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Bayesian Priors for Classifier Design in RSVP Keyboard

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Abstract. We design an adaptive classifier using Bayesian priors for RSVP Keyboard^{TM}, a brain-interfaced alternative augmentative communication system designed for people with locked-in syndrome. RSVP Keyboard^{TM} employs regularized discriminant analysis classifier optimized by cross-validation using noninvasively acquired evoked response potentials from electroencephalography (EEG) in sequential symbol-by-symbol typing. Using EEG data recorded by RSVP Keyboard^{TM}, we perform offline analysis on the effect of online updates of the classifier on the system performance. Results indicate that instead of using a long calibration session, a shorter calibration session with online updates to the classifier would provide similar typing accuracy.
Keywords: EEG, ERP, Bayesian Inference, Classification, Conjugate Priors

1. Introduction

RSVP Keyboard^{TM} is a brain-interfaced alternative and augmentative communication system in development [Orhan et al., 2012]. This typing system is based on rapid serial visual presentation (RSVP) of symbols and utilizes electroencephalography (EEG) signals for classification of event related potentials (ERP). EEG signals from the 500ms interval following stimulus onset are used in a regularized discriminant analysis (RDA) classifier [Friedman, 1989]. In the current closed-loop on-line RSVP Keyboard^{TM} implementation, this classifier is calibrated using k-fold cross-validation with data collected immediately prior to testing and the parameters of this model remain fixed throughout use. However, it is conceivable that these parameters could continue to be updated during test as decisions are made and estimated labels become available. This would be especially useful if nonstationarity (due to environmental factors, as well as fatigue, attention, and vigilance levels of the operator) in test session changes signal statistics significantly enough to cause degradation in performance. To overcome this issue, in this study, we propose to use a classifier that can be adaptively and sequentially updated during a typing session.

2. Methods

From each of 4 healthy participants, we collected EEG data during 3 calibration sessions. Each calibration session consists of 100 sequences, each sequence having 1 target and 9 non-target symbols (2 classes). Data collection is done using 8 EEG channels with 256 Hz sampling frequency, which is then downsampled by a factor of 4 such that each channel contains 32 vector-valued samples. The first calibration session data (100 sequences) is used to train an RDA classifier. For the proposed classifier, we employ different number of sequences in calibration, whereas RDA calibration sequence count is 100. Using half of the data from second and third sessions, the proposed classifier is then updated to simulate system operation providing on-line EEG data (in two simulated test sessions). The performance of the proposed classifier update scheme and the RDA classifier obtained from 100 sequences is tested by using the second halves of session 2 and 3 data sets. Test data is kept separate from data used for batch calibration and on-line adaptation to prevent over-fitting and over-estimating the performance. We report the difference between the proposed and static-RDA classifiers' accuracies averaged over time and subjects as a function of number of sequences used for the initial calibration of the proposed method. The accuracy is defined as the ratio of correctly detected target ERP samples to the total number of sequences in (held-out) test data.

The proposed online update to the classifier is obtained by modeling temporal EEG features for each class with multivariate Gaussian distributions and then by employing the Expectation Maximization (EM) algorithm assuming conjugate priors for the class means and covariance matrices [Bishop, 2006]. Gaussian and Wishart probability density functions are assumed as the regularization priors for mean and covariance, respectively. The posterior expected values for these parameters are computed using the priors and the observed data according to following equations:

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$$\beta_k^n = \beta_k^{(n-1)} + N_k^n \qquad \mathbf{m}_k^n = \frac{1}{\beta_k^n}(\beta_k^{(n-1)}\mathbf{m}_k^{(n-1)} + N_k^n \overline{\mathbf{x}}_k^n)$$
$$(\mathbf{W}_k^n)^{-1} = (\mathbf{W}_k^{(n-1)})^{-1} + N_k^n \mathbf{S}_k^n + \frac{\beta_k^{(n-1)} N_k^n}{\beta_k^{(n-1)} + N_k^n}(\overline{\mathbf{x}}_k^n - \mathbf{m}_k^{(n-1)})(\overline{\mathbf{x}}_k^n - \mathbf{m}_k^{(n-1)})^T \tag{1}$$

In (1), k is the class label, n is the time index, β_k^n is the confidence (scaling) parameter, N_k^n represents the number of observed data points, $\mathbf{m}_k^n$ is the mean value of the prior distribution of class mean, $\overline{\mathbf{x}}_k^n$ is the mean value of the observed data, $\mathbf{W}_k^n$ represents expected value of the inverse covariance prior and $\mathbf{S}_k^n$ is the covariance of observed data. These expected values are used in QDA to calculate the scores (EEG features) for each symbol.

3. Results

Fig. 1 illustrates the average accuracy difference between the proposed and the RDA classifiers as a function of different initial calibration lengths for the proposed method. This preliminary result indicates that with on-line adaptation, the EEG classifier module of RSVP Keyboard^{TM} could be on average as accurate as using data from 100 sequences by only requiring less than 50 sequences a 50% reduction in initial calibration time).

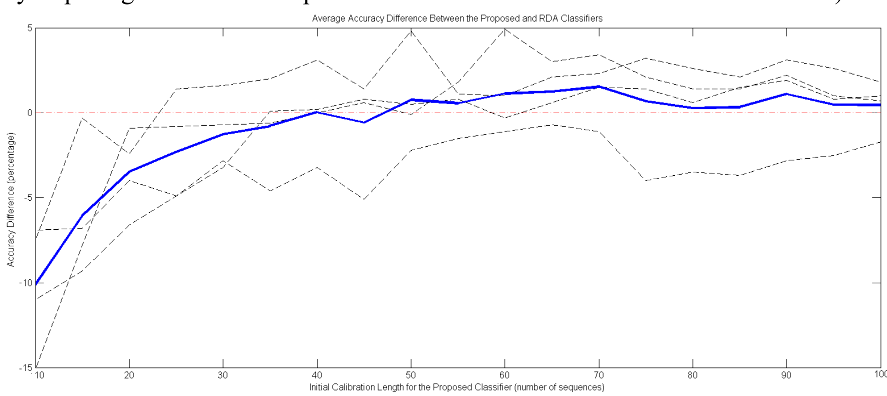

Figure 1. *Accuracy difference between the proposed method and RDA as a function of initial calibration length for the proposed method: (blue) average, (black dashed) individual subjects, (red dash-dot) zero difference line.*

4. Discussion

We demonstrated that a Bayesian conjugate prior based calibration of RDA-based EEG classifier in RSVP Keyboard^{TM}, an ERP-based spelling interface, can allow for short calibration sessions if followed by in-use on-line adaptive calibration. Regularization is a useful procedure for systems suffering from the curse of dimensionality, as in this case, and our plans include the incorporation of regularization into the calibration process in future. We will also incorporate adaptive calibration procedures to track possible nonstationarity in EEG signal/feature. This will allow us to have longer periods of use without the need to recalibrate from scratch.

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