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Classification of Error-Related Negativity (ERN) and Positivity (Pe) potentials using kNN and Support Vector Machines

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ABSTRACT

Error processing in subjects performing actions has been associated with the Event-Related Potential (ERP) components called Error-Related Negativity (ERN) and Error Positivity (Pe). In this paper, features based on statistical measures of the sample of averaged ERP recordings are used for classifying correct from incorrect actions. Three feature selection techniques were used and compared. Classification was done by means of a kNN and a Support Vector Machines (SVM) classifier. The use of a leave-one-out approach in the feature selection provided sensitivity and specificity values concurrently higher than or equal to 87.5%, for both classifiers. The classification results were significantly better for the time window that included only the ERN, as compared to time windows including also Pe.

1. Introduction

Event-Related Potentials (ERPs) are a class of electroencephalographic (EEG) recordings, which are generated when a subject is presented with external stimuli or events. Their high temporal resolution provide for non-invasive measurement of brain electrical activity related to cognitive operations, which are activated for processing the stimuli or the events. The potential curves possess local maxima and minima called components of the ERP. The components are denoted by their positive or negative sign and their approximate time of appearance, in ms after the administration of the stimulus or the occurrence of the event, e.g., N100, P300, N400 and P600. Relations have been established between measurable characteristics of the components and specific brain processes concerning attention, orienting reaction, expectancy and decision making [1–3].

Error processing, an aspect of performance monitoring, is necessary for detecting errors, as fast as possible, and for optimizing future response behavior [4]. The electrophysiological mechanisms and the psychological correlations of error processing have been intensively investigated using the Error-Related Negativity (ERN), also called error negativity (Ne) [5–8]. ERN is a distinct ERP component, appearing as a negative deflection in response-locked averaged EEG recordings, elicited immediately after an error has been committed by the subject whose EEG is recorded. It peaks at approximately 50–100 ms after the erroneous response. ERN is consistently observed when a mismatch occurs between representations of anticipated and actual responses [5,6,9]. A second ERP component, associated with erroneous responses, the Error Positivity (Pe) generally follows the ERN. It is a positive deflection, peaking at around 200–500 ms after the error [8,10,11]. The role of Pe is still rather unclear [12]. Pe amplitude has been found to be diminished on unaware errors compared to consciously perceived errors [11,13], and it has therefore been related to error awareness [14], reflecting conscious error processing or updating of the error context [11,15,16]. Although ERN and Pe seem to be at least partially independent, for example attentional control of action monitoring appears to be reflected by Pe and not ERN during a task-switching paradigm [17], both error-related components might indicate aspects of negatively valenced violations of expected outcomes, to be used in executive control functions [15,18]. In addition, both components seem reliable and are well-suited for assessing trait characteristics and individual differences [19]. ERN has also been found in experimental paradigms exploring aspects of error monitoring, reaching beyond the "immediate" brain response of a subject to his/her own actions. For example, ERN is elicited in subjects making choices, after the presentation of a feedback stimulus that indicates incorrect performance of the subject [20]. When subjects observed the incorrect actions of another person, an ERN component was recorded (termed in the following "observation" ERN), albeit with a lower amplitude than the ERN for self-generated errors and a later occurrence of the peak [21]. ERN presents special interest for implementing Brain–Computer

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Interface (BCI) systems [22,23]. In such systems it is common that an interface has to recognize a subject's intent. When the subject perceives that the interface made an error in recognizing his/her intent, it has been shown that another kind of error-related potential (termed "interaction ErrP") is elicited [24,25].

Classification algorithms to discriminate between ERPs have been developed for various applications. In [26], ERP data obtained from both normal control subjects and chronic schizophrenic patients were classified, using a parallel principal component neural network. The proposed architecture provided overall classification accuracy up to 90%. In [27], genetic algorithm and a fuzzy ARTMAP classifier were combined to identify the discriminatory subset of the feature set for classification of alcoholics and non-alcoholics using brain rhythm extracted during visual stimulus. The feature set consisted of seven spectral power ratios extracted from multi-channel visual evoked potential (VEP) recordings. The classification accuracy reached 95.9%. A computer-based classification system capable of distinguishing patients with depression from normal controls using the P600 ERP component was presented in [28]. The proposed system used a combination of Support Vector Machines (SVM) classifiers and a majority-vote engine. The obtained classification accuracy was up to 94%. In [29], single-trial EEGs were classified by means of a perceptron artificial neural network (ANN). Features were extracted from multichannel EEG using an algorithm that combined common spatial subspace decomposition with Fisher discriminant analysis. The obtained classification accuracy was 84%. In another approach, scalp-recorded ERPs were first transformed into intracranial electrical currents [30]. Then, multivariate autoregressive (MVAR) model coefficients of the current time series, selected by the simulated annealing (SA) technique, were used as features in order to differentiate between normal controls and first-episode schizophrenic patients. The multi-layer perceptron (MLP) ANN was used as classifier, reaching 93.1% classification accuracy. In a recent investigation of attentional processes, target categorization responses from averaged ERPs were classified into two classes (target and non-target stimuli) using six different classifiers: Euclidean classifier (EC), Mahalanobis discriminant (MD), quadratic classifier (QC), Fisher linear discriminant (FLD), multi-layer perceptron (MLP) ANN and SVM. The best overall classification accuracy (91–92%) was provided by the non-linear and non-parametric classifiers QC, MLP and SVM [31].

The existence of error-related ERPs of subjects, who either commit errors or observe errors committed by other persons or interfaces, creates the challenge to develop classification systems. The ultimate aim of those systems is to discriminate between correct and incorrect responses in real-time, on the basis of single-trial EEG recordings. During the last decade, research efforts have been made in that direction, for improving the performance of BCI systems. In a study classifying ERNs evoked by the subjects' own response, classification performance, as expressed by the area under the Receiver Operating Characteristic (ROC) curve, reached 0.91, using a Gaussian classifier [32]. In another work, more than 85% of errors were detected using Fisher's Discriminant classifier with adapted bias [33]. Ferrez and Millan [25] used a Gaussian classifier for discriminating between correct and incorrect single-trial interaction ErrPs generated during simulated brain–computer interaction. The mean percentage of correctly recognized error trials was at least 79% and the mean percentage of correctly recognized correct trials was at least 82.4%. The same classifier was used in a recent study of Chavarriaga and Millán [34], where the focus was on the observation ERN of a human user observing the performance of an external agent. Mean classification accuracy was 75.81% and 63.21% for correct and error trials, respectively, when the agent's error rate was 20%, and 64.42% and 59.36% for correct and error trials, respectively, when the agent's error rate was 40%.

In a previous work [35], the MLP ANN and the Fuzzy C-Means (FCM) classifiers were used for differentiating both between ERPs generated in correctly or incorrectly responding subjects (referred to as "actors") and between observation ERNs elicited in subjects (referred to as "observers") who observed those actions. Features were extracted through the MVAR model in combination with the SA technique, using the averaged ERPs of the actors and the observers, respectively, for the two classification tasks. From the available set of the whole-head 47 electrodes montage, two sub-regions were used for extracting MVAR features. The first sub-region (SR-1) excluded the outermost electrodes. The second sub-region (SR-2) included only electrodes around the vertex. The contribution of ERN alone, as well as the combination of ERN and Pe, in providing features, was investigated. The classification accuracy for classifying correct and incorrect actions reached 86%, for both classifiers, for both sub-regions. For the MLP ANN, for SR-1 and using the time window that was expected to contain information only about the ERN, all incorrect actions were detected by the classifier. For the MLP ANN, for SR-2, a notable improvement for the classification accuracy – from 76% to 86% – occurred when the time window expected to contain information both for the ERN and the Pe was used. The classification accuracy for classifying observation ERNs reached 84%, for MLP ANN, for both sub-regions, and 87% for the FCM classifier, for SR-2. For the classification of observation ERNs, an improvement in classification accuracy was gained, for both classifiers and sub-regions, when features were extracted from the time window expected to contain information both for the ERN and the Pe, instead of the time window that was expected to contain information only about the ERN. Although the results of that previous study were satisfactory concerning the classification accuracy reached, the intrinsic uncertainty in detecting the MVAR model order, as well as the inexistence of methods other than extensive trial-and-error for selecting an appropriate layer structure for the MLP, was a motivating factor for investigating, on the same data set, other feature selection techniques and classifiers. Future transition from average-based to single-trials classification systems is expected to deteriorate the performance of any classification system. Therefore, the average-based system should have both a reliable performance and as high as possible classification accuracy. In this scope, the main aims of the present work were as follows: (i) to use features mainly based on statistical measures of the sample of the averaged ERPs, (ii) to compare, in a statistically robust manner, different feature selection techniques and two classifiers, the k nearest neighbor (kNN) and SVM, in order to achieve reliable classification results better than in [35] and independent from the internal parameter of the classifiers and, finally, (iii) to test whether classification was statistically significantly improved by including the Pe ERP in the data analysis. In the present work, the investigation was limited to actors' ERPs, in order to facilitate the evaluation of the various feature selection techniques and classification algorithms and the comparisons with the previous research exposed in [35].

2. Material and methods

2.1. Subjects' and ERPs' recording procedure

The ERPs data used in the present study were collected in previous research [21]. The data were acquired from 16 healthy volunteers. Participants were seated in front of a table facing an experimenter, having in front of them, on the table, two joystick devices positioned to the left and right of a LED stimulus device. Participants had to perform an Eriksen flanker task. In this kind of choice reaction tasks, used in cognitive psychology research, a