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Design and implementation of a multi-PNN structure for discriminating one-month abstinent heroin addicts from healthy controls using the P600 component of ERP signals

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Abstract

A multi-probabilistic neural network (multi-PNN) classification structure has been designed for distinguishing one-month abstinent heroin addicts from normal controls by means of the Event-Related Potentials' P600 component, selected at 15 scalp leads, elicited under a Working Memory (WM) test. The multi-PNN structure consisted of 15 optimally designed PNN lead-classifiers feeding an end-stage PNN classifier. The multi-PNN structure classified correctly all subjects. When leads were grouped into compartments, highest accuracies were achieved at the frontal (91.7%) and left temporo-central region (86.1%). Highest single-lead precision (86.1%) was found at the P3, C5 and F3 leads. These findings indicate that cognitive function, as represented by P600 during a WM task and explored by the PNN signal processing techniques, may be involved in short-term abstinent heroin addicts. Additionally, these findings indicate that these techniques may significantly facilitate computer-aided analysis of ERPs.
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Keywords: Heroin addicts; Event-related potentials (ERPs); P600 component; Pattern recognition

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1. Introduction

Event-related potentials (ERPs) are electrical potentials, usually measured on the scalp, and are distinguished for their high temporal resolution, allowing for real-time and non-invasive observation of electrical activity changes in the brain during the processing of information related to the presentation of stimuli (or events) (Fabiani et al., 2000). Late positive components of the ERP waveform, such as the P300 and the P600 components have attracted special attention in ERP research. Both components are related to working memory (WM) processes, i.e. keeping information actively in mind, the P300 being more related to the on-line updating of working memory and/or attentional operations involved in this function (Polich, 1998), while the P600, elicited between 500 and 800 ms after stimulus presentation, has been linked to hippocampal function (Guillem et al., 1998; Grunwald et al., 1999), having much in common with WM operation (Garcia-Larrea and Cezanne-Bert, 1998; Guillem et al., 1999; Frisch et al., 2003). P600 is thought to reflect the response selection stage of information processing (Falkenstein et al., 1994), i.e. the stage that 'assigns a specific response to a specific stimulus'.

The relationship between substance dependence, such as cocaine and/or heroin abuse, and neurophysiological functions has been previously addressed by various workers, using the P300 (Easton and Bauer, 1997; Martin and Siddle, 2003; Papageorgiou et al., 2003; Kouri et al., 1996; Bauer, 1997, 2002; Biggins et al., 1997; Attou et al., 2001) and, to a lesser extent to the P600 (Papageorgiou et al., 2001) concerning six-month, i.e. long-term, abstinent heroin addicts.

As far as the application of P600 component of ERPs in picking up relevant aspects of addiction, in association with neuropsychological operation, Papageorgiou et al. (2001) provided evidence indicating that abstinent heroin addicts manifest abnormal aspects of second-pass parsing processes, as reflected by the P600 latencies, elicited during a WM test.

The aim of the present study is twofold: first, to search deeper into the P600 signals by extracting new P600-signal characteristics and by employing powerful classification procedures, to develop a pattern recognition system for discriminating drug-abusers from controls. The P600 component has only been previously employed (Vasios et al., 2002) for computer-based discrimination of normal controls from patients suffering from schizophrenia. Second, to design a novel classification system, according to which composite information is collected from all fifteen leads simultaneously and is fed into a multi-classifier structure to achieve highest classification accuracies.

2. Material and methods

2.1. Subjects

Sixteen one-month abstinent heroin-abusers (4 females and 12 males), matched on age and educational level to 20 normal controls (5 females and 15 males), were examined. The former were recruited from the outpatient university clinic of Eginition Hospital of Athens, Greece. Drug abstinence was verified by urine tests. The addicts were mainly long users of heroin, they had not made prolonged use of other drugs, and had no history of mental retardation. The controls were recruited from hospital staff and local volunteer groups. All participants had no history of any neurological or hearing problems and were right-handed as assessed by the Edinburgh Inventory Test (Oldfield, 1971). Written informed consent was obtained from both patients and control subjects.

2.2. ERP generation procedure

All subjects were evaluated by a computerized version of the digit span subtest of the Wechsler Adult Intelligence Scale (Wechsler, 1955). The examination procedure followed for each subject is detailed in a previous work by members of our research team (Papageorgiou et al., 2003; Papageorgiou and Rabavilas, 2003). ERPs were recorded using Ag/AgCl electrodes (leads), during the 1 s interval between the warning stimulus and the first administered number and were digitized at a sampling rate of 500 Hz. EEG activity was recorded from 15 scalp leads based on the International 10–20 system of Electroencephalography (Jasper, 1958), referred to both earlobes (leads at Fp1, Fp2, F3, F4, C3, C4, C5, C6, P3, P4, O1, O2, Pz, Cz, and Fz) (see Fig. 4).

2.3. Conventional statistical analysis

To investigate whether the two groups of subjects could be discriminated by conventional statistical analysis methods, a step-wise discriminant method was employed, utilizing the amplitudes (parameter AMP) and latencies (parameter LAT) of the P600 component at all 15 leads. It should be noted that the equality of the covariance matrices of the variables entered for the two groups was ascertained with Box's *M*-test.

2.4. Pattern recognition methods

2.4.1. Feature generation

Nineteen features related to the P600 component (500–800 ms time interval) were extracted from each ERP-signal at each lead by means of a dedicated computer software developed in C++ for the purposes of the present study. The description and relations of the features are given in Table 1. All features were normalized to zero mean and unit standard deviation (Theodoridis and Koutroumbas, 1998), according to relation:

$$x_i' = \frac{x_i - \mu}{\sigma} \tag{1}$$

where x_i and x_i' are the ith feature values before and after the normalization respectively, and μ and σ are the mean value and standard deviation respectively of feature x over all subjects (addicts and normal controls).

2.4.2. The PNN classifier

The probabilistic neural networks (PNNs) (Specht, 1990) are implemented by a feed-forward and one-pass structure and encapsulate the Bayes' decision rule together with the use of Parzen estimators of data's probability distribution function (PDF). The PNN classifier was chosen due to its non-parametric nature and because its training is easy and instantaneous (Specht, 1990), especially in comparison with the back-propagation neural network and the support vector machine classifiers. The discriminant equation of a PNN (equipped with the widely used Gaussian weighting function) for class k is given by the following relation, as described in (Tsai, 2000; Hajmeer and Basheer, 2002):

$$g_k(\boldsymbol{x}) = \frac{1}{(2\pi)^{d/2}\prod_{j=1}^{d}\sigma_j} \times \frac{1}{N_k}\sum_{i=1}^{N_k}\exp\left[-\frac{1}{2}\sum_{j=1}^{d}\left(\frac{x_j - x_{ij}}{\sigma_j}\right)^2\right] \tag{2}$$

where $\boldsymbol{x} = [x_1 x_2 \cdots x_d]^{\mathrm{T}}$ is the test pattern vector to be classified, $\boldsymbol{x}_i$ is the ith training pattern vector, N_k is the number of patterns in class k, σ_j are the standard deviations of the distributions of the pattern vector element variables, and d is the feature space dimensionality. The test pattern $\boldsymbol{x}$ is classified to the class with the larger discriminant function value.

2.4.3. Best feature selection procedure

To optimize classification performance, the best feature combination had to be determined at each one of the 15 leads, giving the highest class-discrimination with the least number of features. This was accomplished by employing the exhaustive search method (Theodoridis and Koutroumbas, 1998) of all possible 2, 3, 4, 5, and 6 feature combinations. Combinations with higher numbers of features were also tested, employing the forward stepwise feature selection technique (Theodoridis and Koutroumbas, 1998) and the PNN classifier. The best-feature combinations thus determined were used to design at each lead the PNN classifier, using the leave-one-out method for discriminating heroin addicts from normal controls.

2.4.4. Compartmental classification

Neural activity leading to the production of P600 signals has been associated with different brain structures such as the frontal, temporal and parietal regions, which participate in information processing during recognition memory (Papageorgiou et al., 2003). A careful observation of the lead placements on the scalp in Fig. 4 will

Table 1
Signal waveform feature descriptions and definitions

s/n	Feature	Description	Definition
1.	Latency (*LAT*)	Time interval to maximum signal value	$t_{s_{\max}} = \{t \mid s(t) = s_{\max}\}$
2.	Amplitude (*AMP*)	Maximum signal value	$s_{\max} = \max\{s(t)\}$
3.	Latency/Amplitude ratio (*LAR*)	LAT/AMP ratio	$\mathrm{LAR} = t_{s_{\max}}/s_{\max}$
4.	Absolute Amplitude (*AAMP*)	The absolute value of AMP	$\mathrm{AAMP} = \lvert s_{\max}\rvert$
5.	Absolute latency/ amplitude ratio (*ALAR*)	The absolute value of LAR	$\mathrm{ALAR} = \lvert t_{s_{\max}}/s_{\max}\rvert$
6.	Positive area (*PAR*)	The sum of the positive signal values	$A_p = \sum_{t=500\,\mathrm{ms}}^{800\,\mathrm{ms}}\{0.5\cdot(s(t) + \mid s(t)\mid)\}$
7.	Negative area (*NAR*)	The sum of the negative signal values	$A_n = \sum_{t=500\,\mathrm{ms}}^{800\,\mathrm{ms}}\{0.5\cdot(s(t) - \mid s(t)\mid)\}$
8.	Absolute negative area (*ANAR*)	The absolute value of NAR	$\mathrm{ANAR} = \lvert A_n\rvert$
9.	Total area (*TAR*)	The sum of all signal values	$\mathrm{TAR} = A_{pn} = A_p + A_n$
10.	Absolute total area (*ATAR*)		$\mathrm{ATAR} = \lvert A_{pn}\rvert$
11.	Total absolute area (*TAAR*)	The sum of absolute signal values	$A_{p\lvert n\rvert} = A_{\mathrm{pos}} + \lvert A_{\mathrm{neg}}\rvert$
12.	Average absolute signal slope (*TAAS*)	The mean of consecutive signal-values slopes	$\overline{\mid \dot{s}\mid} = \frac{1}{n}\cdot\sum_{t=500\,\mathrm{ms}}^{800\,\mathrm{ms}-\tau}(\frac{1}{\tau}\cdot\mid s(t+\tau) - s(t)\mid)$ where τ is the sampling interval of the signal (τ = 2 ms, for the sampling rate of 500 Hz), n is the number of samples of the digital signal (actual n = (800 ms − 500 ms)/2 ms = 150), and $s(t)$ the signal value of the tth sample
13.	Peak-to-peak (*PP*)	The difference between maximum and minimum signal values	$\mathrm{pp} = s_{\max} - s_{\min}$, where $s_{\max} = \max\{s(t)\}$ and $s_{\min} = \min\{s(t)\}$ are the maximum and the minimum signal values, respectively
14.	Peak-to-peak time window (*PPT*)	Time interval between moments where maximum and minimum signal values appear	$t_{\mathrm{pp}} = t_{s_{\max}} - t_{s_{\min}}$
15.	Peak-to-peak slope (*PPS*)	The slope of the line connecting the maximum and the minimum signal points	$\dot{s}_{\mathrm{pp}} = \frac{\mathrm{pp}}{t_{\mathrm{pp}}}$
16.	Zero crossings (*ZC*)	The number of times where the signal is equal to zero	$n_{\mathrm{zc}} = \sum_{t=500\,\mathrm{ms}}^{800\,\mathrm{ms}-\tau}\delta_s$, where $\delta_s = 1$ if $s(t) = 0$,0 otherwise
17.	Zero crossings in peak-to-peak time (*ZCPP*)	The number of times where the signal is equal to zero, within the peak-to-peak time window	$n_{\mathrm{zc}} = \sum_{t=t_{s_{\min}}}^{t_{s_{\max}}}\delta_s$
18.	Zero crossings density in peak-to-peak time (*ZCDPP*)	The frequency of zero crossings within the peak-to-peak time window	$d_{\mathrm{zc}} = \frac{n_{\mathrm{zc}}}{t_{\mathrm{pp}}}$, where n_{zc} are the zero crossings and t_{pp} is the peak-to-peak time window
19.	Slope sign alterations (*SSA*)	The number of slope sign alterations of two adjacent signal values	$n_{\mathrm{sa}} = \sum_{t=500\,\mathrm{ms}+\tau}^{800\,\mathrm{ms}-\tau}0.5\cdot\left\lvert\frac{s(t-\tau)-s(t)}{\lvert s(t-\tau)-s(t)\rvert} + \frac{s(t+\tau)-s(t)}{\lvert s(t+\tau)-s(t)\rvert}\right\rvert$, where τ is the sampling interval of the signal (τ = 2 ms, for the sampling rate of 500 Hz)

reveal that leads have been positioned at five anatomical brain compartments (Zang et al., 1997): frontal (Fp1, Fp2, F3, Fz, F4), central (C3, Cz, C4), parietal (P3, Pz, P4), occipital (O1, O2), and central-temporal (C5, C6). Evidently, leads have been named after those anatomical compartments. Since the latter participate in various brain functions, it was thought appropriate to investigate compartmental P600 differences. Accordingly, compartmental classifications were carried out, each lead participating with its best feature combination.

2.4.5. Multi-PNN classification structure

As shown in Fig. 4, a multi-PNN classification system was developed for classifying a subject as belonging to either the "heroin addicts" or the "controls" category. At each lead there was a PNN classifier designed to use the lead's particular best P600 features and to assign the P600 component to one of two classes. Table 2 gives the best feature combinations at each lead and Table 1 gives an explicit account of each feature. The outcome from each lead (either "heroin addict" or "control") was fed into an end-stage PNN classifier in the form of 1 or 0 (meta-features for addict or control respectively), which was trained to make the final decision on the class of a particular subject. The discriminant function of the end-stage PNN is then takes the form (by normalizing the feature values as described in Section 2.4.1, we can assume equal standard deviation (σ) for all pattern-vector distributions)

$$g_k(z) = \frac{1}{(2\pi)^{p/2}\sigma^p N_k} \sum_{i=1}^{N_k} \exp\left(-\frac{1}{2}\frac{\|z - z_i\|^2}{\sigma^2}\right) \qquad (3)$$

where z are the above-mentioned meta-features input vectors and p the number of leads participated.

The overall system was evaluated by the leave-one subject-out method. Accordingly, each time a subject was left out, the overall system was re-designed with the remaining subjects, and the left-out subject was classified by the re-designed system. Then the left-out subject was re-inserted into its class, the next subject was removed and the whole procedure was repeated for all subjects. Finally classification results were presented in a truth table.

Table 2
Best feature combination after exhaustive search with and without leave-one-out method, using the PNN classifier (σ = 0.24) at each lead

	Lead	LOO* (%)	w/o LOO (%)	Feature combination
1.	Fp1	80.6	97.2	LAT, AMP, PPT
2.	Fp2	77.8	97.2	AAMP, ATAR, PPT
3.	F3	86.1	100.0	LAT, PP, PPT
4.	F4	75.0	97.2	ALAR, TAAS, PP
5.	C3	77.8	94.4	AMP, LAR, AAMP
6.	C4	77.8	100.0	LAT, PPT, ZC
7.	C5	86.1	97.2	ALAR, TAR, SAAS
8.	C6	75.0	100.0	LAT, NAR, TAAS
9.	P3	86.1	100.0	PAR, PPS, SSA
10.	P4	69.4	83.3	PAR, TAAS
11.	O1	77.8	94.4	AAMP, PAR, ZC
12.	O2	80.6	100.0	PAR, TAAS, SSA
13.	Pz	80.6	97.2	LAR, TAAS, ZCDPP
14.	Cz	75.0	94.4	AMP, ATAR, ZC
15.	Fz	80.6	100.0	LAT, ZCDPP, SSA

For feature descriptions see Table 1.

3. Results and discussion

Fig. 1 shows the grand averages of the ERP signals of the two groups of subjects. Dashed lines represent the heroin addicts and solid lines the controls. As it may be observed, differences between the two groups may be visible in some leads but may be insignificant due to large variations about their grand-average signals. This can be seen on the P600 amplitude and latency scatter diagram (Fig. 2) at the FP1 lead. These two features are usually employed by Psychiatrists in assessing ERP signals by visual inspection.

Discriminant analysis, regarding P600 amplitude (parameter AMP), revealed that only one lead entered the discriminant function (C6), being able to classify correctly 69.4%, of the cross-validated grouped cases. Results of comparisons of the latencies (parameter LAT) revealed that only lead P3 entered the discriminant function, being able to classify correctly 69.4%, of the cross-validated grouped cases.

Employing a PNN classifier at each lead, the highest classification accuracy was determined employing the smallest number of features for discriminating heroin addicts from controls. Optimum numbers of features at each lead were determined by the exhaustive search method. Accuracies are presented in Table 2 and concern results obtained with and without the leave-one subject-out (LOO) method. Classification accuracies varied between maximum 86.1% (F3, P3, and C5) and minimum 75% (F4, C6, Cz), signifying the difficulty at many leads to discriminate effectively the two groups by means of the P600 component. The discriminatory ability of the PNN classifier was tested for various values of the σ parameter, retaining at each classification

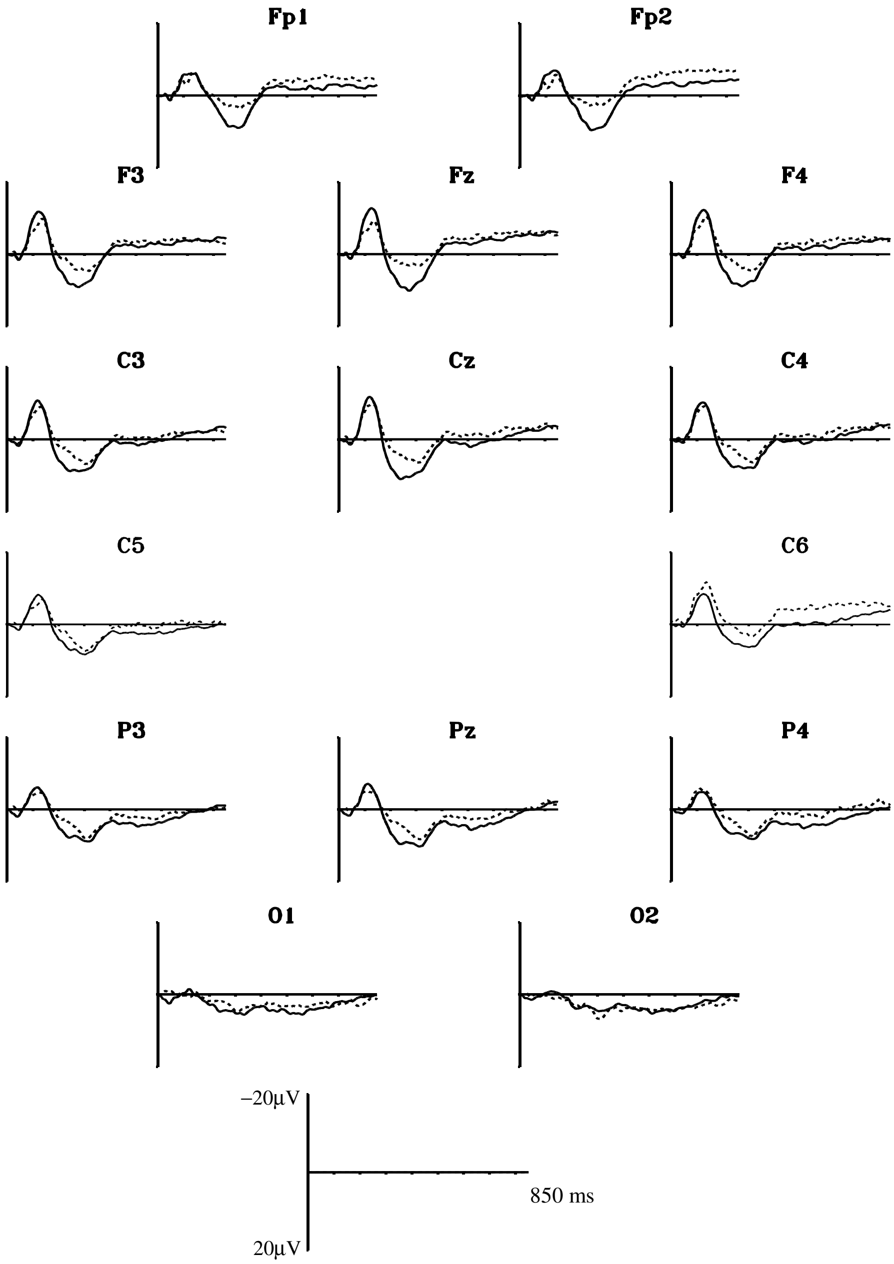

Fig. 1. Grand averages of ERPs of heroin addicts (dashed lines) and normal controls (solid lines) recorded at each lead. The lead notation is based on the International 10–20 system of Electroencephalography (Jasper, 1958).

test the value that provided the highest accuracy. Fig. 3 shows the scatter diagram and decision boundary of the PNN classification achieved at the F3 lead. For highest classification the PNN had to employ three features and to draw a non-linear surface through the points.

For comparison reasons, the PNN algorithm was tested against the multilayer perceptron

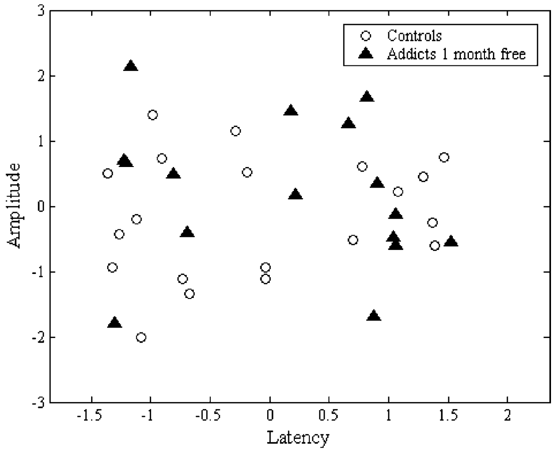

Fig. 2. Feature 'Latency' against feature 'Amplitude' (see Table 1) plot of P600 signals at the Fp1 lead of heroin addicts (triangles) and normal controls (circles). Feature values are normalized to zero mean and unit standard deviation (Theodoridis and Koutroumbas, 1998).

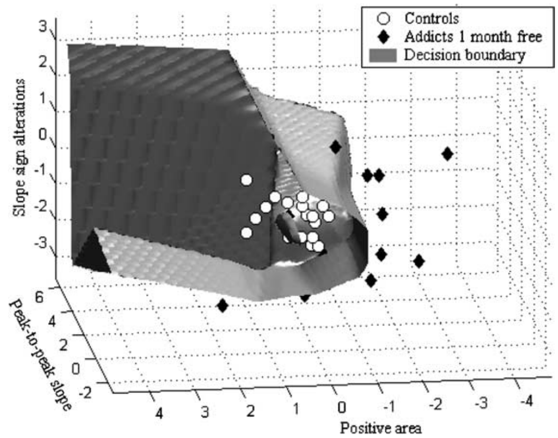

Fig. 3. Best feature/lead (F3) combination scatter diagram with PNN decision boundary.

(MLP) (Khotanzad and Lu, 1990) and the support vector machine (SVM) (Kecman, 2001) classifiers. The maximum overall classification accuracy per lead ranged between 61.1% and 80.6% for the MLP classifier, with two hidden layers and four nodes per layer, and between 69.4% and 83.3% for the SVM classifier, with the radial basis function as kernel. The duration of the training phase for the SVM classifier was about three times more than the PNN's, while the MLP required over 800 times more computational time than the PNN.

An attempt to use the P600 signals of all leads concurrently to design a PNN classifier employing the LOO and exhaustive search methods gave a classification accuracy of 86.1% (see Table 3). Best

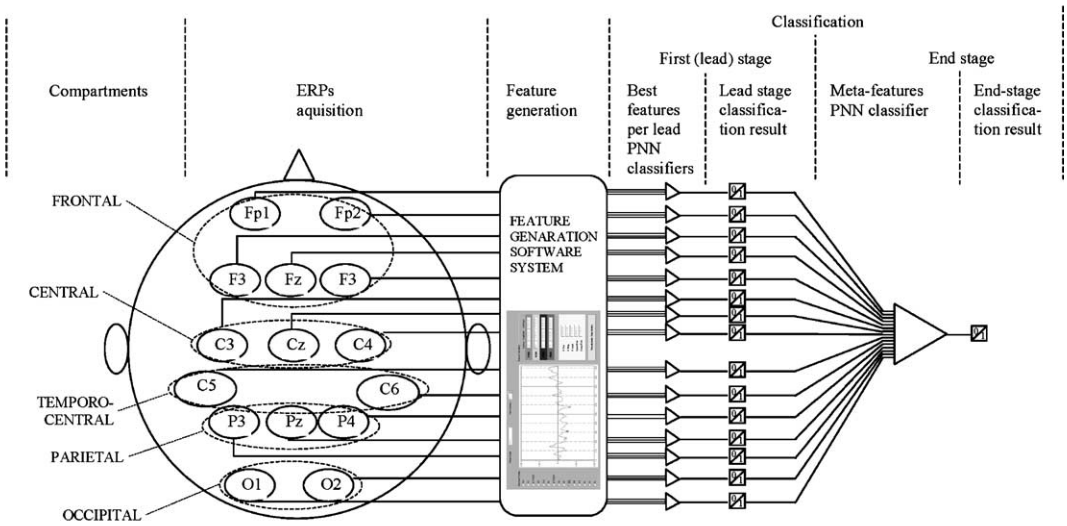

Fig. 4. Schematic diagram of leads distribution and multi-PNN classification system steps: First, a PNN classifier is employed at each lead to classify each subject to one of two classes (heroin addicts and normal controls). Then, on the basis of those lead sub-classifications, each subject is assigned to a particular class using a second PNN classifier.

Table 3
Best feature combination (PPT, PPS, ZCDPP—see Table 1 for descriptions) truth table, using leave-one-out method with PNN ($\sigma = 0.24$) classifier performed at all leads together

Groups	PNN classification		
	Controls	Addicts	Accuracy (%)
Controls	19	1	95.0 (specificity)
Addicts	4	12	75.0 (sensitivity)
			86.1 (overall)

features (PPT, PPS, ZCDPP—see Table 1) were associated with peak-to-peak time and slope of the P600 signal, i.e. the P600 amplitude and its rate of change differences that may exist between heroin addicts and normal controls. As shown in Table 3, the PNN could classify with high precision 95% the controls, misclassifying only one in 20 (high specificity), although failing to correctly distinguish 4 of the 16 heroin addicts (low sensitivity). Based on these results, it is difficult to draw definite conclusions as to existing differences between the two groups.

Table 4 shows the results obtained by employing the multi-PNN classification structure on all leads, using the LOO method, as described in Section 2.4.5. Based on the meta-features (0 or 1) of each lead, the end-PNN could predict the class of each subject (control or heroin-addict) with accuracy, even when that subject was not involved in its design. The meaning of this outcome is that a complex structure may be designed to discriminate one-month abstinent heroin addicts from normal controls, however, since that structure is based on many different features from the P600 signals selected from 15 leads, it is difficult to reach conclusive reasoning of between group differences. It was thus thought appropriate to proceed to a compartmental investigation of probable P600 deviations between the two classes as described in Section 2.4.4.

Table 4
Multi-PNN classification truth table, using leave-one-out method with second-stage PNN ($\sigma = 1.0$) classifier performed at all leads together

Groups	Multi-PNN classification at all leads		
	Controls	Addicts	Accuracy (%)
Controls	20	0	100.0 (specificity)
Addicts	0	16	100 (sensitivity)
			100 (overall)

Table 5 presents the results of regional classification employing the multi-PPN structure and using the LOO method. Results varied between 91.7% at the frontal and 80.6% at the occipital regions. On the other hand, a more careful examination of Table 2 can reveal that of the five leads involved in the frontal compartment, F3 showed the highest classification accuracy (86.1%). Considering the best-feature combination in F3 (latency, peak-to-peak magnitude and peak-to-peak time interval), it may be said that it is their combinational involvement that provided that valuable between-groups discriminatory power, which would not have been otherwise easily discernible by visual inspection.

The next higher compartmental classification accuracy was found in the combined left and right temporo-central compartments in Table 5, giving a discriminatory precision of 86.1% by misclassifying 3 controls and 2 heroin addicts. However, a more careful examination of Table 2 will reveal that the main contributor to that combined precision is the left temporo-central region, whose accuracy is significantly higher (86.1%) than that of the corresponding right region (75%). Considering the

Table 5
Multi-PNN classification results, using leave-one-out method with second-stage PNN ($\sigma = 1.0$) classifier performed at several scalp areas

Scalp area	Leads	Sensitivity (%)	Specificity (%)	Overall accuracy (%)
Frontal	Fp1, Fp2, F3, F4, Fz	87.5	95.0	91.7
Central	C3, C4, Cz	75.0	90.0	83.3
Parietal	P3, P4, Pz	68.7	95.0	83.3
Occipital	O1, O2	87.5	75.0	80.6
Central-temporal	C5, C6	87.5	85.0	86.1

best-feature combination in C5 (absolute latency/amplitude ratio, total area and average absolute signal slope), it may be concluded that P600 signal differences, related to the combined effect of amplitude, latency and rate of change, provide the discriminatory power achieved between groups. Another reassuring fact is that the means of the P600 amplitudes at lead C5 differed statistically between the two groups ($p < 0.05$), with the heroin addicts group showing higher amplitudes. These differences are important since ERPs from the temporo-parietal region have been associated with the subject's effort to respond to evoked stimuli (Papageorgiou et al., 2003). In fact, as it may be observed from Table 2, the discriminatory power of the left parietal lead was equally high (86.1%).

Finally, taking under consideration that significant between-group discriminations were obtained using the left-side leads (F3, C5, P3) separately (see Table 2), when these leads were employed by the multi-PPN structure, a high discrimination accuracy of 94.4% was achieved, misclassifying only 1 heroin-addict and 1 control.

Associating the meaning attributed to the P600 component with the present findings, especially the localization of findings at the left hemisphere—an effect most accentuated in the frontal region—it seems reasonable to suggest that short-term opioids abstinence is related to disruption of neural circuits, coupled with the left hemisphere and underlying processes which 'assign a specific response to a specific stimulus'. This concurs with the view of Davidson et al. (1990) that 'heroin stimuli elicit more pronounced activation in the left hemisphere in heroin abusers'.

As far as the more noticeable classification accuracy present in frontal regions is concerned, i.e. the one located at the left prefrontal cortex (F3 lead site), it appears to be in accordance with results of recent neuroimaging studies demonstrating neurobiological changes of frontal cortex that accompany drug addiction (Goldstein and Volkow, 2002). This idea is broadly consistent with neuropsychological models of information processing, postulating that the valence of information (positive or negative) and its associated action tendency (approach or withdrawal) is coupled with the operation of the prefrontal brain. Specifically, the right prefrontal region is conceptualized as a key part within a brain circuit mediating withdrawal-associated behavior, and the equivalent left prefrontal area is considered a main part within a brain circuit mediating approach-associated behavior (Lane et al., 1997).

Furthermore, present findings, considered in association with the corresponding patterns of P600 waveforms observed in long-term heroin abstinence (Papageorgiou et al., 2001), seem to show both common and distinct features. In particular, the results of the present study imply that short-term heroin abstinence connotes left hemisphere processes in association with the assignation of specific responses to specific stimuli, as thought to be indicated by the P600 component. In contrary, although long-term heroin abstinence has been reported to be also associated with the assignation of specific responses to specific stimuli, this association is connected with right frontal operation.

Conclusively, these findings indicate that cognitive function, as represented by the P600 component, during a WM task and explored by the PNN signal processing techniques, may be involved in short-term abstinent heroin addicts. Additionally, these findings indicate that these techniques may significantly facilitate computer-aided analysis of ERPs.

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