Method of identifying individuals using VEP signals and neural network

Article *in* IEE Proceedings - Science Measurement and Technology · February 2004

DOI: 10.1049/ip-smt:20040003 · Source: IEEE Xplore

1 author:

Ramaswamy Palaniappan
University of Kent

Method of identifying individuals using VEP signals and neural network

R. Palaniappan

Abstract: A method of identifying individuals using visual-evoked-potential (VEP) signals and neural network (NN) is proposed. In the approach, a backpropagation (BP) NN is trained to identify individuals using gamma-band (30-50 Hz) spectral power ratio of VEP signals extracted from 61 electrodes located on the scalp of the brain. The gamma-band spectral-power ratio is computed using a zero-phase Butterworth digital filter and Parseval's time-frequency equivalence theorem. NN classification gives an average of 99.06% across 400 test VEP patterns from 20 individuals using 10-fold cross-validation scheme. This shows promise for the approach to be developed further as a biometric identification system.

1 Introduction

The most common method of identifying individuals is using fingerprints [1]. However, doubts have been raised as to the individuality of fingerprints, i.e. whether the fingerprint is unique to an individual [2]. Therefore, it becomes important to explore newer types of biometric to augment, or as an alternative to, the fingerprint to authenticate or identify individuals. Biometrics involve authenticating or identifying an individual based on his/her physiological or behavioural characteristics. Some of the biometrics that have been utilised are images of the face [3], iris [4], palm [5], hand-geometry [6] and electrocardiogram signals [7].

Very little research work has been published using brain signals as a biometric tool to identify individuals. The method proposed by Poulus *et al.* [8] used autoregressive (AR) modelling of electroencephalogram (EEG) signals and linear-vector-quantisation NN to recognise an individual as distinct from other individuals, with 72–80% success. However, the method was not used to try to recognise each individual in a group. Paranjape *et al.* [9] proposed a method using AR modelling of EEG with discriminant analysis to identify individuals, with classification accuracy ranging from 49 to 85%. Both the methods used EEG signals recorded while the subjects were resting with eyes closed [7] and with eyes open or closed [9].

In this paper, a new biometric method using evoked brain signals to identify individuals is proposed. These signals are known as VEP because they are evoked when the subject perceives a visual stimulus. To the author's knowledge, the use of VEP signals as a biometric to identity individuals is novel. In the technique, VEP signals are recorded from 64 channels while the subjects perceive a single picture. However, only 61 channels serve as active channels, while the remaining three channels are reference channels. Next, these VEP signals are filtered to obtain signals in the gamma-band spectral range of 30–50 Hz using a zero-phase Butterworth digital filter. Zero phase response is achieved using forward and reverse filtering, which cancels the effects of the phase nonlinearity of Butterworth filtering. Parseval's time-frequency equivalence theorem is used to obtain the spectral power of the extracted gamma-band VEP signals without performing frequency analysis. The gamma-band spectral ratio is obtained by dividing the gamma-band spectral power by the total power present in the channel. The BP NN [10] is used to classify (i.e. identify) the individuals using these VEP gamma-band spectral-power ratios. The method could be developed into a unimodal identification system or combined with other biometric methods to form a multimodal identification system.

Gamma-band frequency range is used specifically because of its successful use for optimal classification of alcoholics and nonalcoholics [11]. Furthermore, the gamma-band frequency range of brain signals has been shown to be related to higher brain functions such as perception and memory [12–15]. Visualising a picture evokes perception and memory, thereby being suitable as the stimulus in this case to evoke-gamma band output. These gamma-band VEP signals could be used to identify individuals because the levels of perception and memory access between individuals are generally different. In addition, these differences are made more evident because it is very unlikely for individuals to have similar brain activity in all 61 channels.

In the proposed method, the BP NN is used instead of parametric classifiers or other types of NN architecture. Most NN architectures have good generalisation ability compared with that of parametric classifiers but they are difficult to train and are time-consuming. However, the results from the experimental study show that short training time for BP NN is sufficient to produce good classification accuracy.

IEE Proceedings online no. 20040003
doi:10.1049/ip-smt:20040003
Paper received 17th September 2003

The author is with the Faculty of Information Science and Technology, Multimedia University, Melaka 75450, Malaysia

2 The Method

2.1 Visual-evoked-potential signals

VEP data are recorded from 20 subjects. Each subject completed 40 trials, therefore giving a total of 800 VEP signals. A sample of the VEP signal is shown in Fig. 1.

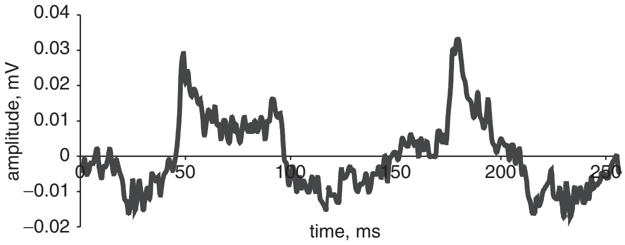

Fig. 1 *An example of a recorded VEP signal*

Measurements are taken for 1 s from 64 electrodes* placed on the subject's scalp, which are sampled at 256 Hz. Therefore, a total of 256 data points is recorded for each VEP signal. The common electrode placement system is the 10–20 international method [16], which contains 19 active plus two reference electrodes. Here, the extension of the method is used to increase the number of electrodes to 64. The electrode positions are shown in Fig. 2. Because this work is the first to use gamma-band spectral power ratio extracted from VEP to identify individuals, it was decided to use the maximum number of channels to see the success/failure of the method. This is to increase the intersubject (individual) difference in collective VEP output from all the channels.

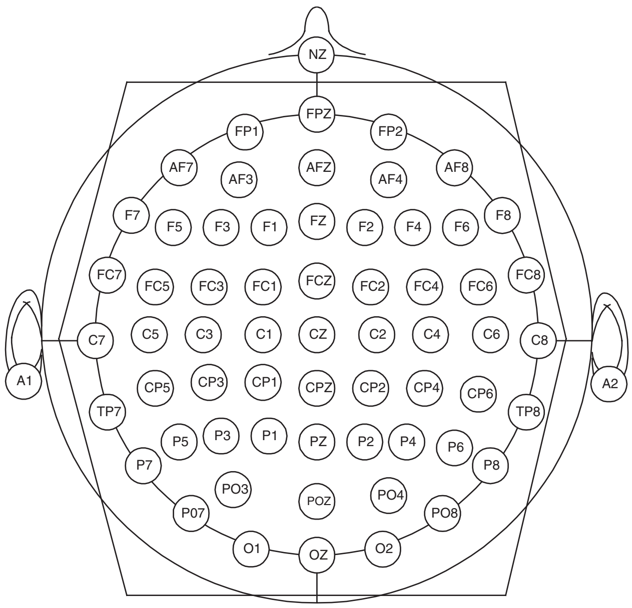

Fig. 2 *64 channel electrode system*
61 active channels inside hexagon

The VEP signals are recorded from subjects while they are being exposed to a single stimulus, in this case pictures of objects chosen from Snodgrass and Vanderwart picture set [17]. These pictures are common black and white line drawings such as a kite, door, bolt, flag etc., executed according to a set of rules that provide consistency of pictorial representation. The pictures are normal pictures that are easily named. In other words, all the pictures are recognisable by all the individuals. Figure 3 shows some of these pictures and Fig. 4 illustrates the presentation of these pictures. The individuals are normal healthy persons in the age range of 19.4 to 38.6 years. All subjects have normal vision or corrected normal vision.

*But only 61 channels are active; the remaining three channels are used as reference channels.

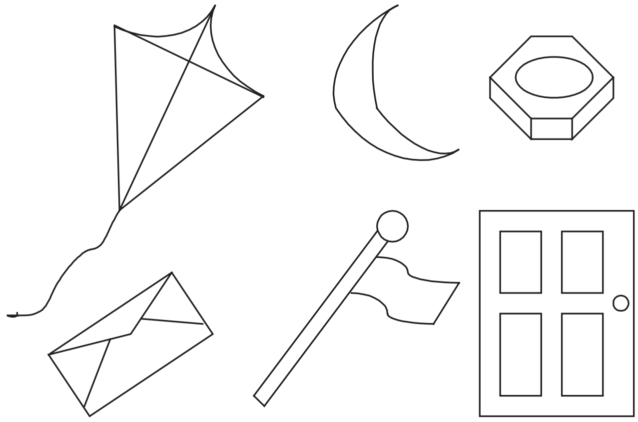

Fig. 3 *Some objects from Snodgrass and Vanderwart picture set*

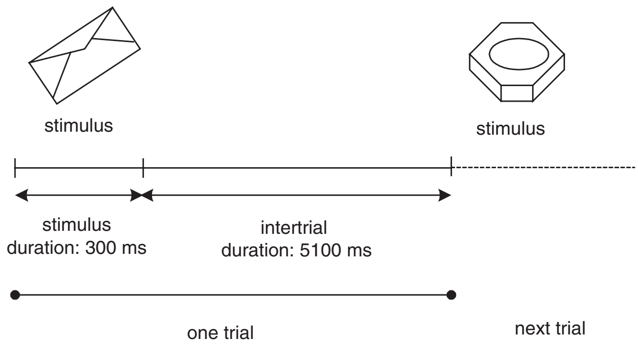

Fig. 4 *Presentation of Snodgrass and Vanderwart picture stimulus*

In this study, VEP signals with eye-blink artifact contamination are removed in the preprocessing stage using a computer program written to detect VEP signals in any one the frontal or prefrontal channels with magnitudes above 100 μV. These VEP signals detected with eye blinks are then discarded from the experimental study and additional trials are conducted as replacements. The threshold value of 100 μV is used since blinking produces 100–200 μV potential lasting 250 ms [18].

Each subject completed 40 trials of 1 s measurements. Actually the number of trials was slightly higher but after removal of eye-blink contaminated artifacts, 40 completed trials remained for each subject. The interval of analysis is 5.1 s. These experimental set-up was designed by Zhang *et al.* [19] for their studies on object recognition using VEP signals.

2.2 Feature extraction

The VEP signals from each channel were filtered using a zero-phase Butterworth bandpass digital filter. MATLAB's *filtfilt* function was used for this purpose. The function filters the data in the forward direction, after which the filtered sequence is then reversed and run back through the filter. The result has precisely zero phase distortion and magnitude modified by the square of the filter's magnitude response. Care was taken to minimize startup and ending transients by matching initial conditions. The 3 dB passband is fixed from 30 to 50 Hz (i.e. in gamma-band range), while the stop band is fixed at 28 and 52 Hz. A model order of 14 suffices to attain a minimum stop-band attenuation of 20 dB in the stop band. This gamma-band frequency range also filters unwanted power-line (60 Hz) interference.

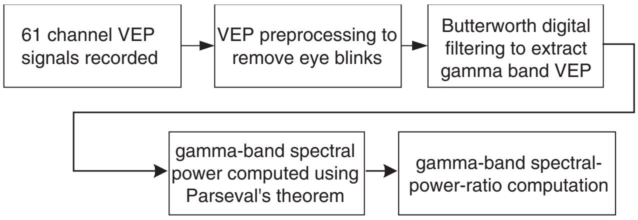

Fig. 5 *VEP feature extraction*

The equivalent gamma-band spectral power for each channel was computed using the filtered VEP signal $y(n)$ and Parseval's time-frequency equivalence theorem. The gamma-band spectral power ratio is then computed using

$$\sum_{n=1}^{N}[y(n)]^2 \Big/ \sum_{n1}^{N}[z(n)]^2 \quad (1)$$

where N is 256, the total number of data in the signal, and $z(n)$ represents the total power of the prefiltered VEP signal. The gamma-band spectral-power-ratio values from each of the 61 channels are concatenated into one feature array representing the particular VEP pattern. Figure 5 shows the process of extracting features from VEP signals.

As mentioned above, the level of perception and memory access between individuals are different. Here, this fact is shown using a one-way-analysis-of-variance (ANOVA) test between the 61-channel gamma-band spectral-power ratios from all the subjects. The one-dimensional ANOVA test is run on a total of 800 signals from each of the 61 channels. The ANOVA is computed using *anova1* function in MATLAB applied to the 800 signals from each of the 61 channels arranged in 40 rows × 20 columns. The arrangement of columns and rows derives from 40 trials and 20 different subjects. Because there are 61 channels, the entire ANOVA test is repeated for 61 times. The results are shown in Table 1.

Table 1 shows the significant difference between the gamma-band spectral-power ratios from 20 subjects. Although all the channels gave significant differences, only the results from three channels are shown, to save space. These ANOVA test results could be validated using the average and variance values for the VEP gamma-band spectral-power ratios from 40 trials, as tabulated in Table 2.

The levels between pictures are not different for each subject. This latter fact is proven using t-test analysis. The significance is based on a probability of 0.00001 and the computations were carried out using the *ttest* function in MATLAB. The following explanation details the method used for this analysis. For each subject, the mean of VEP gamma-band spectral-power ratios from 40 trials for each channel is computed. This value is used with the *ttest* function to test using the null hypothesis whether the sample mean is statistically the same as the computed mean. The results indicate that the null hypothesis should not be rejected at a significance level of 0.00001. This denotes that the VEP gamma-band spectral-power ratios of each channel from 40 trials are statistically the same. These results show that the features used in the method, i.e. gamma-band spectral-power ratio, are suitable for individual identification.

Other authors [12–15] have also shown that gamma-band evoked potential does not vary with the simulation type. However, those papers concentrated on studying the gamma-band response from humans and, as such, their papers did not report differences of gamma-band levels between subjects.

2.3 Neural network

A multiplayer perceptron NN with a single hidden layer trained by the BP algorithm [10] is used to classify the VEP spectral-power ratios in the particular individual class. Figure 6 shows the architecture of the BP NN used in this study. The output nodes are set at 20 so that the NN can classify into one of the 20 individual categories. The hidden-layer nodes are varied from 10 to 50 in steps of 10.

As described above, a total of 800 VEP patterns was used in this experimental study, where half of the patterns were used for training and the remaining half for testing. To maintain a certain level of confidence as to the results, a 10-fold cross-validation strategy was adopted. The data set is divided into 10 equal parts, with an equal number of patterns from each subject. Five out of the 10 parts are used in training (totalling 400 VEP patterns) while the remaining five parts are used in testing (totalling 400 VEP patterns). The selection of the parts for training and testing was made randomly. BP NN-classification experiments were repeated 10 times using different parts of the data for training and testing. Training was conducted until the average error fell below 0.01 or reached a maximum iteration limit of 500. The average error denotes the error limit to stop neural-network (NN) training. The average error is the average of NN target output subtracted from the desired target output from all the training patterns. The desired target output is set to 1.0 for the particular category representing the individual, while for the rest of the categories it is set to 0.

Table 1: ANOVA test results that show significant differences between VEP gamma-band spectral-power ratios from 20 subjects

Channel	*Source of variation*	*SS*	*df*	*MS*	*F*	*P*-value	*F crit*
O1	Between groups	0.374703	19	0.019721	250.421	0	3.099558
	Within groups	0.061427	780	7.88E-05			
	Total	0.436129	799				
PZ	Between groups	0.002794	19	0.000147	57.00393	3.3E-133	3.099558
	Within groups	0.002012	780	2.58E-06			
	Total	0.004807	799				
CPZ	Between groups	0.001946	19	0.000102	206.3925	1.2E-288	3.099558
	Within groups	0.000387	780	4.96E-07			
	Total	0.002334	799				

Table 2: Averages and variances of VEP gamma-band spectral-power ratios from 40 trials for 20 subjects

Channel	O1		PZ		CPZ	
Subjects	Average	Variance	Average	Variance	Average	Variance
1	0.044593	0.000168	0.003307	1.13E-06	0.001117	1.78E-07
2	0.022821	4.93E-05	0.003423	1.16E-06	0.001002	1.46E-07
3	0.020926	7.68E-05	0.003027	7.36E-07	0.000978	7.36E-08
4	0.011109	1.06E-05	0.001904	3.60E-07	0.000707	6.93E-08
5	0.019476	2.64E-05	0.003142	5.54E-06	0.000613	1.69E-07
6	0.015703	2.04E-05	0.004882	2.43E-06	0.001917	4.79E-07
7	0.026036	7.41E-05	0.004778	2.19E-06	0.001419	2.14E-07
8	0.011927	6.41E-05	0.000907	4.28E-07	0.000204	1.89E-08
9	0.01259	1.81E-05	0.007024	6.54E-06	0.002335	4.41E-07
10	0.00761	1.53E-05	0.004198	4.93E-06	0.001612	7.64E-07
11	0.099654	0.000456	0.004731	1.52E-06	0.00112	1.32E-07
12	0.022606	5.68E-05	0.007964	3.72E-06	0.002158	7.57E-07
13	0.016891	4.34E-05	0.003038	1.51E-06	0.00085	1.03E-07
14	0.020875	4.30E-05	0.005813	4.87E-06	0.001594	4.41E-07
15	0.008097	9.02E-06	0.003445	1.93E-06	0.007969	4.23E-06
16	0.004439	4.65E-06	0.001436	5.22E-07	0.000603	8.77E-08
17	0.007845	6.66E-06	0.003070	1.25E-06	0.001778	3.14E-07
18	0.009544	1.42E-05	0.002871	7.43E-07	0.001125	1.25E-07
19	0.016271	2.54E-05	0.007658	7.19E-06	0.002147	7.29E-07
20	0.058673	0.000393	0.004008	2.89E-06	0.001308	4.53E-07

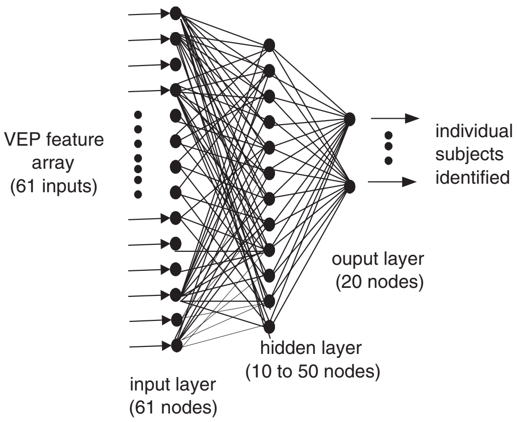

Fig. 6 *MLP-BP NN architecture*

Table 3: Average classification results using 10-fold cross-validation strategy for 400 test VEP patterns

Hidden units	Training Time (s)	Number of iterations	Classification Time (s)	Accuracy (%)
10	39.83	63.3	0.75	98.98
20	62.79	41.5	1.06	99.15
30	95.11	34.8	1.25	99.08
40	91.48	32.3	1.51	99.10
50	113.52	30.3	2.89	98.98
Overall average	**80.55**	**40.4**	**1.49**	**99.06**

3 Results

In this Section, the classification results (i.e. the identification of individuals) by BP NN is discussed. NN classification accuracy (percent) is defined based on the equation:

$$\text{NN classification accuracy (\%)} = (\text{number of VEP patterns classified correctly})/(\text{total number of VEP patterns tested}) \quad (2)$$

The total number of VEP patterns tested was 400, i.e. 20 patterns from each individual. The remaining 20 patterns were used in training the NN. One VEP pattern consists of 61-channel gamma-band spectral-power ratios from one trial.

The average results of the 10-fold cross-validation experiments are tabulated in Table 3. Table 3 also shows the training time, number of training iterations and testing time for 400 VEP patterns. The entire BP NN simulation is written in the C language and run on a Pentium II 266 MHz PC with 256 MB RAM.

In general, the high averaged classification performance of 99.06% validates the ability of the proposed method to identify individuals. The average classification performance of 99.06% mean that 99.06% VEP patterns (or about 396 out of 400 VEP patterns 396 is a rounded figure; the average performance may not result in a round figure) were classified into their corresponding categories correctly. Here the categories represent the 20 different individuals.

The average training time of 80.55 s and average number of training iterations of 40.4 show that a small training time is sufficient to produce good classification accuracy. The results from Table 3 also show that the classification performance does not vary greatly with variation in the number of hidden nodes. Therefore, BP NN classification could be conducted using 10 hidden units because this will result in a shorter computation time and smaller design cost. It takes only 1.9 μs to classify a test VEP pattern for this case. The NN did not converge (i.e. average error did not fall below 0.01) when run with less than 10 hidden units up to the maximum iteration limit of 500 iterations. In general, a NN that does not converge is not suitable for classification purposes.

4 Conclusions

In this paper, we have proposed a method of using VEP signals recorded while perceiving a single picture as a biometric to identify individuals. In the method, BP NN classification of VEP gamma-band spectral-power ratios is used to identify the individuals. The results obtained in the experimental study give recognition accuracy that was close to 100% for all subjects. It is expected that improvement in VEP feature extraction and BP NN training would be likely to result in perfect accuracy. This shows that VEP signals carry genetically specific information and are appropriate for designing biometric individual-identification systems. Nevertheless, further investigation is necessary to determine the changes of VEP over longer periods of time.

The advantage of the method compared with others is that it is difficult to be forged it i.e. the possibility of illegal identification is low. However, it is true that VEP preparation might take longer than other biometric techniques such as fingerprints. For example, in this work, it was decided to use 61 active channels to examine the success/failure of the method. Although there are electrode caps available nowadays, using a high number of channels may be cumbersome in some applications. However, this is a price for added security. Therefore, the method may prove to be more suitable where security is a very important issue as in military applications. Currently, work to determine the success of the method using a smaller number of channels has been initiated to reduce the computational cost and complexity of the design.

5 Acknowledgment

The author thanks Prof. Henri Begleiter of the Neurodynamics Laboratory, State University of New York Health Centre, Brooklyn, USA, who generated the raw VEP data and Paul Conlon, of Sasco Hill Research, USA, for making the data available to us. The author is indebted to Prof. P. Raveendran of University Malaya, Malaysia for his invaluable guidance in the early stages of the work.

6 References

1 Pankanti, S., Bolle, R.M., and Jain, A.: 'Biometrics: the future of identification', *IEEE Comput.*, 2000, **33**, (2), pp. 46–49
2 Pankanti, S., Prabhakar, S., and Jain, A.K.: 'On the individuality of fingerprints', *IEEE Trans. Pattern Anal. Machine Intell.*, 2002, **24**, (8), pp. 1010–1025
3 Samal, A., and Iyengar, P.: 'Automatic recognition and analysis of human faces and facial expressions: a survey', *Pattern Recognit.*, 1992, **25**, (1), pp. 65–77
4 Daugman, J.: 'Recognizing persons by their iris patterns', *in* Jain, A.K., Bolle, R. and Pankanti, S. (Eds.) 'Biometrics: Personal Identification In Networked Society' (Kluwer Academic, Boston 1999)
5 Duta, N., Jain, A.K., and Mardia, K.V.: 'Matching of palmprints', *Pattern Recognit. Lett.*, 2002, **23**, (4), pp. 477–485
6 Jain, A.K., Ross, A., and Pankanti, S.: 'A prototype hand geometry-based verification system'. Proc. 2nd Int. Conf. on Audio and Video-Based Biometric Person Identification (AVBPA), Washington, DC, 22–23 March 1999, pp. 166–171
7 Biel, L., Pettersson, O., Philipson, L., and Wide, P.: 'ECG analysis: a new approach in human identification', *IEEE Trans. Instrum. Meas.*, 2001, **50**, (3), pp. 808–812
8 Poulos, M., Rangoussi, M., Chrissikopoulos, V., and Evangelou, A.: 'Person identification based on parametric processing of the EEG'. Proc. 6th IEEE Int. Conf. on Electronics, Circuits, and Systems, Pafos, Cyprus, 5–8 September, 1999, Vol. **1**, pp. 283–286
9 Paranjape, R.B., Mahovsky, J., Benedicenti, L., and Koles, Z.: 'The electroencephalogram as a biometric'. Proc. Canadian Conf. on Electrical and Computer Engineering, Toronto, ON, 13–16 May 2001, Vol. **2**, pp. 1363–1366
10 Rumelhart, D.E., and McCelland, J.L.: 'Parallel Distributed Processing: Exploration in the Microstructure of Cognition', (MIT Press, Cambridge, MA, 1986), Vol. **1**
11 Palaniappan, R., Raveendran, P., and Omatu, S.: 'VEP optimal channel selection using genetic algorithm for neural network classification of alcoholics', *IEEE Trans. Neural Netw.*, 2002, **13**, (2), pp. 486–491
12 Basar, E., Eroglu, C.B., Demiralp, T., and Schurman, M.: 'Time and frequency analysis of the brain's distributed gamma-band system', *IEEE Eng. Med. Biology Mag.*, 1995, **14**, (4), pp. 400–410
13 Basar, E., Eroglu, C.B., Karakas, S., and Schurman, M.: 'Oscillatory brain theory: a new trend in neuroscience', *IEEE Eng. Med. Biol. Mag.*, 1999, **18**, (3), pp. 56–66
14 Tallon-Baudry, C., Bertrand, O., Delpuech, C., and Pernier, J.: 'Stimulus specificity of phased- locked and non-phase locked 40 Hz visual responses in human', *J. Neurosci.*, 1996, **16**, (13), pp. 4240–4249
15 Tallon-Baudry, C., Bertrand, O., Peronnet, F., and Pernier, J.: 'Induced γ-band activity during the delay of a visual short-term memory task in humans', *J. Neurosci.*, 1998, **18**, (11), pp. 4244–4254
16 Jasper, H.: 'The ten twenty electrode system of the international federation', *Electroencephalogr. Clin. Neurophysiol.*, 1958, **10**, pp. 371–375
17 Snodgrass, J.G., and Vanderwart, M.: 'A standardized set of 260 pictures: norms for name agreement, image agreement, familiarity, and visual complexity', *J. Exp. Psychol. Hum. Learn. Mem.*, 1980, **6**, (2), pp. 174–215
18 Misulis, K.E.: 'Spehlmanns evoked potential primer: visual, auditory and somatosensory evoked potentials in clinical diagnosis', (Butterworth-Heinemann, UK 1994)
19 Zhang, X.L., Begleiter, H., Porjesz, B., Wang, W., and Litke, A.: 'Event related potentials during object recognition tasks', *Brain Res. Bull.*, 1995, **38**, (6), pp. 531–538