Exploiting the P300 paradigm for cognitive biometrics

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Abstract: Automatic identification of a person's individuality is an important issue today. Brain Computer Interfaces (BCI) which uses EEG as a modality is a promising area for cognitive biometrics. A BCI system could be used to recognise a sequence (say letters, colours or images) by the user. This sequence could form a 'BrainWord', which could be used for authentication in a multimodal environment with other technologies for high security applications. In this work, we studied several variations of the well-known P300 BCI paradigm. The influence of irrelevant stimuli during a task was studied by considering the popular *Rapid Serial Visual Paradigm* (*RSVP*). The variation in spatial locations of the presentation stimuli during a task was studied, by designing a *Spatially Varying Paradigm*. Comparison of classification accuracies and bit rates for eight participants from a BCI perspective, highlights that *RSVP* paradigm could be exploited effectively for biometrics.

Keywords: authentication system; bit rate; brain-computer interface; cognitive biometrics; p300 potential; RSVP; rapid serial visual paradigm; spatially varying paradigm.

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1 Introduction and motivation

Cognitive biometrics is a developing research topic which enables user authentication/ identification by exploiting the mental states of an individual (Revett et al., 2010). Electroencephalogram (EEG) is the recording of brain's electrical activity and is an established de facto standard in diagnosis of brain related diseases. Of late, there has been a spurt of activity to exploit EEG for authentication (Ravi and Palaniappan, 2006; Marcel and Millan, 2007; Palaniappan and Mandic, 2007a; Palaniappan and Mandic, 2007b; Palaniappan, 2008; Riera et al., 2008) in addition to others physiological biometrics like Electrocardiogram (ECG) (Palaniappan and Krishnan, 2004). Multiple signal classification (MUSIC) algorithm was used to classify energy features within gamma band (Palaniappan and Mandic, 2007a), Elman neural network with spatial data/sensor fusion (Palaniappan and Mandic, 2007b), singe trials of non-time locked evoked potentials (Ravi and Palaniappan, 2006), non-linear features from simple mental tasks (Palaniappan, 2008), power spectral density feature with Gaussian mixture models (Marcel and Millan, 2007) and a multi-feature (Riera et al., 2008) approaches were used for person authentication in these studies. ERD/ERS pattern was also identified as a possible stable biometric marker, in a BCI context (Pfurtscheller and Neuper 2006). Other classification frameworks explored include autoregressive (AR) features with different classifiers (Poulos et al., 1999). However, most studies until now have failed to investigate the long-term stability of the features. For a reliable and practical implementation, invariance of feature is an absolute necessity. We consider overcoming the stability issue by developing an authentication system from a Brain Computer Interface (BCI) perspective. The system proposes to use evoked brain signals (recorded at certain optimal locations on the scalp) to recognise the sequence of letters/colours/images that are focused upon by the user in real-time. For example, a passcode could be a letter (A), colour (red) and an image (picture). The objective would be to identify the above passcode by using only thoughts with BCI technology, which could be used to authenticate the identity of a person. The possibility of changing the passcode gives the system more flexibility in terms of long-term stability.

Potentials which originate from outer layer of brain in response to an event are called Event-Related Potentials (ERPs) (Misulis, 1994). ERPs can be divided into two categories: namely exogenous ERPs, which arise due to early automatic processing of the physical stimulus; and the endogenous ERPs, which result due to the processing of the stimuli (Coles and Rugg, 1995). P300 is a type of endogenous ERP having a latency of 300–600 ms, where the evoked potential amount depends on the given task and has gained much attention in cognitive and neuro-scientific applications (Sutton et al., 1967). Farwell and Donchin (1988) and Donchin et al. (2000) first demonstrated the use of P300 for BCI in an oddball paradigm. In the oddball experiment, the participant is asked to distinguish between target and non-target stimuli, by performing a mental count of the target stimuli. In the modified three stimulus oddball paradigms, distractor stimulus occurs along with target and non-target stimuli (Courchesn et al., 1975). The target stimulus evokes a P3b component with a latency of 300–600 ms, while the distractor stimulus evokes a P3a component with a latency of 200–400 ms (Courchesn et al., 1975). From a psychological aspect, P3b is considered to be involved in context updating or revising the contents of working memory (Donchin, 1981; Coles and Rugg, 1995). Gupta et al. (2008) presented a preliminary paradigm design using BCI for high security authentication scenarios by effectively overcoming the participant’s gaze effect. This current work extends it to a four class oddball paradigms, proposes and investigates the effect of varying spatial location of stimuli, uses advanced machine learning techniques and presents the results from a BCI viewpoint (i.e. bit rates and classification accuracies). To the best of all authors’ knowledge, varying spatial location of stimuli has not been studied so far in an oddball paradigm.

2 Participants and data acquisition

Four males and four females (aged 22–30) all from University of Essex student community, without any known neurological and visual imparity performed the three experimental paradigms. A basic understanding of oddball paradigm and the purpose of the experiments were explained to the participants for motivated involvement and they voluntarily signed a consent form. All experiments were approved by the University of

Essex Ethical Committee. The EEG data were collected using a Biosemi Active Two system at a sampling rate of 256 Hz. Since the purpose of this study was to investigate suitable paradigms for cognitive biometrics, eight optimum channels reported by Hoffmann et al. (2007) were used. Two recorded mastoid channels were used as reference. The Graphical User Interface (GUI) was developed using Visual Basic software and integrated into the Biosemi data logging software. The participants were asked to refrain (as much as possible) from blinking during the experiment, which was performed in a well-shielded room from electromagnetic interference.

3 Experimental paradigms and task

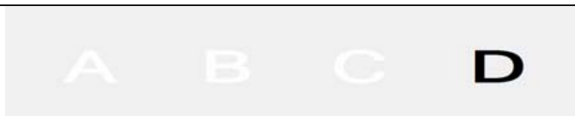
To determine a suitable paradigm for cognitive biometrics, three variations of oddball were studied, namely standard oddball, Rapid Serial Visual Paradigm (RSVP) and spatially varying oddball as explained diagrammatically in this section. This work proposes the design of spatially varying oddball paradigm. Repetition blindness and attentional blink are two common perceptual errors, affecting the classification accuracy of both RSVP and oddball paradigms (Cinel et al., 2004). However, both these phenomena do not occur when the Inter Stimulus Interval (ISI), which is the time between two stimuli flashes, is greater than 500 ms (Kanwisher, 1987; Raymond et al., 1992).

Stimuli letters A, B, C and D were used (i.e. four-class BCI) for all three paradigms. Flash-time and ISI were set to 100 ms and 750 ms, respectively. For all paradigms, the background colour in 8-bit RGB model was light grey (240, 240, 240), the default character colour in 'OFF' state was white (255, 255, 255) and the flashed stimuli colour in 'ON' state was black (0, 0, 0). On executing the experiment, 'target cue stimuli' was presented briefly for 2 seconds. The participant was instructed to count the target cue stimuli mentally. Flashes of four stimuli (say 'A', 'D', 'C' and 'C') are considered a block. Being a four-class BCI, block randomisation flashing was avoided to prevent habituation. The recorded blocks for every experiment were randomly generated by the computer, varying between 40 and 48. Each paradigm had two different target cues as the task, which the participant was required to keep a mental count. Every paradigm had an experiment time between 4.6 and 5.5 minutes depending on block number, which was randomly generated by the computer. The participants reported target cues and number of flashes at the end of each experiment.

3.1 Standard oddball

To illustrate the execution of this paradigm, we explain it diagrammatically in Figure 1 with seven stages for easier understanding. The stimuli were spatially fixed and flash between 'OFF' (white) and 'ON' (black) states. The participants in this case effectively concentrated on the target stimuli (which was spatially fixed) to flash black (ON state), before mentally counting them. Since the participant focused on spatially fixed stimuli each time, a gaze tracker could be effectively used to find the participant's gaze, which would prevent the method from being applied for biometrics. Also during this paradigm, the participant was exposed to irrelevant stimuli flashes.

Figure 1 Standard oddball (see online version for colours)

Stage 1		Loading of GUI (stimuli spatially fixed and in OFF state)
Stage 2		First target cue presented for 2 seconds
Stage 3		Flashing of stimuli
		Flashing of stimuli continues (40–48 blocks)
Stage 4		Two second pause after 1st target cue stage
Stage 5		Second target cue presented for 2 seconds
Stage 6		Flashing of stimuli
		Flashing of stimuli continues (40–48 blocks)
Stage 7		End of experiment

3.2 Spatially varying oddball

This work investigates the spatially varying oddball paradigm. The location of stimuli was not spatially fixed but presented within one of the four squares. To illustrate the execution of the paradigm, we explain it diagrammatically using seven stages as shown in Figure 2. Each stimulus (say 'A') was presented in one of the squares, one at a time. The participant changed his/her gaze at each flash during this paradigm.

Figure 2 Spatially varying oddball paradigm (see online version for colours)

Stage 1		Loading of GUI (four squares where the stimuli flashes occur). Stimuli are not spatially fixed.
Stage 2		First target cue presented for 2 seconds
Stage 3		Flashing of stimuli (one at a time in each square, with varying spatial location)
		Flashing of stimuli (with varying spatial location)
		Flashing of stimuli (continues for 40–48 blocks)
Stage 4		Two second pause after 1st target cue stage
Stage 5		Second target cue presented for 2 seconds
Stage 6		Flashing of stimuli (one at a time in each square, with varying spatial location)
		Flashing of stimuli (continues for 40–48 blocks)
Stage 7		End of experiment

3.3 Rapid Serial Visual Paradigm (RSVP)

In RSVP, the stimulus was presented within a single square block. The paradigm is illustrated diagrammatically in Figure 3 using seven stages. The participant focused his/her gaze at the same rectangle during this paradigm. It minimised the influence of irrelevant stimuli, perceptual errors and was user friendly.

Figure 3 Rapid serial visual paradigms (see online version for colours)

Stage 1		Loading of GUI (single square where the stimuli flash)
Stage 2		First target cue presented for 2 seconds
Stage 3		Flashing of stimuli (within the single square)
		Flashing of stimuli (within the same single square, continues till 40–48 blocks)
Stage 4		Two second pause after 1st target cue stage
Stage 5		Second target cue presented for 2 seconds
Stage 6		Flashing of stimuli (within the same single square, continues till 40–48 blocks)
		Flashing of stimuli (within the same single square)
Stage 7		End of experiment

4 Data analysis and results

To avoid bias, the pre-processing techniques and classifiers used were same for all studied paradigms. The data were referenced to average of mastoids channels. For each single trial, a forward-reverse Butterworth bandpass filter with cut-off frequencies (1 Hz and 12 Hz) was used to filter the data, to obtain signals in the P300 spectral range. The designed filter lost no more than 1 dB in passband and had at least 40 dB attenuation in the stopband. To remove artefact activity, Windsorising as described by Hoffmann et al. (2007) was implemented. The data were then normalised and the recorded eight channels were used to obtain the classification accuracy. The data obtained for each paradigm were between 40 and 48 blocks as discussed in Section 3. The data were divided into four sets of ten blocks each. A threefold cross-validation method using Bayesian LDA (Hoffmann et al., 2007) was used to obtain the classification accuracies. The accuracies obtained from cross-validation were averaged and bit rates calculated using Wolpaw's definition (Wolpaw et al., 2002; Hoffmann et al., 2007). Bit rate B (bits/min), which gives the information throughput, is often used to characterise BCI systems and is computed according to equation (1) (Wolpaw et al., 2002):

$$B(N,p,t)=\log_2(N)+p\log_2(p)+(1-p)\log_2\left(\frac{(1-p)}{(N-1)}\right)\frac{60}{t} \tag{1}$$

where N denotes the number of different commands a user can send, p denotes the probability that a command is correctly recognised by the system and t is the time in seconds that is needed to send one command. The bit rate can be effectively increased by varying parameter N and/or t. All programmes for data analysis were written using MATLAB. The results of eight participants who participated in all three paradigms are depicted in Figures 4–11 and tabulated in Table 1. The classification accuracy and bit rate of *RSVP* were highest for all participants. Participant 2 achieved the maximum classification accuracy of 100% with least number of trials for *RSVP Paradigm*. The averaged bit rates for all participants highlight that *RSVP* achieved higher performance than both *Standard Oddball* and *Spatially Varying Oddball* paradigms. The performance of *Standard Oddball* and *Spatially Varying Oddball* were similar.

Figure 4 Comparison of variations in the paradigm (Participant 1)

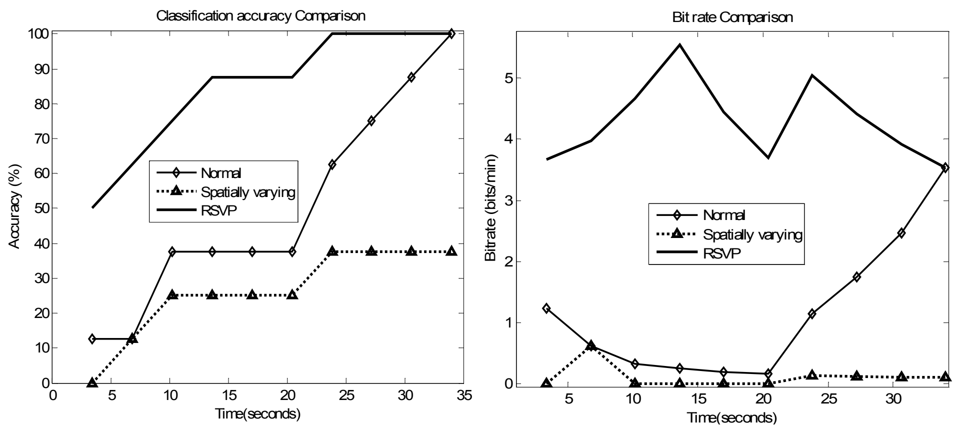


Figure 5 Comparison of variations in the paradigm (Participant 2)

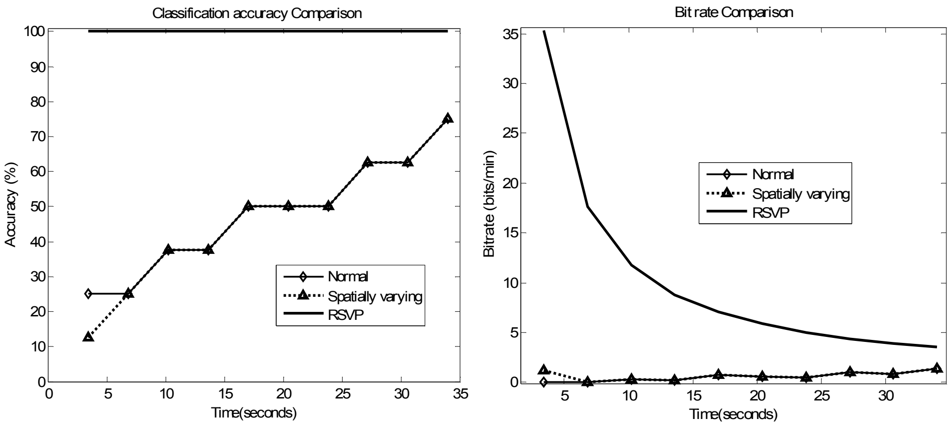


Figure 6 Comparison of variations in the paradigm (Participant 3)

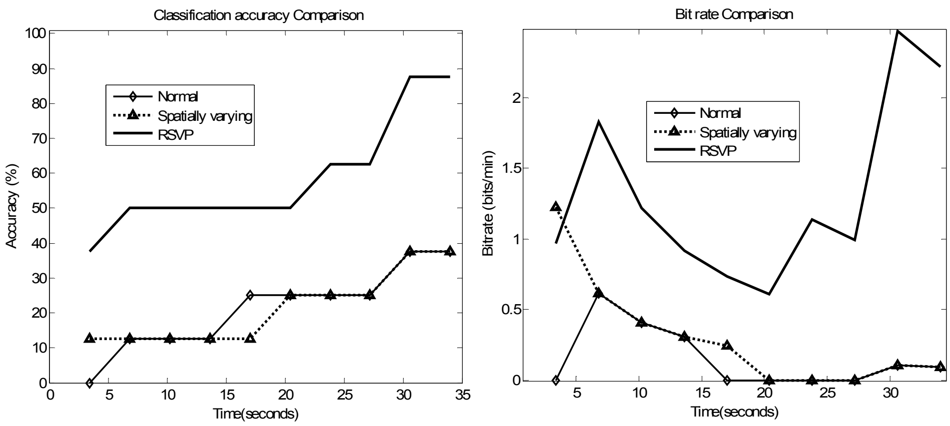


Figure 7 Comparison of variations in the paradigm (Participant 4)

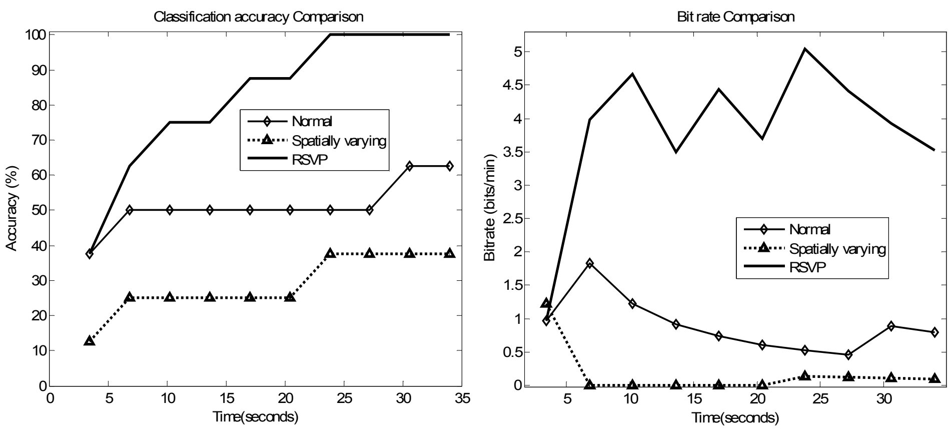


Figure 8 Comparisons of variations in the paradigm (Participant 5)

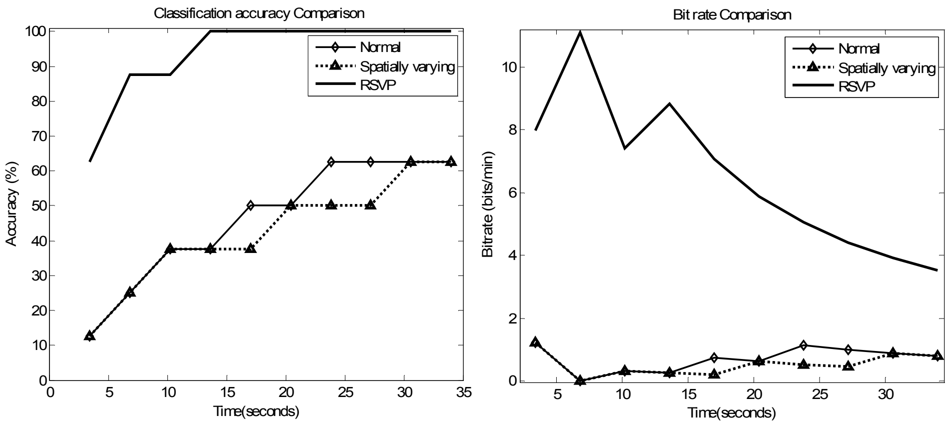


Figure 9 Comparisons of variations in the paradigm (Participant 6)

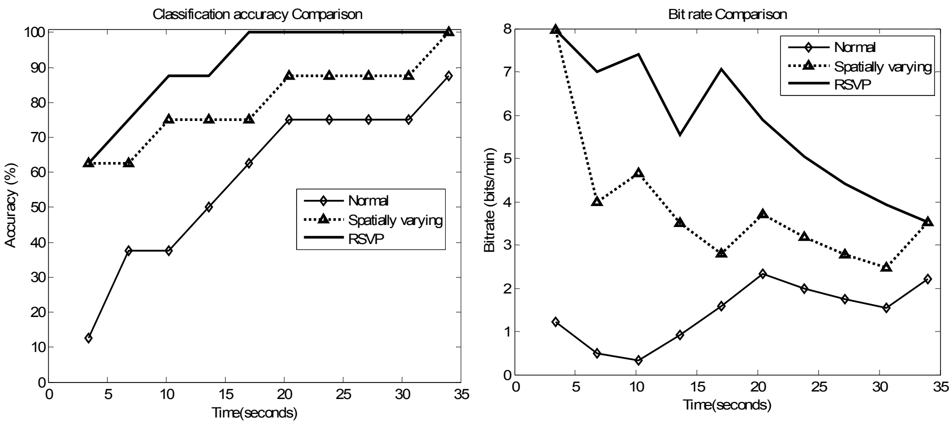


Figure 10 Comparisons of variations in the paradigm (Participant 7)

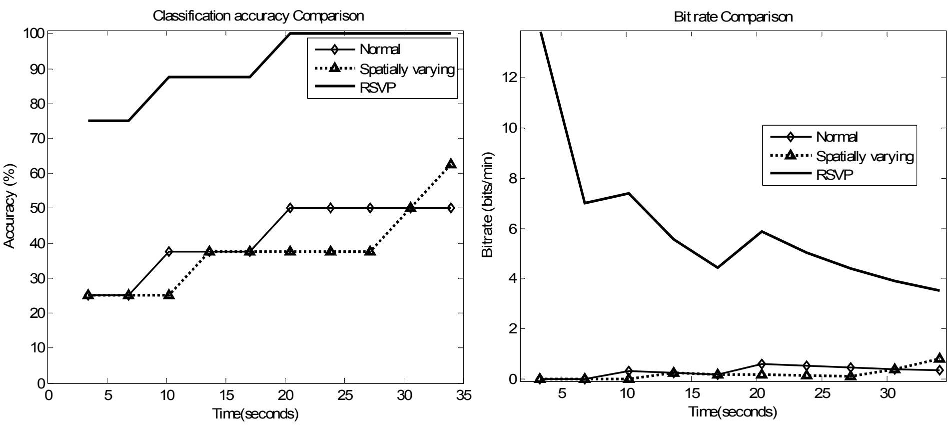


Figure 11 Comparisons of variations in the paradigm (Participant 8)

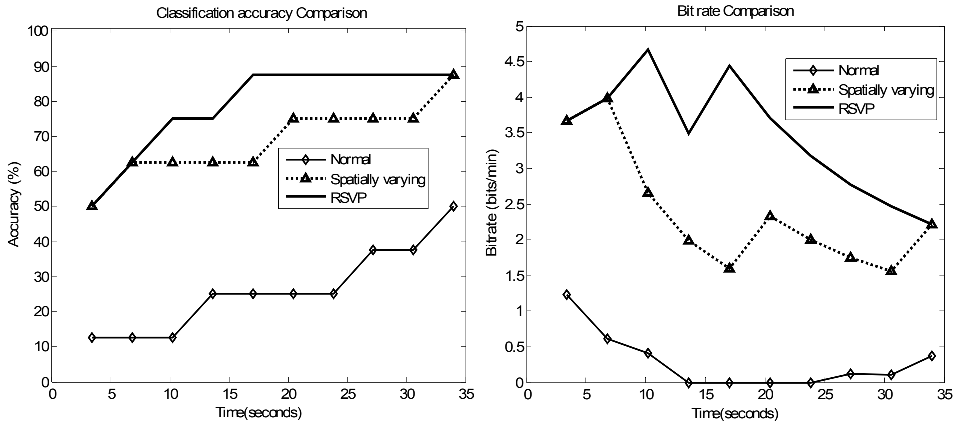


Table 1 Maximum average bit rate per minute for all three paradigms (mean bit rate and standard deviation were computed for all participants)

Participant	*Standard oddball (bits/min)*	*Spatially varying oddball (bits/min)*	*RSVP (bits/min)*
1	3.59	0.614	5.55
2	1.35	1.39	35.29
3	0.61	1.22	2.46
4	1.83	1.25	5.04
5	1.22	1.20	11.10
6	2.33	7.86	7.96
7	0.61	0.78	13.98
8	1.22	3.98	4.66
Avg ± std (all)	1.59 ± 0.98	2.28 ± 2.48	10.75 ± 10.59

5 Discussion and conclusion

Although much research using brain signals for clinical analysis has been done in the past few decades, the application of brain signals for biometric purposes is relatively new. In this work, we exploited the P300 potential within a BCI framework to design an authentication system. This work proposes the spatially varying oddball paradigm and investigates the use of standard oddball and RSVP paradigms for cognitive biometrics. Among the studied paradigms, RSVP is the only paradigm that does not suffer from gaze effect and hence could be used for high security authentication purposes. All paradigms were designed to avoid perceptual errors and made user friendly for naive BCI users. The RSVP was found to be best of all studied paradigms in terms of classification accuracies and bit rates. During a *RSVP* paradigm, the ease in focussing on the same spatial location and the absence of irrelevant stimuli could perhaps be a factor that results in improved P300 potential. As such, we conclude that *RSVP* is more suitable for cognitive-based biometric applications. Overall, it is hoped that this work will provide motivation for further research using BCI for cognitive biometrics.

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