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Cognitive State Estimation Based on EEG for Augmented Cognition

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Abstract **— Augmented cognition is an emerging concept that aims to enhance user performance and cognitive capabilities on the basis of adaptive assistance. An integral part of such systems is the automatic assessment of the instantaneous cognitive state of the user. This paper describes an automatic cognitive state estimation methodology based on the use of EEG measurements with ambulatory users. The required robustness in this context is achieved through the use of a mutual information based dimensionality reduction approach in conjunction with a committee of classifiers, and median filter outlier rejection element. We present classification results associated with cognitive tasks performed in mobile and stationary modalities.**

Keywords — Augmented cognition, Brain computer interface, Electroencephalogram, Mutual information based dimensionality reduction

I. INTRODUCTION

Augmented cognition is an emerging research concept at the intersection of cognitive science, neuroscience, and engineering. The aim of the augmented cognition effort is to enhance the task-related performance of a *human user* through computer mediated assistance based on assessments of cognitive state. The goal of these systems is to mitigate the effect of performance-decreasing cognitive factors inherent in human-computer interaction. Examples of such factors are limitations in attention, memory, learning, decision-making, and concurrent task execution. The effects of these factors on the relevant task performance depends on the current cognitive state of the user, as well as the cognitive capacity of the user, both of which might fluctuate in time due to a number of external and internal factors including fatigue, boredom, and stress. Techniques for noninvasive measurement of the physiological indicators of cognitive load are currently at an advanced stage. The current technological state in computational and wireless communication makes possible practical implementations of cognitive load assessment algorithms.

The augmented cognition approach to human-machine interface design is user-centered; therefore, the system is designed to infer the instantaneous cognitive state and information processing capabilities of the user in the context of multiple and unpredictable situations. These assessments form the basis for adaptive assistance that attempts to compensate for reduced human capacity and processing. The user's instantaneous mental capability can be inferred using a combination of environmental and physiological measurements. These measurements might include limb positions, head and eye movements, electrocardiographs (ECG), electroencephalogram (EEG), and pulmonary plethysmograph measurements.

The assessment of the operator's state is particularly difficult in situations where the operators must be able to move freely and to perform a combination of cognitive and physical tasks. The mobility of the operator increases the complexity of the design, because the measurement of physiological and neurophysiological states is affected by artifacts induced by motion. Our approach is based on state-of-the-art adaptive systems approaches. In particular, we will describe a system that is based on the following scenario: An operator is outfitted with a suite of sensors as well as the equipment required for the performance of tasks. During a short initial period the operator is asked to perform a predetermined set of simple tasks and the data obtained during that period is used to train a cognitive state classifier. Subsequently, as the operator interacts with the task environment, the augmented cognition system attempts to assess cognitive state. The results of these assessments trigger assistance that serves compensate for potentially impaired cognitive abilities. Whenever possible the augmented cognition system uses the measured information to adapt the assessment system to maintain the highest possible accuracy.

This paper will specifically focus on the assessment of cognitive state from EEG measurements. The adaptive system to be described here was designed to estimate the instantaneous cognitive load of the subject using features obtained from a power spectral density (PSD) analysis of the various EEG channels at certain frequency bands. Since these features distributed spatially and over frequency contain irrelevant information as well useful information, the dimensionality of the data is drastically reduced using an adaptive linear subspace projection that filter out the irrelevant content by maximizing the mutual information between the projected set of features and the classes of cognitive states. Finally, a composite classification scheme consisting of a Gaussian-Mixture-Model (GMM) based classifier, a K-Nearest-Neighbor (KNN) classifier, and a nonparametric Kernel Density Estimate (KDE) based classifier is employed to obtain estimates of the cognitive state. These classifiers work on the assumption that the variations on cognitive load during a continuous task will exhibit slow variations in time. Additional robustness and outlier rejection capability is introduced by a temporal median filtering operation on the estimates of the composite classifier.

II. METHODOLOGY

The experimental setting involves a user outfitted with wearable monitoring, communication, and mobile computing equipment walking outside. The monitoring equipment is a BioSemi ActiveTwo EEG system with 32 electrodes (http://www.biosemi.com/). Vertical and horizontal eye

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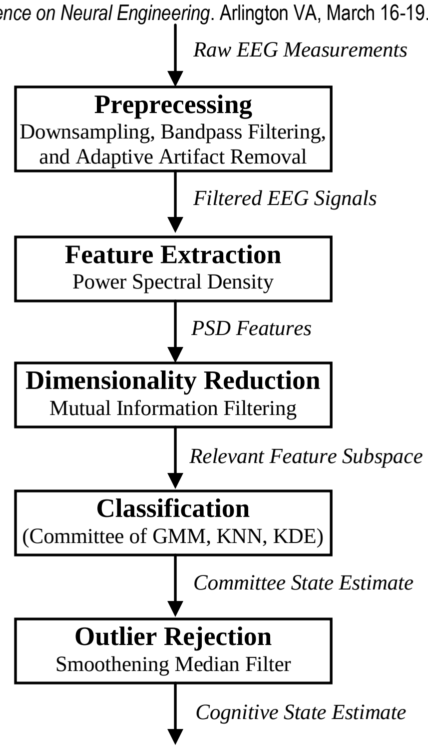

Figure 1. Schematic diagram of the cognitive state estimation architecture.

movements and blinks were recorded with electrodes below and lateral to the left eye. All channels referenced the right mastoid. Although there are several other sensors, the focus of this paper is information extraction from the EEG signals. EEG is recorded at 256Hz sampling frequency from 7 channels (CZ, P3, P4, PZ, O2, P04, F7) while the subject is walking about and performing various prescribed tasks. These sites are selected based on a saliency analysis on EEG collected from various subjects performing cognitive test battery tasks [1]. EEG signals are preprocessed to remove eye blinks using adaptive filters [2]. Information from the VEOGLB ocular reference channel was used as the noise reference source for the adaptive ocular filter. DC drifts were removed using highpass filters (0.5Hz cut-off). A bandpass filter (between 2Hz and 50Hz) was also employed, as this interval is generally associated with cognitive activity. The power spectral density (PSD) of the EEG signals, estimated using the Welch method [3] with 50%-overlapping 1-second windows, is integrated over 5 frequency bands: 4-8Hz (theta), 8-12Hz (alpha), 12-16Hz (low beta), 16-30Hz (high beta), and 30-44Hz (gamma). These bands, sampled every 0.1 seconds, are used as the basic features for the classification. The particular selection of the frequency bands is based on well-established interpretations of EEG signals in prior cognitive and clinical [4].

These PSD features constitute a high dimensional vector that contains information pertinent to the classification of cognitive states, as well as irrelevant components and noise. Direct classification using such input features is undesirable, since the unwanted components have an adverse effect on the overall classification performance and the generalization ability of the system. Consequently, an intelligent and practical technique for extracting the relevant information from these features is necessary. This can be achieved by projecting the high dimensional feature vector to a lower dimensional subspace *optimally* using a linear adaptive topology.[1] The overall schematic diagram of the system is shown in Fig. 1. The selection of the optimality measure will be discussed next.

Dimensionality Reduction: Dimensionality reduction has been shown to be an effective way to improve robustness and has been an active field of research in pattern recognition due to the aforementioned practical benefits. The techniques existing in the literature can be broadly classified into *wrapper* and *filter* approaches. The wrapper approach determines the optimal subspace projection in order to minimize the classification error (or Bayes risk more generally) for a specific classifier topology, while attaining a target reduced input dimensionality. The filter approach, on the other hand, determines the optimal projection by optimizing a suitable criterion, therefore provides a more versatile solution that can be utilized with any classifier topology with good results on average.[2] Since we will employ a committee of classifiers, the filter approach is more suitable for this application.

The filter approach (with linear subspace projections) can be discussed under two main categories: feature selection, feature projection. Feature selection refers to the practice of selecting a subset of existing features from the high dimensional vector. While this method is advantageous in problems where collecting certain measurements are expensive, if this is not the case it remains as a special case of feature extraction with binary-value constraints on the projection matrix weights. In our experiments, EEG data from various spatial channels are collected and processed into five frequency bands with sufficient computational power and time for real-time operation. Therefore, the feature projection scheme is preferred.

Linear feature projections have been studied by many researchers using a variety of *suitable* optimality criteria. Traditional techniques include principal components analysis (PCA) and linear (Fisher) discriminant analysis (LDA) [5,6]. Since feature variances have nothing to do with classification performance in general, PCA is an approach that should *not* be employed for dimensionality reduction purposes in the pattern recognition context. This shortcoming is overcome in LDA by assuming that the class distributions are Gaussian and determining linear projections that minimize the Fisher discriminant function, the ideal optimality criterion under the assumptions. Nevertheless, this method also is not well-suited for general purpose dimensionality reduction, since the Gaussianity assumption is quite restrictive. In the recent years, mutual information between the projected features and the

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[1] While nonlinear subspace projection topologies should be theoretically preferred as linear projections are special cases, their versatility may create a generalization difficulty for the projection filter itself. Linear projections are therefore typically preferred provided that they yield satisfactory results.

[2] Obviously the wrapper approach potentially yields the optimal subspace projection for a specific classifier. However, it also limits the design flexibility greatly, since a decision to change the classifier also means redesigning the subspace projection as well.

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class labels have been proposed and investigated by some researchers as an optimality criterion for this purpose [7-9]. The use of mutual information is motivated by information theoretic lower and upper bounds on the probability of classification error [10]. Besides this formal theoretical support, it is an intuitive extension of the Fisher discriminant criterion to non-Gaussian distributions.

The idea behind LDA is to find projections that maximally separate the classes, while minimizing their individual spreads. In the case of Gaussian distributions these can be measured using the class means and variances. In general, the concept of entropy can be employed. Consider the following family of criteria based on Renyi's entropy definition as a generalization of Fisher's approach:

$$J_\alpha(\mathbf{y}) = H_\alpha(\mathbf{y}) - \sum_c p_c H_\alpha(\mathbf{y} \mid c) \tag{2.1}$$

where $\mathbf{y}=\mathbf{W}\mathbf{x}$ is the vector projected features obtained from the high dimensional original feature vector $\mathbf{x}$, p_c are the *a priori* class probabilities, and $H_\alpha(\mathbf{y})$ and $H_\alpha(\mathbf{y}|c)$ are Renyi's order-α entropy of $\mathbf{y}$ and the class conditional distribution $\mathbf{y}|c$ [11]:

$$H_\alpha(\mathbf{y}) = \frac{1}{1-\alpha} \log \int p^\alpha(\mathbf{y}) d\mathbf{y} \tag{2.2}$$

Renyi's entropy is a generalization of Shannon's and in fact in the limit as $\alpha \to 1$ it approaches Shannon's entropy. Since entropy is a measure of *how spread a distribution is*, maximizing $J_\alpha(\mathbf{y})$ tries to separate the classes by maximizing $H_\alpha(\mathbf{y})$ and minimize the individual class spreads by minimizing $H_\alpha(\mathbf{y}|c)$. We employ an algorithm that maximizes $J_2(\mathbf{y})$ to optimize $\mathbf{W}$ based on a Parzen window estimate of Renyi's entropy and the stochastic information gradient [12].

Classification: The reduced dimensionality feature vectors are used as inputs to a committee of classifiers: GMM, KNN, and KDE. The GMM classifier implements a parametric Bayes classifier [6] assuming that each class distribution can be described by a GMM with 4 components that is fit to the data from each class using the Expectation-Maximization algorithm [13]. The KNN classifier decides based on the votes from $3\times C+1$ neighbors, where C is the number of classes and each vote is weighted inversely proportional to the class prior p_c of the contributing neighbor. It is well known that the KNN classifier asymptotically approaches the optimal Bayes classification error rate [6]. The KDE classifier implements a nonparametric Bayes classifier assuming that the distribution of each class is given by a Parzen window estimate [14] (using Gaussian kernels whose bandwidth parameters are selected according to Silverman's rule-of-thumb [15]). The committee decision is the majority vote. In the rare case of no majority agreement, the KDE decision is assumed. A committee decision is offered in real-time at a rate of 10Hz.

Outlier Rejection: The committee decision is susceptible to undesirable fluctuations in time, since the EEG activity exhibits time variability during the execution of any given mental or cognitive task. To eliminate such fluctuations in the cognitive state assessment, a median filter is employed to smoothen the final decision over a sliding interval of 2 seconds with the assumption that the cognitive load does not vary faster than the corresponding rate and that the integer class labels are assigned to cognitive tasks (the classes) in correlation with their actual corresponding cognitive loads.[3]

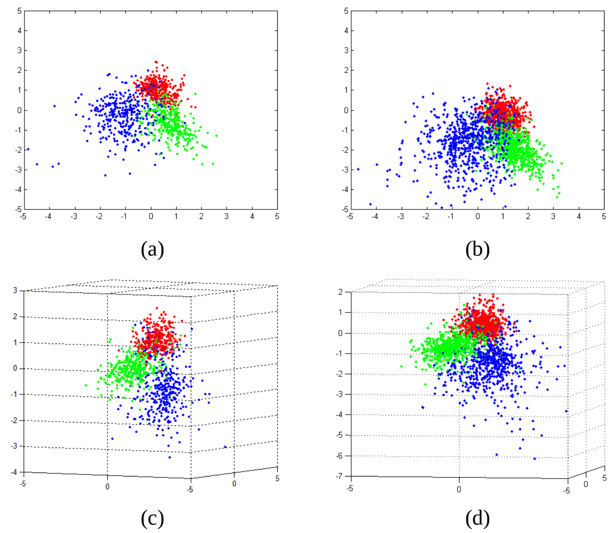

Figure 2. Feature projections obtained by maximizing J_2. (a) 2-dimensional projection of the training data (b) 2-dimensional projections of the testing data (c) 3-dimensional projection of the training data (d) 3-dimensional projections of the testing data.

	STATIONARY	MOBILE
35-Dim Input	$\begin{bmatrix} 1.00 & 0.021 & 0 \\ 0 & 0.979 & 0.098 \\ 0 & 0 & 0.902 \end{bmatrix}$	$\begin{bmatrix} 0.959 & 0.019 & 0 \\ 0.003 & 0.981 & 0.047 \\ 0.038 & 0 & 0.953 \end{bmatrix}$
3-Dim Input	$\begin{bmatrix} 1.00 & 0.015 & 0 \\ 0 & 0.985 & 0.018 \\ 0 & 0 & 0.982 \end{bmatrix}$	$\begin{bmatrix} 0.978 & 0.028 & 0 \\ 0.019 & 0.972 & 0.014 \\ 0.003 & 0 & 0.986 \end{bmatrix}$

Table 1. Confusion matrices for the classifiers in stationary and mobile cases using 35-dimensional and 3-dimensional feature input vectors. The ij^{th} entry of the confusion matrix denotes *Prob*(decide class i|true class j).

III. Results

In order to illustrate the performance of the proposed cognitive state assessment system, we describe the results associated with an experimental evaluation. The results shown here were also verified in conjuntion with a large number of independent data sets and cognitive tasks that are not mentioned here. The sample experiment we consider here consists of classifying between cognitive states associated with three tasks in two modalities: when the subject is stationary and when the subject is mobile. The tasks in the stationary case are labeled *relaxed* (waiting for orders), *communicate* (getting orders from base via radio communication), and *count* (starting from 100 and decreasing by 7). The tasks in the mobile case are labeled *navigate* (walking to a designated target), *navigate and visual search* (walking while looking for snipers), and *navigate and communicate* (receiving and giving mission status reports).

For stationary and mobile cases, EEG is recorded while the subject is performing the three corresponding tasks listed

[3] Note that a mode filter could be employed instead of the median filter to eliminate the last assumption of ordered cognitive loads.

above. After the preprocessing and PSD feature extraction stages, approximately 3000 input-label pairs are obtained, one third of which is used for training the feature projections and classifiers, and the remaining two-thirds is used for testing. The *optimal* 2-dimensional and 3-dimensional projections obtained by the Mermaid-SIG algorithm [12] are shown in Fig. 2 for both training and testing sets (different grayscale levels indicating classes).

The classification results based on the 3-dimensional projections and the classification results based on the original 35-dimensional features are compared in Table 1 for both stationary and mobile cases using the confusion matrices of the classification results. The projection dimensions here are selected to be 2 and 3 for visualization purposes, experiments performed on other data sets demonstrate that this method is effective in determining a lower dimensional projection that achieves at least the same performance as the original high dimensional feature vector. In another experiment where classification between 4 tasks (involving mixed stationary and mobile states) using 8 EEG channels, it achieves the same performance using the optimally selected 10-dimensional projection and the original 40-dimensional feature vector.

The cognitive state estimator described here is employed in a real-time closed-loop adaptive performance enhancement scheme that schedules the communication traffic to the subject during a mission. Experiments conducted demonstrate that the assistance offered by this interface improves task-related performance greatly. For instance, the scheduling of communication based on the cognitive load assessment resulted in 100% improvement in message comprehension and 125% improvement in situation awareness.

IV. Discussion

The ability to detect and to classify the cognitive state of the operator is a prerequisite to successful augmentation of his cognitive performance. With ultimate realizations of such a system, we expect classification to be based on a suite of sensors that include environmental and behavioral measurements. Even in that scenario, however, classification approaches based on EEG will likely play a critical role. In this paper we demonstrated that, using a novel and robust set of techniques for pattern recognition, it was possible to obtain nearly perfect classification performance based only on EEG alone. We expect that the variability and unpredictability of the realistic operators' environments will impair the classification performance to some extent, but we believe that this drop in performance will be compensated for by the availability of additional inputs, such as accelerometers, and environmental sensors.

The performance obtained in this study was achieved by developing effective ways to reduce irrelevant variability using relatively robust information-theoretic techniques for dimension reduction. In particular, the deployment of Renyi's entropy measure enabled to obtain more robust dimension-reduction result than would have been possible with the more traditional entropy measure based on Shannon's formulation.

We note that EEG associated with ambulatory operators is likely to be contaminated with numerous artifacts including motion-generated induced signals and myopotentials. These artifacts would obscure EEG components associated with cognitive activity. In the context of the present study, however, these "artifact" signals may have contained useful information for the cognitive state classification. It is possible that many of these, typically undesirable signals are likely to be directly related to task relevant behaviors of the operator. In our future work, we plan to investigate ways that this information can be incorporated more directly into the classification process.

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