An Intelligent Spelling Framework Based on Brain-Computer Interface

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Abstract:

Brain-computer Interface (BCI) aims to enhance the quality of life for all humans. Spelling is one of BCI applications that is used to type numbers, characters, words, or sentences by recording the user's brain activity. In this paper, A BCI speller framework based on converting mental activity is presented. Such framework uses Independent Component Analysis (ICA) and Auto Regressive (AR) for preprocessing and feature extraction respectively. Both of Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) are utilized at the classification phase. Several experiments have been conducted by four subjects using the pre-described framework achieved high average accuracy of 94.38% for KNN with value of K=9. The performance results have shown that converting mental activity can be used as a mean for spelling applications.

Keywords:

Brain-Computer Interface, Event Related Potentials (ERP), Steady State Evoked Potential (SSEP), and Motor Imagery (MI), mental speller.

1-Introduction:

The Brain Computer Interface (BCI) is building an interface between human brain and outside world. BCI is a controlled system that records the brain signal of user responses and converts it into new artificial outputs that act on environment or on the body itself without any dependence on peripheral nerves and muscles. It does not require any external device or muscle intervention to issue commands and complete the interaction (NAGY, POPENTIU, & Tarca, 2014)(Valeriani, Poli, & Cinel, 2017).BCIs offered great benefits in providing alternative communication tools for persons suffering from motor disabilities such as Amyotrophic Lateral Sclerosis (ALS), spinal cord injuries or brain paralysis, and to enhance functions in healthy individual (Mora-Cortes, Manyakov, Chumerin, & Van Hulle, 2014).

There are many non-invasive techniques for measuring brain responses such as Magnetoencephalogram (MEG), Functional Near Infrared Spectroscopy (FNIRS), Electrocorticogram (ECoG), Functional Magnetic Resonance Imaging (FMRI), and electroencephalography (EEG). Each technique has some advantages and disadvantages compared to other techniques. For instance, in EEG the temporal resolution is high but the special resolution is low compared to FMRI.

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The low cost and portability of EEG made it widly used in both clinical and research applications (Amiri, Rabbi, Azinfar, & others, 2013)(Kaur & Singh, 2017).

The Electroencephalographic (EEG) technique can measure the desired activities of the brain in a particular area from cortex and used to do numerous applications, for example, controlled mobile robots, immersion and interaction with virtual reality, user state monitoring, and brain-control of prosthetic extremity devices in people with paralysis (Han & Kim, 2016).

There are different features which can be extracted from EEG that can be applied as input for BCI system, for example, six brain rhythms can be noticed in EEG based on various frequency domain; delta (up to 4 Hz), theta (4-7 Hz), alpha (8-12 Hz), mu (8-13 Hz), beta (12-30 Hz), and gamma (25-100 Hz). The delta and theta rhythms occur in a sleeping, continuous attention, and high emotional conditions. The alpha rhythm happens when eyes closed at relaxation and wake up. The beta rhythm appears in open eyes at the normal wake up. The gamma rhythm can be acquired from somatosensory cortex and mu rhythm from sensorimotor cortex that shows the rest state of motor neurons (Mühl, Allison, Nijholt, & Chanel, 2014)(Pathak & Jayanthy, 2017).

A great application of BCI is spelling application (which are systems allowing users to type individual characters, words, or even sentences by decoding their brain activity). The spelling application helps to improve the quality of lives for either people who has speaks difficulties or normal people looking for a more easy life (Naz & Bawane, 2016).

The researchers of EEG-based Brain-Computer Interface (BCI) speller application have increased from 2007 until now meaning that it is an active research area(Hwang, Kim, Choi, & Im, 2013). They used several paradigms that are either visual or auditory based according to the stimulus that the subject is exposed to. These speller systems require standing all the time in front of a monitor or near to speaker devices for selecting the desired character in one or many steps.

In this paper, an intelligent mental spelling framework is proposed to detect the character thought of by the subjects in one-step by imagining the writing behavior of the character that want to spell. It uses K-Nearest Neighbors (KNN) for classification as it gives high performance accuracy compared to Support Vector Machines (SVM).

This paper is organized as follows. In section 2, the existing works of EEG-based BCI speller paradigms are presented while the proposed framework is described in section 3. The conducted experiments and results are presented in section 4. Conclusion is introduced in section 5.

2-Related Work:

All systems of spelling that are based on EEG-based BCI paradigm, depend on different types of brain reactions due to the user intentions: Event *Related Potentials* (ERP), *Steady State Evoked Potential* (SSEP), and *Motor Imagery* (MI)(Cecotti, 2011) .

2.1 Event Related Potentials (ERP):

Event Related Potentials (ERP) are change in EEG potential occur after the presence of source of stimulus (auditory or visual stimulus) (GLAYAN, 2014)(Yoon & Kim, 2017). P300 is one of the most important components of an ERP. P300 means a positive peak (deflection in voltage) at about 300 ms to 500 ms after a significant stimulus onset in the EEG (Cecotti, 2010)(Krigolson, Williams, & Colino, 2017).

2.1.1 Visual P300 Speller

Row/Column (RC) paradigm designed in 1988 by Farwell and Donchin is the most common used P300-based BCI device in spelling application. In this paradigm, all the alphabet " 26 letters " and 10 digits from 0 to 9 are arranged in a matrix of 6 × 6 ,that can be seen on the screen of the computer as shown in figure (1-a)(Fazel-Rezai, 2009).Each row and column is flashed in a randomly order as described in (Fazel-Rezai et al., 2012)(Mainsah, Collins, Reeves, & Throckmorton, 2017).

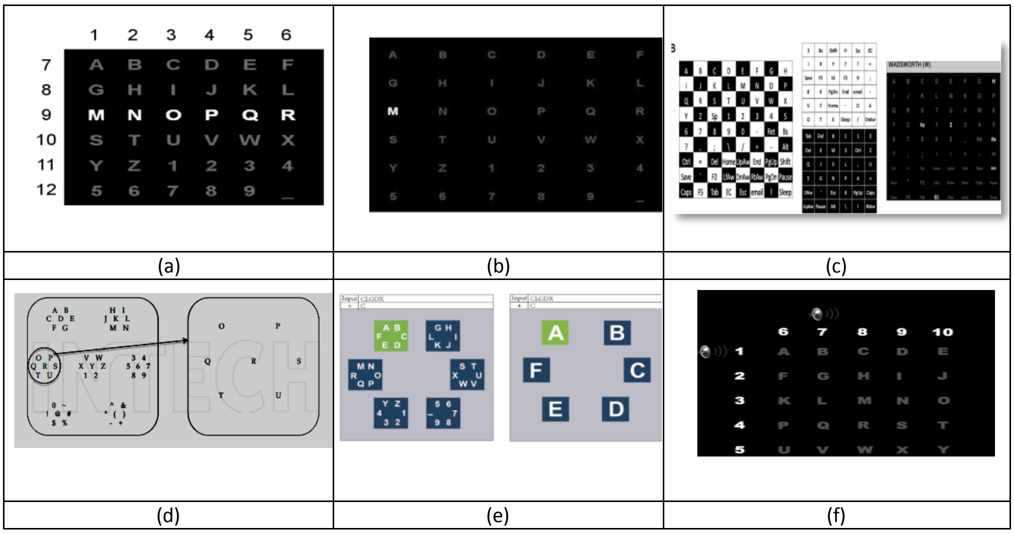


Figure 1: (a) row/column (RC) paradigm, (b)single character (SC) paradigm,(c) Checkerboard (CB) paradigm, (d) seven Region Based (RB) paradigm,(e) six Region Based (RB) paradigm,(f)auditory P300 speller paradigm

Elsawy et al, use RC paradigm to compare the execution of the suggest ensemble classifier to the execution of traditional classifier and feature extraction techniques. This study uses the common average reference spatial filter for preprocessing, Principal Components Analysis PCA for feature extraction, and finally Linear Discriminant Analysis (LDA) and Fisher Linear Discriminant (FLD) for classification. The average classification accuracy for all ensemble classifier methods was 86.29(Elsawy, Eldawlatly, Taher, & Aly, 2014). Kamp et al, asked six healthy participants to type all characters by RC paradigm this work uses a Principal Components Analysis PCA for feature extraction and a Stepwise Linear Discriminant Analysis (SWLDA) as classification method. The online accuracy of classification was between 35% and 76% (Kamp, Murphy, & Donchin, 2013). Bhatnagar et al, used SVM as classifier method for data of two subject to get accuracy about 92.5% after 15 trials after remove noise by band-pass filter (Bhatnagar, Yede, Keram, & Chaurasiya, 2016).

The single character (SC) speller flashes randomly one character at a time, with small tardiness time between flashes as in figure (1-b). The RC speller has a lower tardiness time between flashes than the SC(Gavett, Wygant, Amiri, & Fazel-Rezai, 2012).Guger et al. asked 100 subjects to spell a 5-character of word "water" with training of 5 min, this work use Linear Discriminant Analysis (LDA) for classification. The average classification accuracy of all subjects was 91.0% in (RC) and 82.0 % in (SC), and the average Classification accuracy of 19 subjects who participated in RC and SC was 85.3 % and 77.9% respectively after remove noise by band-pass filter (Guger et al., 2009).

The Checkerboard (CB) paradigm shown stimuli in an 8 × 9 matrix as shown in Figure (1-c left), a virtual CB contain of the 72 components in the matrix (invisible to subjects)as in figure (1-c middle),and the subjects see the standard 8 × 9 matrix as in figure (1-c right). The flashes mechanism is described in (Fazel-Rezai et al., 2012).C.-C. Postelnicu et al, they asked 10 subject to spell a 16-character of text “VERY_S IMPLE_TEST” then comparing the execution of (CBP) and HCBP-based spellers. The average classification accuracy of CBP was 91.25% and for HCBP was 90.625 % using Linear Discriminant Analysis (LDA) after enhance signal by band-pass filtered between 0.5 – 30 Hz(Postelnicu & Talaba, 2013). Townsend, G., et al, they asked 18 subject to spell a ‘‘WADSWORTH” by using the (CBP) and (RCP) spellers then comparing the results. The signal filtered by a 0.1 Hz high-pass ,30 Hz low-pass filter, and classify using Linear discriminant analysis (LDA) to get the average classification accuracy of CBP was 91.52% and for RCP was 77.34%, the test done with three-advanced ALS participants produced similar results. These results show that the CBP has more effective BCI than the RCP. This is especially important for people with severe neuromuscular disabilities(Fazel-Rezai & Ahmad, 2011). Ryan et al, apply different kind of color stimuli, high-pass filtered at 0.5 Hz, low-pass filtered at 30 Hz, and the stepwise linear discriminate analysis (SWLDA) to improve the accuracy (Ryan, Townsend, Gates, Colwell, & Sellers, 2017).

Region Based (RB) paradigm is about six groups of characters arranged in six different regions as in figure (1-e). works in two steps described in (Fazel-Rezai et al., 2012).If the number of characters increased the number of regions will be increased as in figure(1-d),and also It is work in two steps described in (Townsend et al., 2010).Li, Qi, et al, they compare the performance of (SD) and (RB) paradigm spellers. Five subjects was participated the experiment the result was that SD-Speller is superior to RB-Speller when the ISI was set 150ms using Support Vector Machine (SVM) classifier after a series of processing such as filter, down sampling, artifact rejection, ocular artifact rejection and epoch (Li et al., 2015). Ikegami et al. asked seven patients with ALS to spell six characters. So, the average online accuracy of the ALS patients was 24% for the RC and 55% for the RG, and two of seven patients after additional experience their average accuracy jump to 92%(Ikegami, Takano, Kondo, Saeki, & Kansaku, 2014) . Okahara et al, study the performance of this paradigm in nine patients with SCA to show that the accuracy reach good results 82.9% after the signals analyses by downsampled to 21 Hz and classified by Fisher's linear discriminant analysis(FDA) (Okahara et al., 2017).

Table (1): Comparison of P300 based visual stimulus paradigms.

	PARADIGM			
	Row/Column (RC)	**Single Character (SC)**	**Checkerboard (CB)**	**Region Based (RB)**
Advantage	The best choice paradigm for spelling	Lower target probability.	double flash and adjacency problems errors can be cancelled	decresed spatial crowding effect
Disadvantage	perceptual errors can be raises	Tardiness time was Long.	crowding effect	two step to select character

2.1.2 Auditory P300 Speller

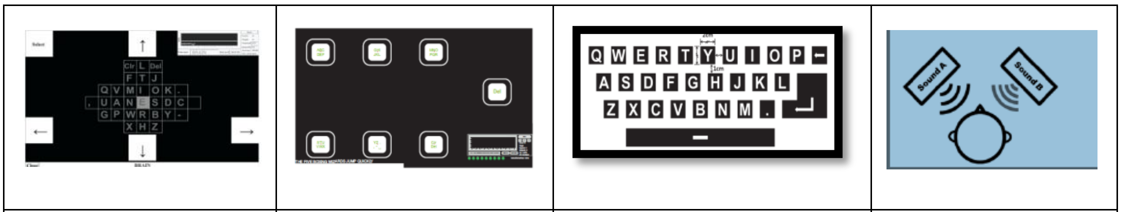
In auditory P300 speller 5*5, visual matrix used as supported matrix as shown in figure (1-f), with auditory stimulus code represented at each row and column instead of flashes described in (Kim, Lee, Park, Kim, & Im, 2012).The stimulus time 450 ms and ISI 175 ms were larger in auditory than visual P300 speller. Furdea et al. want to compare the performance of 13 participants when they use visual and auditory P300 speller paradigm, by using the notch filter to remove noise and the stepwise linear discriminant analysis (SWLDA) method as classifier. The high average classification accuracy achieved at visual speller 94.6% than auditory speller 65% (Furdea et al., 2009).M. Chang et al. also compare between them and get high average classification accuracy achieved at visual speller(Chang et al., 2013). Baykara apply animal sounds as auditory stimulus for 16 healthy subjects to spell different words, the average online accuracy reach ≥70% for only 81% of the subjects by using linear discrimination analysis (LDA) as classification method (Baykara et al., 2016).

2.2 Steady State Evoked Potential (SSEP)

Steady State Evoked Potential can classify in two categories according to stimulus type;

2.2.1 Steady State Visually Evoked Potential (SSVEP) is an EEG signal of brain response by a visual stimulus, flickering at specific frequencies ranging from 6HZ to 100HZ ,so the same frequency or multiples of frequency of the visual stimulus generate the electrical activity (Dutta & Sambandan, 2015)(Mah, 2017).

The SSVEP based Bremen-BCI speller has graphical user interface that presented in Figure (2-a). This interface system is described in (Valbuena, Sugiarto, & Gräser, 2008).



(a)	(b)	(c)	(d)

Figure 2: (a) Bremen-BCI interface, (b) Graphical user interface (GUI), (c) A modified QWERTY keyboard layout,(d)ASSR Paradigm.

Wu et al, show the feasibility of the proposed SSVEP BCI at different viewing distances (60cm, 150cm, 250cm and 350cm) between the user and the visual stimulator, by 10 healthy subjects participated in the experiment. The average classification accuracy is over 75% after using band-pass filter by 1-50Hz , Fast Fourier Transform (FFT) as feature extraction method ,and Canonical Correlation Analysis (CCA) as classification method (C.-H. Wu & Lakany, 2015).

Graphical user interface (GUI) layout, the letters are appears in a several manner and the commands will be increased as shown in figure (2-b), The selection of one of the commands is described in (Kick & Volosyak, 2014). Kick et al ,Asked 38 subjects to spell the words “BCI” and “BRAIN” and sentence" THE FIVE BOXING WIZARDS JUMP QUICKLY”, using two layout (Bremen-BCI speller, graphical user interfaces (GUI)) with three different predefined stimulus frequency sets. The result demonstrate that 71% of subject tend to work on (GUI) because they needs only two commands to select symbol in contrast to Bremen-BCI speller that need more than two commands. The band pass filter between 2 and 30 Hz and a notch filter around 50 Hz were used (Kick & Volosyak, 2014).

A modified QWERTY keyboard layout was designed to achieved the suggest spelling system, as shown in Figure (2-c). In this system, the users can spell one target character per each target selection, in contrast the traditional SSVEP-based spelling systems (Hwang et al., 2012). Won et al, this study asked 4 subject to test modified QWERTY keyboard layout with different frequency stimuli range from (low (6-14.7Hz)to high (26- 34.7Hz)).The result show that higher average classification accuracy was 80% at the high frequency stimuli compare to the results achieved at low frequency stimuli. Fast Fourier Transform (FFT) used as feature extraction method ,and Canonical Correlation Analysis (CCA) apply as classification method (Won, Zhang, Guan, & Lee, 2014).

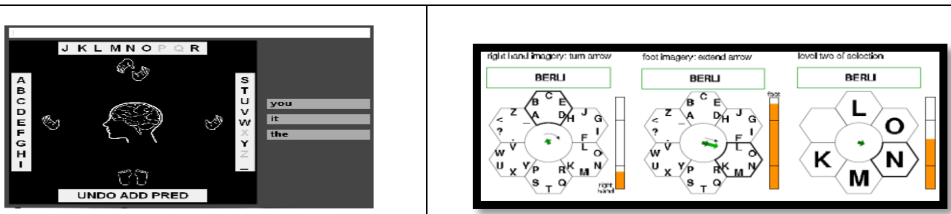
2.2.2 Steady State Auditory Evoked Potential (SSAEP) is an EEG signal of brain response by an auditory stimulus; it also called auditory steady state response (ASSR). In this paradigm two speaker are located at certain distant from each other and from person who do the experiment as shown in figure(2-d),the participants expose to auditory stimulus with different frequency from each speaker as described in(Kim et al., 2012). Kim et al, asked 6 subject to close their eyes and attention to auditory stimulus from each speaker. The offline experiments, the average classification accuracy was 86.33%,and the online experiments was lower classification accuracy (71.4%) by using Fast Fourier Transform (FFT) as feature extraction method and a 10-fold cross-validation as classification method (Kim et al., 2011).

2.3- Motor Imagery (MI)

A motor imagery (MI) BCI is defined as a mental representation of the motor action with absence the real motor output. It is known that the mental imagination of movements include the same brain regions (Pfurtscheller & Neuper, 2001). In the EEG spectra, the power of the (ERD) in the band of beta (13–26 Hz) and mu (8–13 Hz) has been decreased when the subject move or imagine to move(Mora-Cortes et al., 2014).

A predictive BCI speller based on motor imagery suggested at AIRLab. The GUI of this speller is presented in Figure (3-a). The selection strategy is based on target expansions described in (Cecotti, 2010).

D'albis et al , asked three subjects to write the phrase “what a wonderful day" using a BCI spelling application based on motor imagery. The spelling rate was 3 char/min, 2.7 char/min, and 2 char/min respectively after using Spatial Filtering to enhance the signal, Genetic algorithm (GA) and Fisher Discriminant Analysis (FDA) as feature extraction, and finally the classification stage applies linear discriminant analysis (LDA) (D’albis, Blatt, Tedesco, Sbattella, & Matteucci, 2012).



(a) (b)

Figure 3: (a) predictive BCI speller, (b) Hex-o-spell GUI.

Berlin BCI (BBCI) speller based on motor imagery (called Hex-o-Spell) has been proposed at the BCI research group from the Fraunhofer FIRST (IDA), as shown in figure (3-b), and works described in (Cecotti, 2011).

On two days in the course of the CeBIT fair 2006 in Hanover, Germany, two subjects Use hex-o-spell paradigm. The typing speed include the typing mistakes that corrected using backspace was between 2.3 and 5(CPM) for one subject and between 4.6 and 7 (CPM) for the other subject (Blankertz et al., 2006; Williamson, Murray-Smith, Blankertz, Krauledat, & Müller, 2009). K.-R. Muller et al (2008), six subjects who all had no or very little experience with BCI asked to use Hex-o-Spell text entry system so, the average classification accuracy was 89.5% after apply spatial filters as feature extraction and linear discriminant analysis (LDA) as classification(Müller et al., 2008). Cao et al, modified Hex-o-Spell to Oct-o-Spell to achieve 92.13% accuracy during spelling Chinese words by 3 subjects using Support Vector Machine (SVM) for classification stage (Cao et al., 2017).

We can summarize the results of the previous speller paradigms in table 2 shown below.

Table (2): The summary results of the speller paradigm.

Brain Reaction Types	***Type of stimulus***	***Speller paradigm***	***Accuracy***
ERP	Visual P300	RC (Elsawy et al., 2014) RC (Kamp et al., 2013) RC (Bhatnagar et al., 2016) RC (Guger et al., 2009) SC (Guger et al., 2009) CBP (Postelnicu & Talaba, 2013) CBP (Fazel-Rezai & Ahmad, 2011) RC (Fazel-Rezai & Ahmad, 2011) RB (Ikegami et al., 2014) RC (Ikegami et al., 2014) Visual speller(Furdea et al., 2009)	86.29% 35% → 76% 92.5% 91% 82% 91.25% 91.52% 77.34% 24% 55% 94.6%
	Auditory P300	(Furdea et al., 2009)	65%
SSEP	SSVEP	- Bremen BCI speller (C.-H. Wu & Lakany, 2015) - Graphical User Interface (GUI) (Kick & Volosyak, 2014) - Modified QWERTY keyboard(Won et al., 2014)	75% 71% 80%
	SSAEP	(Kim et al., 2011)	86.33%
MI	Visual	Predictive BCI speller (D'albis et al., 2012) Hex-o-spell (Müller et al., 2008)	3cpm 89.5%

In the next section, the proposed speller system with imagined writing character on a single trial basis is described.

3 -The Proposed Imagined Mental Writing Framework

The mental speller detects the character thought of by the participants as shown in **Error! Reference source not found.** Their recorded EEG signals go through preprocessing, feature extraction, and classification to perform the character recognition process.

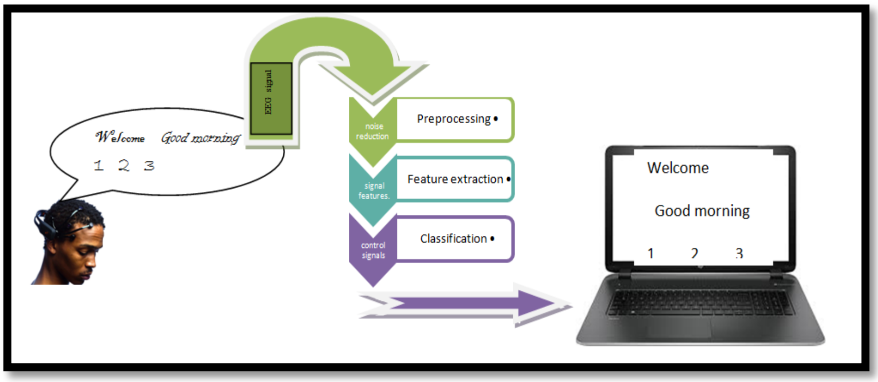


Figure (4): Proposed BCI based speller system.

More details about the involved algorithms in each phase are shown below;

3.1 Preprocessing

The preprocessing signals aims to improve signal to noise ratio (SNR) and enhance signals by remove the noise from signals. One of methods that used to do this is Independent Component Analysis (ICA).

Independent Component Analysis (ICA) is statistical method especially in order to solve the blind source separation (BSS) problem, used to modify the captured signals from each subject (Hyvärinen, Karhunen, & Oja, 2004; Stone, 2004), which no need to previous knowledge on the types of the activity or artifact that generate the EEG signals. So, it has ability to divide the composite signals to its original source. The formula that represents the relation between the EEG signal $x(t)$ and its source $s(t)$ is;

$$x(t) = f\big(s(t)\big) + n(t) \qquad (3\text{-}1)$$

Where $n(t)$ is an additive random noisy vector and f is any unknown mixer function.The number of sources usually affects the input vector's s(t)dimension. Data channels that are measured are equal to the output vector's x(t) dimension(Lee, Lewicki, Girolami, & Sejnowski, 1999).ICA is divided into different models according to f that be either nonlinear function which is so difficult in evaluation or linear function which is easier and specially in brain signal applications , the mathematical formula explain in the following function;

$$x(t) = As(t) + n(t) \quad (3\text{-}2)$$

where A is the mixing matrix. If the noise is weak, we can neglect the noise term from equation (3-2)(Castellanos & Makarov, 2006).at the end the Infomax or further modification of the Infomax algorithms used to get A and $s(t)$ from$x(t)$(Bell & Sejnowski, 1995)(Lee, Girolami, & Sejnowski, 1999).

It has many advantages as facilitate EEG source localization, limitation artifacts, and improve Signal to Noise Ratio (SNR) (Allison, Dunne, Leeb, Millán, & Nijholt, 2012). In this system, ICA works as spatial filtering, because the dimensionality of the output signals is the same as the input. And used the baseline correction as demonstrates (Hu, Xiao, Zhang, Mouraux, & Iannetti, 2014).

3.2 Feature Extraction

Auto Regressive (AR) modeling features are been used to distinguish the contributing signals where the prediction for each value relies on the previous values of the same time series. AR of order six has been calculated using burg method (BURG, 1975).

It is used to get the filter coefficients that work as features of the signal. Transfer function of AR filter depends only on poles of denominator. Their numbers decide the order of the autoregressive model(Nicolas Alonso & Gomez Gil, 2012).

EEG signal y(t)can represent by AR of order p in the following equation;

$$y(t) = a_1\, y(t-1) + a_2 y(t-2) + .. + a_p y(t-p) + n(t) \quad (3\text{-}3)$$

Where n(t) is the noise, and a_i is the filter coefficient that can calculated by different methods like the forward-backward, Yule-Walker, Burg, and covariance. After that we evaluate the power spectrum of the EEG signal y(ω) from this equation;

$$y(\omega) = \frac{1}{|1-\sum_{k=1}^{p} a_k\, e^{ik\omega}\,|} \quad (3\text{-}4)$$

The order p of the input signal has been estimated. There are two cases, if it high the peaks appear in the spectrum not real, else, if it low the spectrum was smooth.

The AR disadvantage is the bad effective performance at non stationary EEG signals, to eliminate this the multivariate adaptive AR (MVAAR) has been used. EEG signal $y_{k=}$ [yk,1 yk,2 …..yk,m]T can represent by (MVAAR) of order p in the following equation;

$$y_k = A_1\, y_{k-1} + A_2 y_{k-2} + \cdots + A_p y_{k-p} + n_k \qquad (3\text{-}5)$$

Where m is the number of channel, and $A_1 \dots . A_p$ are the adaptive coefficients, which get by update the coefficient used the Recursive Least Squares algorithm.

3.3- Classification:

Two main types of mental speller classifiers have been studied, named as Support Vector Machines (SVM) and K Nearest Neighbors (KNN) method.

3.3.1 Support Vector Machine

SVM is a supervised classification method as LDA. It is used to separate feature vectors into distinct classes via selecting a discriminant hyperplane. This hyperplane maximize the margins which identify the distance between the nearest training data and hyperplane (W. Wu, Gao, Hong, & Gao, 2008). It is defined by the support vectors which resides on the margin as shown in figure (5)(Jakkula, 2006);

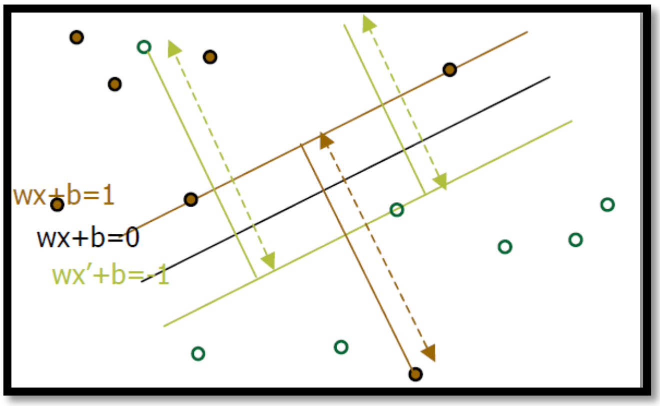


Figure (5): Representation of Hyper planes.

Let the following equation define the function of the discriminant hyperplane for the training data.

$$f(x) = sign(\langle w, x\rangle + b) = \begin{cases} +1\ if\ x\ is\ a\ positive\ sample \\ -1\ if\ x\ is\ a\ negative\ sample \end{cases} \qquad (3\text{-}6)$$

Where x, w is the input vector and weight respectively. According to the sign of the equation's result, the mapping of the input data to its classes is determined.

3.3.2 K-Nearest Neighbors

KNN is a classifier method that makes use a set of labeled objects. It distribute the features into different classes, according to the metric distance (k) among the test feature vector and the feature of classes nearest (nearest neighbors).

KNN starts by calculate the weighting function that increases by decreases the metric distance between the neighbor and the feature vector from next equation(Denœux, 2008);

$$w^{(i)} = \begin{cases} \frac{d^{(k)} - d^{(i)}}{d^{(k)} - d^{(i)}} & \text{if } d^{(k)} \neq d^{(1)} \\ 1 & \text{if } d^{(k)} = d^{(1)} \end{cases} \quad (3\text{-}7)$$

where, $d^{(i)}$is the distance between the test feature vector and the i-th nearest neighbor and, $d^{(k)}$ represent the furthest neighbor while $d^{(1)}$ is the nearest neighbor. In KNN, the decision rule used to add the unknown feature to class that has greatest sum of weights between its k nearest neighbors(* & Gomez-Gil, 2012).
There are many advantage of KNN classification method, as its easy to understand, and implemented. But sometimes it shows sensitivity to the feature vector dimensionality. However, this drawback can be overcome by efficient selection of the feature and reduction algorithms(Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007).

4-Experiments and Results

4.1 Data set

In order to study the performance of the pre-described system, four healthy subjects, one male and three females aged from twenty to thirty-nine, attended the experiment. EEG signal has been recorded using an EMOTIV device(n.d.) with fourteen channels. The channels, distributed according to international 10-20 system, are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 as shown in figure(6).

Figure (6): Electrode placement on the scalp.

During the training phase, the subjects are stimulated using an auditory cue. It instructs the user to recall the character to be mentally spelled. The experiment consists of ten sessions. Each session is composed of twenty trials.

As shown in figure (7), the experiment starts with a baseline period of six seconds followed by the twenty trials of writing imagination activity. Each trial consumes four seconds, one second for presenting the acoustic cue and three seconds for measuring the signals generated from the mental writing activity.

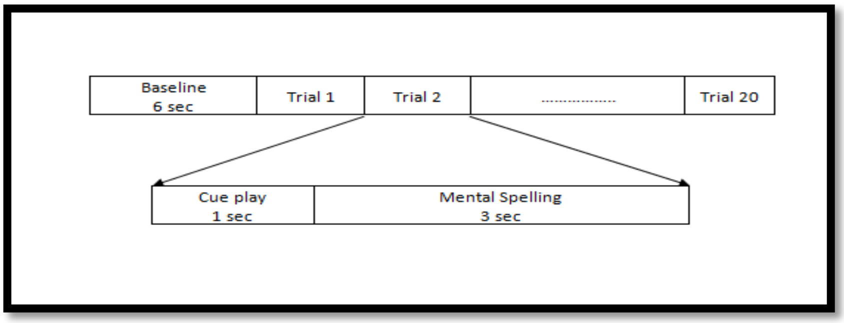


Figure (7): Experiment Description

4-2 Experimental Results

The obtained results are using a 10-fold cross-validation. The performance evaluation and enhancement is targeting the increase of Correct Classification Rate (CCR). The character recognition time per subject is also viewed including the time of signal recording. The results in figure (8) show that using SVM classifier has achieved an average CCR of only 11.6%. KNN on the other hand has achieved a CCR of 82.5% when only the vote from one neighbor is considered. Increasing the number of voters positively affects the average results. This can be seen when k grows to 3, 5, 7, and 9. Their classification results moves to 87.3%, 90%, 92.8%, and 94.3% respectively.
The detailed results of each classification method are viewed in Table . The details of the time consumed in the character detection process, measured in seconds, are shown in **Error! Reference source not found.**.

Table (3): The detailed results of each classification method

	Average Performance rate					
User	SVM	1-NN	3-NN	5-NN	7-NN	9-NN
1	0.105	0.825	0.87	0.91	0.93	0.945
2	0.1	0.83	0.845	0.885	0.935	0.935
3	0.125	0.885	0.895	0.91	0.915	0.935
4	0.135	0.865	0.885	0.895	0.935	0.96
Average	0.11625	0.85125	0.87375	0.9	0.92875	0.94375

Table (4): The details of the time consumed in the character detection process, measured in seconds

	Average total character recognition time(sec)					
User	SVM	1-NN	3-NN	5-NN	7-NN	9-NN
1	3.511817	3.50932	3.508696	3.508696	3.508696	3.508618
2	3.279765	3.277347	3.276879	3.276489	3.276723	3.276957
3	3.102314	3.10013	3.099116	3.099194	3.09935	3.09896
4	3.192092	3.189908	3.18905	3.189128	3.188972	3.188972
Average	3.271497	3.269176	3.268435	3.268377	3.268435	3.268377

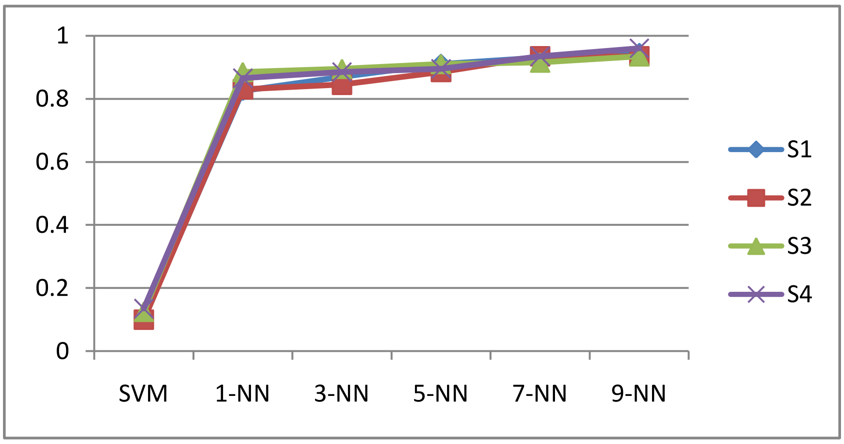


Figure (8): Total CCR of SVM, KNN for different Ks

The results have shown the efficiency of mental speller with imagined writing activity. The system has achieved good results in both performance accuracy and character recognition time. The accuracy results get better when higher values for K are deployed. They also indicate that the proposed framework gives high accuracy while requiring fewer assistive tools compared to other BCI speller paradigm. This makes it more suitable to people with various types of disabilities to spell their thoughts.

5. Conclusion

Brain-Computer Interface (BCI) is an interface that allows direct communication path between central nervous system and external devices without relying on the peripheral nerves. Spelling still remains as one of the main challenges in BCI applications. Writing a simple message, an e-mail... remains a difficult task to achieve for people with severe disabilities.

In this paper, a survey of EEG-based BCI speller paradigms that based on one type of brain activity has been presented. They include their designs, advantages, and disadvantages.

This paper also proposed a system for mental spelling application. It uses ICA and baseline correction for preprocessing, AR for feature extraction, and the 9NN for classification, to get high accuracy classification for our new mental speller system to spell numbers from 0 to 9 by thinking of them.

In the future work, we will focus on going to type the letters and sentence by new mental speller design.

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نموذج التدقيق الإملائى الذكي المرتكز على واجهة الحاسوب المخية

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الملخص:

تهدف واجهة الحاسوب المخية (BCI) الى تحسين كيفية الحياة لجميع البشر.التدقيق الأملائي هو أحد تطبيقات واجهة الحاسوب المخية (BCI) المستخدمة فى كتابة الأرقام أو الحروف أو الكلمات أو الجمل عن طريق تسجيل النشاط ال مخي للمستخدم.وفي هذة الورقة ،نستعرض إطار عمل لل تدقيق ا لإملائي ل(BCI) يرتكز على تحويل النشاط الذهنى .يستخدم هذا الإطار طريقة تحليل المكونات المستقلة للمعالجة المسبقة وطريقة ذاتي الأرتداد لأستخلاص الخصائص.كما أستخدم أيضا طريقتان فى مرحلة التصنيف هما ألة دعم المتجة و (ك) أقرب الجيران. واجريت عدة تجارب من قبل اربعة أشخاص باستخدام هذا الإطار الموصوف ،وحققت النتائج متوسط دقة عالية 94,38% لطريقة أقرب الجيران عند(ك= 9) . وأظهرت النتائج ان تحويل النشاط الذهنى يمكن ان يستخدم كوسيلة لتطبيقات التدقيق الأملائي.