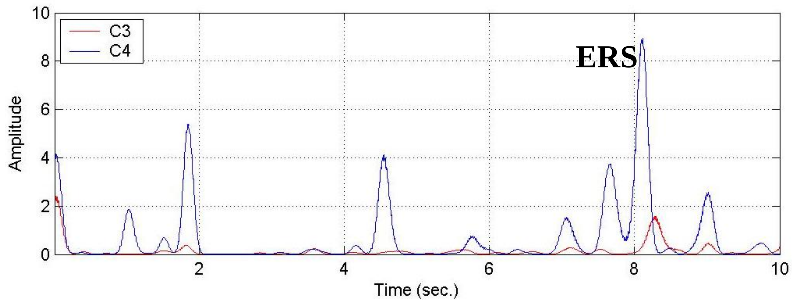


Fig. (15) The ERS of randomly chosen trial during left index finger movement for (male, 24 years old).

2. Signal classification

The classification of EEG signal is made by using a hybrid adaptive pattern classification system which is consisting of the Kohonen SOM combined with LVQ1. The unsupervised network SOM is used to extract small set of features that classified using a supervised LVQ1 network as shown in **Figure. (16)**

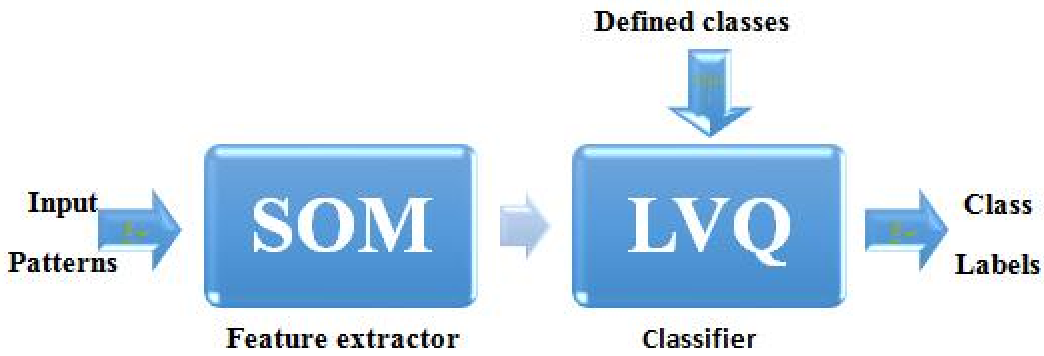


Fig. (16): Adaptive pattern classification system using Kohonen SOM and LVQ.

The classifier was trained using a training vector consists of 12 sub trials of the first session (6 trials for left index finger movement and the other 6 for right index finger movement). The classifier training involves two steps: the first step is to train the Kohonen SOM network of 300 neurons, and the second step is to train the LVQ1 network of 3 classes with the generated weight vectors of the Kohonen SOM.

The class vectors are used to classify each point of the input trials. That is class 1 for the right index finger movement, class 2 for the left index finger movement, and class 3 for non-movement. **Figure. (17)** shows the input training vector drawn in topological form of C3 as x-axis and C4 as y-axis, with 300 weight vectors of SOM and 3 classes of LVQ1.Therefore the weight vectors of SOM are adapted to the spreading of sample points, so that it minimizes the number of points required to represent all samples. The classes of LVQ1 grouping the closely associated SOM weight vectors and produce three classes (three types) of points to represent the type of movements.

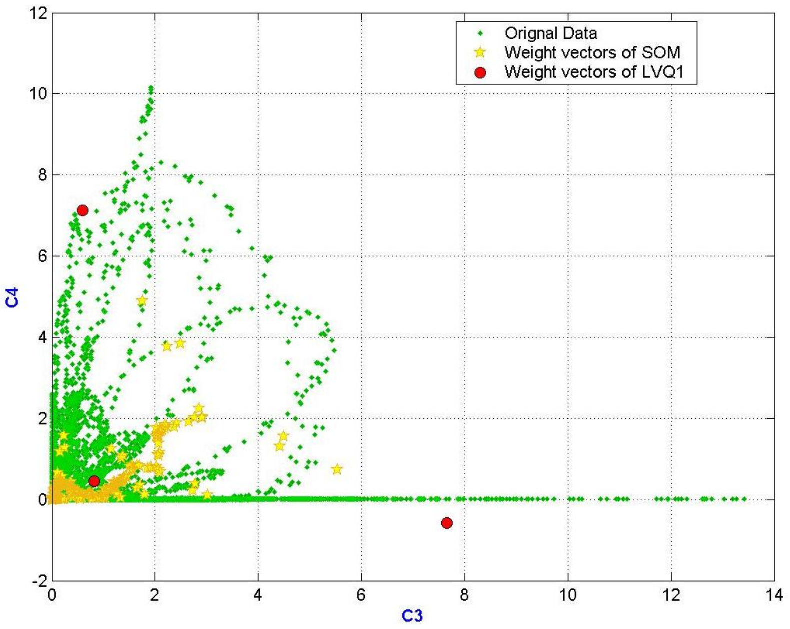


Fig.(17): C3 vs. C4 of the training vector, with the weight vectors of SOM and LVQ1.

Section VI: Result and discussion

The proposed system was implemented using a laptop of (2.27 Core I5, and 4GB RAM, Microsoft Windows 7 platform) with a MTLAB v.7.10 (R2010a) program. Three sessions of 24, 60, and 35 trails respectively were recorded. The continuous EEG signals were recorded using 19 electrodes covered the whole scalp and filtered temporally by Band-Pass filter of 5-45 Hz and spatially by Fast ICA. Then the task-related components related to motor cortex were reconstructed, filtered and envelop recovered in order to prepare it for classification. A hybrid classifier which is consist of combining SOM and LVQ1, were trained using 12 trails and tested. The recognition rates are shown in **Figure. (18).**

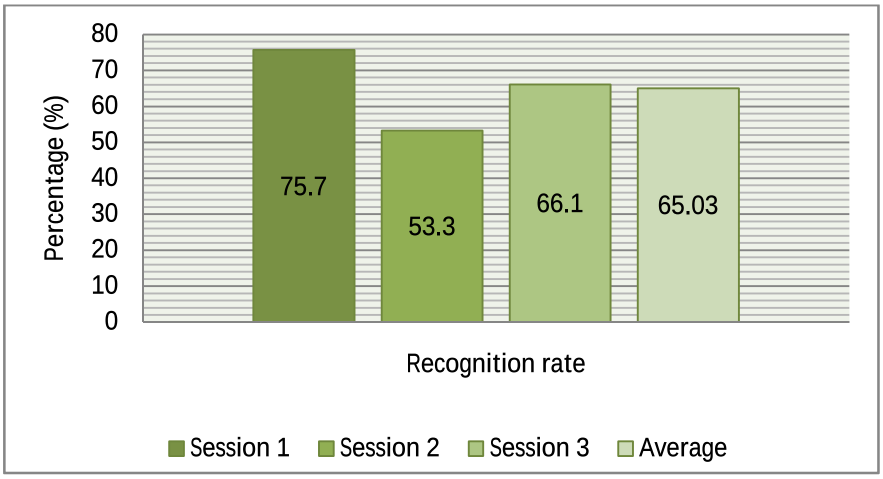


Fig. (18): The recognition rate of the hybrid classifier.

To examine whether the ICA improves the recognition rate or not, the trials of the three sessions are filtered with their reactive frequency bands. Then the envelopes of C3 and C4 are computed and normalized. Then the classifier was trained, and the recognition rates are shown in **Figure. (19).**

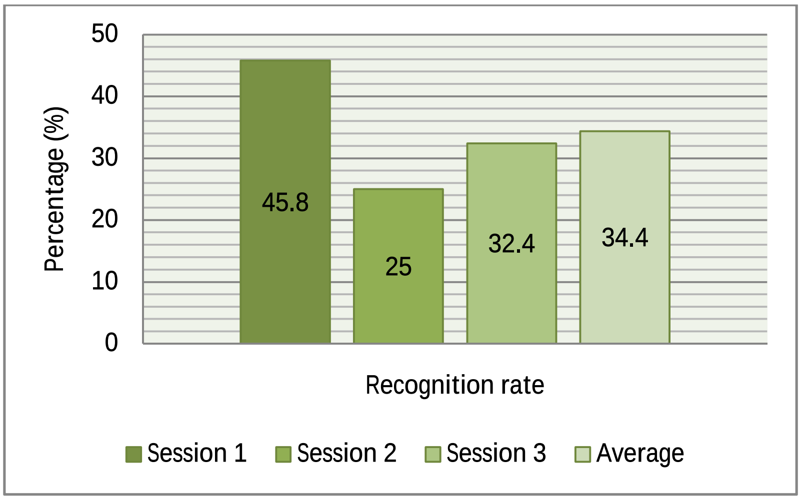


Fig. (19): The recognition rate of the classifier without using the ICA.

The ICA improves the recognition rate of the classifier as shown in **Figures (18**) and **(19),** since the ICA separates the task-related components, that their corresponding spatial maps have large projection values at electrodes C3, Cz, and C4.

The ERS is varying among different trails that is depend on subjects' performance mental state, linking to the fluctuation in expectation, and attention. Figure (20) describe the variation between the ERS of two randomly chosen trials. In order to overcome this problem, each trial is normalized; this normalization makes almost all the ERS have similar amplitudes.

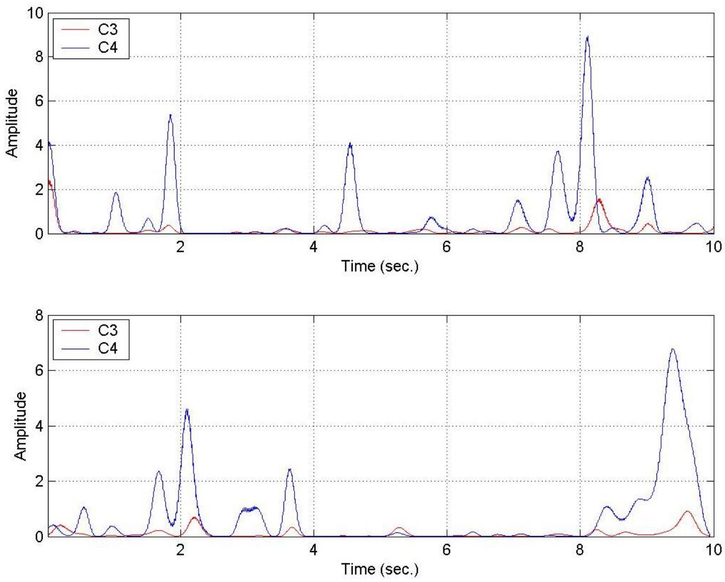


Fig. (20): The variation of ERS of two randomly chosen trials during left index finger movement for (male, 24 years old).

In general, the number of electrodes covered the sensor motor cortex which are three electrodes, are considered insufficient for the BCI systems. There for the recognition rates are decline. Session 2 of **Figure. (18)** has a small recognition rate than the others because of the bad or inaccurate measurements of EEG signal that makes the detecting of ERS impossible, as shown in **Figure.(21)**.

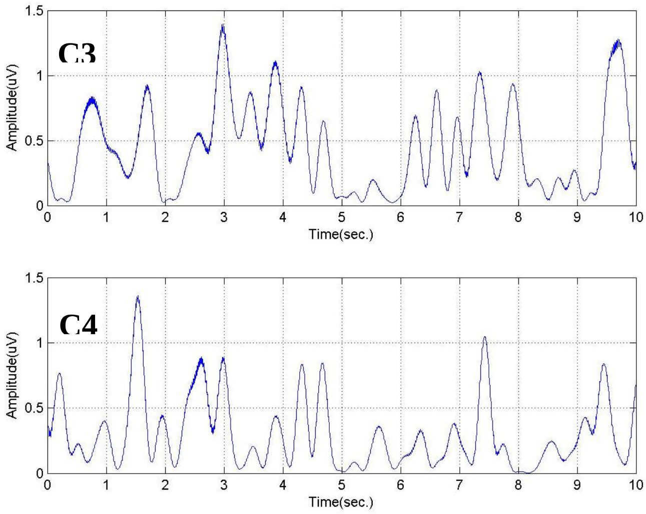


Fig. (21): Undetectable ERS during left index finger movement of one trial.

Section VI: Conclusion

This paper describes the design and implementation of BCI system. The propose system consist of three stages, which are EEG signals processing, Signal classification, and computer interaction. A comparison was made to discover the performance of ICA algorithm. Thus the experimental results show that the recognition rates are risen from 34 to 65 by using ICA. However, the problem that should be considered in the design of the BCI system is the spatial resolution of the scalp. So that, low number of electrodes that are used for EEG measurements provides inaccurate localization of the brain sources at the scalp. Moreover, The ERS is different slightly from trial to trial in amplitude and shape because of the different kind of movements (if it's slow or brisk), and the mental activity performed by the brain during the movement.

References:

1. **B. Allison, *"P3 or not P3: Toward a Better P300 BCI"*, Ph.D. Thesis in cognitive science, University of California, San Diego, 2003.**
2. **J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller and, T. M. Vaughan, *"Brain-Computer Interfaces for Communication and Control"*, Clinical Neurophysiology, Vol. 113, 2002.**

3. **K.E. Hild, U. Orhan, D. Erdogmus, B. Roark, B. Oken, S. Purwar, H. Nezamfar, and M. Fried-Oken, *"An ERP-based Brain-Computer Interface for text entry using Rapid Serial Visual Presentation and Language Modeling"*, Proceedings of the Association for Computational Linguistics, USA, 2011.**
4. **J. del R. Millán, *"Brain-Computer Interface"*, In *"The Handbook of Brain Theory and Neural Networks"*, (ed. M. A. Arbib), 2nd Edition, MIT press, England, 2003.**
5. **Bernhard Graimann, Brendan Allison, and GertPfurtscheller, *"Brain–Computer Interfaces: A Gentle Introduction"*, Springer-Verlag Berlin Heidelberg, 2010.**
6. **J. Lehtonen, *"EEG-Based Brain Computer Interfaces"*, M.Sc. Thesis, Electrical and communication Engineering Department, Helsinki University of Technology, 2002.**
7. **A. K. Jain, J. Mao, *"Artificial Neural Networks: A Tutorial"*, IEEE Computer Society, Vol. 29, No. 3, pp. 31-44, 1996.**
8. **Amar Kachenoura, Laurent Albera, LotfiSenhadji and Pierre Comon, *"ICA: a potential tool for BCI systems"*, IEEE Signal Processing Magazine, 2008.**
9. **PayamAghaei Pour, TauseefGulrez, Omar AlZoubi, Gaetano Gargiulo and Rafael A. Calvo, *"Brain-Computer Interface: Next Generation Thought Controlled Distributed Video Game Development Platform"*, IEEE Symposium on Computational Intelligence and Games, 2008.**
10. **G. Pfurtscheller, D. Flotzinger, S. Gölly, Ch. Neuper, and J. Kalcher, *"Graz Brain-Computer Interface"*, Springer Berlin / Heidelberg, Vol. 860, pp. 170-176, 1994.**
11. **S. W. Yeo, C. H. Lee, *"On-line Independent Component Analysis of EEG Signals for Brain-Computer Interfacing"*, Department of Electrical Engineering, Inha University, 2001.**
12. **J. del R. Millán, F. Renkens, J. Mouriño, and W. Gerstner, *"Non-Invasive Brain-Actuated Control of a Mobile Robot"*, 18th Joint International Conference on Artificial Intelligence, Acapulco, Mexico, 2003.**
13. **C. I. Hung, P. L. Lee, Y. T. Wu, L. F. Chen, T. C. Yeh, and J. C. Hsieh, *"Recognition of Motor Imagery Electroencephalography Using Independent Component Analysis and Machine Classifiers"*, Annals of Biomedical Engineering, Vol. 33, No. 8, 2003.**
14. **O. Konopka, J. Štastnỳ, and, P. Sovka, *"Movement-Related EEG Separation using Independent Component Analysis"*, the 3rd European Medical and Biological Engineering Conference, Prague, Czech Republic, 2005.**
15. **J. del R. Millán, *"Brain-Computer Interface"*, In *"The Handbook of Brain Theory and Neural Networks"*, (ed. M. A. Arbib), 2nd Edition, MIT press, England, 2003.**
16. **Haider Hussein Alwasiti, 1 2Ishak Aris and 3Adznan Jantan, *"Brain Computer Interface Design and Applications: Challenges and Future"*, World Applied Sciences Journal, 2010.**
17. **AneesaAkmalNooh, JasmyYunus and SalwaniMohdDaud, *"A Review of Asynchronous Electroencephalogram-based Brain Computer Interface Systems"*,International Conference on Biomedical Engineering and Technology, 2011.**

18. **M. Teplan, *"Fundamentals of EEG Measurement"*, measurement science review, Vol. 2, section 2, 2002.**
19. **F. H. Lopes da Silva and J. P. Pijn, *"EEG and EMG Analysis"*, In *"The Handbook of Brain Theory and Neural Networks"*, (ed. M. A. Arbib), 2nd Edition, MIT press, England, 2003.**
20. **T. Nykopp, *"Statistical Modelling Issues for the Adaptive Brain Interface"*, M.Sc. Thesis, Department of Electrical and Communications Engineering, Helsinki University of Technology, 2001.**
21. **J. N. Knight, *"Signal Fraction Analysis and Artifact Removal in EEG"*, M.Sc. Thesis, Department of Computer Science, Colorado State University, Colorado, 2003.**
22. **J. B. Ochoa, *"EEG Signal Classification for Brain Computer Interface Application"*, EcolePolytechniqueFederale De Lausanne (EPFL), 2002.**
23. **A. C. Guyton, *"Physiology of the Human Body"*, Saunders College Publishing, 6th Edition, 1984.**
24. **L. Laitinen, *"Neuromagnetic Sensorimotor Signals in Brain Computer Interface"*, M.Sc. Thesis, Department of Electrical and Communications Engineering, Helsinki University of Technology, 2003.**
25. **P. L. Lee, Y. T. Wu, L. F. Chen, Y. S. Chen, C. M. Cheng, T. C. Yeh, L. T. Ho, M. S. Chang, and J. C. Hsieh, *"ICA-Based Spatiotemporal Approach for Single-Trial Analysis of Postmovement MEG Beta Synchronization"*, NeuroImage, 20:2010-2030, 2003.**
26. **G. Pfurtscheller, F. H. Lopes da Silva, *"Event-Related EEG/MEG Synchronization and Desynchronization: Basic Principles"*, Clinical Neurophysiology, 110:1842-1857, 1999.**
27. **W. S. Smith, *"The Scientists and Engineer's Guide to Digital Signal Processing"*, Second Edition, 1999. URL: [http://www.dspguide.com/.](http://www.dspguide.com/)**
28. **J. M. Zurada, *"Introduction to Artificial Neural Systems"*, Jaico Publishing House, 1996.**
29. **F. M. Ham, Kostanic, Ivica, *"Principles of Neurocomputing for Science and Engineering"*, McGraw-Hill, 2001.**
30. **A. J. Bell, *"Independent Component Analysis"*, In *"The Handbook of Brain Theory and Neural Networks"*, (ed. M. A. Arbib), 2nd Edition, MIT press, England, 2003.**
31. **A. Hyvärinen, J. Karhunen, E. Oja, *"Independent Component Analysis"*, John Wiley & SonsInc., 2001.**
32. **Ahmed Kareem Abdullah, Zhang Chao Zhu, LianSiyan, andSalim Mohammed Al-Wasity, *"Stone Blind Source Seperation based Ocular Artifact Rejection in EEG"*, Research Journal of Applied Science, Engineering and Technology, 2012.**
33. **T. Kohonen, *"Self-Organizing Maps"*, Springer-Verlag Berlin Heidelberg, 3rd Edition,2001.**