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Calibration-less detection of steady-state visual evoked potentials - comparisons and combinations of methods

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***Abstract*— Brain-Computer Interfaces (BCIs) represent a great challenge in signal processing and machine learning, because it is difficult to extract discriminant features corresponding to particular brain responses due to the low signal-to-noise ratio of the EEG signal. Steady-state visual evoked potentials (SSVEPs) are one of the most reliable brain responses to detect in the EEG signal. Although advanced supervised machine learning techniques can improve the classification performance of SSVEP responses, obtaining robust techniques that do not rely on training a classifier is also important. We propose to analyze, compare, and combine the performance of three state-of-the-art techniques for the detection of SSVEP responses across 10 subjects and different time segments to determine if robust classification can be obtained without subject-specific rigorous analysis using a combination of one or more techniques. The methods include two approaches based on spatial filtering, and canonical correlation analysis. The results support the conclusion that the choice of the method does not depend on the time segment, and the current techniques provide equivalent performance.**

I. Introduction

The research field of Brain-Computer Interface (BCI) is currently a new hope for severely physically impaired as this new means of communication would allow some patients to communicate through direct neural activity measurements [1], [2], [3]. In addition to those prospects for physically impaired [4], [5], BCIs based on non-invasive scalp electroencephalography (EEG) have also become of great interest for healthy people as a new and alternative way of controlling devices, particularly in video games [6]. Among the different types of brain responses that are currently used in BCI: event-related potentials (ERPs), visual evoked potentials (VEPs), event-related desynchronization/synchronization (ERD/ERS), and slow cortical potentials, steady-state visual evoked potentials (SSVEP) are brain responses that can be detected reliably, and they do not necessarily require a calibration session [7], [8], [9]. For this reason, SSVEPs seem better suited for users who would not accept a regular calibration session. Furthermore, SSVEP based BCI typically offer a high information transfer rate (ITR) compared to other BCIs, *e.g.,* 58 bits per minute for an SSVEP based BCI [9], 23 bits per minute for an ERP based BCI [10]. This type of BCI has a long history of applications with various signal processing methods [11], [12], [13].

BCIs based on SSVEP use the response of the users' attention to an oscillating visual stimulus. When a person focuses on a particular oscillating object, *i.e.,* a visual stimulus, then the person's brain response can provide information about which stimulus the user is attending to produce a BCI. Usually, the stimuli that are used for inducing SSVEP responses are flickering lights at different frequencies. When an object flickers at a frequency f, then a response occurs in the visual cortex. This response corresponds to the frequency of the stimulus and its higher harmonics [14]. Therefore, it is possible to obtain different responses in relation to different frequencies. In relation to these responses, it is possible to create a BCI where each response is related to a command (selecting a symbol, using a device,...) [15].

In addition to the drawbacks common to every non-invasive BCI such as the preparation time, *e.g.,* mounting cap and electrodes, SSVEP based BCI require gaze control. In fact, BCIs based on SSVEP are 'dependent' BCIs as the generation of the VEP depends on the gaze control via extraocular muscles and particular nerves. However, new studies have explored the effect of electrodes on non-hair-bearing areas for the detection of SSVEP responses [16]. For BCIs that require special external stimuli, their quality and their sources are a bottleneck for increasing the number of basic commands in a BCI. Because there exists a direct relationship between the characteristics of the visual stimulus (frequency, phase, amplitude, image content) and the brain evoked response, the stimuli shall be reliable, stable and should not involve any risk or inconvenience such as visual fatigue for the user [17]. The SSVEP responses are described as reliable in the literature [18], [19], [20]. The amplitude and the phase that define an SSVEP response depend on three main parameters that can be considered as features to discriminate different responses [21]: the frequency of the visual stimulus (the SSVEP responses with maximum amplitude are usually obtained in three frequency bands: 5-12 Hz, 12-25 Hz and 30-50 Hz [22]), the phase of the visual stimulus, the intensity of the flickering light, and the structure of the repetitive visual pattern [23]. SSVEP-BCIs are described as more accessible than other BCI systems. They have been used for several applications They include several advantages among and little user training.

Despite the interest of using a specialized classifier for the detection of SSVEP responses to obtain a high recognition rate with a short time segment for the analysis (1 second) [24], most of the methods employed in SSVEP based BCI do not rely directly on machine learning, *i.e.,* with a training database for tuning the model, but on statistical measures comparing the current input signal and models of the potential brain evoked response based on the stimuli.

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Among those methods, canonical correlation analysis and minimum energy combination are described as the most efficient methods. Although they have been compared with a limited number of subjects in [25], a comparison with more subjects and other methods would provide further evidence of the best method to use. Moreover, while there may be no difference of performance across subjects, a change of performance across trials could indicate that combining the detection scores from the different methods may produce a higher accuracy. Additionally, the methods could be applied sequentially as the minimum energy combination is based on the creation of spatial filters, and canonical correlation analysis is based on a statistical measure. These measures may complement each other. The goal of the study is to assess if there is a difference of performance across methods, if this difference depends on the choice of a predefined time segment, and if combining methods may improve performance.

The remainder of this paper is organized as follows. First, we present the most efficient detection techniques for SSVEP responses. In section III, we define the experimental protocol. Then, the performance analysis is detailed for each method and their combinations, for different time segments in section IV. Finally, the results are discussed for their application in SSVEP based BCI for able-bodied people.

II. Methods

A. Signal definition

The following definitions of the evoked SSVEP response and the signal corresponding to the stimulus have been used for the detection of SSVEP responses [20]. We consider a visual stimulation flickering at f Hz. The signal $y_i(t)$ as the voltage between the electrode i and a reference electrode at a time t is considered as:

$$y_i(t) \quad = \quad \sum_{k=1}^{N_h} a_{i,k}\ sin(2\pi kft + \Phi_{i,k}) + b_{i,t} \qquad (1)$$

where N_h is the number of considered harmonics. The signal is divided into two parts: the SSVEP response and the remaining EEG activity, which is considered as noise. The first part corresponds to the evoked SSVEP response signal, which is composed of a number of sinusoids with frequencies in relation to the stimulus frequency, and a number of N_h harmonic frequencies. Each sinusoid is defined by its amplitude and phase: $a_{i,k}$ and $\Phi_{i,k}$. $b_{i,t}$ corresponds to the background EEG activity. The detection of an SSVEP response on an EEG signal requires a time segment of N_t samples of EEG signal, with a sampling frequency of F_s Hz:

$$y_i \quad = \quad X_f a_i + B_i \qquad (2)$$

where $y_i = [y_i(1), \ldots, y_i(N_t)]^T$ contains the EEG signal for the i^{th} electrode in one time segment. The SSVEP model of the frequency f, X_f, is contained in a matrix $N_t \times 2N_h$ defined by

$$X_f(t, 2k-1) \quad = \quad sin(2\pi kft) \qquad (3)$$

$$X_f(t, 2k) \quad = \quad cos(2\pi kft) \qquad (4)$$

with $1 \leq k \leq N_h$. The vector a_i of size $2N_h$ contains the amplitudes. For N_y electrodes, the signal is defined as:

$$Y \quad = \quad X_f A_f + B \qquad (5)$$

where $Y = [y_1, \ldots, y_{N_y}]$ contained the sampled EEG signals from all the electrodes. A_f contains all the amplitudes for all the expected sinusoids for every electrode signal related to the expected frequency to detect.

B. Minimum energy combination

For enhancing discriminant features from the signal, the signals from the electrodes shall be combined. A spatial filter is used for a combination of the signals measured by different electrodes. A vector of channel data is denoted by s. Its purpose is to enhance the information contained in the EEG while reducing the nuisance signals. With spatial filtering, the signal is defined as a linear combination of y_i.

$$s \quad = \quad \sum_{i=1}^{N_y} w_i y_i = Yw \qquad (6)$$

where w_i is the weight for the i^{th} electrode. We note S the set of N_s signals after spatial filtering by:

$$S \quad = \quad YW \text{ with } S = [s_1, ..., s_{N_s}] \qquad (7)$$

In the BCI literature, spatial filtering is often a necessary preprocessing step for both feature reduction, and feature enhancement [26], [27], [14]. We consider the minimum energy combination (MEC) approach, which is based on the principal component analysis (PCA), which was first described in [20]. The method assumes for each frequency that it is the right frequency to detect and removes the noise considering this hypothesis. It can generate a frequency power estimation of each potential stimulus frequency. The spatial filtered signals are set in relation to hypotheses of the expected frequency to observe. First, the technique removes any potential discriminant components from all electrode signals, by projecting them onto the orthogonal complement of the formal model of the signal X.

$$\tilde{Y} = Y - X(X^TX)^{-1}X^TY \text{ and } \tilde{Y} \approx B \qquad (8)$$

PCA is applied on $\tilde{Y}$, and the eigenvectors will correspond to W. Its purpose is to have an optimal combination of the electrode signals, which cancel as much of the nuisance signals as possible. This method allows the combination of a fixed number of electrodes that minimize the nuisance signals. Once the channels are created, the power of the expected frequencies and their harmonics are calculated for each channel. For each frequency, the evaluation of the SSVEP response is defined by:

$$R(f) = \frac{1}{N_s \cdot N_h} \sum_{k=1}^{k=N_s} \sum_{j=1}^{j=N_h} \left\| X(f)_j^T S_k \right\|^2 \qquad (9)$$

In the next sections, we denote by W_{MEC}, the set of weights obtained with MEC.

C. Maximum energy optimization

Spatial filters are used to enhance the SSVEP response in the signal. A spatial filter is represented by a linear combination of the signals measured by different electrodes. We denote by s, a linear combination of y_i, the EEG after a spatial filter:

$$s = \sum_{i=1}^{N_y} w_i y_i = Yw \quad (10)$$

where w_i is the weight for the i^{th} electrode. Several components can be created by using several sets of weights w. We note N_s as the number of channels. We first estimate the background activity by removing the potential SSVEP components from the signal. It is achieved by projecting the signal onto the orthogonal complement of the SSVEP model matrix (X).

$$\check{Y}_f = Y - X_f(X_f^T X_f)^{-1} X_f^T Y \quad (11)$$

Spatial filters $\hat{W}_f$ that maximize the Signal-to-Noise Ratio (SNR) are obtained though determining the generalized Rayleigh quotient that maximizes the following expression:

$$\hat{W}_f = \mathrm{argmax}_W \frac{Tr(W^T Y^T Y W)}{Tr(W^T \check{Y}_f^T \check{Y}_f W)} \quad (12)$$

We define the following expression $\hat{Y}_f = X_f^T Y \hat{W}_f$ where $Y\hat{W}_f$ is the signal after spatial filtering. The power of the expected frequencies and their harmonics are calculated for the N_s components. For each frequency, the evaluation of the SSVEP response is defined by:

$$R(f) = \frac{1}{N_s \cdot N_h} \sum_{i=1}^{N_s} \sum_{k=1}^{N_h} \left(\hat{Y}_f(i, 2k-1)^2 + \hat{Y}_f(i, 2k)^2 \right) \quad (13)$$

In the next sections, we denote by W_{MAX}, the set of weights obtained with the spatial filters that maximize the SNR.

D. Canonical correlation analysis

Canonical correlation analysis (CCA) is a popular detection technique that has been used in several BCI studies [28], [9]. Let Σ_x, Σ_y, and $\Sigma_x y$ denote the covariance matrices of X_f the model of the stimulus, and Y the EEG signal, and the cross-variance matrix, respectively. The goal of CCA is to find pairs of linear projection of the couple of transformations $(w_x' X_f, w_y' Y)$ that are maximally correlated:

$$(w_x^+, w_2^+) = \mathrm{argmax}_{(w_x, w_y)} \rho(X_f, Y, w_x, w_y) \quad (14)$$

where

$$\rho(X_f, Y, w_x, w_y) = corr(w_x' X_f, w_y' Y) \quad (15)$$

$$= \mathrm{argmax}_{(w_x, w_y)} \frac{w_x' \Sigma_x y w_y}{\sqrt{w_x' \Sigma_x w_x w_y' \Sigma_y w_y}} \quad (16)$$

CCA is applied for each model of the stimulus, *i.e.,* for each frequency, and the detection of the stimulus observed by the subject corresponds to the model of stimulus associated to the highest correlation value.

E. Combination techniques

In this section, we propose to combine the methods presented in the previous subsection in two ways. First, the output values corresponding to the confidence score of each type of stimulus are normalized :

$$R(f_i) = \frac{R(f)}{\sum_{i=0}^{N_f} R(f_i)} \quad (17)$$

where N_f is the number of visual stimulus, *i.e.,* the total number of classes in the problem. Then, the combination score, for each class, is obtained by considering the mean value of the scores from the different methods (MEM, MAX, CCA). The second strategy for combining the methods consists in using MEC or MAX to obtain a subspace corresponding to spatially filtered signals, and then to use CCA. In this approach, CCA is applied on X and YW_{MEC}, by using MEC, or on X and YW_{MAX} by using MAX.

III. Experimental protocol

Ten healthy able-bodied subjects (age=27.2$\pm$2.4 years old, two females) participated in a study where the goal was to pay attention to a series of different flickering lights (black and white) at the following frequencies : 6.66 Hz, 7.50 Hz, 8.57 Hz, 10.00 Hz, and 12.00 Hz on a computer screen (diagonal size=15.4 inches, vertical refresh rate=60 Hz, luminance= 180.0 cd/m^2, with an estimated contrast of 280 : 1). Subjects were sitting in a comfortable chair at about 60 cm from the computer screen, in a non shielded room. Impedances were kept below 10 $k\Omega$. Each stimulus on the computer screen had a luminance of about 0.46 cd. The experiments were carried out sequentially. The order of the flickering boxes on which the subject had to pay attention was identical across subjects. The EEG was recorded with a g.USBamp EEG amplifier from g.tec with a sampling rate of 128 Hz. The electrodes were placed on AF_Z for ground, C_Z for the reference and PO_3, PO_4, P_Z, O_9, O_{10}, and O_Z for the input electrodes, as depicted in Figure III.

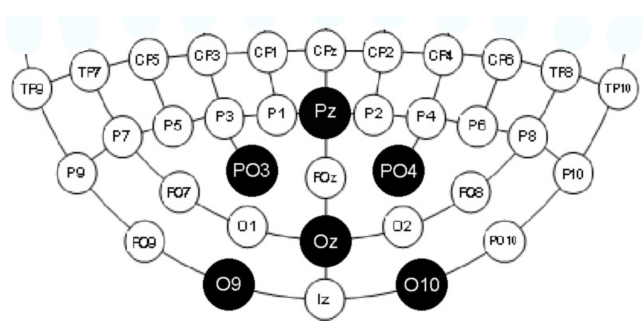


Fig. 1. Location of the electrodes in the 10-10 system.

A. Signal pre-processing

An analog bandpass filter between 2 and 40 Hz, and a notch filter around 50 Hz (main frequency in Europe) were applied directly inside the amplifier during the EEG acquisition. For the classification, we consider the responses corresponding to the presentation of the stimulus frequencies, *i.e.,* 7.50 Hz, 6.66 Hz, 8.57 Hz, 10.00 Hz, and 12.00 Hz. The frequency power for a single subject observing a visual stimulus flickering at 6.66 Hz is presented in Figure III-A.

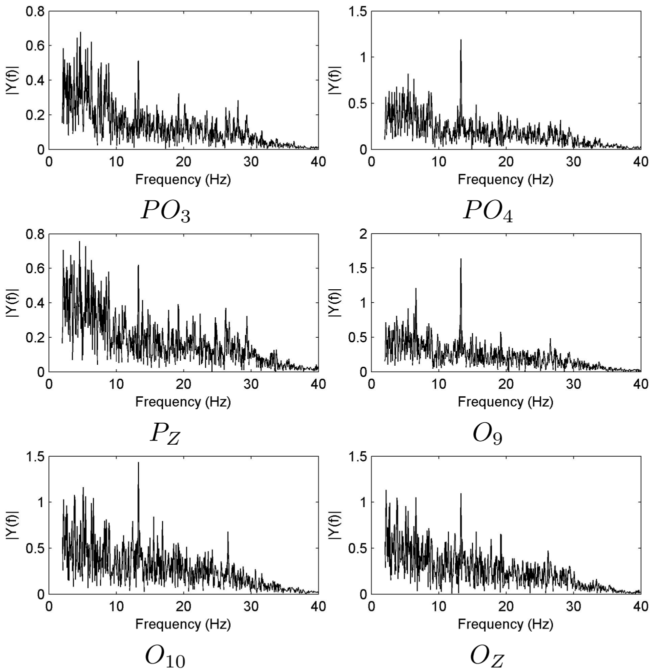


Fig. 2. Frequency power at each electrode for a subject observing a visual stimulus flickering at 6.66Hz during 10s.

B. Classification

The classification of the SSVEP responses was performed according to the methods presented in the previous section. In the experiment, $N_h = 3$, the detection of an SSVEP response is performed by selecting the frequency with the maximum associated value for the minimum energy combination, maximum energy optimization, and for canonical correlation analysis.

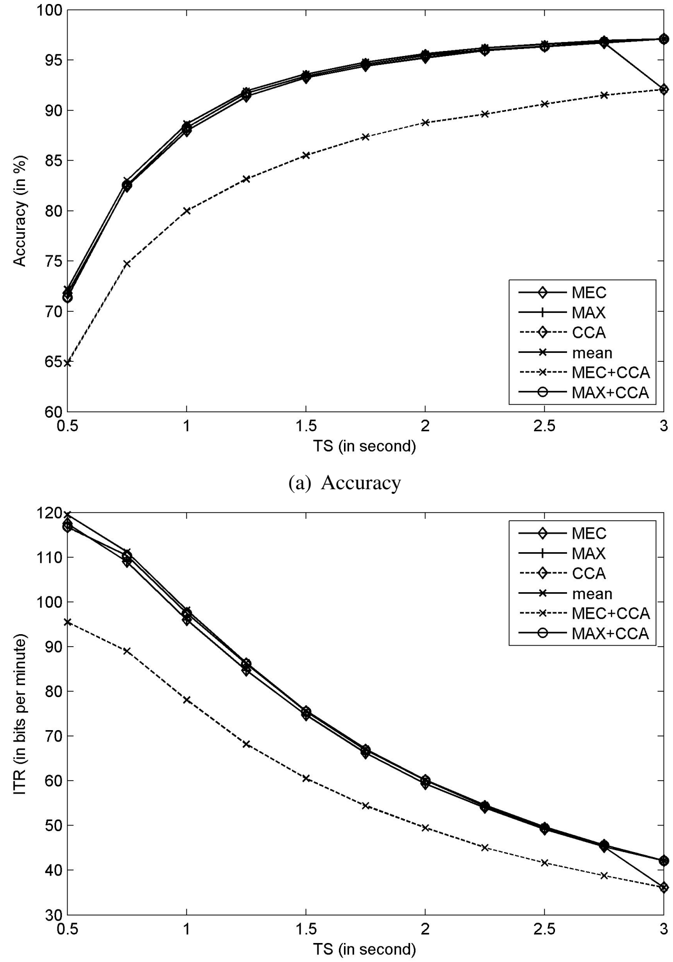
IV. Results

In this study, we report the performance by considering the mean and the standard deviation (SD) of the accuracy, in %, across classes. In addition, we determine the information transfer rate (ITR) [29] in bits per minute (bpm) defined by $ITR = \frac{60}{T} \cdot \vartheta$ where

$$\vartheta = log_2(N_{out}) + Plog_2(P) + (1-P)log_2(\frac{1-P}{N_{out}-1}) \quad (18)$$

and P being the probability of the good detection, *i.e.,* the accuracy, N_{out} being the number of possible different outputs, and T being the time in seconds of recorded EEG signal that is required to take the decision among the N_{out} outputs.

The accuracy for the detection of the five types of SSVEP responses is presented in Table I. The accuracy for the three combination techniques is presented in Table I. The accuracy and the associated ITR are depicted in Figure 3 as a function of the time segment that is considered for the analysis. The highest ITR is obtained with the mean combination strategy



(a) Accuracy

(b) ITR

Fig. 3. Accuracy and ITR as a function of the time segment used for the detection.

and TS=0.5 s: 119.48 bpm. The highest accuracy is 97.10% with TS=3 s and methods MAX and CCA. A Friedman's test indicated a significant difference across methods ($p < 10e{-}5$) by using the performance results with a time segment of 0.5 s to 3 s with a step of 0.25 s. After post-hoc analysis with a false discovery rate correction, a significant difference was observed across the three single methods: CCA is better than MAX, and MAX is better than MEC. A more detailed analysis indicated that there is no difference between the three methods for all the time segments, except for the last time segment of 3 s.

V. Discussion and conclusion

In this study, we have evaluated the best techniques for the detection of SSVEP responses based on an offline analysis of real EEG signals. We have shown that despite possible complementarities between methods, they are all relatively equivalent. While BCI studies have been mainly dedicated to physically impaired people, to allow a new communication mean to people who are not able to communicate with conventional devices, SSVEP based BCI allow high performance systems as it is possible to reliably detect an SSVEP response

TABLE I
MEAN AND STANDARD DEVIATION (ACROSS COMMANDS FOR EACH SUBJECT, ACROSS SUBJECTS FOR THE MEAN) OF THE ACCURACY (IN %) FOR EACH METHOD AND DIFFERENT TIME SEGMENTS (TS) IN SECONDS.

(a) MEC

	Subjects											
TS (s)	1	2	3	4	5	6	7	8	9	10	Mean	STD
0.5	88.17	71.63	54.29	76.61	97.45	48.35	62.17	80.37	70.15	68.57	71.78	14.09
1.0	95.95	86.61	79.61	88.95	99.39	70.16	82.19	95.90	91.51	89.27	87.95	8.33
1.5	97.61	91.70	88.98	93.30	99.53	79.16	91.01	99.30	96.86	94.99	93.24	5.79
2.0	98.03	93.74	92.32	95.01	99.72	83.67	95.20	99.62	97.69	97.22	95.22	4.49
2.5	99.15	94.65	94.84	96.08	99.67	86.29	96.88	99.72	98.44	97.78	96.35	3.79
3.0	98.53	88.73	83.49	97.29	97.67	81.19	91.12	86.17	98.10	98.38	92.07	6.45

(b) MAX

TS (s)	1	2	3	4	5	6	7	8	9	10	Mean	STD
0.5	88.17	71.63	54.29	76.61	97.45	48.35	62.17	80.37	70.15	68.57	71.78	14.09
1.0	95.95	86.61	79.61	88.95	99.39	70.16	82.19	95.90	91.51	89.27	87.95	8.33
1.5	97.61	91.70	88.98	93.30	99.53	79.16	91.01	99.30	96.86	94.99	93.24	5.79
2.0	98.03	93.74	92.32	95.01	99.72	83.67	95.20	99.62	97.69	97.22	95.22	4.49
2.5	99.15	94.65	94.84	96.08	99.67	86.29	96.88	99.72	98.44	97.78	96.35	3.79
3.0	99.57	95.91	97.53	96.63	99.90	85.04	98.05	99.95	99.24	99.19	97.10	4.23

(c) CCA

TS (s)	1	2	3	4	5	6	7	8	9	10	Mean	STD
0.5	89.33	74.55	53.26	75.86	97.17	44.78	62.59	79.90	68.20	68.06	71.37	14.91
1.0	96.97	89.41	81.89	89.56	99.25	64.15	84.29	95.52	91.93	89.74	88.27	9.52
1.5	98.32	93.30	91.51	93.40	99.63	73.91	91.71	99.20	97.09	95.78	93.38	7.09
2.0	99.06	94.68	94.91	95.43	99.67	79.15	96.00	99.72	98.12	97.74	95.45	5.73
2.5	99.29	95.18	96.12	96.17	99.76	82.84	97.26	99.81	98.68	98.44	96.35	4.76
3.0	99.57	95.77	97.53	96.63	99.90	85.08	98.05	99.95	99.29	99.19	97.10	4.23

within 0.5 s. Yet, this performance depends on the subject. For instance, subject S3 only obtained about an accuracy of 54% with TS=0.5 s.

Whereas the theoretical ITR indicates a higher performance for a short time segment, the study does not consider the time that is necessary to shift attention from one stimulus to one other, and the dynamic of the SSVEP response at the beginning of the presentation of a visual stimulus. Although an SSVEP response shall be detected during the presentation of a particular visual stimulus, the attention of the subject can fluctuate. Drops of attention may result in a drop in the amplitude of the SSVEP response, and therefore a drop of the accuracy for its detection. In fact, time segments used in the literature are typically around 2 s. We have shown that the pattern of performance across methods was stable across different time segments, which is a critical issue for speeding up BCI with a dynamic time segment.

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TABLE II

MEAN AND STANDARD DEVIATION (ACROSS COMMANDS FOR EACH SUBJECT, ACROSS SUBJECTS FOR THE MEAN) OF THE ACCURACY (IN %) FOR EACH COMBINATION METHOD AND DIFFERENT TIME SEGMENTS (TS).

(a) Mean score combination

	Subjects											
TS (s)	1	2	3	4	5	6	7	8	9	10	Mean	STD
0.5	89.33	73.16	54.93	76.65	97.35	47.38	62.87	81.11	69.83	69.41	72.20	14.29
1.0	96.46	88.24	81.66	89.70	99.39	68.39	84.01	96.18	92.40	90.11	88.65	8.55
1.5	97.99	92.73	91.00	93.58	99.58	77.10	92.08	99.30	97.05	95.55	93.60	6.21
2.0	98.87	94.44	94.16	95.34	99.72	82.02	96.05	99.76	98.21	97.46	95.60	4.93
2.5	99.24	94.99	95.88	96.50	99.76	84.78	97.64	99.86	98.82	98.34	96.58	4.24
3.0	99.57	95.82	97.53	96.63	99.90	85.04	98.05	99.95	99.24	99.19	97.09	4.24

(b) MEC+CCA

TS (s)	1	2	3	4	5	6	7	8	9	10	Mean	STD
0.5	89.94	64.29	36.95	76.42	93.23	38.42	57.07	54.83	73.17	64.07	64.84	18.10
1.0	96.18	79.61	55.46	90.02	96.88	55.62	74.68	70.57	93.38	87.50	79.99	14.82
1.5	96.96	84.81	66.89	94.00	97.24	65.43	82.48	77.75	95.97	93.72	85.52	11.56
2.0	97.79	87.24	73.80	95.25	97.32	73.41	86.96	82.68	96.80	96.42	88.77	9.07
2.5	98.25	88.41	79.31	96.31	97.54	77.26	90.16	84.06	97.26	97.73	90.63	7.67
3.0	98.58	88.83	83.40	97.29	97.62	81.14	91.16	86.27	98.10	98.38	92.08	6.45

(c) MAX+CCA

TS (s)	1	2	3	4	5	6	7	8	9	10	Mean	STD
0.5	89.29	74.51	53.40	75.77	97.22	44.73	62.59	79.95	68.20	68.15	71.38	14.91
1.0	96.97	89.41	81.94	89.56	99.25	64.15	84.29	95.52	91.93	89.74	88.28	9.51
1.5	98.32	93.30	91.51	93.40	99.63	73.91	91.71	99.20	97.09	95.78	93.38	7.09
2.0	99.06	94.68	94.91	95.43	99.67	79.15	96.00	99.72	98.12	97.74	95.45	5.73
2.5	99.29	95.18	96.12	96.17	99.76	82.84	97.26	99.81	98.68	98.44	96.35	4.76
3.0	99.57	95.77	97.53	96.63	99.90	85.08	98.05	99.95	99.29	99.19	97.10	4.23

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