Detecting EEG Evoked Responses for Target Image Search with Mixed Effect Models

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***Abstract*— There is evidence that brain signals associated with perceptual processes can be used for target image search. We describe the application of mixed effect models (MEMs) to brain signature detection. We develop an MEM detector for detecting brain evoked responses generated by perceptual processes in the human brain associated with detecting novel target stimuli. We construct the model using principal component analysis and linear discriminant analysis (LDA) bases. We adopt the LDA for dimension reduction. For parameter regularization we use 10-fold cross validation and report experimental results from six subjects. Four out of six subjects achieve very good detection performance with more than 0.9 areas under receiver operating characteristic curves. The results demonstrate that the MEM can provide reliable inference on single-trial ERP detection on the task of target image search.**

I. INTRODUCTION

Target image search through large volumes of images has become an important issue in many domains. Recently researchers began to exploit brain signals associated with split second perceptual judgments as the basis for visual target image search [1-5]. The goal of our research is to develop algorithms for detecting electroencephalography (EEG) evoked responses efficiently based on the visual and cognitive systems of the human expert. Our system exploits EEG as the main indicator to see if an image seen briefly by the expert contains a target (object of interest) or a non-target (distractor) as shown in Figure 1. The main task is to detect the event-related potentials (ERP) as shown in Figure 2, which generated from the human brain in response to critical events, such as interesting/novel visual stimuli in the form of a target image. Our initial study [6] demonstrates the ERP-based image triage system is viable for target image search.

In this study, we present an alternative classifier – mixed effect model (MEM) to the task of detecting evoked response potentials in EEG — ERPs. This is a novel application of the MEM. The MEM [7], first proposed by Laird and Ware [8] for solving the highly unbalanced longitudinal problem, is a hierarchical model with a complex, multilevel and hierarchical structure. It has been widely used on the analysis of longitudinal data [8] and

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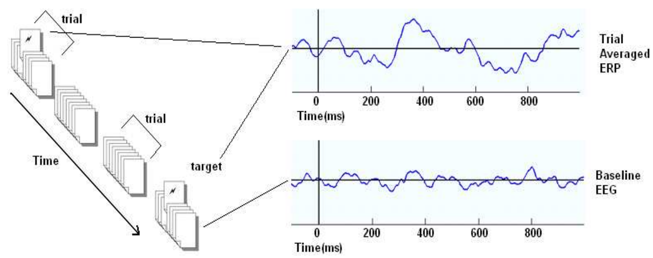

Figure 1: An illustration of the RSVP image display modality is shown on the left. On the right, the upper trace is an ERP averaged over trials (in one representative channel) and the lower trace is the average baseline EEG signal recorded in response to distracter stimuli. Time-zero corresponds to stimulus onset.

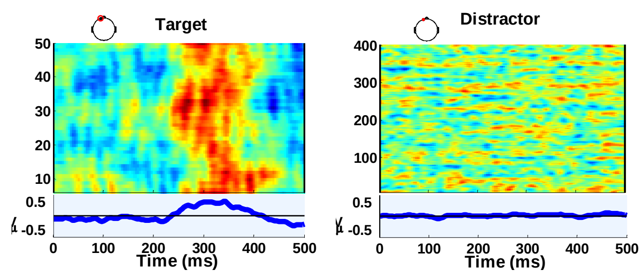

Figure 2: Images of ERP and non-ERP signals over many trials (each row) associated with targets and distractors for subject #1 at channel FP1, colors adjusted to match scales across images. Time-zero corresponds to stimulus onset in each trial. The traces at the bottom of each image are the EEG signals averaged over trials.

shape and image analysis [7]. It assumes that observations between levels or clusters are independent, but observations within each cluster are dependent. An advantage of the MEM is the ability to genuinely combine the data by introducing multilevel random effects. Therefore it is well suited for the analysis of longitudinal data and biomedical data.

Use of the mixed modeling techniques in the EEG detection is exciting and promising. The most challenging issue of detecting neural signatures is the high dimensionality and lack of large training sets. Since it is impractical to have extensive training, we attempt to train classifiers based on data aggregated across multiple subjects. An MEM can easily meet this need by combining the random effects (within and between subject variance) and fixed effects (consistent patterns across subjects). This work reveals the power of this statistical approach to the nontraditional statistical data — EEG data. The results establish that the MEM can be a reliable detector for the ERP patterns on the task of visual target image search.

II. MIXED EFFECT MODELS

2.1 Model description

In general, a linear MEM is written as, for each *i*,

$$\mathbf{y}_i = \mathbf{X}_i\boldsymbol{\alpha} + \mathbf{Z}_i\mathbf{b}_i + \boldsymbol{\varepsilon}_i, \quad (1)$$

where $i = 1,..., N$, N is the number of individuals.

- $\mathbf{y}_i$ is an $n_i \times 1$ vector of observations for the *i*th individual and n_i is the number of observations for the *i*th individual.
- $\boldsymbol{\alpha}$ is an $p \times 1$ population fixed effects vector.
- $\mathbf{X}_i$ is an $n_i \times p$ population design matrix of fixed effects.
- $\mathbf{b}_i$ is a $k \times 1$ individual random effects vector . We assume that the random effects are independent and have a normal distribution $\mathbf{b}_i \sim N(0, \mathbf{D})$ where $\mathbf{D}$ is a $k \times k$ matrix of positive definite covariance.
- $\mathbf{Z}_i$ is an $n_i \times k$ individual design matrix of random effects.
- $\boldsymbol{\varepsilon}_i$ is an $n_i \times 1$ vector of independent and identically distributed (iid) errors with zero mean and positive definite within-individual variance. We assume that the error terms have a normal distribution $\boldsymbol{\varepsilon}_i \sim N(0, \sigma^2 \mathbf{I}_{n_i})$, where $\mathbf{I}_{n_i}$ denotes an $n_i \times n_i$ identity matrix.

Thus $\mathbf{y}_i$ has a multivariate normal distribution $\mathbf{y}_i \sim N(\mathbf{X}_i\boldsymbol{\alpha}, \sigma^2\mathbf{I}_{n_i} + \mathbf{Z}_i\mathbf{D}\mathbf{Z}_i^T)$. In Equation (1), $\mathbf{y}_i$, $\mathbf{X}_i$ and $\mathbf{Z}_i$ are known and $\boldsymbol{\alpha}$, $\mathbf{b}_i$ and $\boldsymbol{\varepsilon}_i$ are unknown. The variance parameters, σ^2 and $\mathbf{D}$ are unknown and subjected to be estimated along with the population-averaged parameter $\boldsymbol{\alpha}$.

2.2 Model Parameter Estimation

We apply expectation-maximization (EM) algorithm [9] for maximum likelihood (ML) estimates: the model parameters, $\boldsymbol{\alpha}$ and $\mathbf{b}_i$, and random variance parameters, σ^2 and $\mathbf{D}$.

2.2.1 ML Estimation of $\boldsymbol{\alpha}$ and $\mathbf{b}_i$

Writing $Var(\mathbf{y}_i)$ as $\mathbf{V}_i = \sigma^2\mathbf{I}_{n_i} + \mathbf{Z}_i\mathbf{D}\mathbf{Z}_i^T$, if all covariance parameters $\hat{\sigma}^2$ and $\hat{\mathbf{D}}$ were known, then $\mathbf{V}_i$ was known, we could estimate $\boldsymbol{\alpha}$ and $\mathbf{b}_i$. The log-likelihood function for the MEM could be maximized by the generalized least squares estimator,

$$\hat{\boldsymbol{\alpha}} = \left(\sum_{i=1}^{N} \mathbf{X}_i^T \mathbf{V}_i^{-1} \mathbf{X}_i\right)^{-1} \sum_{i=1}^{N} \mathbf{X}_i^T \mathbf{V}_i^{-1} \mathbf{y}_i \ . \quad (2)$$

If $\boldsymbol{\alpha}$ were known, treat $\mathbf{b}_i$ as fixed effects and use least square estimation, from Equation (1), we have

$$\hat{\mathbf{b}}_i = \mathbf{D}\mathbf{Z}_i^T \mathbf{V}_i^{-1}(\mathbf{y}_i - \mathbf{X}_i\hat{\boldsymbol{\alpha}}) \ . \quad (3)$$

2.2.2 EM algorithm for ML estimates of σ^2 and $\mathbf{D}$

<u>*M-step:*</u> If we were to observe $\mathbf{b}_i$ and $\boldsymbol{\varepsilon}_i$, use sample variance, we could easily obtain simple closed-form solution using ML estimation of variance.

$$\hat{\sigma}^2 = \sum_{i=1}^{N} \boldsymbol{\varepsilon}_i^T \boldsymbol{\varepsilon}_i \Big/ \sum_{i=1}^{N} n_i \ , \quad (4)$$

$$\hat{\mathbf{D}} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{b}_i \mathbf{b}_i^T \ . \quad (5)$$

<u>*E-step:*</u> If $\hat{\sigma}^2$ and $\hat{\mathbf{D}}$ were available, we could calculate the sufficient statistics as follows:

$$\sum_{i=1}^{N} \boldsymbol{\varepsilon}_i^T \boldsymbol{\varepsilon}_i = \sum_{i=1}^{N} \hat{\boldsymbol{\varepsilon}}_i(\hat{\boldsymbol{\theta}})^T \hat{\boldsymbol{\varepsilon}}_i(\hat{\boldsymbol{\theta}}) + \sum_{i=1}^{N} tr\left\{Var\left[\boldsymbol{\varepsilon}_i \mid \mathbf{y}_{i,} \hat{\boldsymbol{\alpha}}(\hat{\boldsymbol{\theta}}), \hat{\boldsymbol{\theta}}\right]\right\}, \quad (6)$$

$$\sum_{i=1}^{N} \mathbf{b}_i \mathbf{b}_i^T = \sum_{i=1}^{N} \left\{\hat{\mathbf{b}}_i(\hat{\boldsymbol{\theta}})^T \hat{\mathbf{b}}_i(\hat{\boldsymbol{\theta}}) + Var\left[\mathbf{b}_i \mid \mathbf{y}_{i,} \hat{\boldsymbol{\alpha}}(\hat{\boldsymbol{\theta}}), \hat{\boldsymbol{\theta}}\right]\right\}, \quad (7)$$

where $\hat{\boldsymbol{\varepsilon}}_i(\hat{\boldsymbol{\theta}}) = \mathbf{y}_i - \mathbf{X}_i\hat{\boldsymbol{\alpha}}(\hat{\boldsymbol{\theta}}) - \mathbf{Z}_i\hat{\mathbf{b}}_i(\hat{\boldsymbol{\theta}})$ and $\hat{\mathbf{b}}_i(\hat{\boldsymbol{\theta}})$ were obtained from ML estimation from Equation (3). We can derive $Var\left[\boldsymbol{\varepsilon}_i \mid \mathbf{y}_{i,} \hat{\boldsymbol{\alpha}}(\hat{\boldsymbol{\theta}}), \hat{\boldsymbol{\theta}}\right]$ based on $\boldsymbol{\varepsilon}_i; \boldsymbol{\theta} \sim N\left(0, \sigma^2\mathbf{I}_{n_i}\right)$, $\mathbf{y}_i \mid \boldsymbol{\varepsilon}_i; \boldsymbol{\theta} \sim N\left(\mathbf{X}_i\boldsymbol{\alpha}, \mathbf{Z}_i\mathbf{D}\mathbf{Z}_i^T\right)$ and $\mathbf{y}_i; \boldsymbol{\theta} \sim N(\mathbf{X}_i\boldsymbol{\alpha}, \sigma^2\mathbf{I}_{n_i} + \mathbf{Z}_i\mathbf{D}\mathbf{Z}_i^T)$. Similarly we can calculate $Var\left[\mathbf{b}_i \mid \mathbf{y}_{i,} \hat{\boldsymbol{\alpha}}(\hat{\boldsymbol{\theta}}), \hat{\boldsymbol{\theta}}\right]$ based on that $\mathbf{b}_i; \boldsymbol{\theta} \sim N(0, \mathbf{D})$, $\mathbf{y}_i \mid \mathbf{b}_i; \boldsymbol{\theta} \sim N\left(\mathbf{X}_i\boldsymbol{\alpha} + \mathbf{Z}_i\mathbf{b}_i, \sigma^2\mathbf{I}_{n_i}\right)$ and $\mathbf{y}_i; \boldsymbol{\theta} \sim N(\mathbf{X}_i\boldsymbol{\alpha}, \sigma^2\mathbf{I}_{n_i} + \mathbf{Z}_i\mathbf{D}\mathbf{Z}_i^T)$. Thus we obtain the variance parameter estimates as:

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{N} \hat{\boldsymbol{\varepsilon}}_i(\hat{\boldsymbol{\theta}})^T \hat{\boldsymbol{\varepsilon}}_i(\hat{\boldsymbol{\theta}}) + \sum_{i=1}^{N} tr\left\{\left[\left(\mathbf{Z}_i\mathbf{D}\mathbf{Z}_i^T\right)^{-1} + \left(\sigma^2\mathbf{I}_{n_i}\right)^{-1}\right]^{-1}\right\}}{\sum_{i=1}^{N} n_i} \quad (8)$$

$$\hat{\mathbf{D}} = \frac{1}{N} \sum_{i=1}^{N} \left\{\hat{\mathbf{b}}_i(\hat{\boldsymbol{\theta}})^T \hat{\mathbf{b}}_i(\hat{\boldsymbol{\theta}}) + \left(\frac{\mathbf{Z}_i^T\mathbf{Z}_i}{\sigma^2} + \mathbf{D}^{-1}\right)^{-1}\right\}. \quad (9)$$

At the last iteration of EM algorithm (convergence), we have $\hat{\sigma}^2$ and $\hat{\mathbf{D}}$.

III. ERP DETECTOR CONSTRUCTION

The classification study is to assess the MEM as an indicator of the ERP. The goal is to evaluate the efficacy of MEM on the single-trial ERP detection. We adopt the receiver operating characteristic (ROC) curve to estimate the quantitative efficacy.

3.1 Data Preparation

The EEG data collection was the same as in [6]. The images were labeled whether or not they contained targets and presented at very high rates (durations were 60ms, 100 ms, or 150ms per image). The subjects performed target detection as shown in Fig. 1 by clicking on a button as soon as they saw a target. At the same time, we monitored and recorded their EEG signals by a 32-channel EEG system for subsequent analysis. The sampling rate is 256 Hz.

Six subjects were recruited for the study. Each subject had one training session and one to seven test sessions. In the training sessions the images were randomly displayed while in the test sessions the image chips were displayed in the natural spatial order of a broad-area image. During the test for subject #1, #2, #3 and #6, *fake targets* that were not part of the original broad-area image were introduced randomly to keep the subject alert to prevent the boredom-related ERP-degeneration. We included these fake targets when conducting the detection performance evaluation. There were around 50 targets in hundreds of distractors in the training while there were two to twenty targets (including *fake targets*) within thousands of distractors in the test. The subjects were also asked to press a button as soon as they recognized a target in the fast image sequence and the button responses (which typically occur after 500ms and do not create overlapping brain activity with portion used for our detectors) were utilized as confirmation of the presence of the ERP in response to a target stimulus.

The procedures of data pre-processing [6] were applied to obtain clean training data. We segmented the EEG data into the task-relevant epochs (500 ms after each image trigger), filtered the data through a 1-45 Hz bandpass filter and conducted data normalization. We adopted a disjoint windowing scheme in the training and a sequential windowing scheme in the test. For both training and test, we removed the distractors in the interval of one second before and after the targets and selected the targets with following button responses within 1.5 seconds. If there was more than one targets in sequence, we only selected the first target.

3.2 ERP detector —MEM

Our goal in classification is to build an ERP detector that uses the features as the input, and accurately discriminate the EEG signals containing the *ERP* versus the *non-ERP*.

3.2.1Feature Dimension Reduction

We apply linear discriminant analysis (LDA) [10] on the 32-channel EEG data for dimension reduction and congregate the selected channel projections in each epoch to form a feature vector as the input of the classifier. For the target cluster and the distractor cluster, we can measure the mean and variance respectively. For the linear projections of the target cluster and distractor cluster, we can obtain the best projection $\boldsymbol{\omega}$ by maximizing the ratio of the between-class scatter to the within-class scatter. The optimal projection $\boldsymbol{\omega}$ is the solution of generalized eigen decomposition, so we select a subset of the eigenvectors associated with the large eigenvalues as the optimal projection $\boldsymbol{\omega}$. The number of eigenvectors of LDA can be determined by the users.

3.2.2 Population Design Matrix

We develop the population design matrices for the target cluster and the distractor cluster respectively using principal component analysis (PCA) [10]. To create the target basis matrix, we first calculate the covariance matrix of target training data and calculate the eigenvectors and eigenvalues. Then we sort the columns of the eigenvector matrix according to their associated eigenvalues and select a subset of eigenvectors as the basis vectors by their cumulative energy contents. Similarly we can develop the population design matrix for the distractor cluster. The percentage of the cumulative energy can be chosen by the users. Here we use the same percentage of the eigen energy for both target and distractor population design matrices.

3.2.3 Individual Design Matrix

We develop the individual design matrix using LDA as described in Section 3.2.1. We just simply select a subset of the eigenvectors associated with the large eigenvalues as the individual design matrix. Here we set the number of the eigenvector equals one for simplicity (We investigated larger number of the eigenvectors, but the performances were close).

3.2.4 MEM Training

After we have the target population design matrix $\mathbf{X}_i^t$, the distractor population design matrix $\mathbf{X}_i^d$ and the individual design matrix $\mathbf{Z}_i$, we can estimate the model parameters, $\boldsymbol{\alpha}$, $\mathbf{b}_i$ and variance parameters, $\sigma^2, \mathbf{D}$ using EM algorithm for ML estimation as discussed in the previous Section. We derive a target MEM and a distractor MEM after the training.

3.2.5 MEM Test

After we have the MEM models for the target cluster and the distractor cluster, we can subject the test patterns to the models. For each test pattern, we have

$$\mathbf{y}_i^{Test} = \mathbf{X}_i\boldsymbol{\alpha} + \mathbf{Z}_i\mathbf{b}_i^{Test} + \boldsymbol{\varepsilon}_i, \tag{10}$$

where $\mathbf{b}_i \sim N(0, \mathbf{D})$ and $\boldsymbol{\varepsilon}_i \sim N(0, \sigma^2\mathbf{I}_{n_i})$. Since we have $p\left(\mathbf{y}_i^{Test} \mid \boldsymbol{\alpha}, \mathbf{b}_i^{Test}\right) \sim N(\mathbf{X}_i\boldsymbol{\alpha} + \mathbf{Z}_i\mathbf{b}_i^{Test}, \sigma^2\mathbf{I}_{n_i})$, we can maximize the posterior and obtain the optimal individual random effect parameter for the test pattern,

$$\mathbf{b}_i^{Test\ *} = \mathbf{D}\mathbf{Z}_i^T\mathbf{V}\left(\mathbf{y}_i^{Test} - \mathbf{X}_i\boldsymbol{\alpha}\right). \tag{11}$$

After we obtain $\mathbf{b}_i^{Test^*}$ for the target model and $\mathbf{b}_i^{Test^*}$ for the distractor model, we can apply them to the log likelihood function respectively,

$$\begin{aligned} L\left(\mathbf{b}_i^{Test\ *}\right) &= \ln\left(N(\mathbf{X}_i\boldsymbol{\alpha} + \mathbf{Z}_i\mathbf{b}_i^{Test\ *}, \sigma^2\mathbf{I}_{n_i})\right) + \ln\left(N(0, \mathbf{D})\right) \\ &= \ln C_{\sigma^2} + \ln C_D \\ &- \frac{1}{2\sigma^2}\left(\mathbf{y}_i^{Test} - (\mathbf{X}_i\boldsymbol{\alpha} + \mathbf{Z}_i\mathbf{b}_i^{Test\ *})\right)^T\left(\mathbf{y}_i^{Test} - (\mathbf{X}_i\boldsymbol{\alpha} + \mathbf{Z}_i\mathbf{b}_i^{Test\ *})\right) \\ &- \frac{1}{2}\mathbf{b}_i^{Test\ *T}\mathbf{D}^{-1}\mathbf{b}_i^{Test\ *}, \end{aligned} \tag{12}$$

Where C_{σ^2} and C_D are constants. The discriminant values of the MEM (the estimates of target likelihood) are the difference between the log likelihood values of the target model and distractor model.

3.3 Evaluation Criteria and Parameter Regularization

We adopt the area under the ROC curve (AUC) [10] to quantify the ERP detection performance. We apply the 10-fold cross validation for parameter regularization for each subject. We train the MEM classifier, choosing the optimal number of eigenvectors of LDA (num_eigs1_LDA) in dimension reduction and the percentage of the cumulative energy (perc_eigs_PCA) in population design matrix from discrete sets that give the best validation performance. Validation performance is the average of the AUC of nine classifiers, each of which is trained on a different nine-fold training set, and evaluated on a one-fold validation set.

IV. Results

4.1 Parameter Selection

We conducted the 10-fold cross-validation to select the optimal parameters for each subject. We exhaustively evaluated all combinations (Perc_eigs_PCA=0.6:0.05:1; N_eigs1_LDA=1:1:6.). Figure 3 shows an example of the validation results for selecting the optimal parameters for subject #1 (N_eigs1_LDA=4, Perc_eigs_PCA=1). We conducted the same procedures and obtained the optimal parameters for each subject.

4.2 Test Results

In our experiments, for four out of six subjects we achieved high detection performance. Having selected the optimal regularization parameters, we sought to estimate the ERP detection performance on an *independent* test set not used for training or adjusting regularization. We adopted the AUC to evaluate the test performance. Target images that did not receive button responses from subjects were removed from the analysis. We noticed that one particular target image was consistently missed by all subjects (no button click following this target). We conjecture that some property (to be investigated) of this target makes it challenging to detect visually in the high-speed presentation modality. We removed the targets without button clicks. Figure 4 shows the ROC curves of the test results for six subjects. We can see that four subjects with *fake targets* (overall target probability around 0.5%) achieve high detection performance with AUC >=0.9 while two subjects with less targets (overall target probability around 0.1%) have lower AUC.

IV. Discussion

Our results show that the viability of using the MEMs to make reliable inference for target image search in image databases based on the ERP detection. The expected performance in terms of high AUC is limited by the imbalance between the prior probability of target and non-target images. Similarly, generalization is limited by the low samples-to-parameters ratio. Future work will investigate the application of the MEM to cross subject ERP detection for the purpose of providing a quick training solution for the target image search task using neural signals.

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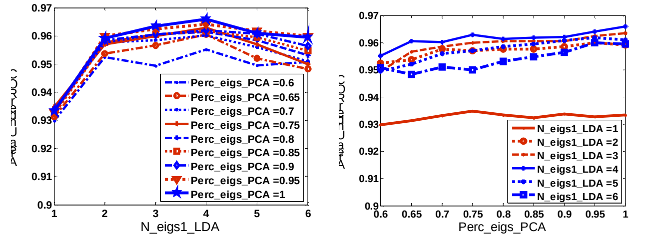

Fig. 3: The 10-fold cross validation result for parameter regularization on subject #1.

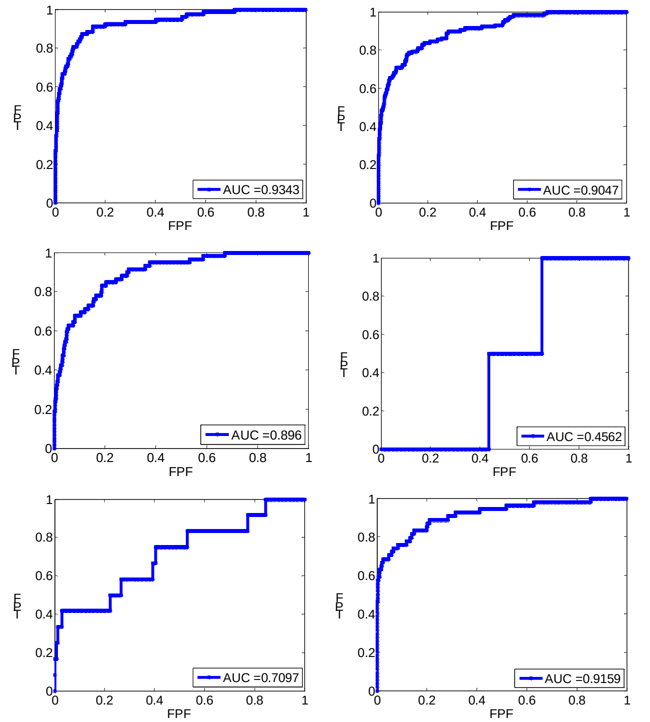

Fig. 4: Test ROC curves of six subjects. The x-axis is false positive fraction (FPF) and the y-axis is true positive fraction (TPF).

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