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Steady-State Visual Evoked Potentials for EEG-Based Biometric Identification

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Abstract: In this paper we propose a biometric recognition system based on steady-state visual evoked potentials (SSVEPs), exploiting brain signals elicited by repetitive stimuli having a constant frequency as identifiers. EEG responses to SSVEP stimuli flickering at different frequencies are recorded, and both mel-frequency cepstral coefficients (MFCCs) and autoregressive (AR) reflection coefficients are used as discriminative features of the enrolled users. An analysis of the permanence across time of the brain response to SSVEP stimuli is also performed, by exploiting EEG data acquired in sessions disjoint in time. The employed database is composed by EEG recordings taken from 25 healthy subjects during two different sessions with 15 day average distance between them. The results show that good recognition performance and a high level of permanence can be reached exploiting the proposed method.

Keywords: EEG Recognition, SSVEP, Biometrics.

1 Introduction

Brain signals have been deeply investigated and exploited for medical and brain-computer interface (BCI) purposes since the beginning of the twenty-first century [Ba99]. In recent years, the interest in using such physiological characteristic also for biometric recognition is rapidly increasing. Many studies in such research field have in fact been focused on the use of electroencephalography (EEG) signals, showing that the brain response to specific tasks can be exploited to extract discriminative features able to guarantee high levels of recognition accuracy [CLR14]. The reason for the interest in using EEG data for biometric purposes is linked to some advantages the aforementioned signals possess, compared to other traditional biometric identifiers: universality is in fact guaranteed, and robustness to spoofing attacks and privacy compliance can be easily achieved. In the context of biometric recognition, EEG signals can be recorded as a response to different kinds of stimuli. Specifically, brain signals can be acquired when visual stimuli are presented, that is, when visual evoked potentials (VEPs) are elicited [DMC16, YSL13], or alternatively as a response to tasks such as imagined body movement or speech [MM07, BK10], or while the involved subject is in resting state conditions [NWS07]. In this paper, we propose an EEG-based biometric recognition system where discriminative features are extracted from steady-state visual evoked potentials (SSVEPs). SSVEPs are a particular kind of VEPs that consist of stationary periodic oscillations observed in brain activity as response to a repetitive visual stimulus in the range of 4 Hz to 60 Hz. When an individual focuses his attention on a flickering stimulus within this frequency range, typically presented on an LED setup or LCD display, an increased oscillatory activity, with spectral

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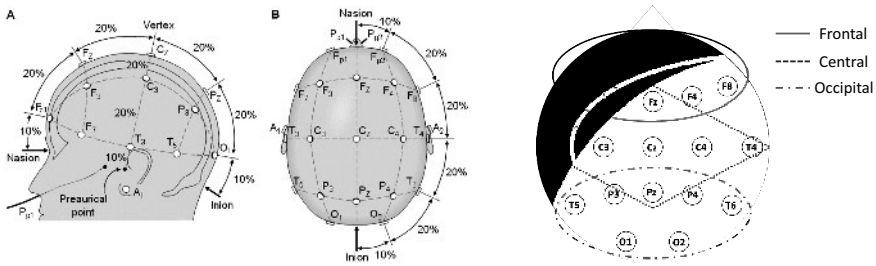

(a) (b)

Fig. 1: (a) Montage of electrodes used during the acquisition stage. (b) Brain regions.

peaks at the stimulus frequency and its harmonics, can be observed in brain signals [RS98]. SSVEPs exhibit a high signal-to-noise ratio and a stable spectrum, properties which have led to their widespread use for the investigation of cognitive processes such as visual attention and working memory, and clinical conditions such as schizophrenia, autism and epilepsy [Vi10]. These characteristics have also led SSVEPs to being widely adopted in BCI systems, that is, systems allowing an individual to communicate or control equipments solely through their brain activity [Zh10]. The consistent, rapid and prominent response of SSVEPs also makes these signals particularly appealing for EEG-based biometric applications. In contrast with their use in BCI systems, where the primary aim is distinguishing between different visual targets for a given individual, in a biometric system the main challenge lies in identifying features that are sufficiently distinct across individuals, whilst ensuring their stability across multiple recording sessions of the same subject [MLRC16]. The use of SSVEP in biometric applications has been so far investigated only in [Ph16] and [Fa17]. In [Ph16], an analysis based on the peak magnitude and frequency of the short-term Fourier transform has been exploited to identify five users, whose signals have been recorded during a single acquisition session. In [Fa17], the performance of SSVEPs has been assessed for the identification of eight individuals across three recording sessions. Feature vectors consisting of the normalised magnitude responses at a number of stimulus frequencies and their harmonics are computed for each participant. The results obtained indicate that SSVEPs can yield features that are distinct enough between individuals whilst also being sufficiently consistent across multiple sessions for the same individual.

In this paper, a novel approach for EEG recognition based on SSVEPs is proposed. Being the issue of permanence across time of paramount importance for real-life applications of EEG-based biometric systems, the stability of SSVEPs is also specifically addressed. The paper is structured as follows. Section 2 gives an overview of the employed acquisition protocol and the tools used to acquire EEG data. Section 3 describes the proposed biometric recognition system, while the achieved performance and permanence results are reported in Section 4. Some conclusions are eventually drawn in Section 5.

2 Employed Acquisition Protocol

In our work, EEG signals from $U = 25$ healthy volunteers are recorded and used for experimental tests. The device employed to elicit SSVEPs consists of a square array of 9 green leds, whose flickering frequency can be manually tuned. Four different elicitation

frequencies are exploited, namely $f_S \in \mathscr{F}_S = \{6, 12, 18, 24\}$ Hz. During each EEG data acquisition, subjects were comfortably seated on a chair in a dimly lit room, and asked to concentrate on the flickering target for one minute for each considered frequency. The involved subjects were asked to perform the proposed experiment during two temporally separated sessions, referred in the following as S1 and S2. The second session S2 is carried out after an average temporal distance of 15 days from the first session. EEG signals are acquired using a GALILEO BE Light amplifier operating at a sampling rate of 256 Hz. Brain activity is recorded from 19 electrodes placed on the scalp according to the 10-20 international system, as shown in Fig. 1.(a), with potentials referred to an electrode placed at the middle of the central region. At the beginning of each acquisition, the electrical impedance between each electrode and the scalp is kept under $30k\Omega$ using conductive gel. The recorded EEG signals are later preprocessed in order to remove noise and improve signal-to-noise (SNR) ratio, before distinctive features are first extracted and then matched for recognition purposes, as described in Section 3.

3 Employed SSVEP-based Recognition System

The preprocessing applied to the acquired EEG signals is described in Section 3.1. The features employed to represent the collected data are introduced in Section 3.2, while Section 3.3 describes the matching procedure employed in the considered identification system.

3.1 Preprocessing

In order to improve the quality of the acquired EEG signals, a spatial filter, namely a common average referencing (CAR) filter, is first applied to the recorded data. The aim of such filter is to reduce artifacts related to inappropriate reference choices in monopolar recordings [SA15] or unexpected reference variations. Having indicated as $\mathbf{v}_m^{(u)}$, with $u = 1, ..., U$ and $m = 1, ..., M$, the u-th user's potential between the m-th electrode and the reference electrode, filtered data are obtained by computing the difference between the considered EEG signal and the mean of the entire electrode montage:

$$\mathbf{c}_m^{(u)} = \mathbf{v}_m^{(u)} - \frac{1}{M} \sum_{m=1}^{M} \mathbf{v}_m^{(u)} \tag{1}$$

A band-pass filtering is then performed on the CAR-filtered signals. Specifically, since EEG data are characterized by a frequency spectrum with significant elements mainly below 40 Hz, the signals are filtered in the $[0.5, 40]$ Hz band. In order to analyze the brain response behavior, different combinations of the subbands related to the main brain rhythms, that is Delta (δ, $[0.5-4]$ Hz), Theta (θ, $[4-8]$ Hz), Alpha (α, $[8-14]$ Hz), Beta (β, $[13-30]$ Hz) and Gamma (γ, over 30 Hz) are also considered in the performed experimental tests when defining the applied band-pass filter. The obtained data are then downsampled at 128 Hz when the frequency interval of interest comprises the γ subband, otherwise the signals are downsampled at 64 Hz. The so-obtained data are then segmented into R consecutive overlapping frames $\mathbf{y}_m^{(u,r)}$, $r = 1, \ldots, R$, lasting $D = 5$ s with a normalized overlapping factor of $O = 75\%$ between each frame and the previous one.

3.2 Feature Extraction

After EEG data have been preprocessed, discriminative features are evaluated to generate a template from each user u's recording. In this work we exploit two different representations, namely mel-frequency cepstral coefficients (MFCCs) and auto-regressive (AR) coefficients, respectively detailed in Sections 3.2.1 and 3.2.2.

3.2.1 Mel Frequency Cepstral Coefficients (MFCCs)

MFCCs are a parametric representation of the signal based on the Fourier spectrum, widely used in speech-based biometric systems [GFK05] and recently applied to EEG data [Ng12] too. The following steps detail the processing carried out for MFCCs extraction:

1. **power spectral estimate**: the power spectral density (PSD) $\mathbf{Y}_m^{(u,r)}$ of each signal $\mathbf{y}_m^{(u,r)}$, $m = 1,...,M$ and $r = 1,\ldots,R$, is computed through the Welch's averaged modified periodogram approach, using 1-s sliding Hanning windows with 0.5-s overlap;

2. **mel-filter bank processing**: a bank of B mel-filters is used to warp the computed spectrum bins into the mel-scale, defined as:
$$Mel(f) = 2595 \log_{10}\left(1 + \frac{f}{700}\right). \tag{2}$$
The generated mel-spectrum is indicated in the following as ${}^{MEL}\mathbf{Y}_m^{(u,r)}[b], b = 1,\ldots,B$;

3. **log compression**: the range of the values of the mel-spectrum is reduced through a logarithmic transformation, that is ${}^{LOG}\mathbf{Y}_m^{(u,r)} = ln({}^{MEL}\mathbf{Y}_m^{(u,r)})$;

4. **discrete cosine transform**: MFCCs are computed from the log-compressed mel-spectrum using the discrete cosine transform (DCT):
$$\mathbf{d}_m^{(u,r)}[l] = \sum_{b=1}^{B} {}^{LOG}\mathbf{Y}_m^{(u,r)}[b] \cos\left[l\left(b - \frac{1}{2}\right)\frac{\pi}{B}\right], \quad l = 1,\ldots,L, \quad L < B. \tag{3}$$

In the adopted implementation, $B = 18$ mel-filters are employed, and $L = 12$ DCT coefficients are used to generate the representation of each considered signal. The template associated to the r-th frame of user u's recording, having length $P = M \cdot L$, is eventually obtained by combining the M representations of each channel:
$$\mathbf{f}^{(u,r)} = [\mathbf{d}_1^{(u,r)},\ldots,\mathbf{d}_M^{(u,r)}]. \tag{4}$$

3.2.2 AR Reflection Coefficients

Each EEG frame $\mathbf{y}_m^{(u,r)}$ extracted from the preprocessed signals can be modeled as a realization of an AR stochastic process of order Q, with $Q = 10$ in the adopted implementation. According to such assumption, the available signals can be expressed as:
$$\mathbf{y}_m^{(u,r)}[n] = -\sum_{q=1}^{Q} a_{m,Q,q}^{(u,r)} \mathbf{y}_m^{(u,r)}[n-q] + \mathbf{w}_m^{(u,r)}[n] \tag{5}$$
where $\mathbf{w}_m^{(u,r)}[n]$ is a realization of a white noise process having standard deviation $\sigma_{m,Q}^{(u,r)}$, and $a_{m,Q,q}^{(u,r)}$ are the autoregressive coefficients representing the model. The Yule-Walker equation [Ka88] is used to estimate the Q autoregressive coefficients, employing the recursive Levinson algorithm and introducing the concept of reflection coefficients. In detail, being $a_{m,Q,q}^{(u,r)}$ a generic AR coefficient, we have:
$$\begin{cases} a_{m,Q,q}^{(u,r)} = a_{m,Q-1,q}^{(u,r)} + K_{m,Q}^{(u,r)} \cdot a_{m,Q-1,Q-q}^{(u,r)}, & q = 1,...,Q-1 \\ \sigma_{m,Q}^{(u,r)} = \sigma_{m,Q-1}^{(u,r)} \sqrt{1 - (K_{m,Q}^{(u,r)})^2} \end{cases} \tag{6}$$
where the term $K_{m,Q}^{(u,r)}$ is referred to as reflection coefficient of order Q. In our work, the reflection coefficients are estimated through the Burg method [Ka88], and employed as

representative features of each user u's EEG data. For the generic r-th frame $\mathbf{y}_m^{(u,r)}$ extracted from the m-th channel of the EEG signal belonging to the user u, we therefore generate a feature vector $\mathbf{K}_m^{(u,r)}$ composed of the Q estimated AR reflection coefficients. The overall template associated to a given frame is obtained by combining the M representations generated for each channel into a single vector having size $P = M \cdot Q$, as:

$$\mathbf{f}^{(u,r)} = [\mathbf{K}_1^{(u,r)}, \ldots, \mathbf{K}_M^{(u,r)}]. \tag{7}$$

3.3 Identification

During the identification stage, the Manhattan (L1) distance is used to evaluate the similarity between features extracted during enrolment, and those obtained from an identification probe. In more detail, having indicated as $\mathbf{f}^{(u,e)}$ the template associated with the e-th frame extracted from user u's enrolment, $e = 1, \ldots, E$, and with $\mathbf{f}^{(x,i)}$ the representation generated from the i-th frame taken from the probe of an unknown subject x, $i = 1, \ldots, I$, the distance between such identification frame and the whole set of enrolment frames is evaluated as:

$$d_i^{(u)} = \min_e \left\{ \sum_{p=1}^{P} \left| \mathbf{f}^{(x,i)}[p] - \mathbf{f}^{(u,e)}[p] \right| \right\}, \tag{8}$$

that is, selecting the minimum among the distances computed between the i-th identification frame and all the recorded enrolment data. A decision $\hat{x}_i = \arg\min_u \{d_i^{(u)}\}$ is then taken for each available identification frame, with the final decision $\hat{x}$ regarding the identity of the presented subject taken according to a majority voting rule, selecting the identity with the highest number of occurrences among the votes $\hat{x}_i$, $i = 1, \ldots, I$.

4 Experimental Results

The aim of the present work is to analyze the recognition performance of an EEG-based recognition system exploiting an SSVEP protocol as stimulus for the involved users, taking into account issues regarding repeatability and stability across time of EEG signals. For this purpose, as remarked in Section 2, the collected database comprises EEG recordings taken, for each user, during two disjoint sessions, separated by an average time distance of 15 days. Data from the first session (S1) are considered as enrolment samples, while testing data are selected from the second session (S2). Comparing EEG samples taken during two distinct sessions allows estimating performance depending only on the peculiar characteristics of subject-specific neural activity. This way, session-specific exogenous conditions, such as the capacitative coupling of electrodes and cables with lights or computer, induction loops between the employed equipment and the body, and so on, cannot affect either inter- and intra-class variability of EEG recordings, as instead it may happen when performing tests by comparing EEG data collected during a single acquisition session [MLRC16].

In order to estimate statistically-significant results, a cross-validation procedure is carried out. Specifically, 30 different runs are performed for each of the scenarios described in the following, with 75% of the frames extracted from S1 employed as enrolment dataset for each considered user, and 75% of the frames generated from S2 randomly selected and employed as testing probes at each run.

Channels	SSVEP	EEG subband					
		$[0.5,40]Hz$	$[0.5,30]Hz$	$[4,40]Hz$	$[4,30]Hz$	$[8,40]Hz$	$[8,30]Hz$
All ($M=19$)	$f_S = 6\ Hz$	70.93	76.67	85.07	86.80	73.60	71.87
	$f_S = 12\ Hz$	92.67	93.73	94.40	92.67	84.80	87.20
	$f_S = 18\ Hz$	**94.53**	90.80	88.27	87.07	84.13	80.00
	$f_S = 24\ Hz$	89.73	88.93	87.87	89.33	85.33	85.73
	$f_S \in \mathscr{F}_S$, feat. fus.	97.47	94.67	**99.73**	98.67	99.33	95.73
	$f_S \in \mathscr{F}_S$, score fus.	95.73	**99.33**	96.27	97.33	97.33	93.33
	$f_S \in \mathscr{F}_S$, dec. fus.	99.47	97.33	99.87	**100.00**	98.87	98.00

Tab. 1: Average correct recognition rate (CRR %) obtained over 30 cross-validation runs, using MFCCs as features. The considered subbands are reported in terms of range of associated frequencies.

Channels	SSVEP	EEG subband					
		$[0.5,40]Hz$	$[0.5,30]Hz$	$[4,40]Hz$	$[4,30]Hz$	$[8,40]Hz$	$[8,30]Hz$
All ($M=19$)	$f_S = 6\ Hz$	72.93	74.67	78.53	79.07	66.93	64.40
	$f_S = 12\ Hz$	88.40	88.93	85.47	82.93	79.47	78.67
	$f_S = 18\ Hz$	93.60	93.47	**94.80**	93.47	86.93	83.87
	$f_S = 24\ Hz$	79.73	79.73	88.80	87.20	82.27	88.80
	$f_S \in \mathscr{F}_S$, feat. fus.	96.27	91.60	**98.93**	96.53	93.87	94.13
	$f_S \in \mathscr{F}_S$, score fus.	94.27	92.27	98.93	**99.33**	96.67	88.27
	$f_S \in \mathscr{F}_S$, dec. fus.	**99.73**	98.80	99.60	97.87	98.27	98.53

Tab. 2: Average correct recognition rate (CRR %) obtained over 30 cross-validation runs, using AR reflection coefficients as features. The considered subbands are reported in terms of range of associated frequencies.

The performance obtained when exploiting the considered elicitation frequencies $f_S \in \mathscr{F}_S = \{6,12,18,24\}\ Hz$, and taking into account all the available channels for template generation ($M = 19$), is reported in terms of average correct recognition rate (CRR) in Tables 1 and 2, respectively for MFCC- and AR-based templates. Besides using the considered stimuli separately, they are also jointly employed by fusing their contributions at:

- **feature level**, by concatenating the templates $\mathbf{f}^{(u,r)}$ generated from the r-th frame of user u's EEG collected at different elicitation frequencies, during both enrolment and identification phases;
- **score level**, summing the distances $d_i^{(u)}$ obtained for each i-th identification frame matched with user u's EEG, for signals collected at different elicitation frequencies;
- **decision level**, adopting a majority voting rule over the final decisions $\hat{x}$ individually taken considering EEG data collected at different elicitation frequencies.

As can be seen, for systems employing a single SSVEP elicitation frequency as stimulus, $f_S = 18\ Hz$ guarantees the best achievable identification rates, with CRR = 94.53% obtained using MFCCs to represent EEG data in the [0.5, 40] Hz subband, and CRR = 94.80% employing AR features estimated from EEG signals in the [4, 40] Hz subband. The considered fusion strategies allow to significantly improve such performance, being able to offer a perfect recognition rate (CRR = 100.00%) when a decision-level fusion is performed on information generated through MFCCs, while CRR = 99.73% when exploiting decision-level fusion with AR features.

Channels	SSVEP fusion	MFCCs			AR reflection coefficients		
		$[0.5,30]Hz$	$[4,40]Hz$	$[4,30]Hz$	$[0.5,40]Hz$	$[4,40]Hz$	$[4,30]Hz$
Frontal	Feature	81.73	85.46	79.60	81.87	75.20	74.00
($M=7$)	Score	**94.13**	90.67	84.67	89.46	**91.20**	82.27
	Decision	87.33	91.06	88.80	89.07	88.13	85.60
Central	Feature	78.13	88.27	90.00	80.40	83.60	84.40
($M=7$)	Score	86.00	90.13	89.60	84.00	84.53	88.13
	Decision	89.33	95.33	**95.87**	86.93	93.60	**94.53**
Occipital	Feature	84.67	85.87	84.40	90.80	86.40	86.27
($M=7$)	Score	74.80	78.13	80.93	77.60	79.47	79.47
	Decision	88.16	86.87	**89.33**	88.13	**90.93**	83.47
$\mathscr{M}$	Feature	92.13	89.60	86.26	91.47	88.13	81.06
($M=5$)	Score	90.40	88.80	86.60	83.60	82.13	72.67
	Decision	**96.00**	94.80	93.73	**91.47**	88.13	84.67

Tab. 3: Average correct recognition rate (CRR %) obtained when different spatial configurations are selected and 30 cross-validation runs are performed.

Given the high accuracy obtained when exploiting all the available 19 channels, further tests are carried out to check whether similar results can be obtained while lowering the number of employed channels. It is worth remarking that minimizing the number of employed electrodes is an issue of paramount importance to reduce user inconvenience. In this regard, Table 3 reports the performance obtained when considering only $M = 7$ electrodes placed in either frontal, central and occipital areas, according to the montages shown in Fig. 1.(b), together with the rates obtained with an even smaller set $\mathscr{M} = \{\mathrm{F}_z, \mathrm{C}_z, \mathrm{P}_z, \mathrm{O}_1, \mathrm{O}_2\}$ with $M = 5$ electrodes, comprising only midline and occipital channels. Only the recognition rates achieved exploiting all the considered elicitation frequencies through fusion approaches, and taking into account the best-performing subbands according to the results shown in Tables 1 and 2, are reported in Table 3. From the obtained accuracies it can be seen that the central area of the scalp seems guaranteeing the best performance achievable with a reduced number of electrodes, achieving CRR = 95.87% for MFCC and CRR = 94.53% for AR representations, when considering EEG recordings filtered in the $\theta \cup \alpha \cup \beta$ subband. An even better result is obtained when considering only the set $\mathscr{M}$ with $M = 5$ in the $\delta \cup \theta \cup \alpha \cup \beta$ subband, for which a CRR = 96.00% is achieved using MFCCs, while AR features provides CRR = 91.47%.

5 Conclusions

This paper evaluates the feasibility of designing an automatic biometric recognition system exploiting EEG signals elicited through protocols generating steady-state visual evoked potentials (SSVEPs). The use of flickering stimuli at specific frequencies and the representation of the acquired EEG data through either MFCC or AR templates, allows achieving high identification rates, thanks to the proved existence of permanent characteristics in SSVEP brain responses across different acquisition sessions. According to the reported experimental tests, the joint use of multiple elicitation frequencies guarantees a notable improvement in recognition rates, thus allowing to reduce the number of electrodes needed during EEG collection, a relevant property to foster the adoption of EEG-based biometric identifiers in practical recognition systems.

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