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Using Rapid Visually Evoked EEG Activity for Person Identification

Koel Das, Sheng Zhang, Barry Giesbrecht and Miguel P. Eckstein

Abstract— **We investigate the potential of using EEG recordings of observers performing a rapid visual categorization task for person identification. We examine a 0.5 s epoch of EEG data using machine learning techniques that, unlike most previous studies, analyze the data in a holistic manner and extracts discriminative spatio-temporal filters. The analysis of the filters suggest sparse feature representation spatially as well as temporally. The filters reveal that the neural activity that discriminates individuals is spatially localized to occipital electrodes located on the scalp above the visual cortex and temporally localized in the interval of 120-200 ms after presentation of the visual stimulus. The results demonstrate the feasibility of EEG-based person identification based on difficult perceptual tasks.**

I. INTRODUCTION

A brain-computer interface (BCI) is a communication link between the brain and an external device, applied primarily in assisting disabled individuals by using neural activity to control prosthetic devices (robots, artificial limb, autonomous vehicles etc.) [18], [13]. BCIs can be classified into two categories: invasive and non-invasive, depending on the type of neural signals and recording technology. While the primary application of BCI lies in the field of neural rehabilitation for disabled individuals, BCI's play an important role as an analytical tool for studying brain mechanisms and testing new hypotheses about brain function. Recent BCI developments have given rise to a new research paradigm: brain activity-based biometry [9], [11]. These biometric systems can potentially become an emerging area of research, using neural signals as an alternate biometric modality or in conjunction with conventional modalities like fingerprints, face images, iris scans [8], [21], [3] to form a robust multimodal biometric system. In this paper we use neural signals recorded from human observers, performing a rapid visual categorization task for person identification and systematically study discriminative patterns arising from variations in individual's response to visual stimuli.

Use of neural signals for person identification has some unique advantages compared to the conventional modalities: 1) Uniqueness: With current technology it is extremely difficult to duplicate neural emissions. Patterns of neural activity are thought to be unique to each individual [10] (Figure 1).Figure 1 shows EEG activity recorded from 64 electrodes at a 170 ms post stimulus onset for 2 observers performing exactly the same visual categorization task (categorizing an image as that of a car or a face). The significant difference in the amplitudes (measured in μV) between the two patterns of EEG activity produced by the observers' brains in response to the visual stimuli forms the rationale behind using EEG signals in person identification. 2) Circumvention: It is difficult to reproduce under duress. Brain activity is sensitive to stress level and mood of the person [9]. We propose to use EEG recordings for person identification due to its non-invasive nature and superior temporal resolution. Moreover, when these unique characteristics are considered in combination with the advent of affordable, wireless, mobile EEG devices, EEG becomes a natural choice for an efficient biometric recording technique.

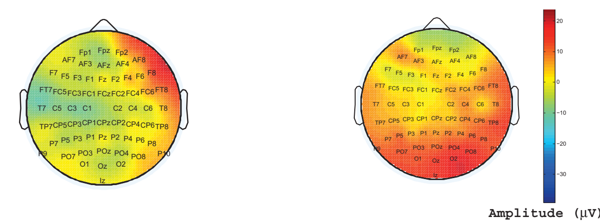

Fig. 1. Individual Differences: EEG activity at 170 ms after stimulus onset (N170) for 2 observers presented with same stimulus (face image).

Most of the early EEG-based biometrics research [12], [15] typically use autoregressive (AR) approaches for modelling the EEG signals, followed by Vector Quantization [15] or discriminant analysis [12] for classification. Recently, Palaniappan [11] developed a technique for EEG-based person identification which involves extracting features based on spectral powers for band-passed signals and fuzzy Neural Network and kNN classifiers for decision making. Marcel et al. [9] proposed a Gaussian Mixture Model-based framework using EEG signals for person authentication applications.

The EEG signals are typically quite noisy and high dimensional. For example, one sample of our EEG data has 22912 (64 spatial channels (electrodes) $\times$358 temporal points) dimension. Consequently, the data analysis is hindered by the *curse of dimensionality* [4], requiring feature extraction. To extract features from EEG signals, most conventional approaches typically assuming space-time separability. The EEG data is first processed spatially, by applying Laplacian filter [20], followed by temporal processing. Temporal processing often relies on spectral decomposition of brain data and the utilization of power in various frequency bands (e.g. μ-band or β-band or γ-band [20], [11]). While physically intuitive under specific task conditions, the use of spectral feature for EEG-based person identification seems largely heuristic, and likely to produce suboptimal results. Pala-

K. Das, S. Zhang, B. Giesbrecht and M. P Eckstein are with the Department of Psychology and Institute for Collaborative Biotechnology, University of California, Santa Barbara, CA 93106, USA, email: das@psych.ucsb.edu

niappan et al. in [11] used the γ-band features for person identification successfully, however features extracted from γ-band using the current data failed to produce above chance performance. One probable reason for poor performance using γ-band feature extraction might be the nature of the task and the duration of the EEG signals used for analysis. Furthermore, some users are unable to control these EEG rhythms [19], and hence the *a priori* selection of these spectral bands as features may not be appropriate in general.

The current study differs from previous studies in several ways. First, we use EEG signals involved in a difficult (to make the task difficult, we add filtered noise to the visual stimuli) visual perceptual task in which amplitude differences between the different stimuli occur within the first few hundred milliseconds after presentation In contrast, most existing work recorded the EEG signals when the observers were performing relatively easy, higher-level, memory-related tasks [11], [9], which required longer duration of EEG recording ($\sim$1s).

Second, since EEG consists of spatio-temporal signals, we model them *holistically* utilizing joint statistical properties of features, bypassing the space-time separability assumption and avoiding the pitfalls of heuristic approaches, such as temporal binning. However, most approaches [12], [15] implicitly assume space-time independence and typically process the EEG data separately in space and time domains. Unlike spectral features, which are usually extracted using fixed (Fourier) basis, the feature basis estimated by our technique is driven by the data, and hence is highly adaptive. Our main contributions include the following:

- We demonstrate the efficacy of EEG as a biometric modality using activity evoked in a difficult perceptual task to identify individuals.
- We present an analytical tool to study the spatial and temporal dynamics of neural activity that systematically discriminates between individual's neural response while performing the visual task.
- We explore the relationship between the visual stimuli and the discriminability of EEG signals.

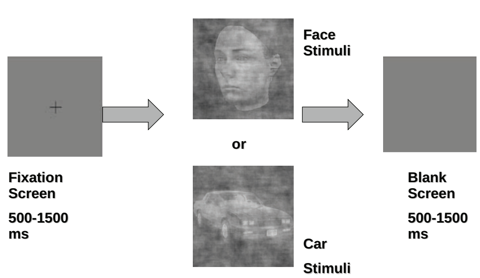

Fig. 2. Illustration of psychophysical experiment

II. Materials and Method

A. Visual Task

An image of a face or a car was presented as a stimulus to the observers who performed the behavioral task. The stimulus set consisted of 290×290 pixel 8-bit gray scale images of faces and cars taken from the Max Planck Institute for Biological Cybernetics face database. Twelve images of each class, face and car, (six frontal view, six 45° rotated) were used as stimuli. Gaussian white noise was then added to these 24 base images to build a stimuli set of 1000 images (500 face, 500 car). Noise was generated by filtering independent $3.53 cd/m^2$ standard deviation white Gaussian noise fields by the average power spectrum of the car/face stimuli and then added to the original stimuli.

Twenty naive observers (ages: $18-26$) participated in the study. The study consisted of 1000 trials split into 5 blocks of 200 trials. On each trial, observers fixated at a central cross and pressed a mouse button to initiate the trial. After a variable delay of 0.5-1.5s, the stimulus appeared for 40 ms The stimulus was followed by a blank screen presented for $0.5-1.5$ seconds after which the response window was presented,at which point the observer was to identify the category (face/car) of the stimulus. Figure 2illustrates the setup of the psychophysical study.

B. Data Collection

EEG activity was recorded, using 64 Ag/AgCl sintered electrodes mounted in an elastic cap and placed according to the International $10/20$ System. The data were sampled at 512 Hz, re-referenced offline to the signal recorded from the central midline electrode (Cz), and then band-pass filtered ($0.01-100$ Hz). Trials containing ocular artifacts (blinks and eye movements) detected by EOG amplitudes exceeding $\pm$100 mV or by visual inspection were excluded from the analysis. The EEG waveforms in all conditions were computed time-locked to stimulus onset and included a 200 ms pre-stimulus baseline and 500 ms post-stimulus interval.

C. Pattern Analysis

We have applied two widely used machine learning techniques, Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA), for discriminating individuals based on their brain activity.

1) Support Vector Machines (SVM): The goal of Support Vector Machines (SVM) [17] is to maximize the margin between two classes. This is achieved by picking the hyperplane so that the distance from the hyperplane to the nearest data point is maximized. We use linear SVM for the purpose of simplicity. SVM is originally designed for 2 class problem and then extended to handle multiple class problem using one vs. rest approach. A few remarks are in order. First, SVM has no distribution assumption. This suggests that SVM might perform well under non-Gaussian distribution. Second, the weight vector of SVM is meaningful only for 2 classes. To find a meaningful weight vector for multiple classes, we turn to LDA.

2) Linear Discriminant Analysis (LDA): The objective of LDA is reduce data dimensionality while maintaining class separability, normally by maximizing an objective function. The most popular form of LDA relies on the maximization

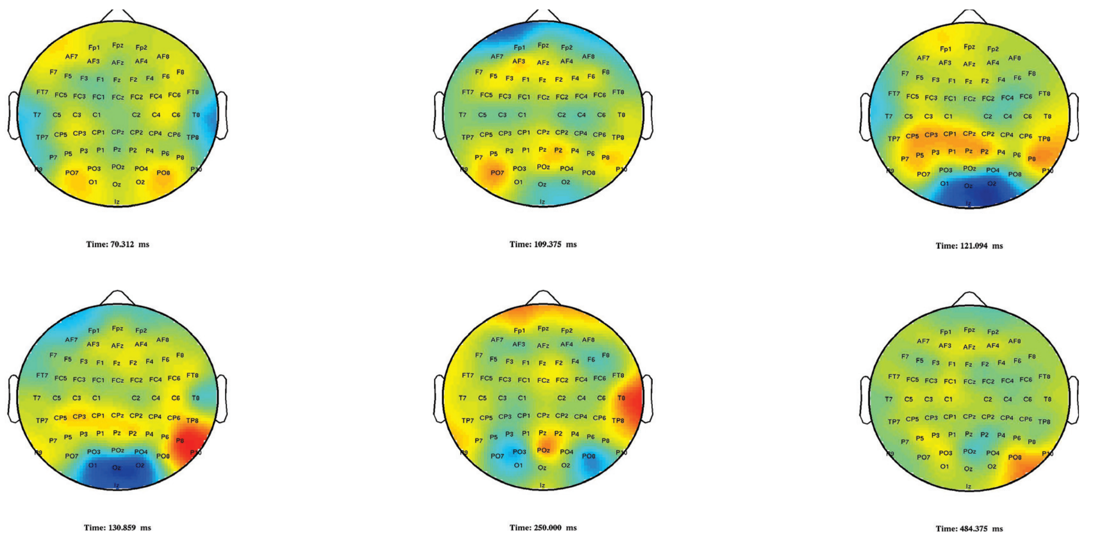

Fig. 3. Fisherbrain: Snapshots of the first Fisherbrain at 6 time points (70.3, 109.4, 121.1, 130.9, 250, 484.4 ms) after stimulus onset. The red and blue regions mark informative electrode locations with the most discriminative information (denoted by highly positive(red) or negative(blue) filter weights).

of the Fisher criterion [5]:

$$J(\mathbf{T}) = \arg \max_{\mathbf{T}\in\mathbb{R}^{m\times p}} \frac{|\mathbf{T}\mathbf{S}_b\mathbf{T}^\top|}{|\mathbf{T}\mathbf{S}_w\mathbf{T}^\top|}, \quad (1)$$

where $\mathbf{S}_b$ and $\mathbf{S}_w$ represent between-class and within-class scatter matrix [4]. $\mathbf{T}$ is a set of eigenvectors associated eigenvalues based on the generalized eigen-decomposition. In Section III-A, we will use the eigenvectors with top eigenvalues to examine EEG signals spatially and temporally. The classification is performed by projecting EEG data onto $\mathbf{T}$, followed by a 1 nearest neighbor rule.

III. Experimental Results

A. Fisherbrains

Using the coefficients of the LDA feature extraction matrix, we analyzed the spatio-temporal patterns responsible for encoding discriminative information used for person identification. Lets recall the projection matrix $\mathbf{T}$ of LDA in Eq.(1) Each column of $\mathbf{T}$ is the so-called spatio-temporal filter in the BCI community. However, unlike abstract features arising in LDA, these filters have a clear interpretation. If a column/filter is reorganized into a spatio-temporal array, it denotes informative electrodes, time scales, and latencies involved in encoding the differences among various individuals. We term these filters as *Fisherbrains*, a concept very similar to the Fisherfaces [1] used widely in face recognition community. The key difference between them is that Fisherbrains contain temporal information for discrimination in addition to spatial information. Fisherbrains act as an analytical tool to study the brain dynamics responsible for discriminating between individuals. Figure 3 shows a snapshot of the first Fisherbrain by illustrating informative electrode locations through various time points.

1) In the temporal domain, there is hardly any discriminative information in the first 100 ms, which can be attributed to the latency of visual information processing. The Fisherbrain shows the period 120-200 ms to be the most informative (red and blue regions denotes highly informative locations) which is consistent with the neuroscience research (Cortical potential studies have demonstrated that about 170 ms after presentation of visual stimulus such as face/object, humans show a negative deflection in voltage (N170 [2]) during EEG recordings). The discriminative ability continues to decrease monotonically 250 ms onwards.
2) In the spatial domain, investigating the informative electrode locations, it appears that electrode locations associated with the visual cortex appear to play a prominent role in identifying individuals. This is congruous with our experimental setup, where we use only the low level visual response of our observers in order to identify them.

B. Performance Evaluation

A priori, we expected activity in visual cortex to be the primary contributor to this task [14], and electrodes over visual cortex should be the most informative. Our intuition is validated by the Fisherbrain which also demonstrated the electrodes in the visual cortex to be the most discriminative. Accordingly, we used a subset of 20 (out of 64) electrodes placed over occipital brain regions (i.e., over visual cortex) for reporting classification rates for person identification. The data were divided into training and testing sets as explained below. We used k-fold ($k = 2,4,5,10$) stratified cross validation scheme [7] for performance evaluation. To reduce the variance of estimated classification rates, the overall k-fold cross validation (CV) procedure was repeated 10 times, and overall performance is reported by the mean classification rate along with the standard deviation.

We designed two datasets:*pre-stimulus* and *post-stimulus* to examine the discriminatory dependency of the EEG signals, based on the onset of the stimulus (face/car). The pre-stimulus dataset consists of the first 200 ms of EEG recording before the face/car appears and the post-stimulus dataset

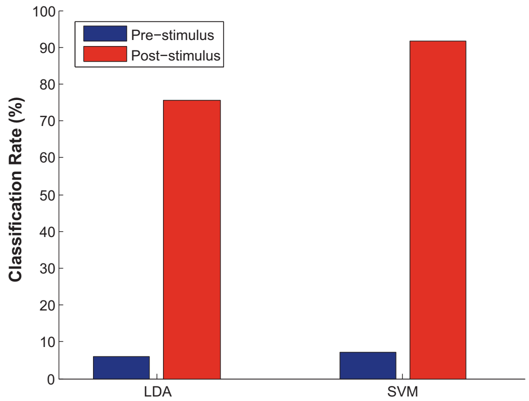

Fig. 4. Classification accuracy with pre-stimulus and post-stimulus data with 2-fold CV. Note that pre-stimulus classification is close to chance (5%)

consists of EEG recordings for 500 ms after the stimulus is displayed. Intuitively, we expected the post-stimulus data to be more informative.However, several studies have demonstrated modulations of pre-stimulus EEG signals in visual attention tasks [6], [16]. Thus we wanted to explore the possibility of the pre-stimulus data playing a role in person identification.

As shown in Fig.4 and Table I, the pre-stimulus data contained negligible discriminant information compared to the post-stimulus data. LDA and SVM give 6.08% and 7.13% in classification accuracy respectively for pre-stimulus data, which is comparable to chance performance ($5\% = \frac{1}{20}$). However, for the post-stimulus data LDA and SVM achieve much better accuracy ($\sim$ 75%-LDA, $\sim$ 91%-SVM), using 2-fold CV. Increasing the size of the training set (from 2 to 10 fold), both LDA and SVM improve in accuracy. For instance, SVM achieves more than 94% in accuracy by using 10-fold cross validation. Finally, SVM outperformed LDA significantly (by $6 - 16\%$ margin) with the post-stimulus data, consistently giving better performance. One possible reason for superior SVM performance might be the highly non-Gaussian distribution of the EEG data. LDA is optimal under Gaussian distribution with equal covariance, whereas SVM has no such requirements.

TABLE I

PRE VS. POST STIMULUS

k-fold CV	LDA	SVM
Post-stimulus		
2	75.52 (±0.24)	91.56 (±0.18)
4	85.36 (±0.12)	93.35 (±0.11)
5	86.30 (±0.23)	93.59 (±0.10)
10	87.78 (±0.16)	**†94.08 (±0.08)**
Pre-stimulus		
2	6.08 (± 0.11)	**7.13 (± 0.23)**

IV. CONCLUSION

We explored the efficacy of using brain activity (measured by EEG) as a biometric modality, using visually evoked neural activity for discriminating between individuals while they performed a difficult visual perception task. We adopt a holistic approach to data analysis, wherein discriminatory information, distributed non-uniformly over time and space, is extracted jointly by low-dimensional features. Based on our results, we conclude that in this task post-stimulus EEG activity, and not pre-stimulus activity, contains relevant discriminatory information for person identification. Furthermore, the resulting Fisherbrains provide useful information about the spatio-temporal dynamics of the human brain.

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