Single trial ERP allows Detection of Perceived and Imagined Rhythm

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Abstract

This study focuses on the traces of neuronal processing of rhythm. A computational method is presented for identifying, on the basis of EEG signals, which rhythm a subject is listing too or imagining. Preprocessing is conducted by independent component analysis. A classification based on correlations was able to correctly identify a single perceptual trial out of five presented rhythms in about half of the cases. Identifying imagined rhythm is harder, but the method still performes significantly better than chance.

1 Introduction

In simple isochronous sequences, a random omission of one note leads to a clear P300 component in the ERP signal [Knight, 1996; Jongsma e.a. 2002]. But for real musical rhythm the effect of a disruption has only been measured in the final part of a passage [Besson, Faïta & Requin, 1994]. However, listening implies an ongoing process of confirmation and violation of temporal expectancies [Desain, 1992; Large & Jones, 1999] and the ERP signal contains traces thereof. These rhythmic signatures can be extracted from the background-noise by an appropriate signal processing method and may allow a direct detection of perceived and imagined temporal patterns from recorded neural activity. For this aim we elaborated a method to identify, on the basis of single trial electroencephalogram (EEG) data, which rhythmic pattern is imagined or perceived by the subject.

For a classification of single EEG trials, the inherent noisiness of the data is of prime concern. This noise stems from eye and body movement, heartbeat and respiration, line hum and, last but not least, neural activity not related to the task under study. Noise suppression is achieved for an ERP signal by averaging over a large number of trials, assuming independence of the noise from the time-locked processing of the stimulus. For reducing noise in single measurements other methods must be used. The different sources of neural activity can be separated by maximizing their statistical independence, i.e. their non-Gaussian character. This Independent Component Analysis (ICA) [Jung e.a., 2000] can provide an extraction and concentration of the relevant signal into a few channels.

This preprocessing was applied to ERP traces recorded while the participant was listening to, or imagining, short rhythmical patterns. The resulting clean signals were matched to a set of templates: the averaged ERP signals for the rhythms under study. A classification decision, based on maximum similarity between a single trial and one of the templates, took into account the distribution of the signal across the scalp and the spectral domain. In contrast to what is common in ERP studies, no analysis of waveforms or ERP components was needed, nor was there a need to average data over a large group of subjects. Using many sessions with a single highly experienced subject, as is more common in psycho-acoustic research, the feasibility of identification of perceived and imagined rhythm by ERP was demonstrated.

Evading the complexities of expressive timing [Desain & Honing, 2003], in this ERP experiment five mechanical rhythmic patterns were used, originating from the musical ditties used in a series of studies by Longuet-Higgins [1976, 1982]. They were selected to be perceptually and musically different (see Fig. 1). The first is a musical cliché with a syncopation: a violation of metric expectation. In the second, expectation changes from duple to triple meter. The next differs from it by only one note, but is perceived rather differently, with an up-beat. The first three notes of the fourth rhythm induce such a strong metrical expectation that the following events are perceived as syncopations. The last pattern is a random series of time intervals and does not induce any metric expectation and thus becomes hard to remember and reproduce.

The rhythms were presented three times, each time at a lower sound level, with a fourth repeat prompted only by its first onset Thus the subject, who was instructed to listen attentively and to actively imagine a fourth repetition, was guided smoothly from pure perceptual processing of a new and unexpected pattern (P-1), via a repeated and expected presentation (P-2, P-3), to imagery of a pattern without any auditory stimulation (I). Only the first and the last segment of the responses (P-1 and I) were analyzed.

Figure 1. *The five rhythmical patterns as used in the ERP experiment. Audio examples are available at http://www.nici.kun.nl/mmm/reading/.*

2 Method

2.1 Subject, stimuli and task

As subject a musician with more than twenty years of experience participated in five sessions. In each session thirty trials were presented for each of five short rhythmic patterns (see Fig. 1), in random order. A button was supplied for the subject to signal when attention slipped or imagery failed About 6 % of the trials were thus marked and excluded from the analysis. A session lasted for about ninety minutes, including three short breaks of about five minutes each. Before every session thirty segments of control data were recorded, without any task performed by the subject. The stimuli were generated by a general MIDI synthesizer (Yamaha MU-90) controlled by a Macintosh G4 running the POCO system [Honing, 1990] and an OMS Midi driver. The sound was presented via a Yamaha MS-20 active loudspeaker at one meter distance in front of the subject. The sound consisted of a short "high woodblock" (General MIDI) percussion sound (1 ms attack, 10 ms decay to 6 dB below peak level). The stimuli were presented three times in succession at a sound pressure level of 81, 71 and 54 dB(A) at the subjects position. Between repetitions a short random pause between one second and the duration of the pattern was inserted and a longer pause (between three and five seconds) separated the trials. The subject was instructed to attend carefully the three repetitions and actively imagine a fourth one, prompted by its first onset only.

2.2 Data collection

The experiment took place in an acoustically and electrically shielded room, digitally recording an EEG from the Fz, Cz, Pz, Fp1, Fp2, F3, F4, F7, F8, C3, C4, T7, T8, P3, P4, P7, P8, O1, and O2 electrodes using the 10/20 system25. No-rhythm data, without a task for the subject, were collected before the actual experiment began. Data were filtered between 0.3 – 100 Hz and captured at a 500 Hz sample rate using the Neuroscan 4.1 Acquire program. A ground electrode was positioned on the forehead and a reference electrode on the left mastoid. The impedance was kept below 3kΩ. The horizontal and vertical EOGs were also recorded and filtered between 0.3 – 30 Hz. Synchronization markers embedded in the MIDI stimulus stream were routed to the Neuroscan equipment, and captured along with the EEG data.

2.2 Data processing

The files with EEG and marker data were converted to ASCII format using CNTTOASC. These files were sliced into individual response-files (with a lead of 100 ms before the start of the stimulus and a tail of one second after the last note onset) using POCO, and downsampled to 250 Hz after band-pass filtering in octaves between 2 – 32 Hz using Matlab. A third order Butterworth filter was used, passing twice along the data in both directions to prevent phase-shifts, thereby effectively filtering with a sixth-order filter. For artifact removal, sections were rejected off-line from the raw EEG, whenever in a time-window of 250 ms in one channel any voltage exceeded 50 μV. Similarly, for the eye movement artifacts data from all channels were rejected when a voltage in the vertical or horizontal EOG exceeded 50 μV. Using Fast-ICA the signals from the electrodes are un-mixed using a Tanh non-linearity. Using this method, artifact rejection becomes superfluous [Jung e.a. 2000].

Preprocessing	Perceived		Imagined	
	Correctly Classified	Significance (Chance =.2)	Correctly Classified	Significance (Chance =.2)
Artifact Rejection	.421	< .0001	.208	-
Artifact Rejection and Spectral Separation	.462	< .0001	.178	-
Spectral Separation and Independent Components	.484	< .0001	.243	< .005

Table 1. *Proportion correctly classified perceived and imagined rhythms*

2.3 Analysis

For all calculations a distinction was made between test and training data sets, based on the measurement sessions, and mean results are reported. Classification was based on correlation between single trial data and the averaged templates and was conducted in stages. Correlations between the single trial and all average templates were calculated on the time interval from .250 to 3 s for each frequency band. Separate detectors were defined for each rhythm by logistic regression in JMP on the distribution of correlations over the scalp. A next logistic regression stage combined the information of the spectral bands. The detectors were jointly optimized for all rhythms. Every detector was trained only on its corresponding single trials (for a YES output) and on the no-rhythm trials (for a NO output). The resulting detection probabilities were combined in a discriminant analysis (again in JMP), this time excluding the no-rhythm data, yielding one of the five pattern classes plus their probabilities as identification result. Identification counts were collected into confusion matrices that were subsequently collapsed into correctness scores.

3 Results

Identification of imagined rhythm is hard; yet the success rate using ICA (.243, as compared to the .2 chance-level) is highly significant as Table 1 shows. Classifying perceived rhythm is much easier, but also here the ICA method proves an improvement demonstrating the effectiveness of its concentration of information. As another test, ICA un-mixing was performed on clean data, with artifact rejection. With this additional preprocessing it performs about equally well for imagery (.241) and only slightly better for the perception task (.498) demonstrating the effective removal of artifact information from the relevant channels.

Though highly significant, the size of the effect is still quite small. An improvement of identification success is possible by considering repeatedly perceived or imagined patterns, combining the data either pre-classification, by averaging over a small set of trials, or post-classification, e.g. by majority vote.

The random pattern, though not difficult to identify as perceived pattern, is almost impossible to identify correctly when imagined. Apart from the difficulty for the subject to imagine this rhythm in a constant tempo, it may leave a less clear trace in the ERP because it does not induce a strong metric expectation. Note that also the joint optimization of the detectors for all patterns may be to blame for the poor result in this case.

Allowing the classifier to deny classification in case its confidence (the expected probability that the trials indeed stems from the identified pattern) is below a threshold can also boost the number of correct classifications. For perception the classification reaches perfection at a threshold of about .5, in which case about 40% of the trials are rejected.

4 Discussion

Because for rhythm the temporal structure of a pattern coincides with its content, it is an excellent domain for this kind of research. Although the design of the method easily allows for this, the scaling of the behavior of the method to larger sets of patterns is still unknown. Furthermore what these results tell us about the ongoing processes of rhythm perception is not yet clear [Desain e.a., 1998]. However, as the creation of expectancy (and its violation or confirmation) seems to be the source of the ERP signals –instead of the temporal surface structure of the patterns–, the same methods might be useful for other domains, like the processing of melody, harmony or language utterances [Janata, 2001; Suppes, Han & Lu, 1998]. This will be the focus of further research.

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