A Hybrid SSVEP and Triple RSVP Brain-Computer Interface for Spelling in Right-to-Left Non-Latin Scripts

Fatemeh Javaheri [1], Mohammad Bagher Khodabakhshi [1,*], Rasool Baghbani [1]

*Corresponding author: **mb.khodabakhshi@hut.ac.ir**

[1]Hamedan University of Technology, Department of Biomedical Engineering, Hamedan, Iran, 65155-579

A B S T R A C T

Brain-Computer Interfaces (BCIs) help individuals with severe disabilities communicate using brain activity. Most existing systems are designed for Latin alphabets and overlook the challenges of non-Latin and right-to-left (RTL) scripts (such as connected letters). To address this issue, a hybrid BCI system has been developed using Steady-State Visual Evoked Potential (SSVEP) and Rapid Serial Visual Presentation (RSVP) paradigms. In this method, 36 characters are divided into 3 groups of 12, each further split into 4 subgroups of 3. SSVEP is used to identify the target group, and Triple RSVP is employed to detect the subgroup. The final character is determined using single-frequency SSVEP. Signal processing is performed using Power Spectral Density Analysis (PSDA), wavelet transform, and Support Vector Machine (SVM). Test results on 7 healthy individuals showed a system accuracy of 91.2±3.4% and an Information Transfer Rate (ITR) of 21.5±1.64 bits/min. When SSVEP stimulation time was reduced by 1 second, accuracy remained at 90.5%, while ITR increased to 25.37 bits/min. Unlike Latin-based systems, this one is optimized for complex and right-to-left scripts and performs better than single-modality methods. This advancement marks an important step in developing inclusive BCI technology for non-Latin users.

K E Y W O R D S

Speller, Brain computer interface, event-related potentials, Steady-state visual evoked potential, Rapid serial visual presentation

1- Introduction

In contemporary times, millions of people suffer from severe movement and speech impairments due to various causes including stroke, neuromuscular diseases, etc.[1], [2]. These challenges have motivated researchers to develop alternative communication technologies. Brain-computer interface (BCI) systems have emerged as an innovative solution, providing new possibilities for improving these individuals' quality of life [3]–[5]. Among various BCI applications, brain-controlled spelling systems are particularly significant. The most common method used in these systems is electroencephalography (EEG), which is widely employed in BCI studies due to its high temporal resolution, ease of recording, and low cost [6]. These systems primarily rely on three paradigms: event-related potential (ERP)-based systems, steady-state visual evoked potential (SSVEP)-based systems, and rapid serial visual presentation (RSVP)-based systems.

ERPs are electrical changes in brain activity in response to sensory stimuli. In ERP-based spelling systems, the user's mental focus on a target character produces a distinct response in the EEG signal. These systems identify the target character by detecting these brain responses, as target stimuli elicit a P300 component with higher amplitude compared to non-target stimuli.The P300 component is a positive voltage oscillation that appears with a latency of 250-450 ms after the target stimulus presentation. This response is only evoked when the target stimulus appears among non-target stimuli in an oddball paradigm. For optimal performance, the probability of target stimuli appearance should be at least 20%[7].

The first matrix-based ERP speller was introduced by Farwell and colleagues in 1988 [8]. In this system, rows and columns of the matrix flash randomly, and when the user focuses on the target character, a P300 component is generated in the EEG signal. Subsequent studies [9] compared the performance of 6×6 and 3×3 matrices and examined key parameters such as inter-stimulus interval (ISI). Further improvements were made to the user interface design, including modifications to character colors, background colors, fonts, and character spacing [10] .Several studies have explored Persian-language implementations [11], [12]. Additionally, research [13], presented more advanced algorithms for P300 signal feature extraction and classification.

Despite their advantages, ERP-based spellers face limitations in speed and accuracy due to low SNR, requiring repeated stimuli for reliable character detection. These vision-dependent systems also perform poorly for visually impaired users [7].Initial attempts using auditory stimuli [14], [15] showed unsatisfactory accuracy, leading researchers to adopt SSVEP-based spellers [16]–[20] as a more effective alternative.

SSVEP-based systems analyze brain activity in response to visual stimuli at specific frequencies. Each character is stimulated at a unique frequency, and the user's attention to the target generates an SSVEP response [21]. Character selection is performed in two stages: first grouping letters into multi-character sets, then separating the constituent characters of each group as separate stimuli. At each stage, groups or characters flash at specific frequencies, allowing target identification through signal analysis. In study [16] a Persian keyboard was designed based on Braille alphabet. Also, paper [18] proposed a hybrid eye-tracking and SSVEP system for a high-speed keyboard.

In studies [22], [23] unlike conventional SSVEP methods, a single-frequency stimulus is used at the center of the screen with fixed targets around it. In this method, by focusing the user's attention on each target, the spatial pattern of brain activity changes and is used to identify the target. The SSVEP paradigm offers higher speed and fewer repetitions compared to P300-based methods. However, limitations in the effective frequency range (6-16 Hz) for visual system stimulation restrict its application for large sets such as characters [24].

Subsequently, RSVP spellers [25]–[27] were introduced. In this system, characters are displayed individually at a fixed point, making them gaze-independent. However, due to the need for repeated presentations, they suffer from low information transfer rate (ITR). In the Triple RSVP protocol [28] three characters are displayed simultaneously, reducing testing time, but unwanted P300 responses to non-target characters reduce accuracy. To address this issue, a combination of RSVP and SSVEP [7] has been proposed. In this method, characters are grouped into triplets arranged around a square. First, the target group is identified by detecting P300, and then the character's position is determined by analyzing SSVEP. Selecting each character requires 45 stimuli (9 stimuli with 5 repetitions).

The RSVP-based spelling systems face specific challenges when used with the Persian alphabet. Since the Persian alphabet consists of 32 main characters along with punctuation marks and spaces, totaling 36 characters, according to the protocol in reference [7], it requires presenting 60 stimuli within 14 seconds for selecting each character. The increased number of stimuli not only causes user fatigue but also significantly reduces the system's efficiency and speed.

In this research, a new architecture combining SSVEP and Triple RSVP paradigms is proposed. In this method, the existing 36 characters are first divided into three groups of 12, with each group distinguished by a unique SSVEP stimulation frequency. Then, each 12-character group is divided into four subgroups of three, which are displayed using the Triple RSVP paradigm. This architecture reduces the number of required stimuli for selecting each character from 60 to

20 (4 stimuli and 5 repetitions).Using the three-frequency SSVEP paradigm, the target group is identified, and through the Triple RSVP paradigm, the target subgroup is determined. Additionally, by analyzing the SSVEP signal related to the flashing square in the center of the screen, the position of the target character relative to the square is identified.

The key innovations of this research are as follows:

- *Hierarchical character grouping*: A novel two-tiered structure optimizes target identification for non-Latin scripts.
- *Hybrid paradigm integration*: Intelligent combination of SSVEP and triple RSVP enhances classification efficiency.
- *Stimulus efficiency*: Reduction of required stimuli to 20 per character (vs. conventional methods), minimizing user fatigue.
- *Performance preservation*: Maintains high accuracy and competitive ITR compared to prior systems, despite streamlined stimuli.

This paper is organized as follows: Section 2 provides a detailed description of the research methodology. Section 3 presents and analyzes the experimental results. Finally, Section 4 is dedicated to the conclusion and discussion.

2- Method and Experiment

2-1- Participants

Seven healthy volunteers (4 women and 3 men, mean age 24.7 ± 2.8 years) with normal vision and free from neurological and ocular disorders voluntarily participated in this study with written consent. The registration protocol was approved by the Ethics Committee of Iran University of Medical Sciences with the ethics ID IR.IUMS.REC.1402.1112 dated 6 Mar 2024. Data recording was conducted in the National Brain Mapping Laboratory(NBML) in a regular lab environment with ambient illumination from ceiling lights and without any electrical or acoustic shielding. Before starting the experiment, subject were instructed to minimize eye movements and avoid head movements, blinking, swallowing, or any other muscular activity, and to sit comfortably facing the screen.

2-2 Protocol Design

In the protocol design, 36 characters, including 32 Persian alphabet letters and four symbols, were used. The characters are categorized into three groups of 12 characters each, as shown in Table 1. (It should be noted that, due to the non-use of Persian script in the article’s text, the characters of Group 1 are represented by numbers 1 to 12, the characters of Group 2 by numbers

13 to 24, and the characters of Group 3 by numbers 25 to 36. A correspondence table for the Persian characters and their Latin equivalents is provided in the appendix.)

The pattern presented in this study is a combination of three-frequency SSVEP, Triple RSVP, and single-frequency SSVEP patterns. Therefore, there are three stimuli in this protocol:

a) **Three-Frequency SSVEP Design:** Characters of each group are arranged around a hexagon in a specific order. Each of these three groups flashes at fixed frequencies of 6.0, 7.5, and 8.57 Hz. None of these frequencies are multiples of each other and do not overlap. This pattern, identifies the target character group.

b) **Triple RSVP Pattern (P300 Response Elicitation):** In this case, the 12 characters of each group are divided into four subgroups of three characters each; each subgroup appears as a stimulus. In each trial, these four stimuli are presented five times pseudo-randomly using the oddball pattern. In this pattern, one target stimulus and three non-target stimuli are defined. This pattern identifies the target subgroup.

c) **Single-Frequency SSVEP Design:** A black flashing square with a frequency of 15 Hz and dimensions of 240 × 240 pixels is used. Three characters surround the square from the left, right, and bottom sides. The placement of the characters is determined based on their positions relative to a hexagon. According to Figure 1(a), the characters on the right side of the hexagon are placed to the right of the square, while the characters on the left side of the hexagon are placed to the left of the square. Additionally, the characters at the bottom and center of the hexagon are positioned at the bottom of the square (Figure 1(b)).The selection of characters in each subgroup ensures that similar letters, such as “seh” and “teh” do not appear together or consecutively. This stimulus determines the direction of the target character relative to the square.

Based on the stimuli mentioned in the design of this virtual keyboard, there is a two-part protocol:

The first part involves using the SSVEP pattern to select the target character group. The second part utilizes a combination of SSVEP and Triple RSVP patterns to select the specific target character. The overall structure of this two-part protocol is illustrated in the figure 2.

In terms of appearance, the font used is B Nazanin Bold, with a size of 30 pt in the SSVEP pattern and 60 pt in the Triple RSVP pattern. The distance between each pair of letters is approximately 250 pixels. The characters are black, and the background is white. A computer with a 19.5 inch display and a resolution of 1920 × 1080 pixels was used.

The experiment begins with a "+" sign appearing in the center of the screen for 2 s. Then, a three-letter word is displayed in the middle of the screen for 2 s. Next, the group of three hexagons flashes for 5 s. Finally, 20 stimuli (i.e., five repetitions of four random stimuli) are presented one after another to identify the target character subgroup. Simultaneously, the black square located in the center of the screen also flashes (Figure 3).

2-3 Experiment Setup

In this experiment, two blocks were recorded from each participant, with each block consisting of 10 offline runs. In each run, three characters (three trials) and a total of 60 characters were written. The participant had to identify the target character group among the hexagons and focus on it while ignoring the other two groups. For example, in Figure 4, the target character is “mīm”, which belongs to the first group (right side). During SSVEP stimuli, attention should be directed to the frequencies corresponding to the right hexagon. Then, in the Triple RSVP stimulation, the participant focused on the group containing the target character and silently counted its occurrences. The target character appeared five times in a specific group and position across all repetitions, and the participant needed to focus on that position whenever they identified it. In Figure 4, the character “mīm” appears at the bottom of the square, and the participant had to focus their gaze exclusively on that location.

In each block, the rest time between two trials is 5 s, and between two runs is 7 s. subject can blink or swallow during this interval. After five runs, there is a short one-minute break.

Each SSVEP stimulus takes 5 s. With an inter-stimulus interval of 500 ms, the Triple RSVP stimulation begins. Each stimulus is displayed for 330 ms; thus, the total duration is 12 s (330 ms × 20 + 500 ms + 5 s = 12.1) for selecting one character. Each signal recording, including cap installation, electrode preparation, testing electrode connections after gel injection, takes between 1 to 1.5 hours to spell 60 characters.

2-4 Signal Recording

This experiment was recorded using an 80-channel g.Hlamp device (G.Tech company) with 19 active electrodes according to the international 10-20 system (Figure 5). The signal sampling rate was set at 512 Hz; all channels were referenced to the right earlobe with a ground reference (GND). The stimulation protocol was implemented in the Psychtoolbox environment in MATLAB, and signal analysis was also performed in MATLAB 2021a.

After signal recording, signal preprocessing was performed in the EEGLAB [29] toolbox under the MATLAB software environment. In this toolbox, a band-pass filter of 1 to 60 Hz was used to remove the DC level of the signal, and a notch filter was used to eliminate power line noise. Additionally, to remove blink and horizontal eye movement artifacts, motion artifacts (such as swallowing or neck movement), and heart rhythm, the Independent Component Analysis (ICA) algorithm [29] was used.

2-5 Data Segmentation

In the three-frequency SSVEP stimulation, 5 s of recorded signal are separated based on trigger moments. The data related to the Triple RSVP (for P300 component analysis) and single-frequency SSVEP are divided into epochs of different lengths separately. In the single-frequency SSVEP stimulation pattern, the duration of one trial (6.6 s) is considered as one epoch, as during this time, subject stares at a fixed direction. In the Triple RSVP stimulation pattern, to separate P300 and non-P300 data, the signal is divided into 1000 ms intervals based on the moment of each stimulus occurrence. Each trial contains five target stimuli and 15 non-target stimuli.

2-6 Feature Extraction

Separate methods are used for feature extraction from each pattern:

a) Feature Extraction in Three-Frequency SSVEP Method:

In the analysis of three-frequency SSVEP signals, the occipital lobe electrodes including O1, O2, Oz, and POz are recognized as the most important electrodes, although parietal lobe electrodes are also significant due to their role in visual processing and attention. To select the optimal channels, the Analysis of Variance (ANOVA) method is employed [31], where features from each channel with p-value < 0.05 are first selected, and then various combinations of these channels are evaluated using cross-validation to obtain the combination with the highest accuracy and the fewest number of channels. After selecting the optimal channels, the Power Spectral Density Analysis (PSDA) method is used to calculate the signal power at the stimulation frequencies and their harmonics according to equation (1). Finally, the frequency with the highest power in the signal power spectrum is considered as the SSVEP response. These methods enable the extraction of the most accurate SSVEP features with the minimum number of channels.

$$S_k = 10log_{10}\left(\frac{nP(f_k)}{\sum_{m=1}^{\frac{n}{2}} P\left(f_k + mf_{ref}\right) + P\left(f_k - mf_{ref}\right)}\right) \tag{1}$$

In equation (1), S_k is the spectral power in the range of the stimulation frequency, n is the number of neighboring points of the stimulation frequency, $P(f_k)$ is the power density of the stimulation frequency, and f_{ref} is the stimulation frequency. $P(f_k + mf_{ref})$ and $P(f_k - mf_{ref})$ are the power densities around the target frequency.

The number of neighbors is set to 6, and the stimulation frequencies are 6.0, 7.5, and 8.57 Hz. Two harmonics were considered in the feature extraction. The frequency spectrum related to the Oz channel around each of the stimulation frequencies is plotted in Figure 6. In each figure, the increase in amplitude at the corresponding frequency is clearly visible.

b) Feature Extraction in Single-Frequency SSVEP Pattern:

In single-frequency SSVEP analysis, the CCA method is used for feature extraction. This method identifies the optimal linear combination of channels for detecting the stimulation frequency by calculating the correlation between the EEG signal and sine/cosine waves and their harmonics at the target frequency [22].The CCA algorithm determines the canonical coefficients in matrices A and B for two signals X and Y such that the canonical correlation $r = [\rho_1, \dots, \rho_M]$, between the corresponding rows of the two signals AX and BY is maximized.

In the relation r, $\rho_i = \rho(\mathrm{a(i)X}, \mathrm{b(i)Y})$is the i-th canonical correlation (where ai and bi are the i-th rows of A and B, respectively), and $M = min(\mathrm{rank}(X)\ , \mathrm{rank}(Y))$.Also, the vectors X and Y are the EEG and reference signals, respectively. According to equation (2), the reference signals are considered as a 15 Hz sine-cosine signal:

$$Y = \begin{bmatrix} \sin(2\pi ft) \\ \cos(2\pi ft) \\ . \\ . \\ \sin(2\pi N_h ft) \\ \cos\,(2\pi N_h ft) \end{bmatrix} \qquad (2)$$

$$t = \left[\frac{1}{f}, \frac{2}{f}, \dots, \frac{N}{f}\right]$$

Where f is the SSVEP stimulation frequency (15 Hz here), N_h is the number of harmonics, and N is the total number of data in each run. The matrices A_c and B_c are calculated to maximize the correlation between the corresponding rows of the two matrices A_cX and B_cY for each of the three classes $C = 1,2,3$. All runs when the subject looks at the target c are concatenated and sent to a CCA, and the matrices A_c and B_c are calculated for each target C. Then, the correlation coefficients between A_cX and the reference signals B_cY are calculated. These correlation coefficients are concatenated to form a feature vector. Finally, a feature vector with a length of $\mathrm{C} \times \mathrm{M}$ is obtained, where C is the number of classes ($C = 3$) and M is the minimum number of channels and the number of the sine and cosine harmonics ($M = 6$). Using these features, a three-class classifier can be trained.

In the system evaluation step with new data, the correlation coefficients of the data are first calculated using 3 filters $(A_c X)$ and the reference signal $(B_c Y)$. These values are applied as a feature vector to the classifier. The classifier output predicts the direction the subject is staring at.

c) Feature Extraction in Triple RSVP Pattern:

In this study, EEG signals were initially preprocessed using a Common Average Reference (CAR) filter to remove common noise between channels [33], [34], followed by bandpass filtering between 1-25 Hz. For feature extraction, 1900 features were generated from the amplitude of time samples at a 100 Hz sampling rate across 19 channels. Additionally, Discrete Wavelet Transform (DWT) using Daubechies mother wavelet at four levels produced 608 features from delta, theta, alpha, and beta frequency bands. Given the high dimensionality of features (2508 features per epoch), the SFFS algorithm iteratively selected the optimal feature subset based on accuracy criteria to prevent overfitting [35]. This approach not only effectively reduced data dimensionality and improved processing speed, but also significantly enhanced the classification accuracy of P300 stimuli.

2-7 Classification

A separate classifier was used for each stimulus.

a) In the three-frequency SSVEP method, using the PSDA algorithm, the total spectral power around the three frequencies 0.6, 5.7, and 57.8 and their second harmonic is calculated in each trial. In each trial, the data belongs to the class that has the highest power in the range of the stimulation frequency and its harmonic.
b) In the single-frequency SSVEP method, the Support Vector Machine (SVM) algorithm [36] was used for classification. The SVM algorithm is one of the powerful techniques in machine learning and is specifically designed to solve binary classification problems, but it is generalized for multi-class problems using the one-vs-one (OVO) technique. Since three classes are defined in this SSVEP pattern, three SVM models will also be trained.

SVM uses kernels such as RBF to transform data into a higher-dimensional space for modeling nonlinear problems. The model’s performance depends on two parameters: C, which controls the error tolerance, and γ, which determines the complexity of the decision boundary. Large values of these parameters lead to complex decision boundaries and increase the risk of overfitting, while small values result in a simpler model with higher chances of underfitting [37]. Optimizing these parameters is essential for balancing accuracy and generalizability.

In this research, the grid search method was used in the SVM model to find the optimal values of parameters C and γ within the range of 0.1 to 100,000. The process involved calculating accuracy for different values and gradually adjusting the ranges until no further improvement in accuracy was observed. The final values of these parameters were calculated individually for each participant in single-frequency SSVEP classification.

c) In ERP-based EEG signal processing, a linear SVM was employed for P300 and non-P300 data classification. Given the importance of temporal information, features were typically extracted from either the raw signal or its reduced version, resulting in high-dimensional feature vectors. SVM was chosen for its effective performance in high-dimensional spaces and optimal decision boundary determination. In this study, the linear SVM method was used for binary classification, with parameter C being individually tuned for each participant through cross-validation.

After the stage of optimal feature extraction and selection with dimensions of 300×N_O for the target class and 900×N_O for the non-target class (N_O, Total number of selected optimal features), the challenge of data imbalance between P300 and non-P300 classes was addressed [38]. To solve this problem, the Pasting method was used [39], where the non-P300 class data was divided into three equal subsets of 300 samples each. Then, three separate SVM models were trained, with each model incorporating all the P300 class data along with one subset of the non-P300 class data. For the final classification, a soft voting method was employed, where the distance to the decision boundary was considered as probability. For every 20 stimuli, the sum of the models' predictions was calculated, and the final target was determined based on the highest probability (a summary of the steps is provided in Figure 7).

2-8 Evaluation

To evaluate the proposed protocol, Leave-One-Out Cross-Validation (LOOCV) was used by dividing the data into 60 parts, where in each iteration one part served as test data and 59 parts were used for model training, with the final accuracy calculated from the average of all iteration results. In addition to the accuracy metric, the system's performance was evaluated using ITR, which is a key metric in BCI studies and speller systems that measures the amount of information transferred per minute, calculated according to equation (3):

$$ITR = \left\{log_2^N + Plog_2^P + (1-P)log_2^{\frac{1-P}{N-1}}\right\}/T \qquad (3)$$

In this relation, N is the number of classes, P is the classification accuracy, and T represents the time to select a character in minutes.

3- Results

In single-frequency SSVEP analysis, EEG signal power topography for the highest-accuracy participant revealed maximum activity in occipital regions. According to Figure 8, right-side stimulation had the greatest effect, where gazing right (left visual field) increased right hemisphere activity and gazing left (right visual field) enhanced left hemisphere activity. Downward gaze distributed signal power toward the centro-occipital area. These findings align with previous studies [7].

The average ERP of brain signals related to the P300 and non-P300 components for the Cz and Pz channels is plotted in Figure 9. This component has the highest amplitude in the range of 300-350 ms after the onset of stimulation.

The evaluation results of the proposed protocol, including the calculated accuracy and ITR metrics for all subjects, are presented in Table 2. In this system, the average accuracy is 91.2%, and the ITR is 21.5 bits/min. Most subjects achieved an accuracy close to 90% and an ITR of 20 bits/min.

To analyze the performance of the proposed system, the accuracy and ITR in terms of the number of repetitions for each subject are shown in Figures 10 and 11. It is evident that accuracy increases with the number of repetitions. In the case of ITR, because the first 5 s of the experiment are fixed across all repetitions and each repetition takes 1.32 s, the time required for spelling characters at lower repetitions is not very short. Consequently, with an increase in the number of repetitions, ITR does not decrease but rather increases due to the improvement in accuracy. Additionally, the average accuracy and ITR values obtained from all subjects in terms of the number of repetitions are provided in Table 3. The highest ITR is achieved using five stimulation repetitions. Considering the classification of 36 classes, the chance level is 2.7%, and with just one trial repetition, an accuracy higher than chance accuracy (35.95%) is achieved. Furthermore, the average three-frequency SSVEP accuracy for all participants is 98.80%.

The analysis results using repeated-measures ANOVA across repetitions 1 to 5 (Table 3) revealed statistically significant differences in both accuracy and ITR.

$$\begin{aligned} &\text{For accuracy: } F(4,24) = 148.59, p < 0.001, \eta^2 = 0.96 \\ &\text{For ITR:} F(4,24) = 92.34, p < 0.001, \eta^2 = 0.8 \end{aligned} \tag{4}$$

All pairwise comparisons were also significant (p<0.01), with the maximum performance improvement (55.2%) observed between repetitions 1 and 5. The non-zero 95% confidence intervals confirm these findings, demonstrating systematic and non-random performance enhancement with increasing repetitions.

According to Table 5 results, accuracy improved in both single-frequency SSVEP and triple RSVP paradigms as the number of repetitions increased. In the protocol design, the on/off time for hexagons in the triple-frequency SSVEP was set to 5 seconds, which reduced ITR due to its extended duration. Findings from Table 6 demonstrate that when stimulation duration was reduced to 4 seconds, 90.5% accuracy and 25.37 ITR were achieved - maintaining comparable accuracy while yielding higher ITR than reference [7].

The current study identified increased theta waves and decreased alpha waves as indicators of mental fatigue through analysis of EEG signals from the Fz channel (sensitive to cognitive changes). The results showed that fatigue leads to reduced concentration (increased theta) and impaired mental relaxation (decreased alpha), which aligns with previous findings about the role of these waves in alertness and cognitive balance.

3-1- Comparasion with state-of-the-art approaches

A comparative study was conducted to assess the performance of this study in terms of accuracy, ITR, the number of characters spelled during algorithm training, the number of characters in the protocol, time required to spell one character, the number of participants, and the spelled word during the experiment in comparison to other studies. The performance of othe approaches is listed in Table 6. By comparing the results obtained from accuracy, it can be concluded that the proposed protocol has achieved an accuracy close to other studies, while the ITR rate is even higher than 27-character protocols.

In this research, EEG signals were recorded only once from each participant; 60 characters were spelled in each recording. As a result, we encountered with the lack of data for model training. However, in most studies, signal recording is performed several times and on different days. As a result, in addition to increasing the amount of training data, participants become familiar with the recording process and the position of characters in the protocol, leading to better results in test data. In the proposed protocol, like most studies, 36 characters were used on the virtual keyboard. Increasing the number of characters increases the duration of the experiment, but the duration of this experiment is lower than all 36-character protocols [8], [11], [12], [16].

Although the Persian speller based on SSVEP has a shorter execution time, spelling in this protocol is based on Braille, and there are few people who can master this language [16]. In the combined SSVEP and TripleRSVP paper, despite using 27 characters and applying 9 stimuli in each repetition, 45 stimuli appear in 10.5 seconds, resulting in an ITR of 23.4[7]. Implementing this protocol on Persian letters, despite having 36 characters, 12 stimuli appear in each repetition, which with 5 repetitions and displaying 60 stimuli requires 14 seconds. Using the designed two-part protocol, we were able to reduce the experiment time to 12 seconds, and in each repetition of the protocol in the triple RSVP stimulus pattern, 4 stimuli appear, which with 5 repetitions displays 20 stimuli. This method reduces user fatigue. In addition to reducing spelling time, we were able to achieve a higher ITR compared to the combined SSVEP and TripleRSVP paper. Based on Table 7 and the comparisons made, the superiority of the proposed model over other models is proven.

4- Conclusion and Discussion

The historical progression of BCI spellers reveals that early systems based on P300 matrix paradigms faced fundamental limitations including low SNR and demanding visual focus requirements [8]- [13]. Alternative approaches such as SSVEP [16]–[20] and RSVP [25]–[27] were developed, yet each presented distinct challenges: SSVEP implementations were constrained by class number limitations while RSVP paradigms suffered from prolonged experimental durations.

The introduction of Triple-RSVP [28] significantly reduced experimental time, representing an important advancement. However, the presence of non-target P300 components in this paradigm led to decreased classification accuracy. The hybrid SSVEP and Triple RSVP approach [7] successfully combined the advantages of both paradigms, enabling target group identification through P300 components while utilizing SSVEP for precise character position determination.

Triple RSVP alone improved ITR but reduced accuracy, whereas single RSVP offered high accuracy with low ITR. The hybrid Triple RSVP+SSVEP protocol achieved better balance, though longer experiment durations led to user fatigue and negative performance impacts.

To address the challenges and limitations of existing protocols, we propose an innovative recording framework in this study. This protocol consists of two key components:

- Stimulation of Three-Frequency SSVEP: In this subsection, 36 characters (32 Persian letters and four symbols) are divided into three groups of 12 characters. For a duration of 5 s each of these three groups lights up at a fixed and different frequency (6.0, 7.5 and 8.57 Hz), the target group is identified using the PSDA Algorithm which calculates the spectral power around the stimulation frequencies and their harmonics. The SSVEP frequency is defined as the frequency of the most dominant power present around the stimulation frequency and its harmonics.

- The hybrid Triple RSVP + SSVEP paradigm: In this paradigm the each group of 12 characters will be to four subgroups of three characters. Each subgroup has three characters written around a flashing square. The target subgroup and the direction of target character in the square is distinguished using two different stimulation paradigms. Subgroup stimuli were shown via the Triple RSVP paradigm (see Supplementary material for more details). For each iteration of the Triple RSVP paradigm, four stimuli are presented. The target character in the flashing square is recognized simultaneously by the SSVEP stimulation paradigm. The arrangement of characters and subgroups is kept the same across each trial and is presented to the user in five random trials. For each character in this section, a total of 20 stimuli are applied to spell the character.

A P300 component identification and target subgroup are detected from features extracted from wavelet transform and time-domain sampled signal data and used by the SVM algorithm in a newly formulated Triple RSVP paradigm. Then, based on the single-frequency SSVEP stimulation signal via the CCA algorithm, the feature vector is obtained and applied to a three-class nonlinear SVM algorithm corresponding to the right direction of the target character in the square. So the character of interest is identified by finding both the target subgroup and the target position within this subgroup. The proposed protocol achieved an accuracy of about 91.2% and an ITR of 21.5 bits/min with five iterations of the algorithm within a time period of 12 s. The accuracy obtained from the proposed protocol is not far from that in paper [7]. In paper [7], the ITR is 23.4 bits/min, but when the duration of the three-frequency SSVEP stimulation is set to 4 s, the ITR rises to 25.37 bits/min, representing an approximate increase of 2 bits/min. Although the number of characters increases significantly, our protocol also maintained a desirable level accuracy while improving ITR and spelling speed. The study confirms a robust communication transceiver for spelling words after combining these paradigms.

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Author Biography:

Fatemeh Javaheri received her bachelor's degree in Electrical Engineering in 2019 and her master's degree in Biomedical Engineering in 2024 from Hamadan University of Technology. Her areas of interest include brain-computer interfaces, biomedical signal processing, and rehabilitation engineering.

Mohammad. B. Khodabakhshi received his Bachelor's degree in Biomedical Engineering from Shahed University in 2008. He also received his Master's and Ph.D. degrees in 2011 and 2017 from Iran University of Science and Technology and Amirkabir University of Technology, respectively. Dr. Khodabakhshi also served as a researcher at Technology Services Complex at Sharif University of Technology. In 2023, he joined the faculty of Shahed University, Tehran, Iran, where he is currently an Assistant Professor in biomedical engineering. His research interests include biological signal and image analysis, deep neural networks, and their applications in the medical signal and image processing.

Rasool Baghbani received the B.S. degree in electrical engineering from Bu-Ali Sina University, Hamedan, Iran, in 2003, the M.S. degree in biomedical engineering from Esfahan University, Isfahan, Iran, in 2006, and the Ph.D. degree from Amirkabir University of Technology, Tehran, Iran, in 2018. He is currently an Assistant Professor with the Biomedical Engineering Department, Hamedan University of Technology (HUT), Hamedan. His research interests include bioimpedance measurement, bioinstruments, noninvesive measurement, and biomedical signal processing.

Figure Captions

Figure (1). (a) The direction of the characters in the square is determined by their positions in the hexagon.(b) In three directions, a flashing square displays three characters in a specific order.

Figure (2). An overview of the two-part protocol: Part 1 involves grouping the 36 available characters into 3 groups of 12 characters each and presenting stimuli using the SSVEP pattern. Part 2 involves further categorizing the 12 characters in each group into 4 subgroups of 3 characters each and presenting stimuli using a combined SSVEP and Triple RSVP pattern.

Figure (3). In each trial, a '+' sign is displayed for 2 s, followed by the word to be spelled for 2 s, and then the target character is displayed for another 2 s. After 5 s of displaying the three-frequency SSVEP stimuli, the three-sequence RSVP stimulation appears

Figure (4). The process of selecting a character in the registration protocol

Figure (5). Electrode locations according to the 10-20 system. The occipital channels (marked with red circles) are used for SSVEP analysis, while the other channels are employed for P300 analysis.

Figure (6). The frequency spectrum chart is plotted using the Oz channel data. (a) Frequency spectrum corresponding to 6.0 Hz, (b) Frequency spectrum corresponding to 7.5 Hz, (c) Frequency spectrum corresponding to 8.57 Hz.

Figure (7). The process of training the SVM algorithm and evaluating the method with new data.

Figure (8). The SSVEP power topography is plotted for three classes.

Figure (9). The average ERP of brain signals for all participants. (a) Average ERP at channel Cz (b) Average ERP at channel Pz.

Figure (10). The accuracy (%) in terms of the number of repetitions for each subject.

Figure (11). The ITR (bits/min) in terms of the number of repetitions for each subject.

Figure (12). A comparative analysis of theta (4-8 Hz) and alpha (8-12 Hz) wave patterns during the first character (non-fatigue condition) versus the last character (fatigue condition) spelling tasks, recorded from the Fz channel.

Table Captions

Table (1). How to categorize the 36 characters available in the design of the spelling protocol.

Table (2). The accuracy obtained from character spelling and ITR has been calculated for each subjects.

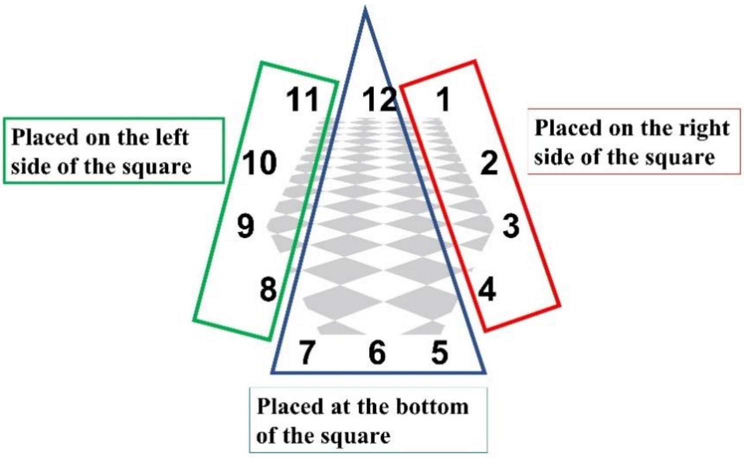
Table (3). Average accuracy (%) and ITR (bits/min) in terms of the number of repetitions.

Table (4). Results of pairwise comparisons across five repetitions for accuracy and ITR. Values represent mean difference , p-values, and 95% confidence intervals. All comparisons were performed using paired t-tests with Bonferroni correction.

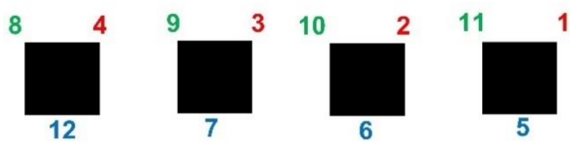
Table (5). Average accuracy (%) of Triple RSVP and SSEVP in terms of the number of repetitions.

Table (6). The accuracy and ITR obtained from spelling words at different times for the three-frequency SSVEP stimulus

Table (7). Comparison of other studies with the proposed approach



A



b

Figure (1).

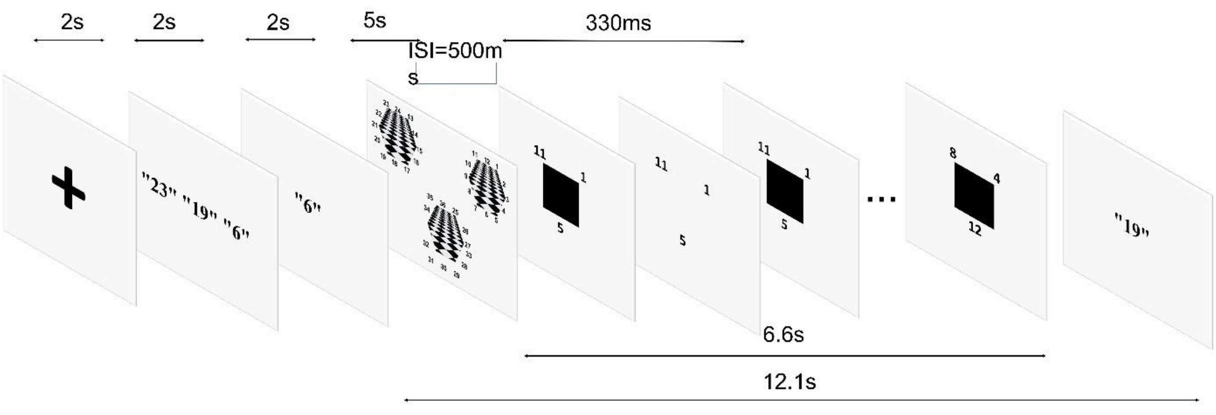


Figure (2).

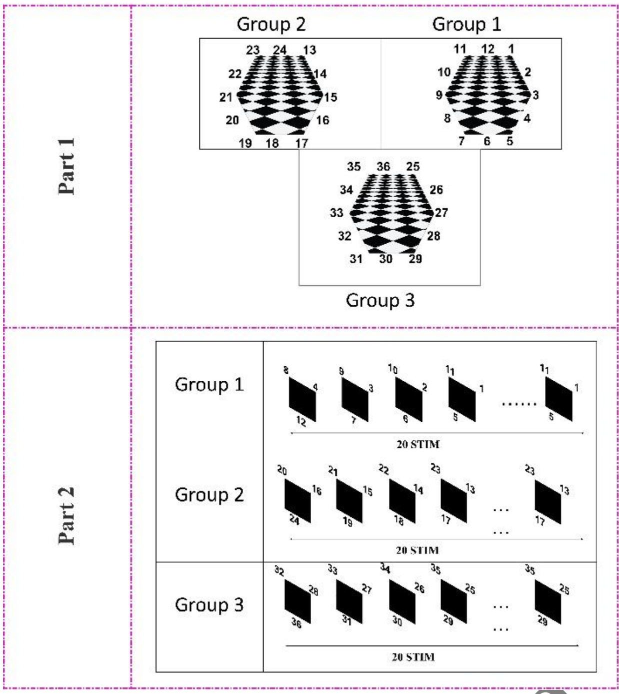


Figure (3).

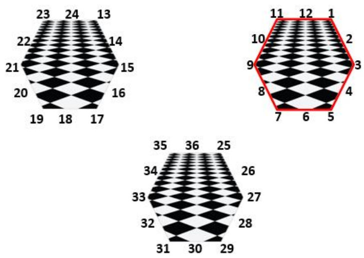
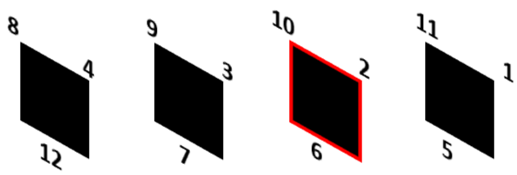
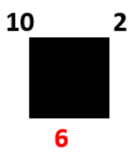
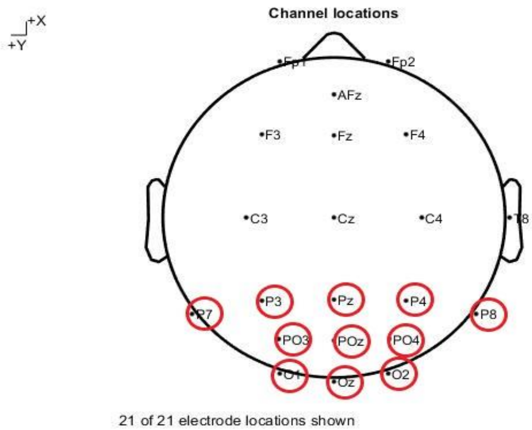
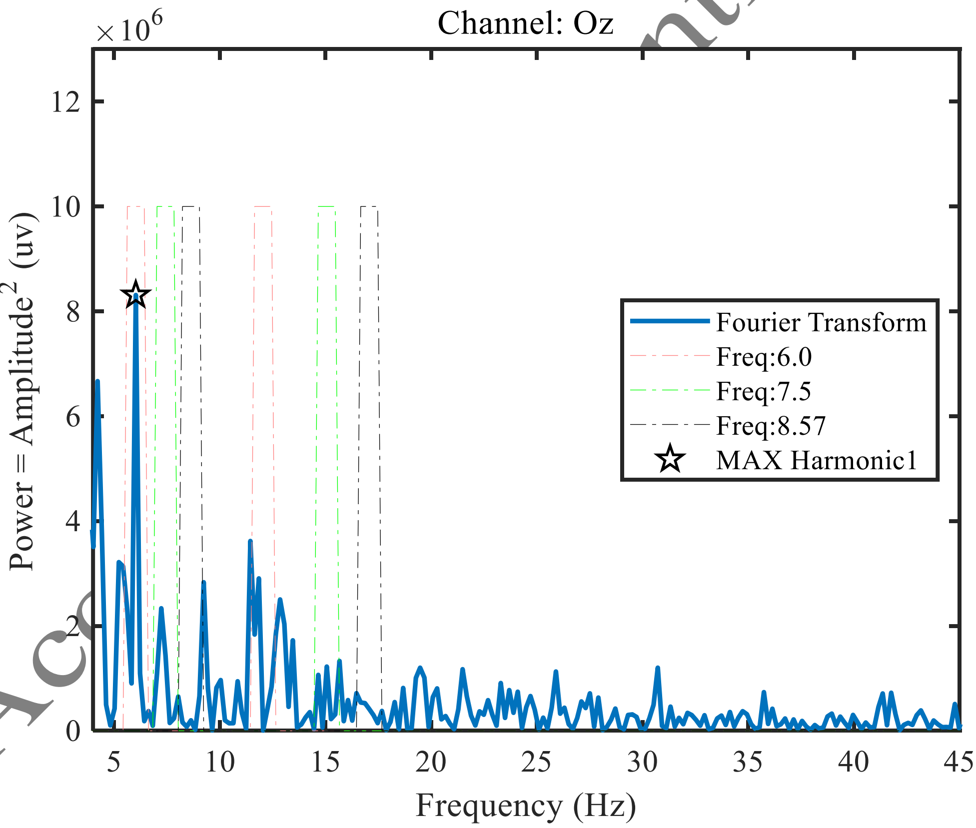
Target word	"m" "gh" "z"
Target character	m(Mim)
SSVEP three-frequency stimulus	
Triple RSVP stimulus in a single trial	
SSVEP single-frequency stimulus	

Figure (4).



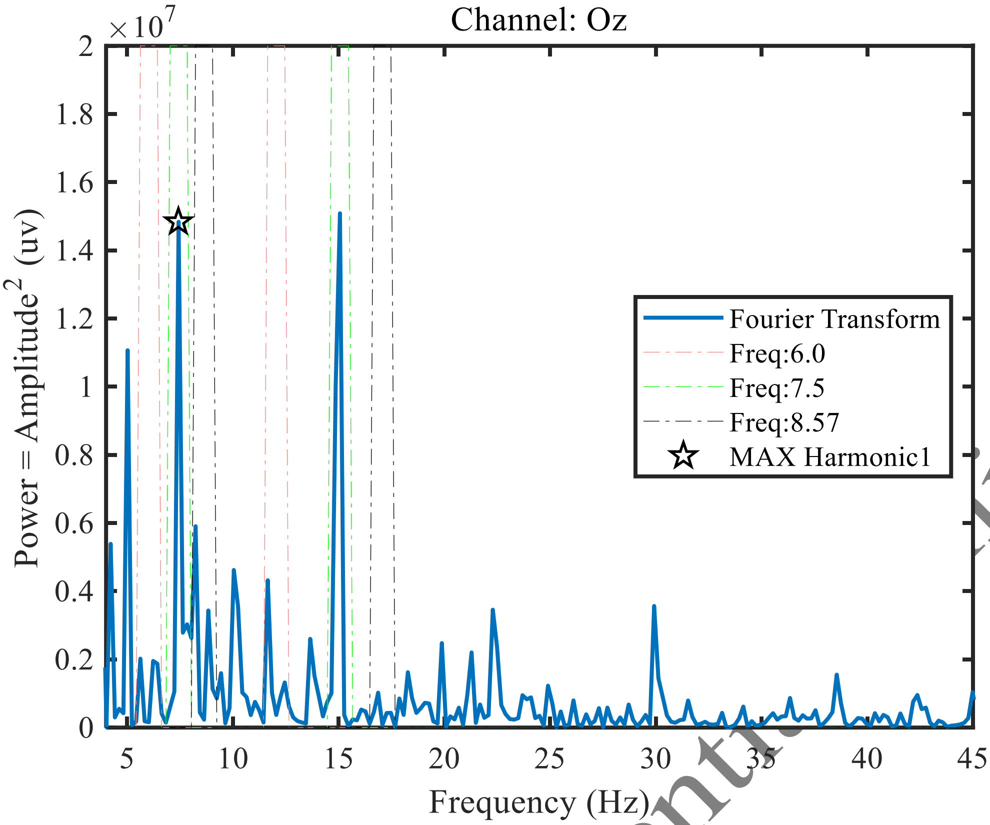
+X
+Y
Channel locations
Fp1
Fp2
AFz
F3
Fz
F4
C3
Cz
C4
T8
P7
P3
Pz
P4
P8
PO3
POz
PO4
O1
Oz
O2
21 of 21 electrode locations shown

Figure (5).

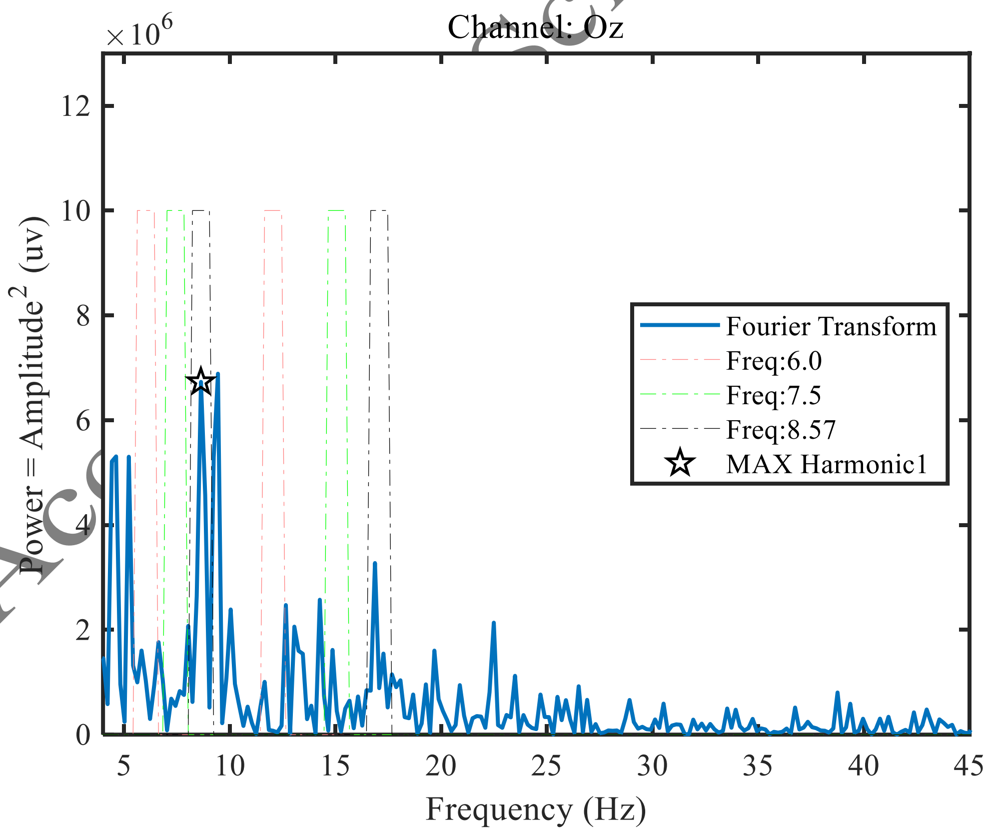


Channel: Oz
$\times 10^6$
12
10
8
6
4
2
0
Power = Amplitude^2 (uv)
5
10
15
20
25
30
35
40
45
Frequency (Hz)
Fourier Transform
Freq:6.0
Freq:7.5
Freq:8.57
MAX Harmonic1

(a)


Channel: Oz
×10^7
Power = Amplitude^2 (uv)
Frequency (Hz)
Fourier Transform
Freq:6.0
Freq:7.5
Freq:8.57
MAX Harmonic1

(b)


Channel: Oz
×10^6
Power = Amplitude^2 (uv)
Frequency (Hz)
Fourier Transform
Freq:6.0
Freq:7.5
Freq:8.57
MAX Harmonic1

(c)

Figure (6).

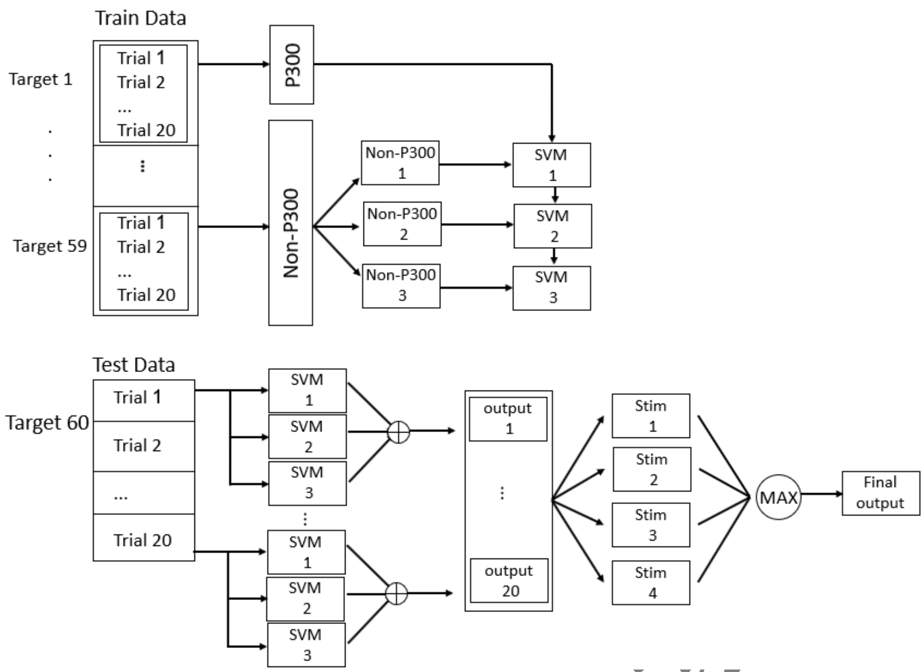


Figure (7).

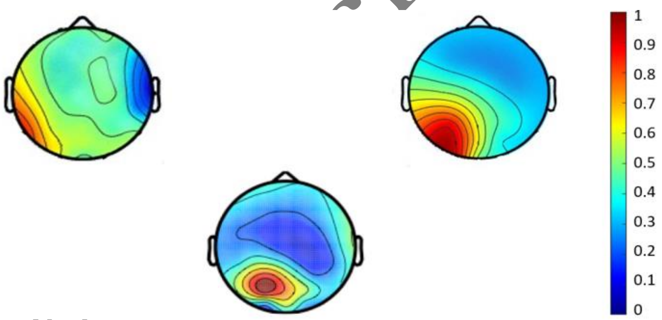
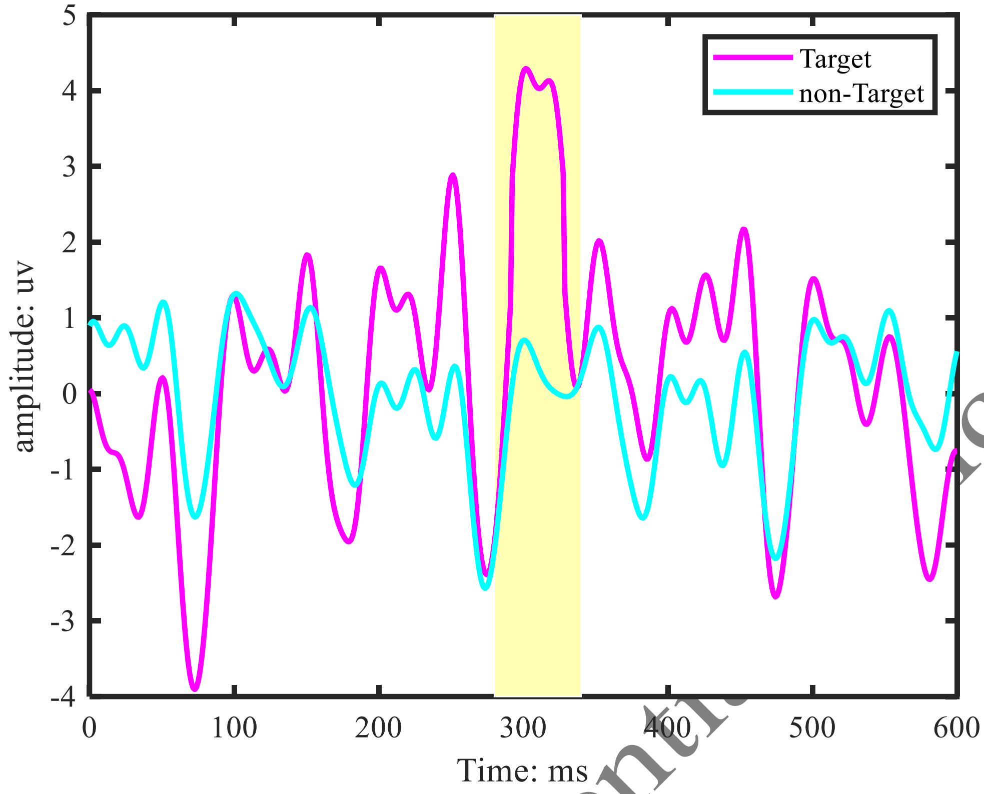
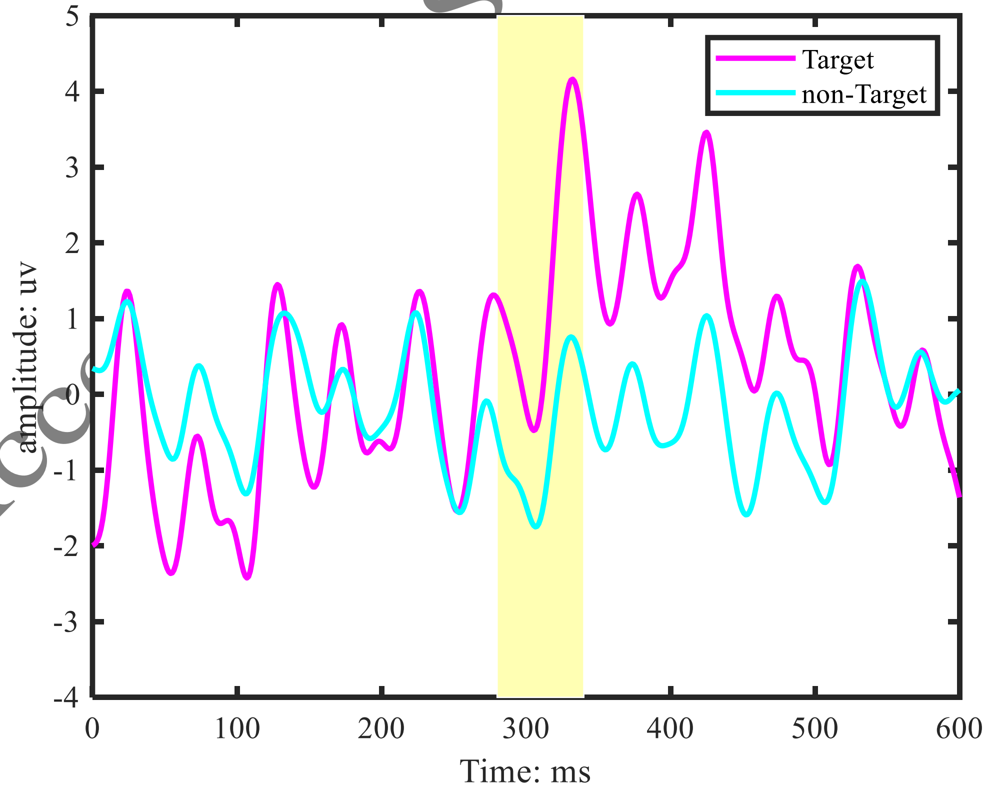


Figure (8).


5
4
3
2
1
0
-1
-2
-3
-4
amplitude: uv
Target
non-Target
0
100
200
300
400
500
600
Time: ms

(a)


5
4
3
2
1
0
-1
-2
-3
-4
amplitude: uv
Target
non-Target
0
100
200
300
400
500
600
Time: ms

(b)

Figure (9).

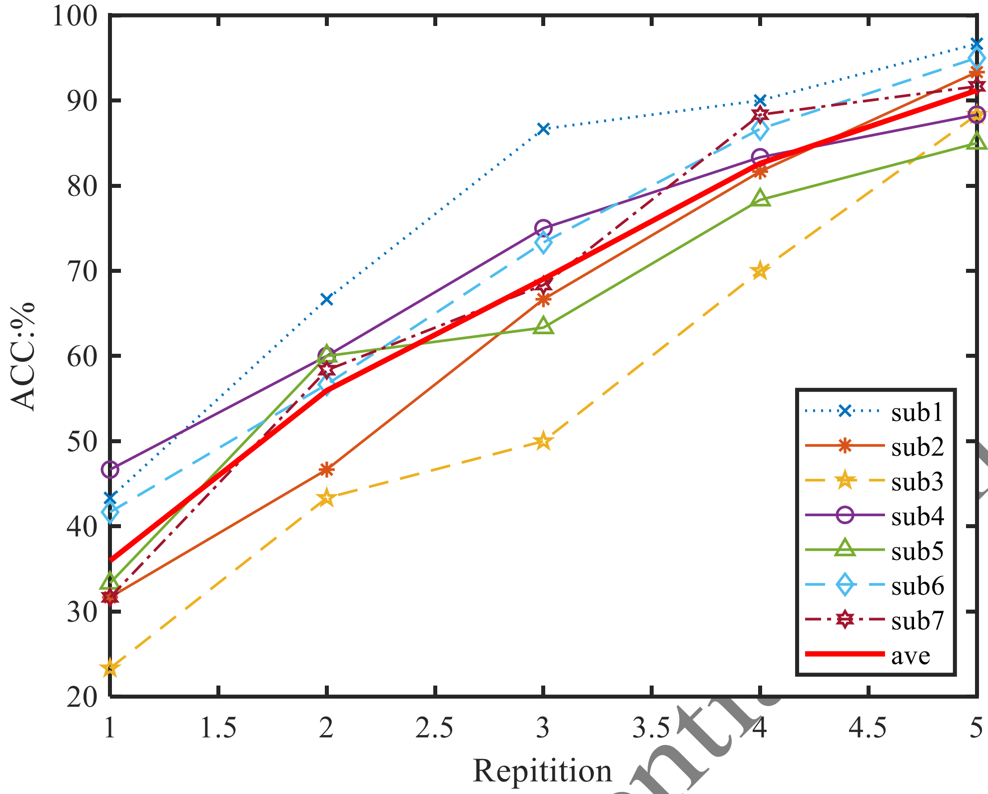


Figure (10).

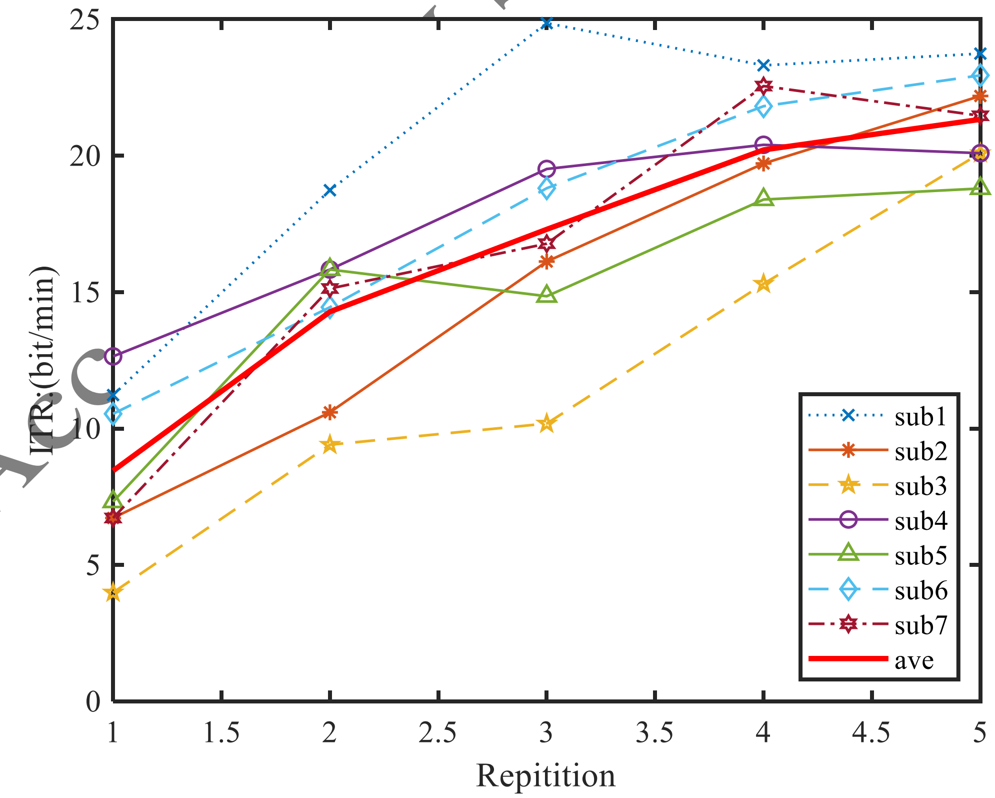


Figure (11).

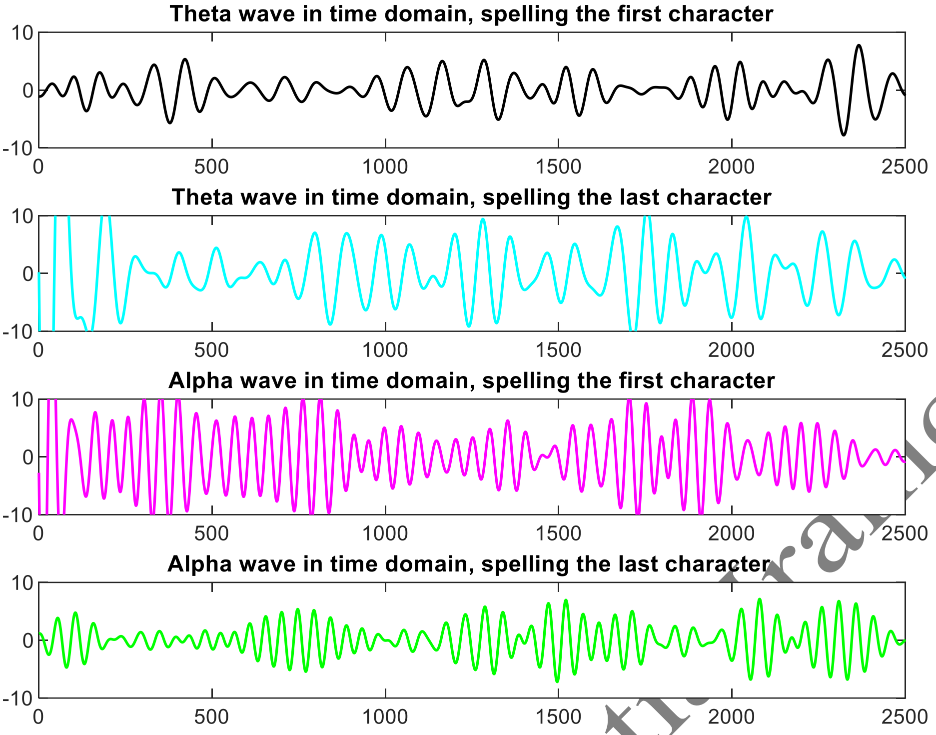

Theta wave in time domain, spelling the first character
Theta wave in time domain, spelling the last character
Alpha wave in time domain, spelling the first character
Alpha wave in time domain, spelling the last character
10
0
-10
0
500
1000
1500
2000
2500

Figure (12).

Table (1)

groups	characters
1	(1-12) alef, ke, re, se, dal, he, ʻain, mim, se, tah, vav, lam
2	(13-24) ., gaf, ze, zhad, zhe, je, ghin, nun, khe, zha, be, fe
3	(25-36) pe, se, zhe, ?, te, che, -, ye, she, !, he, qaf

Table (2).

subjects	ACC(%)	ITR(bit\min)
Sub1	96.66	23/94
Sub2	93.33	22.37
Sub3	88.33	20.26
Sub4	88.33	20.26
Sub5	85	18.95
Sub6	95	23.13
Sub7	91.66	21.64
average	**91.2**	**21.5**

Table (3).

Num of repetitions	Acc (%)	ITR (bits/min)
1	35.95	8.45
2	55.95	14.28
3	69.05	17.30
4	82.62	20.21
5	91.19	21.32

Table (4).

	ACC			ITR		
Repetition	Diff	pValue	95% CI	Diff	pValue	95% CI
Rep1 vs 2	-20	0.0005	[-28.07, -11.92]	-5.82	0.0030	[-9.07, -2.58]
Rep1 vs 3	-33.1	3.03E-05	[-41.21, -24.97]	-8.84	0.0005	[-12.47, -5.29]
Rep1 vs 4	-46.67	5.37E-06	[-55.18, -38.14]	-11.76	8.32E-05	[-15.19, -8.32]
Rep1 vs 5	-55.23	9.10E-06	[-66.27, -44.20]	-12.87	0.0001	[-17.06, -8.68]
Rep2 vs 3	-13.1	0.01056	[-22.39, -3.79]	-3.02	0.11	[-6.72, -0.69]
Rep2 vs 4	-26.67	8.67E-05	[-34.50, -18.82]	-5.93	0.0023	[-9.07, -2.78]
Rep2 vs 5	-35.24	0.0001	[-47.09, -23.38]	-7.05	0.0074	[-11.72, -2.38]
Rep3 vs 4	-13.57	0.0058	[-22.13, -5.01]	-2.91	0.0108	[-6.478, -0.65]
Rep3 vs 5	-22.14	0.004	[-35.20, -9.07]	-4.03	0.0121	[-9.13, -1.06]
Rep4 vs 5	-8.57	0.0226	[-15.72, -1.43]	-1.11	0.2593	[-3.90, -1.66]

Table (5).

Num of repetitions	**RSVPAcc. (%)**	**SSVEP Acc. (%)**
1	63.80	44.99
2	72.61	60.94
3	78.80	76.90
4	85.24	88.56
5	93.57	95.23

Table (6).

Time(s)	**Acc (%)**	**ITR (bits/min)**
2	83	24.3
3	87.95	24.13
4	90.5	25.37
5	91.19	21.32

Table (7).

Pattern	Acc (%)	ITR (bit\min)	Num Trials	Num Character	Time (s)	Num sub	Spelled Word	Ref
ERP	95	10.68	1020	36	26	4	BRAIN	[8]
	88.21	6.74	150	36	36	4	Random Persian Words	[11]
	89.7	6.2	55	36	40	5	scoring, fellow countrymen, visual, former news, hot, influencer, greasy, housing, Thursday, effective, pool.	[12]
SSVEP	90	20.7	210	36	8.36	-	Seek knowledge from the cradle to the grave	[16]
	89	14.7	144	48	62	20	I LIVE IN KOREA	[18]
RSVP	91.85	2.62	40	27	90	55	SUBJECT, NEURONS, IMAGINE, QUALITY	[26]
Triple RSVP	79	20.2	-	36	37.5	13	-	[28]
Triple RSVP +SSVEP	93.6	23.4	72	27	10.5	6	GLI,DFN,EPT,DRB,TAS,AKX,FGY,RWS, BWP,QHW,USC,VQV,LZX, FYM,BJX,UUQ	[7]
Proposed Protocol	90.5	25.37	60	36	11	7	brain, shell, palm, war hammer, perfume, dog receipt, Peugeot, size, memorization, food, print, discussion, corn candle,sharp,story, night.	

Appendix

	Persian Letter	Latin Name	English Equivalent
1	ا	alef	a
15	ب	beh	b
25	پ	peh	p
36	ت	teh	t
33	ث	seh	s
20	ج	jeh	j
32	چ	cheh	ch
8	ح	heh	h
17	خ	kheh	kh
9	د	dal	d
21	ذ	zāl	z
11	ر	reh	r
23	ز	zeh	z
35	ژ	zheh	zh
5	س	seh	s
29	ش	sheh	sh
10	ص	sah	s
22	ض	zah	z
4	ط	tah	t
16	ظ	zah	z
7	ع	'ain	’
19	غ	ghain	gh
14	ف	feh	f
26	ق	qāf	gh
12	ک	kāf	k
24	گ	gāf	g
2	ل	lām	l
6	م	mīm	m
18	ن	nūn	n
3	و	vāv	v
27	ه	heh	h
30	ی	ye	y
34	؟		
28	!		
31	-		
13	.		