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Extended Abstract

Cognitive models for emotion recognition: Inverse big data problems and deep learning

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Abstract

This research concerns cognitive modeling and emotion recognition based on collections of the real time human brain waves (EEG). In this talk, we present the current status of the research field as it is known to us and discuss the two-phase modeling approach under consideration in our study. The raw temporal EEG data are collected from the humans performing a set of given tasks. The data is analyzed using standard signal processing techniques plus some more specific methods, such as the correlational, wavelet and fractals analysis. The EEG electrodes are located in the areas of the scalp specified by American Electroencephalographic Society Standard (in the experimental part of our study, we use Emotiv wireless headset with 14 electrodes located according to the Standard). The collected EEG data corresponding to different cognitive states and emotional responses of the human subjects are used to feed the supervised learning models. The research relies on the Deep Learning models with different levels of depth. The task is to identify the most effective parameters of the learning procedure that would allow to reliably recognizing such emotions, considered to be basic, as anger, disgust, fear, happiness, sadness, and surprise as well as their derivatives: amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame. The EEG potentials reflect, indirectly, the spatially distributed brain neuronal signals induced by human cognitive and emotional activities. We suggest that the information about such localized (voxel based) data will be a better input for the Deep Learning model than the surface cranial information since it should provide the larger dimensionality of the supervised learning. Thus, the two-phase model is introduced: The first phase concerns the solution of the large scale inverse problem requiring the Big Data representation while at the second phase the Deep Learning model is used with the output of the first phase as its input. Assuming a model with a given number of the cranial measurements and a number of voxels obtained by subdividing, uniformly, the brain volume, the task is to find the density of the localized currents as a solution of the inverse problem. The method called LORETA is considered to be useful for solving the inverse problem. We work towards some specific applications of human emotion recognition such as Brain Computer Interface (BCI), and evaluation of educational materials and presentations. The methodology and the results obtained so far will be presented.

the measure of the electrical fields produced by the active brain, is a brain mapping and neuroimaging technique widely used inside and outside the clinical domain. Specifically, EEG picks up the electric potential differences, on the order of tens of μV , that reach the scalp when tiny excitatory post-synaptic potentials produced by pyramidal neurons in the cortical layers of the brain sum together. The potentials measured therefore reflect neuronal activity and can be used to study a wide array of brain processes.

Thanks to the great speed at which electric fields propagate, EEG has an excellent temporal resolution: events occurring at millisecond timescales can typically be captured. However, EEG suffers from low spatial resolution, as the electric fields generated by the brain are smeared by the tissues, such as the skull, situated between the sources and the sensors. As a result, EEG channels are often highly correlated spatially. The source localization problem, or inverse problem, is an active area of research in which algorithms are developed to reconstruct brain sources given EEG recordings.

There are many applications for EEG. For example, in clinical settings, EEG is often used to study sleep patterns or epilepsy. Various conditions have also been linked to changes in electrical brain activity, and can therefore be monitored to various extents using EEG. These include attention deficit hyperactivity disorder (ADHD) disorders of consciousness [48, 54], depth of anaesthesia [68], etc. EEG is also widely used in neuroscience and psychology research, as it is an excellent tool for studying the brain and its functioning. Applications such as cognitive and affective monitoring are very promising as they could allow unbiased measures of, for example, an individual's level of fatigue, mental workload, mood, or emotions. Finally, EEG is widely used in brain–computer interfaces (BCIs)—communication channels that bypass the natural output pathways of the brain—to allow brain activity to be directly translated into directives that affect the user's environment

Although EEG has proven to be a critical tool in many domains, it still suffers from a few limitations that hinder its effective analysis or processing. First, EEG has a low signal-to-noise ratio (SNR) as the brain activity measured is often buried under multiple sources of environmental, physiological and activity-specific noise of similar or greater amplitude called 'artifacts'. Various filtering and noise reduction techniques have to be used therefore to minimize the impact of these noise sources and extract true brain activity from the recorded signals.

EEG is also a non-stationary signal that is its statistics vary across time. As a result, a classifier trained on a temporally-limited amount of user data might generalize poorly to data recorded at a different time on the same individual. This is an important challenge for real-life applications of EEG, which often need to work with limited amounts of data.

Finally, high inter-subject variability also limits the usefulness of EEG applications. This phenomenon arises due to physiological differences between individuals, which vary in magnitude but can severely affect the performance of models that are meant to generalize across subjects Since the ability to generalize from a first set of individuals to a second, unseen set is key to many practical applications of EEG, a lot of effort is being put into developing methods that can handle inter-subject variability.

To solve some of the above-mentioned problems, processing pipelines with domain-specific approaches are often used. A significant amount of research has been put into developing processing pipelines to clean, extract relevant features, and classify EEG data. State-of-the-art techniques, such as Riemannian geometry-based classifiers and adaptive classifierscan handle these problems with varying levels of success. Additionally, a wide variety of tasks would benefit from a higher level of automated processing. For example, sleep scoring, the process of annotating sleep recordings by categorizing windows of a few seconds into sleep stages, currently requires a lot of time, being done manually by trained technicians. More sophisticated automated EEG processing could make this process much faster and more flexible. Similarly, real-time detection or prediction of the onset of an epileptic seizure would be very beneficial to epileptic individuals, but also requires automated EEG processing. For each of these applications, most common implementations require domain-specific processing pipelines, which further reduces the flexibility and generalization capability of current EEG-based technologies.

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