Abstract—Emotion estimation is an active field of research that has an important impact on the interaction between human and computer. Among the different modality to assess emotion, electroencephalogram (EEG) representing the electrical brain activity presented motivating results during the last decade. Emotion estimation from EEG could help in the diagnosis or rehabilitation of certain diseases. In this paper, we propose a dual method considering the physiological knowledge defined by specialists combined with novel deep learning (DL) models initially dedicated to computer vision. The joint learning has been enhanced with model saliency analysis. To present a global approach, the model has been evaluated on four publicly available datasets and achieves similar results to the state-of-the-art approaches and outperforming results for two of the proposed datasets with a lower standard deviation that reflects higher stability. For sake of reproducibility, the codes and models proposed in this paper are available at github.com/VDelv/Emotion-EEG.

Index Terms—EEG, Affective-Computing, Deep-Learning.

I. INTRODUCTION

Emotion estimation is a trending topic in a various research application. The motivation is explained by the fact that it could help to have a better understanding of language processing and non-verbal communication, the resulting applications could help in the context of Human-Computer-Interaction (HCI). Different modalities can be considered to evaluate emotional state: voice/sound, video, images, text, but also biomedical signals. For instance, in their work, Song et al. [1] presents a dataset composed of physiological recordings, i.e. EEG, electrocardiogram (ECG), respiration and galvanic skin response (GSR), with an initial benchmark aiming to estimate emotional state are presented. Furthermore, Zheng et al. [2] show that eye-tracking signals can also be considered to estimate emotion.

For a long time, the brain has been a major source of inspiration for the scientific domain. Especially in computer science with the creation of the artificial neural networks by Werbos and John [3] mimicking the functioning of biological neurons. Other recent works are also inspired by the biological behaviour of our brain with for instance neural network pruning inspired by the neuronal concentration in the brain as shown by Blalock et al. 2020 [4].

In the context of nature-inspired science, Artificial Intelligence (AI) and specially Machine-Learning (ML) based algorithms have known an increase in interest during the last decade. The reasons are varied: higher robustness, higher accuracy, technological democratisation or the growing simplicity of their development. Through the scientific community, ML-based algorithms are used in a wide range of technologies and domains including medical field with for instance: diseases and infections detection from physiological recordings [5], understanding of the human genomes [6], human behaviour prediction [7] or drugs discovery [8].

On another side, the recent researches on Brain-Computer Interfaces (BCI) have led to an increase in their use in innovative applications and projects. A BCI is an application connecting a computer with the user’s brain through physiological signals, e.g. EEG, Magnetoencephalogram (MEG), Magnetic Resonance Images (MRI), etc. This link can be invasive/non-invasive or in an open loop (e.g. recording signals during a specific task on a computer) or closed-loop (e.g. video game evolving with the brain activity) depending on...
the considered application and its purpose.

One of the fields in which an increase of BCI applications has been noted is that of the emotion estimation from physiological signals and especially from EEG. As reported by Craik et al. [9] in their review, one paper out 6 considering the use of DL algorithm for EEG is dedicated to emotion estimation tasks. The existing works present datasets to assess emotional state [1], [10]–[12] and different models often based on DL algorithms to retrieve the emotional state from EEG signals [13]–[16]. The proposed methodologies consider EEG under different form, e.g. graph with electrodes as nodes and vertices proportional to the distance separating them [14], [16] or also in sequences to extract the spatial relationship between electrodes and/or the differences between hemispheres [13], [15]. Other approaches to represent EEG or to estimate emotion from these last have been considered lately as reported by Craik et al. [9].

One of the major preoccupations for the use of ML algorithms in medical applications and especially for EEG processing is the development of models as understandable as possible. In their recent works, Li et al. [17] have shown that several papers presented in top-tier conferences and considering ML-based estimation from EEG were biased and therefore their results were impacted. In this context, it is important to consider interpretable models. Different approaches have been designed for this purpose, for instance, the signal projection in a latent space to have a better visualisation of the model classification [18]. Another approach may be to have a better visualisation of the temporal series that composed EEG signals. For this purpose, considering novel feature extraction and representation methodologies may be considered. For instance, Bashivan et al. [19] developed an algorithm, initially dedicated to images analysis, to classify biomedical signals by creating a visual representation of EEG.

In this context, a framework aiming to estimate emotion from EEG is presented. This last is composed of two parallels modules: (1) a higher-level network considering an image inspired representation of EEG to benefit from advantages of computer vision models; (2) a lower-level network considering each electrode contribution through an array representation of EEG. The contributions of the two networks are then pooled to estimate the corresponding emotion state from a given EEG trial.

II. PROPOSED METHOD

In this paper, a model aiming to estimate emotion from EEG is proposed. To combine the improvements provided by deep-learning approaches with the physiological information provided by specialists knowledge, it has been chosen to consider in this framework, the combination of two types of models: an approach inspired by computer vision models and a lower-level approach inspired by motion capture models. The first one is based on an image representation of EEG features passed through images dedicated ML networks. For the second approach, a hierarchical RNN has been considered with each stages aiming to extract region information at different levels: the electrodes levels for the 1st stage; brain regions for the 2nd stage and hemisphere for the 3rd stage.

A. Feature extraction

We consider an EEG sample of dimension $\in \mathbb{R}^{n_{\text{trials}} \times n_{\text{channels}} \times n_{\text{samples}}}$ with $n_{\text{trials}}$ being the number of trials during the experimentation, $n_{\text{channels}}$ the amount of electrodes on the EEG headset and $n_{\text{samples}} = \text{duration} \times f_{\text{sampling}}$ the sample size for each trial. It is possible to manually extract $n_{\text{features}}$ for each EEG segments considered as time series to have a representation of EEG in a smaller subspace $\in \mathbb{R}^{n_{\text{trials}} \times n_{\text{channels}} \times n_{\text{features}}}$. The considered features may represent temporal (i.e. feature representing the temporal evolution), spatial (i.e. feature related to electrodes location on the scalp) or frequential/spectral (i.e. feature related to the contribution of different frequential bands) information from signals. Due to the difficulty to characterize raw EEG signals and their trend to be affected by noise (e.g. electrical noise and muscles given their close frequency to EEG [20]), a majority of dataset proposed denoised EEG and pre-extracted features [1], [10], [11]. Among the most commonly considered feature extraction methods for emotion estimation, two have been kept: the power spectral density (PSD) representing the contribution of each frequential bands in the EEG signal and the differential entropy (DE) reflecting the temporal evolution of EEG segments [21]. The feature extraction methods can be considered separately or combined by computing DE in frequency bands. The choice of this feature extraction methods is motivated by their encouraging results for emotion estimation [10], [21], [22].

From the array representation, it is also possible to consider a more visual representation of information with an image-based representation of the feature map [19]. Given the location of the electrodes in a 3D frame (i.e. cartesian coordinate of the position on the scalp), it is possible to consider an azimuthal projection to represent their locations in 2D. Finally, after assigning the feature values for each electrode in the 2D discrete representation it is possible to form an image by interpolating the values in the two projected dimensions. Finally, the constituted images will have the following shape $[n_{\text{trials}} \times n_{\text{features}} \times h \times w]$ with the height $h$ and width $w$ taken arbitrarily.

B. Images estimation

From the image representation of EEG signals $\in \mathbb{R}^{n_{\text{feat}} \times h \times w}$ it has been decided to consider DL models initially dedicated to images processing to estimate emotion from electrophysiological recordings. Among the existing approaches, two-family of models have been considered: convolutional neural networks (CNN) and capsule networks.

The CNN approach consists of a VGG inspired model [23] with an architecture composed of three modules each of them respectively composed of 4, 2 and 1 convolutional followed by batch normalization layers. Each stack is separated by a max-pooling layer.
The capsule-based model consists of the general architecture presented by Sabour et al. [24]. One of the advantages of these networks is their ability to extract the spatiality between elements composing an image, e.g., automatically taking into account the nose or mouth position for face detection systems. In our method, the initial dynamic routing between capsules has been adapted to match EEG images. The consideration of this novel approach allows us to study the spatial relevance among EEG images. Moreover, their consideration remains also interesting for their lower computational cost compared to other DL architectures.

C. Array estimation

On another hand, a more understandable approach compared to the previously presented models has also been considered. This last consists of a recurrent neural network (RNN) composed of the succession of hierarchical sub-networks, each of these networks aiming to extract information at different levels: electrodes, physiological regions or hemispheres based relationship. This model has been inspired by the hierarchical RNN proposed by Du et al. [25] aiming to classify motor movements from skeleton recordings at different location and levels, e.g. fingers, hands, arms, trunk.

In addition to its more understandable form compared to image representation of information, the use of this type of models has also presented interesting results for emotion estimation from EEG, among which some are the best on some public datasets [13].

D. Merging models methodology

From the results provided by the models presented above, a combination of these last has been considered to merge their strengths and improve the classification accuracy. Different methodologies can be considered depending on the fusion location of the models: 1) output fusion considering a linear combination of both output after the softmax layer of each network; 2) feature fusion consisting of a concatenation of the DL feature vectors estimated by both approaches, the created vectors are after passed through a fully-connected network to estimate the class.

To promote the synchronous learning of both networks and help learning transfer between modules, it has been thought to estimate the most salient electrodes from the RNN, i.e. computing the most important electrodes for attention estimation in the RNN. The saliency for each elements constituting feature array is computed by considering the gradient backpropagation with respect to the input layer as expressed in the following equation [26]:

\[ \text{Saliency} = \left| \frac{\partial \text{Class}}{\partial X} \right|, \]

representing the gradient of the model prediction Class considering the EEG segment X. After computing this saliency map representing the most discriminant electrode to estimate emotion (from the grey model), it is possible to deduce the corresponding image representation of the saliency map for each electrode. This saliency image is used to concentrate the training of the image-based model around the most discriminant electrodes deduced during the training of the lower-level model.

III. EXPERIMENTS

In this section, the considered datasets for training the proposed model are presented, then its implementation details and an adversarial training methodology to enhance generalization are proposed.

A. Datasets

We consider four different datasets to evaluate our approach. The choice of working with several datasets, despite optimizing only one of them, is to promote a general approach working on different participants of different background.
• SEED IV [11] contains EEG recordings of 15 different participants spread over 3 sessions each consisting of 24 trials. One trial consists of the vision of video clips promoting several emotions, during which several physiological signals are recorded (eye positions and EEG). In this dataset, four emotion classes have been considered: happy, sad, neutral and fear.
• SEED [10] that is also composed of recordings from 3 sessions repeated for the 15 participants, each session being composed of 15 trials. The experimental setup consists of the recording of EEG during video promoting specific emotion. In the SEED dataset, emotions have been separated into three more general classes: positive, negative and neutral emotion.
• MPED [1] contains the recordings of several physiological signals (EEG, ECG, GSR) for a total of 30 participants. Similarly, the recordings have been made during video vision. The promoted emotion during the videos have been separated into seven classes: joy, funny, anger, disgust, fear, sad and neutrality.
• DEAP [12] is a multi-modal dataset composed of EEG, electromyogram (EMG) and electrooculogram (EOG) recordings of 32 participants. During the datasets creation, it has been asked to participants to look at the video and to self-assess emotion state in three dimensions: arousal (i.e. from excitation to disinterest), valence (i.e. from pleasant to unpleasant) and dominance (i.e. the ability to control the feelings from weak to empowered) considered as the labels of the physiological recordings.

Each dataset has been recorded with biomedical EEG headsets following the 10/20 electrodes placement of the 62 electrodes for [1], [10], [11] and 32 electrodes for [12] (proposed model has been adapted to fit the number of considered electrodes). Moreover, the provided feature vectors have been considered in this experiment despite the raw EEG signals, in [10], [11] DE entropy in five frequency bands (δ, θ, α, β and γ bands) has been considered. For [1], [12] PSD has been considered with the same frequency bands limit and methodologies than in the original paper [12].

B. Implementation details

In image-based representation, the number of channels for the three CNN sub-modules has been respectively set to: 16, 64 and 128. Moreover, we consider $32 \times 32$ images to consider square shape images that better fit with convolution. For the other representation, the hidden dimension of the RNN has been set to 32. During the training phase, a cross-entropy loss has been considered to quantify the error from the network estimated class and actual class, moreover, adam optimize has been considered with an adaptive learning rate, $l_r = 10^{-3}$ and a weight decay, $w_d = 10^{-8}$. The number of epoch has been fixed to 150 but the training was stopped if the loss was locked and/or in case of overfitting. All the models have been implemented with Pytorch library and were trained on one 24 GB Nvidia Titan RTX GPU. For the sake of reproducibility, the model architecture is freely available online [1]

C. Domain classification

It has been noted that the recent advance in DL leads to novel training methodology increasing estimation accuracy. One of them consists of considering after the DL feature extraction a classifier aiming to estimate if the input was from the training or test sets [27]. A training competition between the domain classifier and initial model has led to improvements to this one and helps to extract feature regardless of their belonging to the training or test part of the dataset. A representation of the considered model is proposed in Fig. [1] It is important to note that the domain adaptation method aims to extract the feature as general as possible. Furthermore, the labels of the testing set are considered as not known during the training phase and then are not used for other purposes than validation. Finally, if we consider the full model in three-part: the DL feature extractor with its corresponding parameters $\theta_f$, the classifier aiming to estimate the class to which belongs the EEG sample with parameters $\theta_c$, and the discriminator estimating the domain belonging with parameters $\theta_d$, it is possible to re-express the optimization problem as follows: $L(X, \theta_f, \theta_c, \theta_d) = \min L(X_{train}, \theta_f, \theta_c) + max L(X_{train}, X_{test}, \theta_f, \theta_d)$. $X$ is the sample composed of training and test part and the considered losses being cross-entropy.

IV. RESULTS

To assess the results provided by the proposed models, we have first considered the training and validation of the different approaches proposed above on the SEED-IV dataset [11]. Then, the best approaches have been compared on three other datasets [1], [10], [12] with the state-of-the-art models.

The considered metric for model evaluation is the leave one subject out (LOSO) cross-validation accuracy. With this evaluation methodology, all the subjects except one are used to train the model and its evaluation is made on the remaining one. This evaluation is repeated for each participant and the corresponding mean and standard deviation are computed. The LOSO cross-validation accuracy has been chosen to assess the model ability to generalise to never met participants. EEG signals being very person-specific [17], a large gap is often noted for the cross-validation between participant dependant and participant independent cross-validation (i.e. LOSO). Nevertheless, BCI applications are supposed to be used directly on the participant without a pre-training of the proposed approach.

As reported in Table [1] all the described approaches previously mentioned have been trained on the SEED-IV [11] dataset. As shown, the best results for the primary study (standalone approach without models combination) were found for the image-based approach with CNN. Besides, lower results were also noted for the hierarchical RNN with higher stability

https://github.com/VDelv/Emotion-EEG
among participant (i.e. lower standard deviation). For this reason, it has been chosen to consider the combination of these two models to merge their advantages.

Three different approaches have been considered to merge the models: concatenating the output after softmax layers of both models (Output Fusion), concatenating feature vectors with saliency extraction from the low-level model (Saliency Fusion) and without (Feature Fusion). As reported in Table I the results of this combination present better results and especially the saliency-based combination that exceeds the best results from the previous state of the art methods and our experiments. Another advantage of the saliency-based feature fusion is its low standard deviation compared to other models. The latter shows that the model will have similar results independently of the participants. The improvements provided by the saliency-based approach are explained by this dual methodology considering in parallel the sequential information provided by the H-RNN and the more general region activation highlighted by the CNN. Furthermore, focusing the training on the specific region of the image-based EEG with a raw attention mechanism presents higher results than a simple concatenation.

In Table I a comparison of the results of two of the previously mentioned models is presented with state of the art models for emotion estimation from EEG. As shown, our approaches present the best results for some datasets and remain on the same scale for other datasets that proved its ability to estimate emotion in various cases. As seen in Table I the results obtained by our approach exceed those obtained by previous works. Although this last may seem only slightly better than previous works, it is important to note that the proposed approach is able, at least, to achieve a comparable subject independent cross-validation accuracy than previous works. The purpose of the proposed method is to present a general model instead of a finely tuned approach working only in a specific context.

V. CONCLUSION

In this paper, we proposed a novel framework aiming to estimate the emotion from EEG. The proposed model is composed by a dual approach considering the physiological relationship of EEG signals through a hierarchical RNN and a DL representation through CNN. The proposed method shows interesting results among the best on three datasets. In the further work, it could be interesting to consider novel ML, with different representation (e.g. graph neural network) and more understandable approaches with other feature extraction methods. In future work, an emotion estimation approach from EEG could be used in various applications covering several fields, e.g. entertainment or medical domain.

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