TIME-FREQUENCY TRANSFORM BASED PANIC DISORDER CLASSIFICATION

Hubert Dietl[1], Stephan Weiss[1], Paul Pauli[2]

[1] Dept. Electronics & Computer Science, University of Southampton, UK,
[2] Dept. of Biological & Clinical Psychology, University of Würzburg, Würzburg, Germany
{hwd,s.weiss}@ecs.soton.ac.uk, pauli@psychologie.uni-wuerzburg.de

Abstract - Event-related brain potentials (ERP) within the electroencephalogram (EEG) can be used to differentiate between the responses to neutral or panic disorder triggering stimuli when presented to anxiety patients. In this paper, we employ time-frequency (TF) revealing transforms to identify a small number significant parameterising coefficients that permit us perform — as well as quantify — this differentiation.

1. INTRODUCTION

Individuals with panic disorder suffer from an abnormal fear of certain sensations usually connected to anxiety, such as palpitation, breathlessness, or dizziness [1]. The research into this disorder has been driven by behavioural science as well as clinical applications, and led to studies investigating possible explanations as well as diagnosis of its symptoms by means of appropriate stimulation and measurement of the subsequent ERPs [2, 3]. These have identified a low frequent transient waveform with a latency of approximately 300 ms after stimulus onset, therefore referred to as P300, as a distinctive feature.

A method of detecting the P300 in panic disorder and normal response ERPs is presented in [4] by means of analyses of variance (ANOVAs). Since the P300 has a transient behaviour, the application of time frequency (TF) analysis appears well suited, as it takes both spectral and temporal information into account. Therefore, in this paper we investigate various transforms, such as wavelet, wavelet packet, and Gabor transforms — with respect to their suitability of revealing the TF characteristics of the transient P300. We aim to optimise these transforms such that the distinction between panic disorder and normal responses is concentrated in only very few coefficients which can yield a distinction. Further, we comment on the selection of a set of distinctive coefficients.

2. PANIC DISORDER ERP

For the measurement of panic disorder ERPs, an anxiety patient was presented with fear-inducing or neutral words tachistoscopically at the perception threshold of panic disorder. The patient's perception threshold for correctly identifying 50% of the words was determined with neutral words not used in the experiment. Based on the assumption that he will recognise a greater number of anxiety words given at their perception threshold than neutral words, the hypothesis examined is the expectation that his EEG exhibits an enhanced P300 wave for presented anxiety words [4].

The EEG was measure at the vertex electrode (Cz) synchrously to the stimulus, whereby the recordings were started 100 ms before the onset of the visual word stimulus. The data exemplarily analysed in this study contains 24 neutral word presentations and 24 anxiety word presentations to one panic patient. Fig. 1 shows the average over the stimulus-synchronous EEG in reaction to the 24 words presented for each word category. There is a visible difference in the two averages with a stronger P300 and more positive EEG until approximately $t = 700$ ms in the panic disorder related data.

3. PARAMETERISING TRANSFORMS

To parameterise the ERPs in Fig. 1, TF lend themselves to account for the transient nature of the waveforms. To capture the impulsive rise of the P300, TF transforms with a good time resolution are required. The discrete wavelet transform generally yields a good frequency resolution and poor time resolution at low frequencies, yielding a too coarse time segmentation in the frequency range of interest. Therefore, instead we consider the wavelet packet (WP) transform, whose level of decomposition can be adapted to fit the nature of the data, as well as the Gabor transform, which yields a uniform tiling of the TF plane and hence can provide a desired resolution in a specific TF segment.

Based on an implementation described in [6], the WP uses on Mallat's wavelet [**?**], whereby the decomposition level of the transformation is adapted to maximise the entropy of the average ERP curves in Fig. 1. The Gabor transform is based on an oversampled filter bank with 64 channels constructed according to [**?**]. The resulting approximate distribution of the coefficient energies in the TF plane is visualised in Fig. 2.

The application of the transform methods lead to a parametrisation of the ERP data whereby the features of the ERP are expressed in as few coefficients as possible. Within these ERP-parameterising coefficients, we will now attempt to isolate those that represent a significant difference between the two data sets.

4. DIFFERENCE EVALUATION

Based on the parameterisations mentioned in the previous section, we want to identify coefficients that allow us to differentiate between the presented anxiety related and neutral words. Here, we apply the t-test, which gives the probability that two data sets sampled from potentially two different distributions with identical variance possess different mean values, for which a significance is returned. Comparing sets $\mathbf{x}_p$ and $\mathbf{x}_n$ containing the panic disorder and neutral ERP response coefficients for

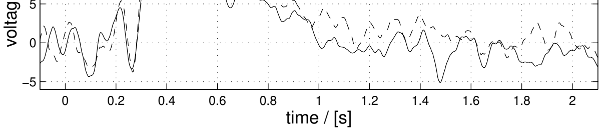

Fig. 1. Averaged over 24 EEG segments showing responses to anxiety related and neural stimuli at the perception threshold.

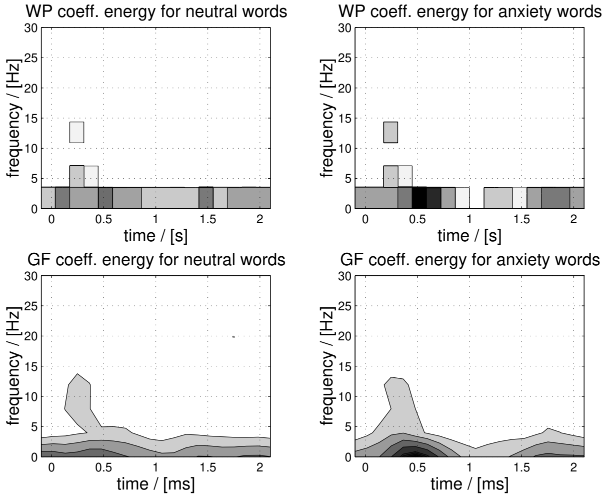

Fig. 2. Average coefficient energy for (left) netural words and (right) panic order related words usinf (top) WP and (bottom) Gabor transforms.

one specific transform coefficient across all 24 measurements, the t-value is given by [5]

$$t = \frac{\overline{\mathbf{x}}_p - \overline{\mathbf{x}}_n}{\sqrt{\frac{\sigma_T^2}{N_p} + \frac{\sigma_C^2}{N_n}}} \quad . \tag{1}$$

The values $\overline{\mathbf{x}}_p$ and $\overline{\mathbf{x}}_n$ represent the means, σ_p^2, σ_n^2 are the variances and $N_p = N_n = 24$ are the number of samples for the two data sets. The t-value corresponds to a certain significance level P, which can be looked up from tables [5]. A smaller value for P indicates that the data sets have a significantly different mean. For example, for $P = 0.01$ the probability that the differences in the means are due to a sampling error is 1%. For our study, a significance level of $P = 0.01$ was used to identify distinctive coefficients. The two tested distributions were the distributions for one coefficient over the presented 24 neutral and anxiety words, respectively.

5. RESULTS AND DISCUSSION

As discussed in Secs. 4 and 2, we have different transform methods and a procedure to identify significant coefficients to being able to separate between presented neutral and anxiety words. In the following, we will show the average coefficient energy obtained by the parametrisation with the WP and GF transforms and finally present the results for separability which we obtained for the data described in Sec. 2.

5.1. Average coefficient energy

The average coefficient energy in the TF plane is presented in Fig. 2 for the different transforms and data. It can be observed that the for both transforms and for both word categories most of the energy is concentrated at the P300 and slow positive wave area what confirms our approach.

5.2. Identified coefficients

Fig. 3 shows the resulting coefficients when performing the t-test on the parametrised data.

We see that two coefficients (black and grey) for both transforms are identified. They cover approximately the area of the slow wave as it was expected in Sec. 2. However, the P300 area in the TF plane was not identified.

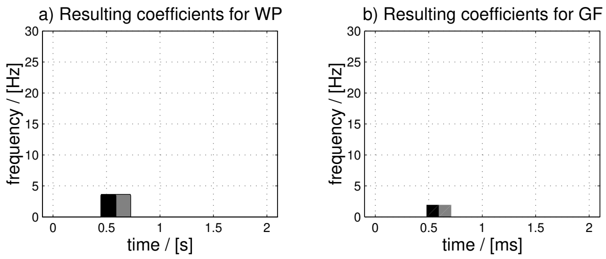

Fig. 3. Resulting coefficients

6. CONCLUSIONS

We have presented a WP and GF analysis comparison for parametrising ERP with the aim of differentiating between presented neutral and anxiety words to a patient with panic disorder. We have motivated the use of TF methods, and proposed an approach to obtain distinctive transformation coefficients by t-test. The obtained results appear reasonably robust and encourage panic disorder diagnosis via TF analysis of ERP.

REFERENCES

[1] D. M. Clark, "A cognitive approach to panic," *Behaviour Research and Therapy*, vol. 24, pp. 461–470, 1986.

[2] E. A. Kostandov and Y. L. Arzumanov, "Average cortical evoked potentials to recognised and nonrecognised verbal stimuli," *Acta Neurobiologica Experimentalis*, vol. 37, pp. 311–324, 1977.

[3] E. Naumann, D. Bartussek, O. Diedrich, and M. Laufer, "Assessing cognitive and affective information processing functions of the brain by means of the late positive complex of the event-related potential," *Journal of Psychophysiology*, vol. 6, pp. 285–298, 1992.

[4] P. Pauli and et al., "Behavioral and Neurophysiological Evidence for Altered Processing of Anxiety-Related Words in Panic Disorder," *Journal of Abnormal Psychology*, vol. 106, no. 2, pp. 213–220, 1997.

[5] I. Bronstein and K. Semendjajew, *Taschenbuch der Mathematik*. Thun und Frankfurt/Main: Verlag Harri Deutsch, 23rd ed., 1987.

[6] H. Dietl, S. Weiss, and U. Hoppe, "Comparison of Transformation Methods to Determine Frequency Specific Cochlear Hearing Loss Based on TEOAE," in *Digest 02/110 IEE Colloquium on Medical Applications of Signal Processing*, pp. 16/1–16/6, IEE, London, October 2002.