2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

SAT: A Switch-And-Train Framework for Real-Time Training of SSVEP-based BCIs*

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Abstract— **Reducing the training time for brain computer interfaces based on steady state evoked potentials, is essential to develop practical applications. We propose to eliminate the training required by the user before using the BCI with a switch-and-train (SAT) framework. Initially the BCI uses a training-free detection algorithm, and once sufficient training data is collected online, the BCI switches to a subject-specific training-based algorithm. Furthermore, the training-based algorithm is continuously re-trained in real-time. The performance of the SAT framework reached that of training-based algorithms for 8 out of 10 subjects after an average of 179 s $\pm$33 s, an overall improvement over the training-free algorithm of 8.06%.**

I. INTRODUCTION

The development of practical and functional brain computer interfaces (BCIs) for long term users is a significant contribution allowing the use of such systems in the real-world. Even though the performance of BCIs has remarkably improved, the requirement of long and tedious training sessions prior the use of the BCI remains an issue, reducing the practicality of these systems [1]. Since electroencephalographic (EEG) signals, which are the typical inputs to such systems, vary considerably not only across individuals but also across and within the same session, training is required to characterize the user's neural response and improve the detection performance of the BCI.

In this work we focus on steady-state visual evoked potential (SSVEP)-based BCIs which require users to attend to flickering visual stimuli. These evoke a neural response consisting of oscillatory activity at the fundamental frequency and harmonics of the flickering visual stimuli. The SSVEP-based BCI identifies the SSVEP response and generates a particular control signal that is associated to the stimulus the user attends to. In the training process of SSVEP-based BCIs each user is required to attend to every stimulus of the BCI application for several trials in order to collect the subject-specific training data. The training time is thus affected by the number of stimuli in the BCI application and the number of trials required per stimulus. It is known that the performance of subject-specific detection methods improves with increased number of trials per stimulus and therefore calibration may become very time consuming, especially for BCIs with large number of stimuli.

Recently, there have been several proposed solutions to reduce or eliminate training for SSVEP-based BCIs. These have been based on different transfer learning approaches, for example, transfer learning across subjects [2], [3], across sessions [4], [5], stimuli [6] and EEG devices [7]. These methods achieved better performance than training-free methods, but in no case was better performance achieved than when using the subject's own training data for a given session. In fact some transfer learning techniques have been followed by adaptive learning in which the algorithms or classifiers are gradually updated with individual data in real-time [4], [8]. This allows for changes in EEG activity in real-time, for example, as the user becomes fatigued over time, the SSVEP algorithm is adapted to compensate for any changes in the brain signals.

Transfer learning and adaptive learning are a good practical solution for SSVEP-based BCIs. We propose to address this challenge by completely eliminating the prior training required by an individual subject and collect individual training data in real-time as the user uses the BCI. A training-free SSVEP detection method is first used by the user, then online feedback is obtained from the user by rejecting a selection. This can be done by for example, using eye blinks obtained from EEG data. In this manner training data may be collected in real-time. Once enough training data is available, the training-free SSVEP algorithm is replaced by a subject-specific SSVEP algorithm that is trained by the online-collected training data. Furthermore, the training-based algorithm is continuously updated with new online-collected training data. To the best of our knowledge this is the first SSVEP-based BCI that switches from a training-free method to a subject-specific method in real-time.

II. MATERIALS AND METHODS

A. Proposed method

Figure 1 is a detailed flow chart of the proposed switch and train (SAT) framework for SSVEP detection.

1) Switching mechanism: Initially, the proposed BCI uses a training-free algorithm on unlabelled trials to process and estimate a target. Once a trial is labelled, the target is shown to the user. If the estimated target is incorrect, the user carries out an eye gesture, such as a double blink which may be detected from the EEG signals, providing a feedback signal to stop the corresponding control function of the BCI. In this case the corresponding EEG data is discarded; conversely if the user does not indicate an incorrect detection, the trial data

*This work was partially supported by the project BrainApp, financed by the Malta Council for Science & Technology through FUSION: The R&I Technology Development Programme 2016.

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978-1-7281-1178-0/21/$31.00 ©2021 IEEE

is stored to be used as training data. This process is repeated until the minimum number of training trials per target are collected to train the supervised training model. Different subject-specific algorithms require a minimum number of training trials before their performance exceeds that of the training-free method. Once enough training trials are collected, this is trained using a supervised training algorithm and switches to processing new unlabelled trials with the trained model.

2) Adaptive mechanism: Once the system switches to make use of a trained model, new correct trials are continuously stored as training data. When more representative trials of each target are available, the model is retrained. As a result the performance of the subject-specific algorithm may improve in time as new training data is added.

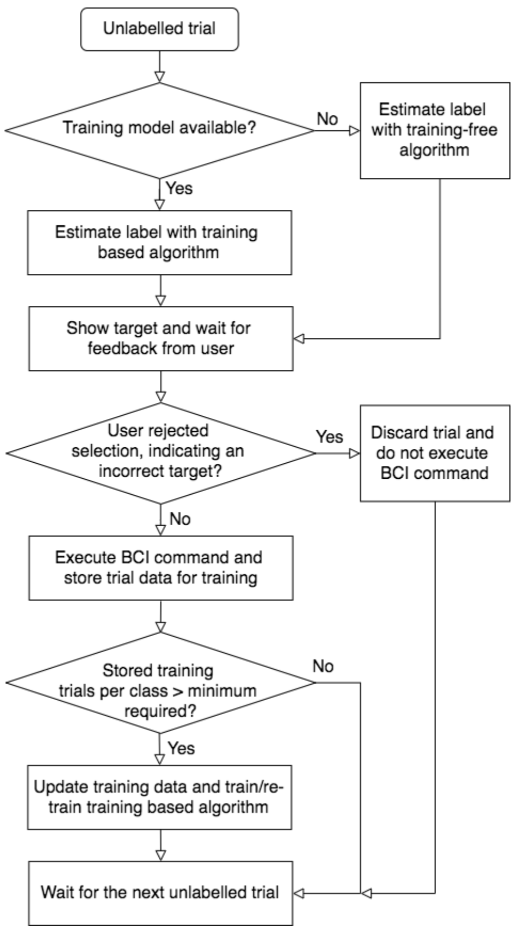

Fig. 1: Flow chart of the proposed real-time training and adaptive framework for an SSVEP-based BCI.

B. Training-free and subject-specific methods

The proposed method can be used with any training-free and subject-specific training methods. In this work the standard canonical correlation analysis (CCA) [9] has been employed as the training-free method since this has been the most extensively used multi-channel training-free detection method for SSVEP detection with generally good performance. The Combined-CCA [10] and the task-related component analysis (TRCA) [11] methods are state-of-the-art subject-specific methods for SSVEP detection that have both achieved significantly high performance in terms of classification accuracy and information transfer rate (ITR) compared to other methods [1]. Both of these methods are used in this work to demonstrate the effect of reducing training time for subject-specific methods using the proposed framework. The filter bank technique described in [11] was employed as a pre-processing step in both the subject-specific methods.

C. SSVEP dataset

The proposed framework was evaluated using a 12-class frequency and phase modulated SSVEP dataset acquired from 10 subjects that is freely available online [12]. The 12 stimuli were presented simultaneously in matrix form, each having different frequencies ranging between 9.25 Hz to 14.75 Hz and phases between 0π to 1.5π. EEG data was recorded with eight Ag/AgCl electrodes covering the occipital region. At the beginning of each trial, a visual cue appeared for 1 s to indicate the target stimulus. After that, all stimuli started to flicker simultaneously for 4 s. Each stimulus was selected in a random order for 15 repetitions. The EEG data was down-sampled to 256 Hz and then band-pass filtered from 6 Hz to 80 Hz. A latency delay in the visual system of 135 ms was allowed after each stimulus onset to cater for eye-movement delay.

D. Real-time simulation

The data was split in such a way to use 80% of the data for implementing the proposed SAT framework and 20% of the data as a hold-out set for comparing the proposed method with the training-free approach. This split was repeated 5 times to randomize the train and test sets. In the training set the data was again randomised for 10 repetitions such that the order of the trials being processed by SAT mimicked the actual use of the system. Since both TRCA and Combined-CCA require a minimum of 2 training trials, the minimum time for the training-free method to switch to the subject-specific method is after 24 trials (12 stimuli x 2 training trials). However, since the trials were randomised, the time taken for the switch and thereafter the training to occur may take longer. The hold out test was used to evaluate the expected classification performance of the system on a new dataset given the training stage the algorithm is in. Specifically, at the start, only the CCA algorithm is available so the hold out set is used to evaluate performance using CCA where no training is done. As soon as 2 trials per target become available, the TRCA/Combined-CCA algorithm is trained and again the hold out set is used to quantify the expected performance with the newly trained algorithm. The process continues by retraining every time a new trial per class is available, each time quantifying performance on the hold out set. Different time windows between 0.5 s and 2 s were considered in this analysis. In the proposed SAT algorithm, the system requires feedback from the user to be able to extract the training data. In the lack of such user feedback, in this simulation, the label given by the CCA algorithm is compared to the true label and in the case of a correct classification, the corresponding trial data is saved for training.

III. RESULTS

The proposed SAT framework was tested on the available dataset using time windows ranging from 0.5 s to 2 s in steps of 0.5 s. Since in this analysis, the switch from CCA to Combined-CCA/TRCA is based on the performance of CCA, it was realised that with shorter time windows where classification performance is low, there were a lot of cases where the switch did not occur. However, with a 2 s time window, a switch occurred in every realisation of the cross-validated framework, for 8 out of 10 subjects. For Subject 3 a switch only occurred 60% of the time and no switch was recorded for Subject 1. Based on this, the following results will focus on the results using a 2 s time window.

The results for the proposed SAT framework, averaged over 5 cross validations and 10 repetitions each, are shown in Figure 2 for each subject. It can be observed that there was a sharp increase in performance when the switching of the SSVEP detection method occurred, reaching the performance of the subject-specific methods. However, Subject 1 never switched to a training based algorithm and hence the performance is capped to that of CCA. This is discussed further in the next section.

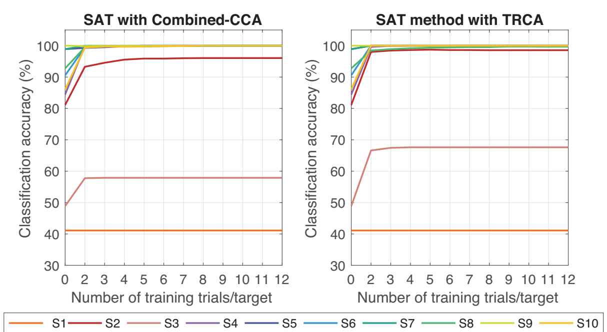

Fig. 2: Averaged classification accuracy (%) for each subject using the SAT framework with CCA as the training-free algorithm and (a) Combined-CCA and (b) TRCA as the subject-specific algorithms with 2 s time windows.

Table I shows the results for each subject using CCA with no training, Combined-CCA and TRCA with 2 training trials, and the proposed SAT after switching with 2 training trials for 2 s time windows. The proposed method reached the performance of the subject-specific algorithms excluding the results for Subjects 1 and 3 who did not switch or switched for only a fraction of the realisations respectively. SAT with Combined-CCA obtained an average accuracy over 8 subjects of 99.13% comparable to 98.24% obtained with the training based Combined-CCA. SAT with TRCA obtained an average accuracy over 8 subjects of 99.66% comparable to 98.22% obtained with the training based TRCA.

Figure 3 shows the classification accuracy using the proposed framework averaged over all subjects after eliminating

TABLE I: Classification accuracy (%) for each subject averaged across 5 cross validations and 10 randomised repetitions.

	Classification accuracy (%)				
Subject	**CCA**	**Combined-CCA**	**TRCA**	**SAT with Combined -CCA**	**SAT with TRCA**
1	41.11	89.83	97.28	41.11	41.11
2	81.11	91.61	96.33	94.56	98.44
3	48.89	62.89	77.67	57.89	67.44
4	84.44	99.72	99.61	99.89	99.94
5	98.89	98.83	100.00	99.50	100.00
6	90.56	98.28	100.00	99.67	100.00
7	98.89	99.94	100.00	100.00	100.00
8	92.78	98.83	97.83	99.72	98.89
9	100.00	99.89	100.00	99.94	100.00
10	86.11	98.83	100.00	99.72	100.00

Subjects 1 and 3 who did not seem to always gain from the proposed SAT framework. The results demonstrate a clear jump in performance as soon as the SSVEP detection algorithm switches to Combined-CCA or TRCA with 2 training trials per target. The performance increases marginally as the number of training trials is increased.

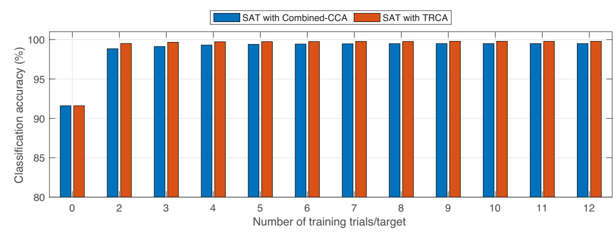

Fig. 3: Classification accuracy (%) averaged across subjects using the proposed SAT framework with 2 s time windows.

IV. DISCUSSION

A. Identifying trials for training

The proposed framework requires user feedback to reject incorrectly classified targets. The remaining trials are then used for training of the subject-specific methods. For this to work the proposed eye gesture carried out by the user needs to have a true positive rate close to 100% so that incorrect trials are not fed for training. A preliminary analysis on double blink detections based on blink peak heights and duration between successive blinks, showed that a detection accuracy of 99.79% is achievable over three subjects with one electrode placed at FP1. The g.tec g.SCARABEO EEG acquisition system was used for this analysis. The user can also be given the possibility of repeating the eye gesture during the time that the BCI is providing feedback to the user or generating a control function, so as to reduce the chance of an eye gesture being unrecognised. Since the training algorithm is being continuously updated, the effect of the erroneously labelled data will become less significant in time.

B. Suitability of the SAT framework across subjects

The results of Table I showed that the proposed framework improved the classification performance for 8 out of 10 subjects. For Subjects 1 and 3, a switch did not always occur. There are several reasons why this is happening. One reason is that the data we are using is limited to 12 training trials per target and more trials may be required for poorly performing subjects to accumulate the minimum number of correct trials for all stimuli to switch to the training based algorithm. Secondly, if trials associated with a specific stimulus are never correctly classified by CCA, then the switch will not be made under the current framework. For example, the 12.75 Hz stimulus for Subject 1 was never detected with CCA using a 2 s time window, with the problem repeated more often as the time window is reduced. Future work will consider relaxing the requirement of having an equal numbers of training trials for each stimulus. It may also be wise to consider a relatively long time window at the beginning so as training data is made available as quickly as possible, but then shift to a shorter time window, of around 0.5 s or 1 s, where TRCA and Combined-CCA are still known to perform well [11].

For those subjects for whom sufficient training data was available, the proposed SAT framework succeeded in boosting the performance of CCA to that achievable by Combined-CCA and TRCA, without prior BCI training. This transition occurred as soon as the minimum number of 2 training trials per target became available.

C. Training Cost Requirements

In our previous work [1] we have defined the training cost for an SSVEP-based BCI system as: $Training\,Cost = F \times K \times T \times S$, where F represents the number of stimuli in the user interface, K represents the number of training trials per stimulus, T represents the training trial length and S represents the number of subjects used for training. For a training based system such as Combined-CCA or TRCA, the training cost for an interface with 12 stimuli and 2 trials per stimulus, amounts to 99.24 s. This considers a 2 s time window, 0.135 s gaze delay, 1 s cue and 1 s break between trials. In comparison, the training time for the proposed SAT framework is 0 s, the same as that of training-free methods, since no training trials are required for a user to operate the BCI. However, the user will only reach the performance of the training based methods after a period of time, during which time the BCI performance will be capped to that of the training free SSVEP detection algorithm. The average number of trials across subjects, excluding Subjects 1 and 3, until the switch is made was found to be 57 trials. Considering once again a 2 s time window, a 0.135 s gaze delay and a 1 s feedback time, during which the user can also reject the trial through an eye gesture, the average time to switch was found to be 179 s. Thus the user may either invest in 99.24 s of training before using the system and expect a classification accuracy beyond 95% from the beginning or else avoid prior training completely, start using the system with a subject-dependent accuracy ranging between 80-100% and expect to switch to a performance above 95% after 179 s. The advantage of the latter is that the user is unaware of any training being carried out and can use the system right away with relatively good performance.

V. CONCLUSIONS

This work proposed a Switch-and-Train (SAT) framework for SSVEP-based BCIs. The major advantage of this framework is that the user does not have to undergo a time consuming training session before using the BCI system. The initial classification performance of the BCI system will be equal to that of the training-free algorithm, however, once enough training data is collected online, the BCI system experiences a relatively sharp increase in classification performance, reaching the level expected with standard, subject-specific, training based SSVEP detection algorithms. The results over 8 subjects showed that a switch to the Combined-CCA or TRCA algorithm was achieved after an average of 179 s, an overall improvement over the training-free algorithm of 7.53% or 8.06% when considering a 2 s time window and a switch to the Combined-CCA or TRCA algorithm respectively. Future work will investigate how a switch to the training based algorithm can be made in a shorter time, possibly by allowing training of the algorithms even when unequal trials per target are available for training.

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