SOM-Based Class Discovery for Emotion Detection Based on DEAP Dataset

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ABSTRACT
This paper investigates the possibility of identifying classes by clustering. This study includes employing Self-Organizing Maps (SOM) in identifying clusters from EEG signals that could then be mapped to emotional classes. Beginning by training varying sizes of SOM with the EEG data provided from the public dataset: DEAP. The produced graphs showing Neighbor Distance, Sample Hits, and Weight Position are examined. Following that, the ground-truth label provided in DEAP is tested, in order to identify correlations between the label and the clusters produced by the SOM. The results show that there is a potential of class discovery using SOM-based clustering. It is then concluded that by evaluating the implications of this work and the difficulties in evaluating its outcome.

KEYWORDS
Class discovery, DEAP, Emotion, SOM

1. INTRODUCTION
There has been an increase in the use of Electro-encephalography (EEG) and other physiological signals, in part motivated by the existence of relatively low-cost hardware, e.g. modern fitness devices. This naturally has led to new possibilities of user-device interaction and equally to higher expectations by the users. Many users now expect personalization, by user preferences and by adaptation, as a standard function of many mobile and wearable devices. An emerging and ever-expanding approach to such personalization is emotion recognition in which the mood or affective state of the user is approximated and then used to modify or adapt the system functionality or appearance (Arevalillo-Herra’ez et al., 2014). This is particularly ever more apparent in recommender systems, such as (Posner, Russell, & Peterson, 2015; Qin, & Zhang, 2016; Rosa, Rodriguez, & Bressan, 1980) few but to give examples.

Many approaches to emotion recognition from EEG signals rely on identifying a very small number of classes and to train a classifier. The interpretation of these classes varies from a single emotion such as stress to features of emotional model such as valence-arousal. There are two major issues here. First classification approach limits the analysis of the data within the selected classes and also highly dependent on training and limits generalization. If we are to advance on personalized emotion models (Ayesh, Arevalillo-Herra’ez, & Ferri, 2016) we need more dynamic framework to model and identify emotions. This can then be naturally extended to include implicitly or explicitly other intertwining factors, such as personality, in representing and updating user affective states. Second issue is that it does not explore the inter-relationships between the data collected missing
out on any correlations that could tell us interesting facts beyond emotional recognition. This second issue would be of particular interest to psychologists and medical professions.

In this paper, we investigate the use of Self-Organizing Maps (SOM) in identifying clusters from EEG signals that could then be mapped to emotional classes. We trained varying sizes of SOM with EEG data using DEAP (Koelstra et al., 2012), a publicly available dataset. The produced graphs showing Neighbor Distance, Sample Hits, Weight Position are analyzed holistically to identify patterns in the structure. Following from that, we compare node density and sample clustering to the sample classification provided in (Koelstra et al., 2012) to identify correlation between the sample classification and some of the generated clusters. The results show the potential for class discovery. We conclude with a discussion on the implications of this work and the difficulties in evaluating its outcome.

The paper is organized as follows. First, we start by giving background on the data used and how it was analyzed and prepared. The experiments with SOM and the analysis of the results are presented and the main conceptual contribution of this paper discussed in detail. We then conclude the paper with a critical discussion covering outstanding research questions.

2. EEG DATA

2.1. Motivation

In a number of neuropsychological studies, EEG data showed to exhibit correlates of emotion (Kim, Kim, Oh, & Kim, 2013) e.g. event-related potentials (ERPs) (Olofsson, Nordin, Sequeira, & Polich, 2008) that can be analyzed through the spectral power in several frequency bands (Balconi, & Lucchiari, 2006; Balconi & Guido Mazza, 2009). The results of these studies motivated the rapid development of emotion recognition techniques based on EEG data. The availability of public data sets has also played a role in advancing these techniques. We identified at least four possible datasets, these are DEAP (Koelstra et al., 2012), DECAF (Abadi, et al., 2015), DREAMER (Katsigiannis, & Ramzan, 2017), and MAHNOB-HCI (Soleymani, Lichtenaier, Pun, & Pantic, 2012). DEAP (Koelstra et al., 2012) stands out as one of the most frequently used, in fact it was referenced by DECAF and DREAMER for comparison. It is also most frequently used to evaluate the performance of emotion recognition methods e.g. (Atkinson, & Campos, 2016; Jadhav, Manthalkar, & Joshi, 2017; Liu & Sourina, 2014; Mert & Akan, 2016; Velchev, Radeva, Sokolov, & Radev, 2016; Xu, & Plataniotis, 2016). As a result, it has become a de facto benchmark in the context of EEG based emotion recognition.

The analysis of the collected EEG signals produced a total of 216 features. These features were then used in a baseline experiment. In the experiment a binary classification setting using a Naïve Bayes Classifier was applied using the ground truth labels extracted from the self-reported Self Assessment Manikin (SAM) ratings (Bradley, & Lang, 1992). We expound the DEAP dataset and the analysis applied to it in section 2.2.

Similar approaches have been reported in (Pablo Arnau-Gonzalez, Miguel Arevalillo-Herráez, and Nacim Ramzan, 2017; Atkinson et al., 2016; Jadhav et al., 2017; Liu et al., 2014; Mert et al., 2016; Velchev et al., 2016; Xu, & Plataniotis, 2016; Xu, & Plataniotis, 2016), to give examples but a few. These approaches utilized typical classification frameworks in which the recorded EEG signals are pre-processed by using spatio-temporal filtering and noise reduction methods, to abate artifacts and enhance the Signal-to-Noise Power ratio (SNR). Relevant features were then extracted to provide training samples to a classifier. The samples were labeled according to a specific approach to describe emotions (Tkalcic, Kosir, & Tasic, 2011). This may assume a set of distinct emotional categories, such is the case in Ekman’s Basic Emotions Model (Eckman, 1992). Another approach is to describe the emotion as a point in a continuous multidimensional space. In such models, each dimension represents one aspect of emotion concept such is the case in Millenson’s Model (Blewitt, Ayesh, John, & Coupland, 2008); other examples of this approach can be found in (Ayesh & Blewitt,
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