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THE CHALLENGE OF DRIVING BCI WITH EMOTIONAL SIGNALS COLLECTED BY EEG

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ABSTRACT: The paper describes the important challenges of driving a BCI through EEG signals of emotions. In particular, the complex emotional processing activated by the human brain and the necessity of generating elicitation protocols to synchronize the acquisition of EEG signals from emotions are presented. Besides, the limitations of EEG in dealing with signals from emotions are also discussed. Then, the specific neuropsychological issues related to the use of protocols for eliciting emotions are described. Due to the huge difficulty in managing the uncertainty deriving from the above issues, the surprising results obtained by recently proposed automatic strategies for emotion classification and recognition, also raising doubts about the correctness of the results, are reported and discussed. Finally, suggestions are presented regarding some procedures for uncertainty reduction and for the future complete development of EEG-based emotional BCIs.

INTRODUCTION

A Brain-Computer Interface (BCI) [1] is a computer-based communication system that collects signals generated by the evoked neural activity of the Central Nervous System (CNS) and its goal is to provide a new channel of output for the brain and requires voluntary adaptive control by the user [2]. Electroencephalography (EEG) is one of the most commonly used techniques to measure neural activity, through electrical signals, by placing electrodes outside the skull [3]. EEG provides high temporal resolution responses, is easy to use, safe, low-cost, and, for these reasons, effective in providing the necessary brain feedback for a BCI. A sketch of a BCI driven by EEG signals is provided in Fig. 1. BCIs, mainly those used as an alternative communication tool for disabled people, are based on event-related signals induced by external stimuli and synchronized with them (an example is the P300 [4]). Another consistent part is based on sensory–motor rhythm amplitudes [5]. For patients with impaired vision, or suffering from seizures attacks caused by too fast visual stimuli such as those used in P300, or that have never experienced the control of the motor part of their body, or whose signals produced by sensory–motor rhythms, mostly at the alpha band, can be easily confused with those due to artifacts caused by involuntary and frequent movements, other paradigms, such as auditory [6] and tactile [7], have been explored. However, cases in which also these paradigms have little or no effect are frequent [6]. Moreover, there are some situations in which some well-known techniques to build a BCI are not possible, like severe brain injuries that affect, for example, P300 elicitation [8]. For this reason, new ways have been explored and one of the most promising is that BCIs are based on the voluntary brain activity produced by emotions, being emotions mostly related to the deeper parts of the brain, mostly unaffected by disabilities [9–14]. Emotions were first explored in the field of affective computing where some fascinating studies are dedicated to making the computer more empathic to the user and involved in the measurement of the user's emotions and representing them into human–computer interaction systems [15]. They aim to find the activation of specific

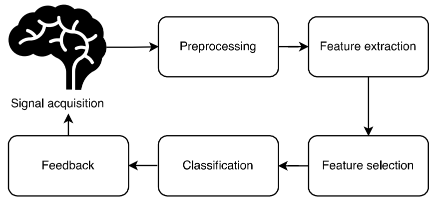

Figure 1: Overview of an online BCI system. The signal undergoes acquisition (not shown), preprocessing, feature extraction, feature selections, and classification before feedback is produced depending on its final classification.

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brain regions in response to specific emotions but, while some regions are more active than others when experiencing specific emotions, no specific region is activated by a single emotion [16–18]. The brain regions most responsible for emotions are the amygdala, insula, anterior cingulate cortex, and orbitofrontal cortex. Through fMRI, it has been found that there exist specific patterns of brain activity, i.e. groups of brain districts, related to specific emotions and that these patterns are common across individuals [18]. A scheme of the brain regions mostly involved in the processing of emotions is indicated in red in Fig. 2. Despite these advances, it remains very difficult to recognize emotions, especially across individuals, because their patterns are very similar and can confuse each other and because they are also subjective (i.e. different individuals can have different ways of dealing with emotions). Moreover, complex multi variable pattern analysis techniques have to be used to identify distributed patterns associated with specific emotions, especially from EEG. Indeed, in EEG the sensitivity of the electrodes is higher for external neurons and decreases for deeper neurons (yellow part in Fig.2). This means that not all neurons equally contribute to the EEG signal, with an EEG predominately reflecting the activity of cortical neurons near the electrodes on the scalp. Deep structures within the brain, mainly involved in the emotional process, are further away from the electrodes and will not contribute directly to an EEG. Furthermore, EEG signals have an intrinsic nonlinear and nonstationary nature. The basic source of the nonstationarity in EEG signal is a reflection of switching of the inherent quasi-stable states of neural assemblies during brain functioning and is not due to the casual influences of the external stimuli on the brain mechanisms. EEG signal recorded from a scalp electrode is influenced by different deeper sources, each 'transmitting' with different and variable intensity, thus making the main source of the registered signal from one brain structure to another. Nonstationarity also arises because of different time scales of the dynamic processes of brain activity. Finally, the signals are affected by noise and artifacts which, in some cases, are difficult to reduce effectively. Despite that, recently proposed nonlinear automatic strategies, learning by data collected during task-related protocols execution, promise to recognize emotions with very high accuracy, starting from EEG signals collected by eliciting protocols. In what follows, we first discuss the complex emotional processing activated by our brain, the disagreement in creating a commonly accepted model for representing emotions, and the necessity of generating elicitation protocols to synchronize the acquisition of EEG signals from emotions. Then we describe the specific neuropsychological issues related to the use of protocols for eliciting emotions. Moreover, we emphasize the surprising results obtained by recently proposed automatic strategies for emotion classification and recognition from EEG signals collected by these elicitation protocols, also raising doubts about the correctness of the results in light of the great uncertainty of the data and protocols. Finally, we propose some cues for the future of EEG-based emotional BCIs.

BRAIN EMOTIONAL PROCESSING AND EMOTIONAL MODELS

The neural locations involved in the genesis and processing of emotions are multiple, including the Autonomic Nervous System (ANS), the hypothalamus, the ascending reticular system, the limbic system, some cortex lobes, and the amygdala [19]. In recent years, attention has also been focused on the network of interconnected regions involved in emotional processing, even if neuropsychological data do not confirm the theory of a single emotional network, but of multiple networks that control multiple emotions [19]. In these networks, structures such as the thalamus, somatosensory cortex, somatosensory association cortex, amygdala, insula, and medial prefrontal cortex have been clearly recognized [19]. Although there is no single shared definition of emotion, many researchers define an emotion as a feeling related to an event occurring during a subjective experience characterized by a complex brain function including information acquisition, manipulation, storage, and recall [20]. Ochsner and Gross [21] assumed that emotions are consequences of external stimulations or internal mental representations with valence and well-defined characteristics. Furthermore, some researchers [19] hypothesize that emotions have three components: physiological reaction, behavioral response, and feeling, i.e. a subjective response to emotions. Emotion recognition aims to detect the affective state of a subject directly by brain activity and recent works focalized the attention on the correlation between brain oscillations and emotions [22, 23]. Actually, besides the lack of an univocal definition of emotion, there is also no consensus in the scientific community on a general theory of emotions. Indeed, the theory of emotions is divided into two main models: discrete and dimensional models [24]. Discrete models classify emotions without considering any axis to quantify the specific characteristics of each one. Furthermore, the number of emotions depends on the theoretical framework. Dimensional models define some common continuous features and place each emotion in a point of the space based on the values of the considered features. One of the most accepted dimensional models is the Russel Circumplex Model [25]. It has two dimensions: Arousal (degree of activation) and Valence (degree of pleasure). More complex dimensional models, besides Valence and Arousal, also include Dominance (degree of attention) to produce a Valence Arousal-Dominance (VAD) or Pleasure-Arousal- Dominance (PAD), creating a 3D space of emotions [26]. Valence goes from unpleasant to pleasant, Arousal goes from passive to active, and Dominance goes from submissive to dominant, representing the degree of controllability of a specific emotion. Another model [27] is composed of Valence, Arousal, Dominance, and Predictability, where the last element

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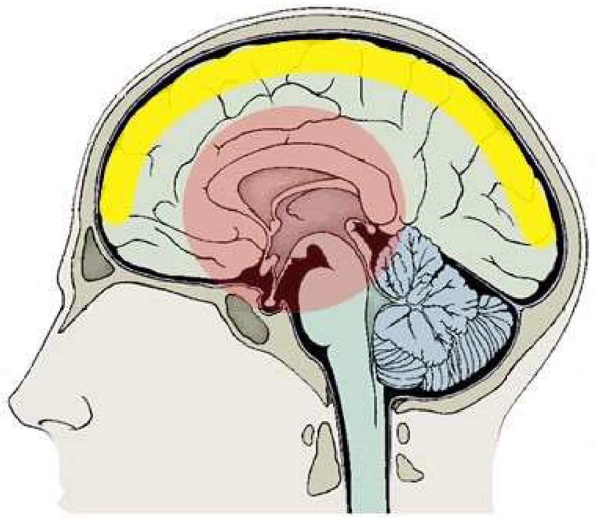

Figure 2: EEG brain sensitivity map (in yellow), with sensitivity decreasing with depth, and the main circuits of the limbic system, where emotions mostly originate (in red).

represents the level of surprise. Among many, EEG is one of the technique to measure brain activity in real-time and in almost normal, minimally invasive, conditions. It has the advantage to have great time resolution but low spatial resolution, and, compared to others, it is cheaper and more portable. However, the accurate study of emotions would require their direct measurement. The measurement of spontaneous emotions in daily-life conditions is challenging, due to many condunding variable that occurs during the recording. Usually, for EEG, an external stimulation (videos, sounds, images, etc.) or memory recall is required to elicit emotions in well-defined experimental sessions and environments. The resulting signals are usually stored in public datasets [28] to allow open-source recovery, processing, and analysis. In particular, many of them use external stimuli such as videos or/and audios [29–31] and some of them use self-stimulation from their memory [32, 33]. Emotion recognition is a particularly difficult domain due to the number of variables influencing emotions, including the elicitation mode, the experimental protocol, the subject's basal emotional state, and the used instrumentation. The main problem with datasets collected through external elicitation is the presence of biases, mainly related to the used protocol. For this reason, in the last years, many signal datasets of emotions have been proposed, each with pros and cons, but no one is completely free from biases.

ELICITATION PROTOCOLS, EEG DATASETS, AND CHALLENGES

An important aspect necessary for recognizing emotions by EEG is to get specific features characterizing their signals, collected from several analyzed subjects. This is done through the design of specific elicitation protocols and the organization of measurement sessions during which the elicited emotions are synchronized with the measurement, making it very difficult to measure spontaneous emotions in a real-life context. The protocols produce stimuli in the form of items, events, or conditions that cause a person to elicit emotional responses or behaviors for studying and understanding various psychological processes. Stimuli can include situations, scenarios, or social interactions. Well-known stimuli for eliciting the targeted emotions are virtual reality (VR), images, video games, music, audio/video clips, audio, and/or videos [28, 34–36]. Based on the type of stimulus, various emotions are elicited which are manually ranked to be used by nonlinear processing strategies. Without going into specific details about the elicitation protocols and the related datasets that originated from them, it is worth noting that several criticalities take origin from every stimulation protocol we can define. Overall, significant challenges arise to obtaining reliable and representative EEG data of emotions, with many limitations stemming from elicitation approaches, lack of adequate baselines, reduced number of sensors, equipment instability, etc. In summary, we can observe numerous challenges that must be overcome in order to obtain EEG data that more accurately represent emotions, aiming to surpass current limitations caused by stimulation protocols, lack of adequate baselines, limited number of sensors during acquisition, and instrument instability. The number of EEG channels should always be very high (> 64) to allow for high-density acquisition, which can then be reduced during preprocessing to identify the most significant channels, and a multimodal acquisition should always be used rather than a single system (e.g., EEG + ECG). Additionally, environmental parameters should be measured to verify and correct instrumental errors. User interaction with the experiment (e.g., evaluation of each stimulus) introduces numerous artifacts and interruptions that could introduce further bias and noise into the measured signal. Furthermore, a simple limit to overcome concerns acquiring all possible demographic, physical conditions (age, hair, health...) and psychological data to control for potential confounding variables (e.g., lateralization) and using validated psychological scales for assessing emotional states. Additionally, using many different trials for each recorded emotion allows for intra-subject and inter-subject analyses, and the acquisition context should be as neutral as possible to avoid introducing additional biases due to the environment. Finally, the subject's adaptation time to the new experiment should be respected to allow them to feel comfortable, and consideration should be given to the subject's fatigue for long-duration experiments, including assessing their mental workload at another time. Among the current limitations specifics for emotional studies, we found the use of individual emotional elicitation trials for each participant, as well as the significant subjectivity of responses to individual external emotional stimuli, which thus require prior and/or posterior evaluation to assess whether such stimuli are appropriate for the subject. Often, there is a lack of adequate baseline in databases, which should instead be recorded

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at numerous points before, after, and during EEG data acquisition and also is needed the acquisition of their personal "ground truth" of the stimuli used, acquiring their evaluation of the stimuli used in the experiment. Finally, there is the ethical problem that must be taken into account during emotional stimulation. In emotional stimulation protocols, images or videos containing emotional situations are often used to elicit emotional reactions in participants that are commonly referred to external situations (e.g. people in critical situations) and not related to the participant's personal situation. It is important to note that this approach tends to focus mainly on negative emotions, as these cannot be induced directly in participants. In contrast, positive emotions can be evoked either directly or through indirect stimulation that shows third parties experiencing positive emotions. It is crucial to consider that, under normal conditions, participants are in a state of relaxation, which can be interpreted as a positive emotion according to many theories, including Russell's model, which posits that there are no "neutral" emotions [25]. Finally, the advancement in using EEG for recovering emotions depends on the ability to overcome the above issues effectively, when possible.

THE SURPRISING PERFORMANCE OF THE RECENT EMOTION RECOGNITION MODELS

In the last few years, with the advent of non-linear AI-based models, there has been a huge effort to improve emotion recognition by EEG [37, 38] and many more have been added since the above reviews. In particular, deep learning (DL) methods with convolutional neural networks (CNN) [39] and long short-term memory (LSTM) [40] have provided better performance, in terms of accuracy, than traditional deterministic processing algorithms. Indeed, over the years these models have been refined to include intrinsic characteristics of the problem, to get any potential spatial/temporal unknown relationship, and to better fit the data at hand. For example, the dynamic relationship among EEG channels in different regions has been represented graphically through dynamic graph CNN [41] and adaptive graphs [42], for taking into account the spatial correlations of EEG data. Besides, to include the cross-subject variability and non-stationarity of the EEG signals, transfer learning has been introduced to solve the inconsistencies between training signals and the signals used for the test. To this aim, new hypotheses were added to the models regarding brain symmetry/asymmetry, as in the bi-hemisphere domain adversarial neural network [43] and in the bi-hemispheric discrepancy model [44]. Other methods try to reduce subject variability in EEG by introducing specific domain residual networks [45, 46]. These models are similar to residual networks with the advantage that they do not require any prior information during training. Several other model adaptations have regarded the proposal of a dynamic adversarial adaptation network that dynamically learns domain-invariant representations both on a local and a global scale. One of these methods [46], proposed a joint distribution adaptation to take into account the joint distribution differences across individuals. Another recently proposed model [47] proposed an adversarial discriminative temporal convolutional network for cross-domain (cross-subject and/or cross-dataset) emotion recognition with further achievements in emotion recognition. Without going into further details, several other methods for emotion recognition have been proposed, some of them are here reported [48–54], whose results have allowed to improve the accuracy that, for a three-class emotion dataset [55] (e.g. Positive, Negative and Neutral), ranged from about 60%, from the first moves of DL, to above 90% and, for a four-class emotion dataset [56] (e.g. Neutral, Sad, Fear, Happy), ranged from 38% to above 80%, with a huge improvement in the result stability (standard deviation passed from about 13% of the first DL models, to about 7% of the recently proposed models).

DISCUSSION AND CONCLUSION

Recent DL models applied to EEG have become ever more and more complex to include any sort of prior information and/or to highlight any sort of potential relationship among the measured data. In some cases, they also included constrained based on findings provided by other diagnostic tools, like fMRI, to push the performance toward ideal values. Since most of the intrinsic mechanisms of brain behavior are still not completely understood, in particular regarding emotions, and because complementary measurement tools collect different parameters of the same phenomenon, consider different measurement brain places, are differently affected by noise and artifacts, and use different protocols, it could be improper to use the results of one to design constraints for the other. According to EEG, its main limitation on emotion recognition is that its measurements take place far from the source of emotions and that it probably measures the brain processing of emotions more than the emotions themselves. However, this does not mean that EEG measurements are not useful for emotion recognition but just that the task could be difficult. Besides, the EEG signals are intrinsically nonlinear and nonstationary, and, those from emotions, are strongly subject-dependent and related to other brain processing tasks. Last, but not least important, emotions are not collected during real-life experience but during the execution of a task elicited by a specific activation/synchronization protocol. Despite that, the performance of the recent DL models for emotion recognition by EEG is surprisingly good and doubt arises: the designed models could unintentionally use plenty of heuristics, producing unaware data overfitting. The present article aims at giving rise to a reflection on the goodness of these results, to push, for the future, to a substantial verification of the proposed methods, to define further elicitation protocols to collect data to be used in this verification, to apply explainable AI for comprehend

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which features, brain regions, and brain connections (spatial and temporal) are mostly involved in the emotional process and, finally, to apply these verified findings for EEG, emotion-driven, BCI.

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