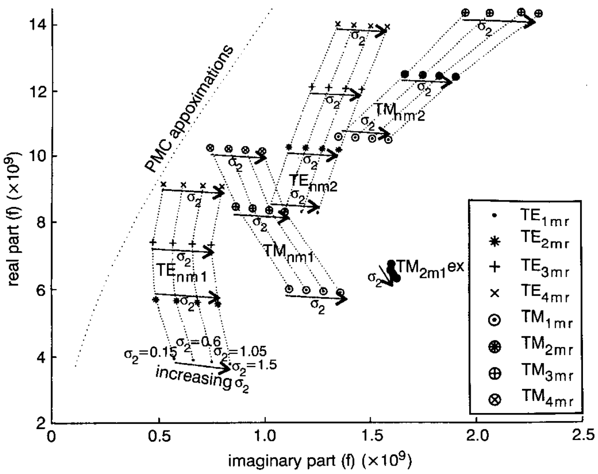

Fig. 2 *Real part (f) (vertical axis) and imaginary part (f) (horizontal axis) of complex natural resonances (in Hz) of spherical target against constitutive parameters*

In Fig. 2, $e^{j2\pi ft}$ notation is assumed where the complex resonant frequency $f = \mathrm{R}\{f\} + j\mathrm{I}\{f\}$ so that the real part $\mathrm{R}\{f\}$ may be considered the oscillation frequency and the (positive) imaginary part $\mathrm{I}\{f\}$ corresponds to the damping (attenuation) factor. For lossless spheres in lossless medium, the damping factor is entirely due to radiation losses, while for the lossy situation considered here it incorporates both ohmic losses and radiation damping. The PMC approximations for the interior modes replaces the outside medium with a perfect magnetic conductor and serves as the asymptotic boundary for those solutions. The mode designation, e.g. TE_{nmr}, follows standard practice [6, 7], whereby n refers to the order of the (ordinary) Bessel function employed, m to the φ-variation in the form of $e^{jm\varphi}$, and r to the order of the zero (solution) of the associated eigenvalue equation. A detailed discussion of the various resonant modes of lossy spheres is not the objective here. From our perspective of intended medical imaging applications, it can be seen in Fig. 2 that the low-order complex natural resonances (CNR) of biological targets (sphere radius = 5 mm) lie (as expected) in the GHz range (both the real and imaginary parts), and more importantly, can be correlated with their constitutive parameters (in this example, the variable conductivity of the sphere). While both the real and imaginary parts of a complex natural resonance change with the target conductivity, the imaginary part $\mathrm{I}\{f\}$ of the CNR is clearly a much more useful predictor of the target conductivity. These preliminary results provide support for the potential use of an ultra-wideband-pulse microwave sensor in breast cancer diagnosis for the characterisation of suspicious growths via their complex natural resonances.

19 July 2002
Electronics Letters Online No: 20021141
DOI: 10.1049/el:20021141

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Individual identification technique using visual evoked potential signals

R. Palaniappan and P. Raveendran

A new individual identification technique using visual evoked potential (VEP) signals is proposed. The technique uses fuzzy ARTMAP (FA) classification of gamma band VEP response from 61 channels extracted while the individual is seeing a single picture. All ten subjects tested are classified correctly with an overall maximum classification rate of 95% across 200 test patterns. The method could be developed into a stand-alone identification system or as an addition to existing identification systems, especially for identifying a group of individuals in a company or factory.

Introduction: Electrical brain activity could be used as a biometric to identify individuals. In this Letter, visual evoked potential (VEP) signals are proposed for this purpose. To our knowledge, the use of VEP signals to identify individuals is novel. The technique uses VEP signals from 61 channels extracted while the individual is seeing a single visual picture. Gamma band spectral powers are extracted from each of the 61 channels using bandpass filtering and Parseval's time-frequency equivalence theorem. Fuzzy ARTMAP (FA) neural network [1] uses these spectral powers to identify different individuals.

Gamma band spectral range is chosen in particular because it has been shown to be related to higher brain functions like perception and memory [2]. Visualising a picture evokes perception and memory, thereby being suitable as the stimulus in our case. This is because the level of perception and memory access between individuals are generally different. Furthermore, these differences are made more evident because it is very unlikely for individuals to have similar brain activity in all 61 channels.

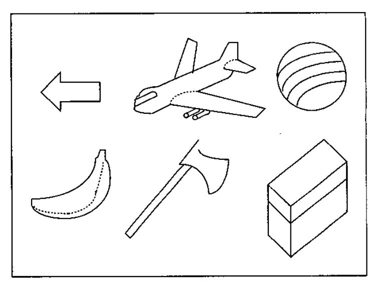

Fig. 1 *Pictures from Snodgrass and Vanderwart set*

Experimental study: Forty VEP signals are extracted from ten subjects. One-second measurements are taken from 61 electrodes placed on the subject's scalp, which are sampled at 256 Hz. The electrode positions are located at standard sites (Standard Electrode Position Nomenclature, American Encephalographic Association). The VEP signals are extracted from subjects while being exposed to a single stimulus, which are pictures of objects chosen from the Snodgrass and Vanderwart picture set [3]. These pictures are common black and white line drawings, e.g. an airplane, a banana, a ball, executed according to a set of rules that provide consistency of pictorial representation. The pictures have been standardised on variables of central relevance to memory and cognitive processing. These pictures, as shown in Fig. 1, represent different concrete objects that are easily named, i.e. they have definite verbal labels.

For this study, VEP signals with eye blink artifact contamination are removed in the pre-processing stage using a computer program written to detect VEP signals with magnitudes above 100 μV. These VEP signals detected with eye blinks are then discarded from the experimental study and additional trials are included as replacements. The threshold value of 100 μV is used since blinking produces 100–200 μV potential lasting 250 ms [4]. Each subject gave 40 artifact free VEP signals, therefore producing a total of 400 VEP signals for the experimental study. Each trial is conducted with an interval of 5.1 s. Fig. 2 shows an example of the presentation of these pictures.

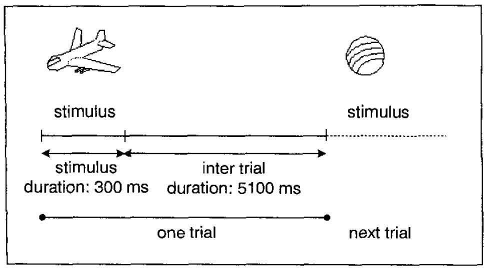

Fig. 2 *Example of stimulus presentation*

The VEP signals are filtered using a bandpass filter (BPF) centred at 40 Hz. The BPF design is based on a previous study that used VEP signals to classify alcoholics [4]. The BPF filter can be designed using a lowpass filter (LPF) and highpass filter (HPF). It can be implemented by

$$y(n) = \sum_{r=0}^{M} {}^{M}C_r x(n-r) \quad \text{and} \quad z(n) = \sum_{r=0}^{N} (-1)^r\, {}^{N}C_r y(n-r) \qquad (1)$$

where ${}^{Q}C_r = Q!/[r!(Q-r)!]$, $y(n)$ is the output of the LPF, $z(n)$ is the HPF output and $x(n)$ is the input signal. Filter orders of $M = 28$ and $N = 8$ are used because these give the approximate 3 dB bandwidth from 32 to 48 Hz (i.e. in gamma band spectral range). Power spectra are computed for each channel using Parseval's time-frequency equivalence theorem from the filtered signal.

FA is trained with gamma band power spectra from 200 VEP signals (20 VEP signals from each subject). The gamma band power spectra from the remaining VEP signals are tested with FA to classify (i.e. to identify) the subjects. FA is run with fast learning and voting strategy of ten simulations.

Table 1: FA classification results (based on 200 test VEP signals)

VP	Classification (%)
0	88.50
0.1	88.00
0.2	89.00
0.3	90.50
0.4	92.50
0.5	91.50
0.6	92.00
0.7	89.50
0.8	93.00
0.9	95.00
Average	90.95

Table 2: FA classification results for VP = 0.9 (based on 20 test VEP signals for each subject)

Subject	VEP signals (correct/total)	Recognised correctly
1	20/20	Yes
2	19/20	Yes
3	19/20	Yes
4	18/20	Yes
5	19/20	Yes
6	20/20	Yes
7	19/20	Yes
8	19/20	Yes
9	18/20	Yes
10	19/20	Yes

Results: Table 1 shows the classification results using FA. The vigilance parameter (VP) of the FA network is varied from 0 to 0.9 in steps of 0.1. The average and maximum classification percentage across 200 test VEP patterns is 90.95 and 95%, respectively. On an individual basis, all ten subjects are identified correctly as shown in Table 2. The subject is identified correctly if the majority of the VEP signals are correctly classified out of the total 20 VEP signals tested for each subject. These results validate the proposed method to identify individuals.

Conclusion: We have proposed an approach that uses VEP signals as a biometric to identify individuals. The results show that gamma band power spectra of VEP signals extracted while seeing a picture could be used to identify individuals successfully. The method is simple for individuals to use since the only stimulus involved is seeing a picture. However, further work is necessary to determine the changes of VEP over longer periods of time.

Acknowledgments: We wish to thank H. Begleiter at the Neurodynamics Laboratory at the State University of New York Health Centre at Brooklyn, USA, who generated the raw VEP data, and P. Conlon, of Sasco Hill Research, USA, for making the data available to us.

4 August 2002
Electronics Letters Online No: 20021104
DOI: 10.1049/el:20021104

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Portable system for data acquisition and transmission based on handheld PC technology

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A portable system is developed to monitor physical activity by acquiring and storing data from body-mounted sensors; a handheld PC is used for managing data acquisition and storage, including radio-transmission to a remote host. An application related to the use of a gyro-accelerometric sensor for determining walking distance is discussed.

Introduction: Applications of physical activity monitors which require measurements from body-mounted sensors are reported in rehabilitation and sport medicine for functional performance assessment [1, 2], in wearable and pervasive computing, where context-awareness (i.e. the ability to detect aspects of the subject's internal state) is essential [3]; in addition, physical activity monitors are important for the improvement of public health, in particular for the prevention and treatment of cardiovascular diseases [4].