EEG Biometrics Using Visual Stimuli: A Longitudinal Study

Rig Das, Emanuele Maiorana, and Patrizio Campisi,

***Abstract*—In this paper we investigate the permanence issue of electroencephalographic (EEG) signals, elicited by visual stimuli, for biometric recognition purposes. Specifically, we evaluate the discriminative capabilities of generic visually-evoked potentials (VEPs) and of visual event-related potentials (ERPs) associated to specific cognitive tasks. Furthermore, we analyze the permanence issue of the considered EEG traits by verifying the stability across time of the achievable recognition rates. Experimental tests performed on a longitudinal database, comprising EEG data taken from 50 subjects during 3 different sessions, give evidence of the presence of repeatable discriminative characteristics in the individuals' EEG activity [1].**

I. Introduction

In the very recent past, the use of electroencephalographic (EEG) signals as biometric identifiers has attracted the interest of the research community, thanks to the several advantages they offer over conventional biometrics, like confidentiality and security [1]. EEG signals can be captured in response to a presented stimulus or while performing a given task. Most of the studies carried out so far have focused on EEG signals acquired in resting states conditions, mainly because of the simplicity to implement the acquisition protocol. Nonetheless, several other elicitation protocols, based on the response to audio or visual stimuli, real or imagined body movements, imagined speech, etc., can be exploited for designing an EEG-based biometric recognition systems as detailed in [2].

Specifically, in this paper we focus on the use of EEG signals elicited by visual stimuli and analyze the feasibility of their use for biometric recognition purposes. It is well known in literature that presenting a generic flashing pattern to an observer induces a spontaneous time-locked response of the visual cortex, indicated as visually-evoked potential (VEP) [3]. Moreover, a specific target, appearing at a low occurency rate *wrt* to the other visual stimuli and designed to invoke the execution of a cognitive task, is able to draw out a specific event-related potential (ERPs) [4]. Both responses are commonly elicited when a sequence of non-target stimuli is infrequently interrupted by a target event [**?**]. In this paper we design two distinct protocols to analyze the discriminative capabilities of responses to both target and non-target events.

In addition, carrying on our previous study in [5], we analyze the stability across time of EEG signals elicited with the proposed protocols. Since EEG patterns may vary from session to session, due to several preconditions such as position and conductivity of the electrodes, level of attention and wakefulness, or task involvement of the subject [6], investigating the permanence issue is of paramount importance for the deployment of EEG-based biometric recognition system in practical scenarios. Experimental results obtained over a large database, comprising EEG acquisitions taken from 50 subjects during 3 distinct sessions spanning a period of one month and a half, support the hypothesis that individuals' EEG signals actually possess repeatable discriminative traits.

II. State of the art: VEP based EEG biometrics

EEG signals elicited by visual stimuli have been already employed as biometric identifiers in a few works. Nonetheless, most of the already proposed approaches are flawed either in terms of the dataset dimension, or the number of involved EEG acquisition sessions, or due to the fact that EEG data employed for enrollment and recognition purposes rarely taken from disjoint sessions. A review on the state of the art follow. Face and car images, each rapidly shown for 40ms, have been employed as visual stimuli in [7], where pre- and post-stimulus responses are employed to discriminate between 20 considered individuals. A classification accuracy at about 94% has been achieved exploiting the best performing post-stimulus set. VEP data have been recorded in [8] from 20 subjects when presenting a single kind of stimulus, consisting of a picture with common objects represented by black and white line. A classification accuracy of 99.6% has been achieved with ANOVA tests performed on each of the 61 employed channels. The influence of irrelevant stimuli during a task has been studied in [9] by means of a rapid serial visual paradigm (RSVP). EEG data acquired with 8 channels from 8 subjects have been used to this aim, achieving an overall correct recognition rate (CRR) of about 97%.

While the aforementioned approaches have been tested over EEG data collected during a single session, exploited for generating both enrollment and recognition datasets, EEG data from 5 subjects have been recorded during 5 sessions on the same day in [10]. The combined use of EEG responses to both target and non-target visual stimuli has allowed to achieve a CRR up to 97.6%. Unfortunately, such performance has been reached by randomly assorting EEG data from different sessions when generating enrollment and testing datasets, thus affecting the reliability of the obtained results. An analogous approach has been followed for creating enrollment and recognition datasets in [11], where EEG differences between responses to self- and non-self- face images have been exploited to discriminate 10 subjects, with a CRR of about 86.1%.

R. Das, P. Campisi, E. Maiorana are with the Section of Applied Electronics, Department of Engineering, Roma Tre University, Via Vito Volterra 62, 00146, Rome, Italy e-mail: (rig.das@uniroma3.it, patrizio.campisi@uniroma3.it, emanuele.maiorana@uniroma3.it), Phone: +39.06.57337064, Fax: +39.06.5733.7026.

[1]Cite this paper as "R. Das, E. Maiorana and P. Campisi, "EEG Biometrics Using Visual Stimuli: A Longitudinal Study," in IEEE Signal Processing Letters, vol. 23, no. 3, pp. 341-345, March 2016. doi: 10.1109/LSP.2016.2516043"

TABLE I: Overview of state-of-the-art EEG based biometric systems based on the use of visual stimuli.

Paper	Users	Channels	Protocol	Type of Stimuli	Features	Classifier	Performance	Sessions
Das et al. [7]	20	20	VEP	rapid visual categorization task	LDA	KNN	CRR=94%	1
Palaniappan [8]	20	61	VEP	snodgrass & vanderwart pictures	spectral power ratio	BP NN	CRR=99.6%	1
Gupta et al. [9]	8	8	VEP/ERP	rapid serial visual paradigm	P300	LDA	CRR=97%	1
Touyama [10]	5	1 (Cz)	VEP/ERP	target and non-target images	PCA	LDA	CRR=97.6%	5 (same day)
Yeom et al. [11]	10	8	VEP/ERP	self and non-self face images	Adaptive discriminative feature	Non-Linear SVM	CRR=86.1%	2 (different days)
Armstrong et al. [12]	15	1	ERP	text reading	ERP signal	Correlation	CRR=89.0%	2 (1 week)
	8						CRR=93.0%	2 (over 6 months)

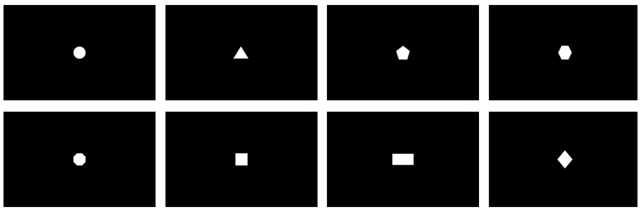


Fig. 1: Visual stimuli employed for the “Geometric” protocol.

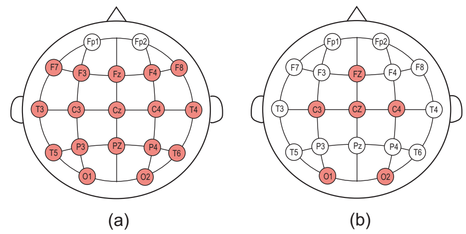


Fig. 2: Electrodes montages. (a): $M = 17$; (b): $M = 6$.

Conversely, two disjoint recording sessions have been properly used as enrollment and testing datasets in [12]. Specifically, two scenarios have been there investigated: the first one with EEG data acquired from 15 subjects at a time distance of one week, and the second one with only 8 subjects recorded at an inter-session temporal distance of 6 months. The CRRs achieved exploiting the generated ERPs have been respectively of 89.0% and 93.0%. Nonetheless, it is worth remarking that, besides being obtained over relatively small databases, the results reported in [12] cannot provide proper information about the permanence in EEG-based biometric recognition systems, having been evaluated over two distinct databases.

Table I provides a summary of the aforementioned papers. Given the limits of the contributions so far described, the present work presents the first analysis on the permanence of EEG signals generated using visual stimuli for the purpose of biometric recognition.

III. Employed EEG data acquisition protocol

Two distinct stimulation protocols are here employed to elicit EEG potentials, both involving the presentation of rare target images, among a large series of non-target stimuli.

A. “Geometric” protocol

This protocol consists in the display on an LCD monitor of 8 images each containing a different geometric shape, as shown in Fig. 1. The appearance of each image represents a stimulus lasting for 250ms and followed by a black screen lasting 450ms. Each geometric shape is presented in a random order for 60 times, therefore resulting in a total acquisition time of 5min and 36s for each session. While the appearance of each image generates a VEP in the observer, a peculiar response is elicited when the target shape is shown [**?**]. Specifically, the considered subjects are requested to concentrate on the occurrences of the “circle” shape, which is therefore used as target stimulus, while the other 7 images are considered non-target.

B. “Letters & Numbers” protocol

The second protocol involves the presentation of a total of 62 images, including 26 images showing capital letter characters, 26 images with lowercase letter characters, and 10 images containing digits from 0 to 9. Out of these images, subjects are requested to concentrate when numbers appear on the screen, with both capital and lowercase letter acting as non-target stimuli. Similarly to the geometric protocol, the target images are randomly shown for a total of 60 occurrence, while letters are randomly presented for a total of 660 times. Since each image is shown for 250ms, and a 450ms of delay is implemented between every two images, each recording session therefore lasts 8min and 24s, during which a total of 720 stimuli are presented to a subject.

IV. Employed EEG based biometric system

Once acquired, EEG data are first preprocessed as outlined in Section IV-A. The processing then performed during the enrollment phase is described in Section IV-B, while the verification phase is detailed in Section IV-C.

A. Preprocessing

At the beginning of both enrollment and verification phases, a preprocessing step is carried out on the recorded EEG data, to increase their signal-to-noise ratio. Specifically, a common average referencing (CAR) filter is first applied by computing the mean signal from all the M considered acquisition channels, and then subtracting this value from each of them, thus reducing artifacts related to unsuitable reference choices. [2]. The CAR-filtered channels are then normalized using z-score transformation, thus generating zero-mean data with unit variance. Eventually, each of the M signals is also detrended by individually subtracting their best-fit line, thus allowing to focus only on the data fluctuations about the estimated trend.

B. Template generation

In order to generate a template from the acquired EEG signals, it is worth remarking that EEG potentials amplitudes tend to be significantly low, when compared to the overall behavior of EEG fluctuations. In order to resolve such low-amplitude potentials against the background of ongoing EEG, signal averaging is performed on the available data for each user. Specifically, being the responses to both target and non-target stimuli time-locked to the originating events, it is possible to collect R reactions to such stimuli, each lasting T ms from the beginning of the associated event, and averaging them thus having the undesired noise filtered out. For a given user, the obtained template is therefore generated as the collection of the M time-dependent potentials registered from each of the M considered EEG channel, in correspondence to either target or non-target stimuli.

C. Verification

In the verification stage, the template is generated as described in Section IV-B. The responses observed in corresponding channels during enrollment and verification are then compared by evaluating their cosine distance. The M distances thus computed are fused into a single score by taking their average. A comparison with a threshold completes the verification procedure.

The aforementioned process is performed when working on either target or non-target-stimuli. It can be however observed that, for a fixed number R of stimuli responses to be collected in both scenarios, the time needed for performing the enrollment or verification phases of a system exploiting non-target occurrences are typically much lower than the corresponding amounts required when considering target events, given the modalities through which the employed protocols are designed.

V. Results and Discussion

The EEG database employed for the performed experimental tests is collected using a Galileo BE Light amplifier with 19 electrodes, placed on the subjects' scalp according to the 10-20 international system [13]. EEG signals are taken from 50 healthy subjects, whose age ranges from 20 to 35 years with an average of 25, according to both protocols described in Section III. During each EEG data acquisition, subjects are comfortably seated on a chair in a dimly lit room, with a viewing distance and screen sizes selected in order to satisfy the preferred viewing distance (PVD) [14]. Three distinct acquisition sessions, indicated in the following as S1, S2, and S3, are performed for each subject. Specifically, the second recording session of each user is taken one week after the first one, while the temporal distance between the first and the third sessions of the considered users ranges from 25 to 49 days, with an average of 34 days.

All the tests are carried out by selecting, as enrollment and testing datasets, EEG data from distinct sessions. Moreover, in order to present statistically significant results, each considered scenario is evaluated by means of cross-validation procedures, consisting of 20 distinct runs, each performed by randomly selecting 40 users out of the available 50. Specifically, at each run the performance associated with the responses to either target or non-target stimuli is estimated by considering, for all the 40 selected subjects and in both the considered protocols:

- 10 different templates, each generated as described in Section IV-B on the basis of $R = 50$ consecutive responses captured during the enrollment session;
- for each enrollment template, 10 distinct probes for intra-class comparisons, each time obtained by randomly selecting $R = 50$ consecutive responses from the recognition session;
- for each enrollment template, a testing probe for inter-class comparison from each of 30 users distinct from the enrolled one, each obtained by randomly selecting $R = 50$ consecutive responses from the recognition session.

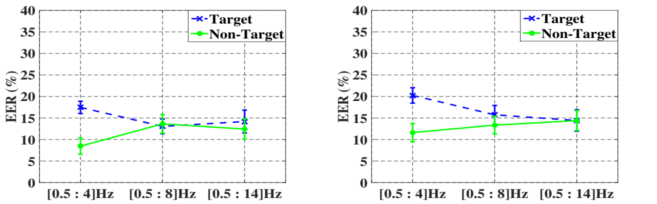
At each iteration, the associated recognition performance is therefore evaluated on the basis of $40 \cdot 10 \cdot 10$ intra-class matches, and $40 \cdot 10 \cdot 30$ inter-class comparisons.

Within the considered framework an analysis on the most discriminative subbands and time intervals to consider is given in Sections V-A and V-B respectively. Such analysis is performed using S1 as enrollment datasets and S2 as verification data (S1 *vs* S2). Furthermore, we analyze the permanence of the EEG signals elicited using the employed visual stimuli by means of the achievable recognition performance in Section V-C, where three different scenarios with an increasing temporal distance between the enrollment and the identification stages, namely S1 *vs* S2, S2 *vs* S3, and S1 *vs* S3, are considered. Results are given in next Sections in terms of the 95% confidence intervals of the equal error rates (EERs) for both the "Geometric" and the "Letters & Numbers" protocol. Confidence intervals are reported as $[\mu_{EER} - 1.96\sigma_{EER} : \mu_{EER} + 1.96\sigma_{EER}]$, being μ_{EER} and σ_{EER} respectively the mean and standard deviation of the EER obtained during the 20 performed iterations of the employed cross-validation procedure.

The aforementioned analysis are conducted considering two different EEG montages, depicted in Figure 2, with either $M = 17$ or $M = 6$ employed channels. In the former case, only the two frontal electrodes, i.e. F_{p1} and F_{p2}, are discarded due to the most relevant presence of EEG potentials in the central and occipital regions. In order to reduce the number of employed electrodes, thus lowering the user inconvenience, we also consider the latter configuration, selected by sorting each individual channel in terms of associated recognition performance, and selecting the top six for both the target and non-target scenario. It is worth observing that this latter montage resembles those commonly employed to exploit ERP for brain-computer applications [15].

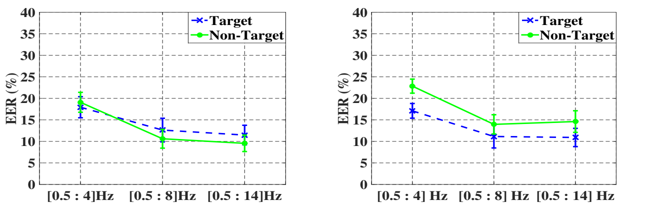
A. Frequency subband selection

Three different subbands are evaluated for determining the EEG frequency range containing the most discriminative characteristics: $[0.5 : 4]$Hz, corresponding to δ waves, $[0.5 : 8]$Hz, including both δ and θ waves, and $[0.5 : 14]$Hz, comprising δ, θ and α rhythms. The considered EEG potentials are analyzed over a time interval following the presentation of a stimulus and lasting $T = 600$ms, for both target and non-target. Figures 3 and 4 show the EER 95% confidence intervals



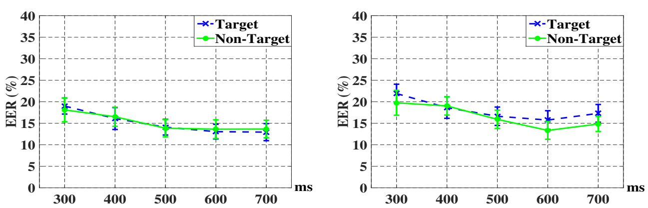
(a) $M = 17$ Ch. (b) $M = 6$ Ch.

Fig. 3: "Geometric Protocol": EER confidence intervals of EER for different frequency bands.



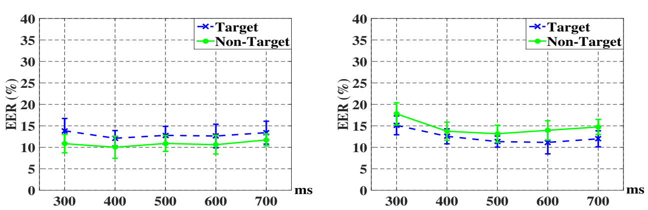
(a) $M = 17$ Ch. (b) $M = 6$ Ch.

Fig. 4: "Letters & Numbers" protocol: EER confidence intervals for different frequency bands.



(a) $M = 17$ Ch. (b) $M = 6$ Ch.

Fig. 5: "Geometric" protocol: EER confidence intervals for different time intervals.



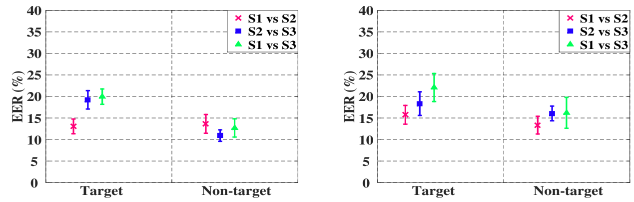
(a) $M = 17$ Ch. (b) $M = 6$ Ch.

Fig. 6: "Letters & Numbers" protocol: EER confidence intervals for different time intervals.

when exploiting the considered subbands, respectively for the "Geometric" and the "Letters & Numbers" protocols. It can be seen that, for both the considered protocols, the $[0.5:8]$Hz and $[0.5:14]$Hz subbands perform similarly, with the former one showing a slightly lower performance variance. Therefore, we select the $[0.5:8]$Hz subband to perform the subsequent analysis. The obtained results also show that focusing on non-target responses generally guarantees higher recognition rates than the ones obtained when considering target events.

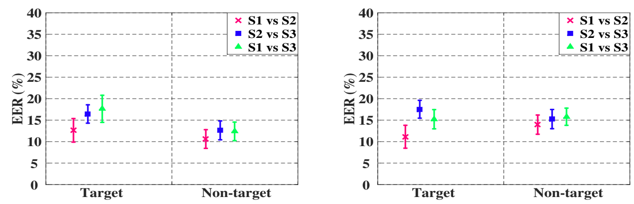
B. Time interval selection

The responses to both target and non-target responses are then analyzed considering different time intervals



(a) $M = 17$ Ch. (b) $M = 6$ Ch.

Fig. 7: "Geometric" protocol: EER confidence intervals comparing different sessions.



(a) $M = 17$ Ch. (b) $M = 6$ Ch.

Fig. 8: "Letters & Numbers" protocol: EER confidence intervals comparing different sessions.

following the presentation of the stimuli, with $T \in \{300, 400, 500, 600, 700\}ms$. The shortest considered interval is set to 300ms in order to include the P300 behavior, characteristic of ERP responses, in all the evaluated scenarios. Figures 5 and 6 show the 95% confidence intervals obtained for both the considered protocols, showing that a proper selection for the interval to be analyzed is $T = 600$ms, therefore employed for the following EEG permanence evaluation.

C. Permanence of EEG signal across time

The permanence of the recognition performance achievable with the considered EEG based biometric system, is then evaluated by considering three different scenarios with increasing temporal distance between the enrollment and the verification stages. Figure 7 and 8 report the 95% confidence intervals evaluated for the considered protocols, showing that for both of them a satisfactory performance permanence can be achieved over different comparisons. Specifically, a more stable behavior is observed when exploiting responses to non-target events, with respect to the use of target stimuli. The obtained results also show that a montage with $M = 6$ electrodes results in only a slight worsening of the achievable performance with respect to the use of $M = 17$ channels, while significantly improving the usability of the proposed system in terms of user comfort, and therefore preferrable for practical implementations [2].

VI. Conclusions

In this paper we have investigated the feasibility of using EEG biometrics elicited with visual stimuli for automatic people recognition. Specifically, we have verified, on a longitudinal dataset, that a satisfactory level of permanence across

[2]Cite this paper as "R. Das, E. Maiorana and P. Campisi, "EEG Biometrics Using Visual Stimuli: A Longitudinal Study," in IEEE Signal Processing Letters, vol. 23, no. 3, pp. 341-345, March 2016. doi: 10.1109/LSP.2016.2516043"

time of the so-obtained EEG signals, measured in terms of stable recognition performance, can be obtained. According to the obtained results, EEG channel montage with 6 electrodes, and the analysis of responses to non-target stimuli, can be recommended for practical implementations. The performed analysis can be considered as a preliminary step towards the use of VEP-based EEG signals as a stable biometric identifier [3].

REFERENCES

[1] K. Revett, F. Deravi, and K. Sirlantzis, "Biosignals for user authentication - towards cognitive biometrics?" in *IEEE ICEST*, 2010.

[2] P. Campisi and D. La Rocca, "Brain waves for automatic biometric-based user recognition," *IEEE Transactions on Information Forensics and Security,*, vol. 9, no. 5, pp. 782–800, May 2014.

[3] M.-Z. Yu and B. Brown, "Variation of topographic visually evoked potentials across the visual field," *Ophthalmic Physiol. Opt.*, vol. 17, no. 1, pp. 25 – 31, 1997.

[4] S. Bressler, "Event-related potentials of the cerebral cortex," in *Electrophysiological Recording Techniques*, ser. Neuromethods, R. P. Vertes and R. W. Stackman Jr., Eds. Humana Press, 2011, vol. 54, pp. 169–190.

[5] E. Maiorana, D. La Rocca, and P. Campisi, "On the permanence of EEG signals for biometric recognition," *IEEE Transactions on Information Forensics and Security,*, October 2015.

[6] M. Arvaneh, C. Guan, K. K. Ang, and C. Quek, "Robust eeg channel selection across sessions in brain-computer interface involving stroke patients," in *Neural Networks (IJCNN), The 2012 International Joint Conference on*, June 2012, pp. 1–6.

[7] K. Das, S. Zhang, B. Giesbrecht, and M. Eckstein, "Using rapid visually evoked eeg activity for person identification," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, Sept 2009, pp. 2490–2493.

[8] R. Palaniappan, "Method of identifying individuals using vep signals and neural network," *Science, Measurement and Technology, IEE Proceedings -*, vol. 151, no. 1, pp. 16–20, Jan 2004.

[9] C. Gupta, R. Palaniappan, and R. Paramesran, "Exploiting the p300 paradigm for cognitive biometrics," *International Journal of Cognitive Biometrics, Inderscience Journal on*, vol. 1, no. 1, pp. 26–38, May 2012.

[10] H. Touyama, "Eeg-based personal identification," *Biomedical Engineering, InTech Journal on*, no. 22, pp. 415–424, October 2009. [Online]. Available: http://www.intechopen.com/books/biomedical-engineering/eeg-based-personal-identification

[11] S.-K. Yeom, H.-I. Suk, and S.-W. Lee, "Person authentication from neural activity of face-specific visual self-representation," *Pattern Recogn.*, vol. 46, no. 4, pp. 1159–1169, Apr. 2013. [Online]. Available: http://dx.doi.org/10.1016/j.patcog.2012.10.023

[12] B. C. Armstrong, M. V. Ruiz-Blondet, N. Khalifian, K. J. Kurtz, Z. Jin, and S. Laszlo, "Brainprint: Assessing the uniqueness, collectability, and permanence of a novel method for {ERP} biometrics," *Neurocomputing*, vol. 166, pp. 59 – 67, 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0925231215004725

[13] J. Malmivuo and R. Plonsey, *Bioelectromagnetism: Principles and applications of Bioelectric and biomagnetic fields*. Oxford University Press, 1995.

[14] *Methodology for the subjective assessment of the quality of television pictures*. Rec. ITU-R BT.500-11, 2002.

[15] S. Amiri, A. Rabbi, L. Azinfar, and R. Fazel-Rezai, "A review of P300, SSVEP, and hybrid P300/SSVEP brain- computer interface systems," in *Brain-Computer Interface Systems - Recent Progress and Future Prospects*, R. Fazel-Rezai, Ed. Intech, 2013.

[3]Cite this paper as "R. Das, E. Maiorana and P. Campisi, "EEG Biometrics Using Visual Stimuli: A Longitudinal Study," in IEEE Signal Processing Letters, vol. 23, no. 3, pp. 341-345, March 2016. doi: 10.1109/LSP.2016.2516043"