# P300 Classification in the RSVP Experiment Using DeepCNN and Convex Optimization

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## A B S T R A C T

Background: P300 potential is evoked as a positive peak in electroencephalography (EEG) signal around 300 ms after visualizing the target visual stimulus. Target stimulus is the expected picture in one's mind. Classification of the target stimulus of characters from non-target characters is the subject of brain-computer interface (BCI) speller systems, enabling paralyzed subjects to write their mind. Therefore, developing algorithms for detection of the P300 evoked potentials (EPs) is an important task in this regard.

Objective: The objective of this article is to propose an imaging-based method of P300 classification using convex optimization and deep convolutional neural network (deepCNN).

Material and Methods: In this methodological and experimental paper we used the EEG data from a recent published experiment called rapid serial visual presentation (RSVP), during which the subjects were continuously shown different three-character images in each trial. We applied our deepCNN classifier to the high resolution images, the time-electrode amplitude color-map of the denoised EEG signals, in 0.9 s duration from the start of each stimulus. To increase the classification accuracy, we used a convex optimization based denoising method to suppress high frequency transients in order to better visualize the low frequency P300 potentials.

Results: Our proposed method on the EEG data of 6 healthy subjects led to an average P300 classification accuracy of 95.43 %.

Conclusion: Our accuracy result is comparable to those obtained using manual feature extraction and classification methods; despite the deepCNN with an internal feature extraction block is simpler, which makes it suitable to be used in P300-based BCI speller systems.

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Keywords: Brain-computer interface; Convex optimization; Deep convolutional neural network; electroencephalogram; P300 evoked potential

## 1. INTRODUCTION

Brain-computer interface (BCI) systems aim at facilitating the life of paralyzed people by reading their mind through their electroencephalogram (EEG) signals, and transforming the derived information to useful control commands for rehabilitation of the paralyzed subjects, enabling them to move again, write with their mind, and control the surrounding devices [1].

Analyzing EEG signals for the aforementioned BCI applications means to detect meaningful potentials like readiness potential (RP) [2, 3], P300 evoked potential (EP) [4], steady state visual evoked potential (SSVEP) [5], and so on. RP is emerged in the EEG signal by movement intention or imagination [2, 3]. It is a slow potential in the delta frequency range with a negative ramp starting about 400 ms before the movement onset [3]. Accurate detection of the RP for the purpose of neuromodulation of paralyzed subjects is the subject of many studies [6-8]. SSVEP is detected as an oscillatory signal in the EEG occipital electrodes when the subject looks at a flickering stimulus [5]. The EEG signal oscillates at the frequency of the flickering visual stimulus [9]; hence, different images showing at diverse flickering frequencies at each time can be discriminated by their different oscillations in the EEG signals. P300 potential is evoked as a small positive peak (smaller than 10 μV) around 300 ms after watching a target stimulus image [3]. The target stimulus is the expected or predefined image in one's mind. The stimulus image which is used in the BCI speller systems is made up of characters [10, 11]. The target character in the subject's mind, while watching different consecutive characters in an EEG experiment, is recognized when the P300 is evoked and detected from the subject's EEG signal. P300 is better detected in the central and parietal electrodes [4]. Our focus in this study is to propose a P300 classifier for a recent BCI speller experiment [11].

In most studies the classical oddball paradigm is designed for P300 detection [10], in which a matrix of characters is presented to the subject and the subject expects a predefined character in each trial from the consecutive flickering rows or columns of characters. The authors in a recent P300-SSVEP based study [11] proposed an experiment, called rapid serial visual presentation (RSVP), for detection of the target stimulus, a three-character image by P300 classification and the target character by SSVEP analysis. Each of the 9 different three-character stimulus images is defined as a flickering square with three English letters on three sides; left, bottom, and right. At the beginning of a trial, the subject is shown the target stimulus and the target character (English letter). The EEG data from this experiment is less prone to eye movement compared with the oddball paradigm since the subject gazes at a predefined location and the flickering square has less distraction than the flickering rows or columns of characters used in the oddball experiment. Having EEG with less artefact leads us toward a more accurate P300 classification in real-time applications. From this experiment, the authors detected the target stimulus by P300 classification using time samples and wavelet coefficients as features and regularized linear discriminant analysis (RLDA) as classifier, and achieved average 96.29% accuracy. From the detected three-character stimulus, they detected the target character by analysing the direction of the subject's sight from the oscillatory SSVEP signals in the occipital and parietal electrodes, elicited by the flickering stimulus. Extracting the canonical correlation features [12, 13] around the harmonics of the flickering frequency (15 Hz) in three locations; left, central, and right parietal and occipital electrodes and a trained SVM classifier determined the target direction, and the corresponding target character. The reader is referred to [11] for more details.

Our purpose in this study is to propose an imaging based method of P300 detection using deep convolutional neural network (deepCNN) on the EEG data from the aforementioned study.

Compared with other machine learning approaches, deepCNN does not need manual feature extraction since it has the feature extraction block in its heart [14]. That's why we plan to evaluate its performance for P300 classification. This method has been used for P300 classification in an oddball experiment [15, 16]. We plan to use it in an RSVP experiment from a new perspective. We derive the matrix of EEG signals as an image, time-electrode amplitude color-map, in the 0.9 s duration from each stimulus image in a trial of the experiment. The reason for this is that P300 signals peak strikingly in the central, parietal, and occipital electrodes around 300 ms after watching the target stimulus [4], and these peaks are visualized as a hot-color column in the time-electrode amplitude map. The deepCNN task is to learn the P300 pattern from the input color-maps (images) corresponding to the target character. To achieve higher classification accuracy, we applied a high frequency transient suppression technique to the EEG signals based on convex optimization, which resulted in input data with higher signal to noise ratio (SNR), i.e., better P300 color-map visualization.

As a result, our denoising and imaging based deepCNN approach shows satisfactory results to be used in real-time P300 based BCI speller systems.

## 2. MATERIAL AND METHODS

### *2.1 Dataset*

We considered a recent experiment [11], called rapid serial visual presentation (RSVP), during which the subjects were presented 9 different three-character stimulus images. Each stimulus image was a flickering square with three characters on the three sides; left, bottom, and right. The characters were 26 English letters and one ".". Each of the 9 stimulus images was repeated 5 times in a trial with a period of 0.233 s. The square changed color between black and white with the flickering frequency of 15 Hz, which is used in the SSVEP analysis for detection of the direction of the subject's look and the corresponding character (English letter). This part is not the subject of our study. Our focus is to detect which one of the 9 three-character stimulus images is the target stimulus in the subject's mind by P300 detection at the time of each stimulus image. A RSVP trial, as is shown in Figure 1, is an experiment in which the subject is shown 9 different stimulus images, with 5 repetitions of each stimulus, and is primarily asked to focus on a predefined stimulus and a specific character. The experiment for each subject takes 50 trials. The EEG is recorded at 500 Hz sampling frequency (fs). The reader is referred to Figure 1 and Table 1 in [11] to see the visualization of a trial and the group of triple characters in each stimulus.

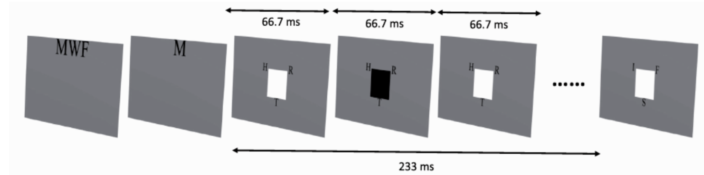


**Figure 1:** A trial of the RSVP experiment (copied from [11]). The three-character target stimulus and target character are shown in the beginning.

### *2.2 Preprocessing*

The main idea of the EEG preprocessing method is to suppress the high frequency transients and the low frequency high amplitude artefacts (eye blinking or myogenic) for better visualization of the low amplitude and low frequency P300 potentials and the time-electrode amplitude color-maps which provides the deepCNN classifier with better inputs. In our recent study about movement potentials [7], we proposed a preprocessing scenario for better visualization of the low frequency and relatively low amplitude RPs [2, 3]. RP, triggered by real movement intention or imagination, is a negative ramp potential followed by a positive ramp in the delta band frequency [2, 3]. In [7], we suppressed the high frequency transients and the high amplitude artefacts (myogenic and eye blinking) in order to make the low frequency RPs visually dominant both in the time domain and the time-frequency spectrogram color-map. As the P300 is a positive low amplitude peak followed by a negative ramp in the same frequency band [4], the same approach is applied to the EEG signals from the RSVP experiment. The EEG preprocessing steps are described in Figure 2. First, the signal's baseline is removed by subtracting the signal's average value from the whole signal in a trial. The next step is transient suppression using a nonlinear method called total variation denoising [17, 18]. TVD filter employs a nonlinear optimization approach for noise suppression whereas preserves the low frequency sharp edges and shape of the underlying signal [17, 18]. Let's define $\boldsymbol{y}$, the noisy signal as the following:

$$\boldsymbol{y}(n) = \boldsymbol{x}(n) + \boldsymbol{w}(n), n = 0, \ldots, \mathrm{N}-1 \quad (1)$$

where $\boldsymbol{x}$ is (an approximately) piecewise constant signal with a sparse derivative, N is the number of samples of signal in discrete time, and $\boldsymbol{w}$ is white Gaussian noise. The nonlinear convex objective function, $F(\boldsymbol{x})$, is defined as [17, 18]:

$$\underset{x \in R^{\mathrm{N}}}{argmin}\{F(\boldsymbol{x}) = \frac{1}{2}\|\boldsymbol{y}-\boldsymbol{x}\|_2^2 + \lambda\|\boldsymbol{D}\boldsymbol{x}\|_1\}. \quad (2)$$

The first statement after equation equals power 2 of the $L_2$-norm ($\|.\|_2^2$) and the second statement, $\|.\|_1$, is the $L_1$-norm of the signal's derivative. The latter one is called the total variation ($TV$) of the signal $\boldsymbol{x}(n)$ with N points, which is also written as:

$$TV(\boldsymbol{x}) = \|\boldsymbol{D}\boldsymbol{x}\|_1 = \sum_{n=1}^{N-1}|\boldsymbol{x}(n) - \boldsymbol{x}(n-1)| \quad (3)$$

where $|.|$ denotes the absolute value. $\lambda$ is the regularization and smoothing factor whichcontrols the degree of smoothness in $\boldsymbol{x}$. TVD determines the signal$\boldsymbol{x}$fromthe noisy signal, $\boldsymbol{y}$, by minimizing the above nonlinear convex objective function $F(\boldsymbol{x})$ [17]. We call the output TVD signal as $\boldsymbol{x}_{TVD}$. As we have explained in [7], the smoothing parameter $\lambda = 70$ was selected in our study since applying more smoothness to $\boldsymbol{x}_{TVD}$ empirically eases the detection of low frequency P300 on $\boldsymbol{x}_{TVD}$. The reader is referred to [7, 17, 18] for details on TVD. The $\boldsymbol{x}_{TVD}$ signal is then filtered by a 0.5-47Hz 25$^{th}$ order FIR bandpass filter. Then, relatively high amplitude artefacts are detected by empirically setting an appropriate threshold. The $\boldsymbol{x}_{TVD}$ segments crossing the predefined threshold are replaced by zero-mean random numbers, resulting in $\boldsymbol{x}_d$. As we have shown in [7], suppressing high amplitudes in this way, not only leads to better visualization of the low frequency potentials (like P300), but also retains the continuity of the signal. This has been

1. Baseline removal of raw EEG data, $\boldsymbol{x}$, total variation denoising (TVD), and 0.5-47 Hz, 25$^{th}$ order FIR filtering resulting in $\boldsymbol{x_{TVD}}$
2. High amplitude artefact detection by thresholding (threshold1 = 20 $\boldsymbol{\mu}$**V**) each 2 s non-overlapping segment of $\boldsymbol{x_{TVD}}$ and removing artefacts by replacing each artefact segment by zero-mean random numbers
3. Repeat number 3 with 0.25 s time segment and threshold2 = 3.3(1/N)$\|\boldsymbol{x_{TVD}}\|_{\boldsymbol{1}}$ resulting in $\boldsymbol{x_d}$ denoised signal (N: length of the signal or number of the samples of $\boldsymbol{x_{TVD}}$ in discrete time**)**
4. 4$^{th}$ order 4Hz butterworth lowpass filter, resulting in $\boldsymbol{x_{dLP}}$

**Figure 2***:* EEG preprocessing steps

argued in [7], in the preprocessing section. Figure 3 shows the original and denoised signal after TVD and high amplitude artefact suppression. The P300 EPs are also marked by red rectangles in the duration of target stimulus in the raw EEG signal. We set two thresholds, one constant and the other one derived from the data. The constant threshold was empirically set at 20 $\mu V$ and applied to each 2 s non-overlapping time segment. Each segment crossing the threshold was replaced with zero-mean random numbers. We showed in [7] that suppressing high amplitude artefacts in this way prevents the discontinuities in the signal, due to signal deviations by artefacts. The data driven threshold was set in order to suppress the remaining high amplitude artefact as the following:

$$Threshold = \frac{3.3}{\mathrm{N}}\|\boldsymbol{x}_{dLP}\|_1, \quad (4)$$

where N is the number of signal samples in the discrete time. The threshold was applied to the absolute value of the signal in each 0.25 s duration. In the last preprocessing step, a 4$^{th}$ order butterworth lowpass filter with cutoff frequency of 4 Hz is applied and results in the denoised signal, $\boldsymbol{x}_{dLP}$. The preprocessing method is applied to 21 electrodes in the central, parietal, temporal, and occipital electrodes since P300 is strongly evoked in these electrodes [4]. The electrode labels are: FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P2, P8, PO7,PO3, PO4.

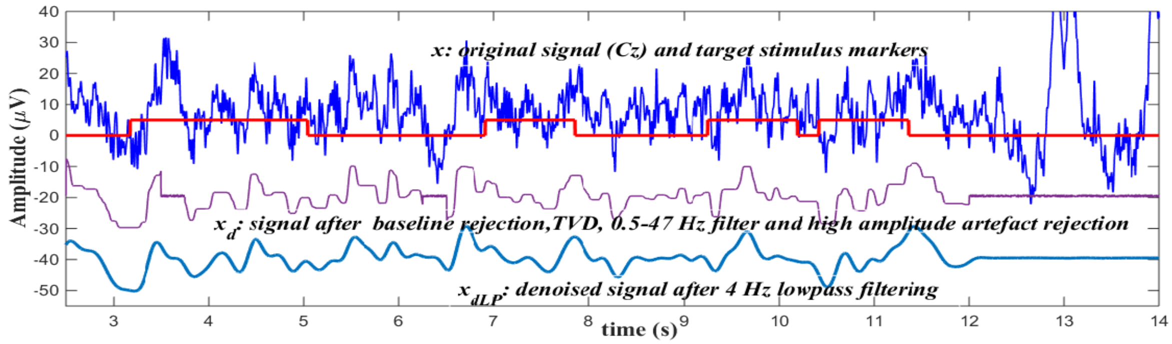
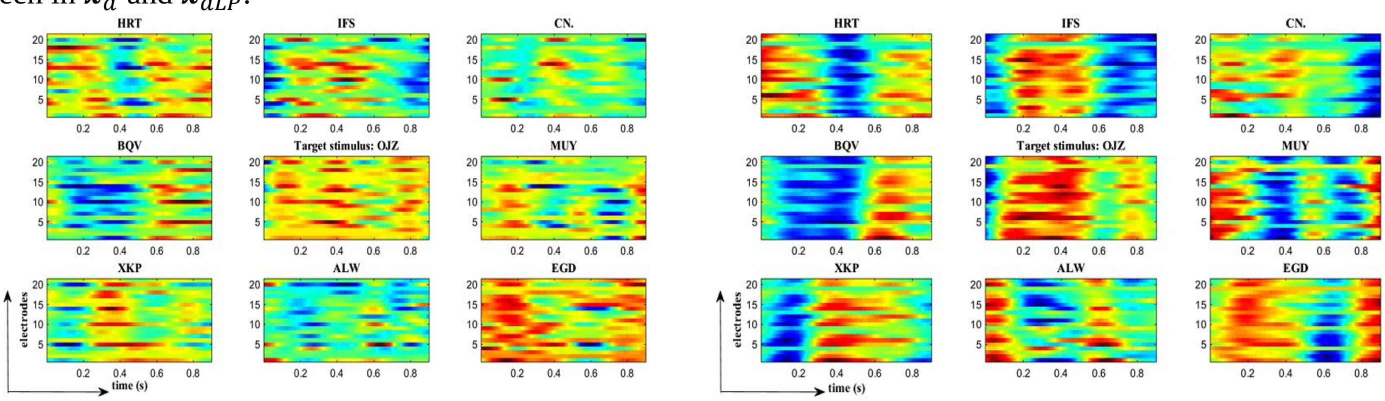



**Figure3:** $\boldsymbol{x}$ (dark blue) the original signal, $\boldsymbol{x}_d$ (purple), signal after transient suppression by TVD ($\boldsymbol{x}_{TVD}$), 0.5-47 Hz 25$^{th}$ order bandpass filter and high amplitude artefact suppression by replacing them with zero-mean random numbers, and $\boldsymbol{x}_{dLP}$ (light blue), $\boldsymbol{x}_d$ after 4 Hz lowpass filter. The red rectanges marked on the original signal define the duration of the target stimulus, in which the P300 potentials are apparantly seen in $\boldsymbol{x}_d$ and $\boldsymbol{x}_{dLP}$.




**(A)** **(B)**

**Figure4:** time-electrode amplitude color-map of 21central, parietal, temporal, and occipitalelectrodesin 0.9 s duration from the start of each three-character stimulus image in a trial of the RSVP experiment, (**A**) without, and (**B**) withemploying TVD in the EEG preprocessing. The images are acquired by synchronized averaging of the preprocessed EEG signals over repetitions of the same stimulus and electrode. The three-character stimulus has been written above each color-map. TVD helps better visualization of the hotspots around 300 ms after the start of the target stimulus. These color-maps are used asinput for the deepCNN classifier with labels 1 for the target and 0 for the non-target image.

The matrix of 21-elecrode preprocessed EEG is plotted as a time-electrode amplitude color-map, as shown in Figure 4, in 0.9 s duration, from the start of each stimulus image. This duraton is four times the duration of each stimulus, 0.233 s, which guarantees a P300 detection after the start of a target stimulus. The images of Figure 4 for each stimulus are acquired by synchronized averaging of the time-electrode amplitude maps over the same electrode and stimulus. Before plotting, the EEG signals are downsampled by factor of 10 in order to reduce the size of the data and the computational load for the deepCNN classifier. Hence, a 0.9 s duration decimated by a factor of 10 and fs=500 Hz, leads to 45 samples. Accordingly, a 21-electrode EEG color-map for each stimulus is a matrix with 21×45 dimensions. 9 matrices (color-maps) are acquired in each trial corresponding 9 different stimulus images. So, for each subject, participating in 50 trials, 450 matrices (epoch data) are acquired as input for the classifier. These color-maps are inputs for the classifier with label 1 for the target stimulus and 0 for the non-target stimulus. From Figure 4, it is deduced that using TVD in the EEG preprocessing, besides filtering and high amplitude artefact suppression, gives better color-map visualization and more accurate discrimination of the target stimulus.

*2.3 P300 classification by deepCNN*

The proposed method takes a two-dimensional input array of size (21, 45) as an input which is the matrix of preprocessed EEG signals, followed by the feature extraction block with two sequential sub-blocks. Each block contains layers such as batch normalization, max-pooling 2D, convolution 2D, leaky ReLU activation layer, and drop out of 0.25 factor. Both convolution layers, C1 and C2, have strides of 1 and valid padding identical with 16 filters, kernel size of 5 for C1 and 32 filters, kernel size of 2 for C2. The feature extraction block is followed by classification head where we used multi-layer perceptron as our classifier which includes layers such as flatten, dropout of 0.25, batch normalization, dense layer with 200 hidden units, and scaled exponential linear unit (Selu) as an activation function. Lastly, to output the predictions we used sigmoid as an activation function for output layer with binary labels.

The three different activation functions are mathematically denoted as sigmoid activation for output layer:

$$f(y) = \frac{1}{(1+e^{-y})} \quad (5)$$

Leaky Relu activation for feature extractor block,

$$f(y1) = 1(y1 < 0)(\alpha y1) + 1(y1 >= 0)(y1) \quad (6)$$

with $\alpha = 0.3$ as the slope constant coefficient, and the scaled exponential linear unit (SELU) activation for classification block as:

$$f(y2) = \lambda \begin{cases} y2, & y2 < 0 \\ \alpha e^{y2} - \alpha, & y2 \leq 0 \end{cases}, \alpha = 1.673, \lambda = 1.0507 \quad (7)$$

For the optimization of the learning objective, we trained our model using Adam [20] optimizer with a learning rate of 3e-4 and binary cross-entropy as a loss function. Furthermore, experiments were performed on Nvidia Tesla K80 GPU with 12 GB RAM and TensorFlow 2.0 as a platform. For assessing the generalization of the model, we used the Stratified 5-fold cross-validation technique. Unlike random sampling, in stratified sampling each fold contains the same proportions of labels. The mean average training time across all of the folds was 60.9 s. The trained classifier in each fold then applied to the epoch data corresponding each stimulus in each trial in order to find the target stimulus and the corresponding target three-character image for each subject.

**Table 1:** Layers in the deepCNN model

| **Layer type** | **Layer dimensions first repetition** | **Layer dimensions second repetition** |
|---|---|---|
| MaxPool2D | (21, 45, 1) | (6, 18, 16) |
| BatchNorm | (10, 22, 1) | (3, 9, 16) |
| Conv2D | (6, 18, 16) | (2, 8, 32) |
| LeakyRelu | (6, 18, 16) | (2, 8, 32) |
| Dropout | (6, 18, 16) | (2, 8, 32) |
| MLP | 200 | |
| Output | 1 | |
| Total Params | 107,541 | |
| Trainable Params | 106,419 | |
| Non-trainable Params | 1,122 | |

## 3. RESULTS

For the P300 detection, the classification accuracy is defined as the percentage of trials with truly detected target stimulus (true positives (TPs)):

$$\text{Accuracy}(\%) = \frac{\textbf{Number of truely detected target stimulus (TPs)}}{\textbf{Total number of trials}} \times 100. \quad (8)$$

We had an accuracy of 95.43±1.46%, from all 6 subjects in the RSVP experiment. Results without using TVD in the EEG preprocessing steps led to a lower accuracy of 92.83±2.03%. This shows the efficiency of our preprocessing approach using TVD. Results from all subjects are gathered in

Table 2. Results of some BCI speller studies using deepCNN are also shown in Table 3.

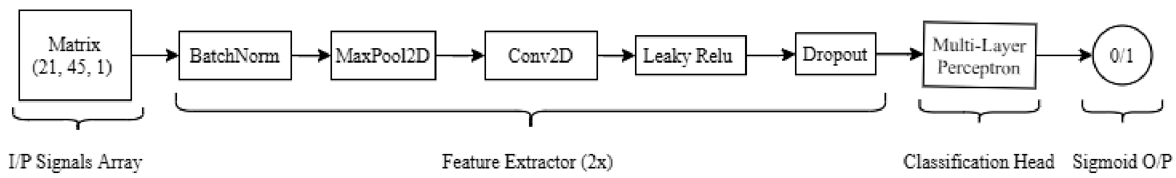



**Figure 5:** Block diagram of the deepCNN approach

**Table 2:** Results of accuracy from subjects in the RSVP experiment, averaged from 5-fold cross-validation

| Subjects | Accuracy (%) with TVD in the EEG preprocessing | Accuracy (%) without TVD in the EEG preprocessing |
|---|---|---|
| Subject1 | 93.354 | 91.442 |
| Subject2 | 94.468 | 94.956 |
| Subject3 | 95.578 | 90.198 |
| Subject4 | 97.712 | 95.266 |
| Subject5 | 95.756 | 91.936 |
| Subject6 | 95.712 | 93.224 |
| Avg. | 95.43 | 92.83 |
| Std. | 1.46 | 2.03 |

**Table3:**Results of P300 classification accuracy using deepCNN from different studies

| **Study** | **Method** | **Task (EEG electrodes)** | **Accuracy (%)** |
|---|---|---|---|
| Cecotti et al. [15] | deepCNN | Oddball experiment (64) | 95.5 |
| Shojaedini et al. [16] | deepCNN optimized with genetic algorithm | Oddball experiment (32) | 98.91 |
| Present study | proposed method | Triple RSVP experiment (21) | 95.43 |

## 4. DISSCUSSION

In this study, an imaging based deepCNN approach to P300 classification in the RSVP experiment was proposed.We applied a previously proposed denoising approach in [7] for better visualization of the low frequency P300 potential both in time domain and in the time-electrode amplitude color-map from the 21-electrode EEG matrix of 21×45 dimensions.45 Samples were the samples in the 0.9 s duration of the signal, from the start of each stimulus image, which were decimated with a factor of 10 (fs=500 Hz). We achieved an average accuracy of 95.43 % from 6 subjects in the RSVP experiment. Our classifier was trained with 5-fold stratified cross-validation. Then we validated the classifier on each subject. Our average accuracy result is comparable to the result from the same datasetsin [11] using signal samples and wavelet coefficients as features for their RLDA classifier. Although the authors' average reported accuracy (96.29 %) is better than ours (95.43 %), but our classification approach is much simpler. We didn't do any manual feature extraction since the deepCNN classifier has the feature extraction block. The only thing we did was an efficient preprocessing method, which provided the classifier with high resolution inputs as shown in Figure 4. Compared with the results from an other triple allocating coefficients to signals of each stimulus based on fisher linear discriminant analysis (FLDA) and logistic regression, and determined the target stimulus with higher score. They used their own datasets which is not in access in order to have better comparison. The authors in [15, 16] applied deepCNN to data from an oddball experiment and reported the average accuracies of 95.5 % and 98.91 %. The better result achieved by optimzing the deepCNN parameters using genetic algorithm in order to have lower variations of the error curvature and better convergence [16]. The reported accuracies using deepCNN (Table 2) are promising to be used in BCI speller systems.

## 5. Conclusion

In this study, we visually detected the low ferquency P300 potentials from a group of preprocessed EEG signals with a time-electrode amplitude color-map, and automatically classifed the target stimulus from the non-target stimulus using a P300 based deepCNN classifier. The efficiency of deepCNN classifier improves giving inputs from more subjects. Feeding deepCNN with large datasets, we are optimistic to have a generalized P300 classifier, amenable to any new data. This would be useful to be integrated in real-time P300 based BCI speller devices used at home by patients after stroke.

## 6. Acknowledgments

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## 7. Conflict of Interest

The authors declare no conflict of interest.

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RSVP experiment [19], our result is more accurate than theirs (79 %). They used an scoring approach;

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