School of Informatics

Informatics Research Review
K-Nearest Neighbours in EEG-Based Emotional Recognition

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Abstract

Emotions are essential in our everyday life for interpersonal activities, making rational decisions and the understanding the surrounding environment. Recently, there has been an increasing interest in the use of electroencephalography (EEG) for emotional recognition, as their systems have become more affordable, mobile and provide a simple solution for emotional recognition. In this paper, I analyse the current literature that applies KNN to this task, as this method yields good results, and give some suggestions for future research directions.

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Contents

1 Introduction

Emotions are essential in the day-to-day life of human beings because of the important role they play in human cognition, especially when making decisions, being aware of our surroundings, and human interaction and intelligence. To be more precise, the area of Human-Computer Interaction has been focusing on many topics, except human emotions, resulting in a very limited scientific knowledge about them. Further progress is required to be able to benefit from the knowledge of human psychology and make good use of it in society.

The ability to integrate systems into machines that help them recognise emotions in an efficient way, would have several applications, such as decreasing costs and therefore increasing profitability and improving productivity and efficiency. One possible application of these systems is in education, where a student's mental state could be determined to evaluate how engaging classes are. A different case would be in the army, where doctors could assess the mental conditions of trainees during combat situations in simulated training environments. This would also allow doctors to provide more accurate and effective suggestions to improve their health.

Because of the positive impact that emotional recognition will have in society, there are several studies on how to automate this process. This automation would result, not only in faster and more efficient systems that can be used in a larger scale, but in more accurate results, because subjective self-reports about the subject's personal mind state can often be misleading – the subjects may describe what they think is the expected feeling instead of what they are actually experiencing.

There are two main categories in which Emotion recognition can be classified: physical and emotional signals. The physical signals include facial expressions [1], speech[2], gestures and others. There has been extensive research within this topic since the signals are easy to collect. The emotional, physiological signals correspond to multi-channel recordings from both the automatic nervous system and the central nervous system. The first one is responsible for reflex actions and regulates body functions, while the latter is formed by the brain and the spinal cord. Some of the most commonly used signals in this area are the Galvanic Skin Response (GSR), Electromyography (EMG) (which measures the frequency of muscle tension), Heart Rate (HR) and Respiration Rate (RR), as well as some functional neuroimaging techniques [3], such as Electroencephalogram (EEG), functional Magnetic Resonance Imaging (fMRI) and Positron Emission Tomography (PET).

EEG works by placing electrodes in a patient´s head which read signals from the brain and is useful to evaluate phased changes in response to stimuli. Moreover, EGG is noninvasive, instantaneous and economical, which makes it one of the preferred methods used to study the brain's responses to emotional stimuli [4]. Nowadays, modern wireless EEG devices are coming to the market because they are light, portable and easy to use. EEG-based emotion recognition can now be applied to areas areas such as e-healthcare applications and e-learning [5], [6] and it is expected that it will have many more applications in the future, for example in online games or aiding psychologists and therapists.

There are several approaches for recognising emotions based on EGG signals. In this review, I survey literature that focuses on applying K-Nearest Neighbours (KNN) to this task. The surveyed literature includes peer-reviewed papers as well as some very recent working papers. Since this is a fairly recent research area that has been largely overlooked, the surveyed literature spans from 2010 to 2019.

This paper is meant to be a simple and comprehensive review of the existing variations of the KNN method being used for both inter- and intrasubject EEG-based emotional recognition. In section 2, I will provide the necessary background to fully understand the analysis of the literature. In section 3, I will do a comparison of the test protocols, EEG recordings, artifact filtering methods and feature exctraction methods being used, in order to illustrate the existing difficulties in comparing the performance of different models, as well present the differences and similarities between the different implementations of the KNN method for this task. As this review is more focused on the application of the KNN method on this task, other methods present in the literature will not be described in detail, but mentioned where relevant.

2 Emotional Recognition Using EEG

2.1 What is an emotion?

An emotion is a "complex psychological state that involves three distinct components: a subjective experience, a physiological response and a behavioral or expressive response" [7]. There are three main topics in affective neuroscience: feelings, moods and affection. Feelings are related to something that happened to a person that generated emotions; moods are mental states thet generally last longer than emotions; and affection is a combination of them. [8]. Emotions can be represented either categorically, or dimensionally. The categories in which they may fall are basic emotions such as surprise, happiness, anger, sadness... while the dimensional representation considers the Valence, Arousal and Dominance (VAD) dimensions, which are based on human cognition [9].

A person's emotional state can be derived by analysing their personal experiences and external and internal involuntary signals. Self-evaluating reports, for instance the Self-Assessment Manikin (SAM), are frequently used to evaluate a person's mental state and provide an alternative to the psychological evaluations done by a medical professional. However, these reports are usually unreliable because patients might have some trouble describing the emotions they are experiencing or may not have the necessary knowledge to evaluate their mental state. Therefore, using physiological signals can provide objective health information that can be used by the medical professionals.

2.2 Electroencephalogram

Electroencephalogram is a medical image technique that records variations of voltage that result from ionic current flows between the brain's neurons. This is achieved by reading electrical activity in the subject's scalp. These signals are divided into frequency bands which are associated with certain emotional states. This technique is particularly useful for emotion recognition as it is more objective than using non physiological indicators, such as gestures and facial expressions.

It has been observed that most information about a person's emotional state is stored in the parietal and frontal lobes and that the gamma, beta and alpha waves can be used due to its discriminatory properties [10]. In previous studies, it has been suggested that emotional stimuli is processed differently in each gender. Generally, men try and recall their personal experiences to determine their emotional state, while woman do this by directly processing the emotional stimuli [11]. There is some evidence that EEG patterns in men tend to be very different, whereas women's have more similarities among them [12].

2.3 Emotion Recognition

The emotion recognition task usually includes the following six main steps. Firstly, the participants are exposed to some sort of emotional stimuli. EEG is use to record the brain's activity. The raw signals are then processed in order to eliminate any existing artifacts and noise. Significant features are then extracted and used to train the emotion classifier. After identifying the participant's current emotional state, some feedback can be given to the user.

In the field of emotion recognition, there is a broad number of classifier methods used to distinguish between the different types of emotional states [13]. The two most popular methods are Support Vector Machines (SVM) and K-Nearest Neighbours, but the list includes Regression Trees, Bayesian Networks, Canonical Correlation Analysis (CCA), Artificial Neural Networks (ANN), Linear Discriminant Analysis (LDA) and Marquardt Back-Propagation (MBP). In addition to the classification method, there are many differences between the works, which makes it hard to compare them as well as draw conclusions about the quality of the results. For this reason, the papers selected were not chosen solely on the classification accuracy achieved by the model developed.

The classifiers can be separated into to categories, depending on whether the classifier was trained using user-dependent or user-independent data. In the former, classification is conducted using training and testing data that belong to the same person. This is called **intrasubject** classification and requires that each user has its own classifier. If, on the other hand, the data is user-independent, the classification is conducted using data from several individuals. This is called **intersubject** classification and it is considered to be a more difficult than intrasubject classification because the classifier has to use different individuals' EEG data and, as it was mentioned before, EEG patterns change from person to person and are not necessarily associated with the same emotional states [10]. Developing and fitting a generalised classifier that works well for all individuals is still the biggest challenge in this research area.

3 KNN in Emotional Recognition

3.1 K-Nearest Neighbours

K-Nearest Neighbours (KNN) [14] is a method used for classification and regression. In the case of this review, I will be focusing on the classification approach. The principle behind this method is to discover the k (which needs to be predefined) training samples that have the smallest distance (according to a predefined distance metric) to the point we are trying to classify. There are several distance metric measures which can be used, such as the standard Euclidean distance for numeric attributes and the Hamming distance for categorical attributes. KNN is particularly useful when the data is labeled correctly and the dataset is small.

3.2 Test Protocol

In this subsection, I compare the papers based on the number of subjects and their gender, the type of stimulus, the emotions to be recognised and whether they are presenting an inter- or intrasubject model. A summary is presented in Table 1.

3.2.1 Subjects

In the reviewed works, the number of participants ranges from 5 to 32. Having a small number of participants makes it hard to evaluate the significance of the data collected and the results. Out of the papers reviewed, only 4 were using more than 30 subjects. This means that most works works use a number of subjects that is not statistically significant and therefore does not provide a solid level of experimental reliability and legitimacy.

As it was mentioned before, there is evidence that men and women stimuli is perceived in different ways and therefore gender distribution must be balanced to guarantee significant results. However, this was not the case in most of the reviewed works, where the gender of the participants was either omitted or unbalanced (in these cases, there were more male subjects than female).

3.2.2 Stimulus

In all the works reviewed, an even-elicited approach was used for emotion elicitation. In this approach, auditory, tactile, odor or visual stimulation can be used. The stimuli used across the different works were images, videos, music and Virtual Reality (VR) clips. Some of the works used their own data, wereas others used existing datasets, such as the DEAP dataset [15]. In addition to the stimuli, the duration exposure to that stimuli also varies from paper to paper and ranges from a few seconds to a few minutes, although most works use 60 second stimuli. The stimuli duration is not specified in Murugappan et al. [16].

3.2.3 Emotions

As mentioned in 2.1, emotions can be represented either in a categorical or dimensional form. Of the papers reviewed, the 4 used a categorical representation, predicting emotions such as sadness, happiness, disgust and fear, and 4 used a dimensional representation, mapping the emotions into valence and arousal (none of the papers used the dominance dimension). In [17], [18] and [19], the authors do not use any of the two most common representations: the first two classify three emotions – positive, neutral and negative – and the later predicts whether the subject liked the music in the stimuli or not.

3.2.4 Inter- or Intrasubject Classification

From the 11 papers identified, 7 build intersubject classifiers and 2 build intrasubject classifiers. Of these, Khosrowabadi et al. [20] presented the intrasubject classification model that achieved the best performance, with an accuracy of 95.6% on the IAPS stimulus set with music. For intersubject classification, the best performance was obtained by Fan et al. [21] with an accuracy of 95% on VR stimuli. The authors of [17] and [16] have not specified what type of classification their classifier is doing, which makes it difficult to interpret their results and understand the real impact of their contributions.

Ref	Stimulus (duration)	Subjects (M/F)	Categorical or Dimensional	Intersubject or Intrasubject
[16]	Standard Emotion Clips (-)	20 (17/3)	Categorical	-
[17]	Video Clips (240s)	15 (7/8)	Positive, Neutral, Negative	-
[18]	Video (57-230s); IAPS (48s)	11 (8/3)	Positive, Neutral, Negative	Intersubject
[19]	Music (15s)	9 (7/2)	Like, Dislike	Intersubject
[20]	IAPS w/ Music (60s)	26 (-/-)	Categorical	Intrasubject
[21]	VR (-)	20 (19/1)	Categorical	Intersubject
[22]	Music Videos (60s)	32 (16/16)	Dimensional	Intersubject
[23]	DEAP (60s)	32 (16/16)	Dimensional	Intersubject
[24]	IAPS (12.5s)	5 (-/-)	Categorical	Intrasubject
[25]	DEAP (60s)	32 (16/16)	Dimensional	Intersubject
[26]	DEAP (60s)	32 (16/16)	Dimensional	Intersubject

Table 1: Analysis of the Test Protocol phase across the works.

3.3 EEG Recordings

The equipment and number of electrodes used to make the recordings has an important role because they determine the time needed to setup the EEG device, the level of comfort of the subjects and the number of features generated. Most present works still require an expensive clinical device with a rather large number of electrodes, even this number should be reduced.

Even though most of the works used a different EEG equipment, all of them used a commercial device, which is less expensive than the existing clinical devices. The two most used devices were Biosemi Active Two (3 papers) and the Emotive wireless headset (2 papers), which is the most easy to use and most portable device used in the works reviewed. The sample frequencies used is also very variable across the works and is independent of the EEG equipment used, with the most common frequencies being $256Hz$, $512Hz$ and $1024Hz$.

The electrode placement system, and, therefore, the number of electrodes used varies across the works, with the numbers ranging from 4 to 72 electrodes. The most commonly used placement system was the 10-20 electrode placement system [27] (Figure 1), used in [21], [22] and [17]. I will not get into the exact electrodes used because that is out of the scope of this review.

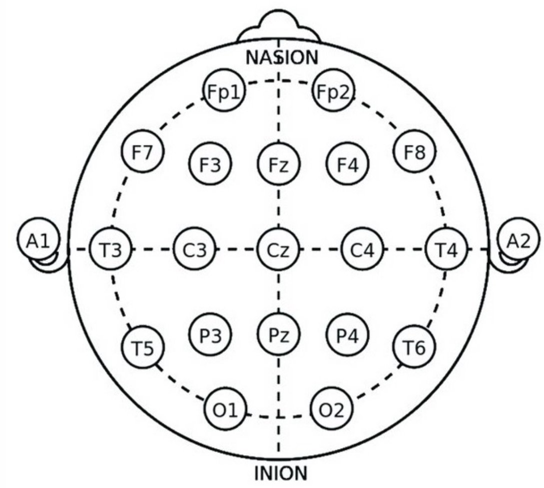

Figure 1: EEG electrode placement 10-20 International system [1].

3.4 Artifact Filtering

Artifacts are noises that are picked up by the electrodes during collection and can be produced from external interferences, such as sense of touch and audio noise or from muscle movements, such as muscle twitches and eye blinks. While some of the works remove the noisy information manually, using techniques such as data normalisation (4 papers), others use methods such as Blind Source Separation (BSS) (2 papers). In some of the works, the electrodes were re-referenced using methods such as Laplacian and Average Mean Reference (AMR). In addition to this, in order to only use frequencies that are appropriate for this task, all authors used some bandpass filters to remove the unwanted frequencies. Finally, most works finalised this data cleaning process by the original EEG signals.

[1] Image taken from [28].

3.5 Feature Extraction

In the following paragraphs I go over the most commonly used features and methods to extract them from the EEG signals.

Most of the works used alpha, beta, delta, gamma and theta bands to estimate the EEG features. Four of the works used all the frequency bands and the remaining works only used some of them: Hadjidimitriou et al. [19] used Beta and Gamma, Xu et al. [24] used Alpha and Beta, Brown et al. [18] used only Alpha and Kimmaktar et al. [17] used only Gamma. Instead of choosing a frequency band, Khosrowabadi et al. used fixed frequency bandwidths [20] to estimate the features. Bastos-Filho et al. [23] and Hatamikia et al. [25] did not provide any information about the features they used.

The process of feature extraction can be done using different methodology. In the reviewed papers, 19 distinct methods were used and most works used more than one, even though they ended up only selecting the best method. The methods used were the Fourier Transform, such as the Fast Fourier Transform (FFT) and Short-Time Fourier Transform (STFT), statistical, Higher Order Crossings (HOC), Differential Entropy (DE), Power Spectral Density (PSD), Discrete Wavelet Transform (DWT), Magnitude Squared Coherence Estimate (MSCE), Spectral Power Features (SPF), time-frequency, Narrow-bad Energy Event (NEE), AR with Bury Method, Fractal Dimension (FD) and Discrite Cosine Transform (DCT).

3.6 Classifier

In this subsection, I go over the differences in the KNN methods used across the works reviewed. I will introduce any extra steps present in the works and that have not been mentioned yet. I will also go over the methods used to pick hyperparameters and how well KNN does compared to other classifiers.

In addition to the feature extraction process, some of the authors applied an extra pre-processing step before feeding the data to their model. In Kimmaktar et al. [17], the authors applied dimensionality reduction to the data. In Xu et al. [24], on the other hand, the authors decided against a dimensionality reduction step in order to avoid error propagation associated with it. In Fan et al. [21], the authors applied a feature calibration method with two steps: baseline feature subtraction accompanied by individualised feature normalisation.

When building a classifier, some decisions need to be made regarding the hyperparameters of the model. In the case of KNN, these hyperparameters are k (number of neighbours used), the distance metric. 5 of the works reviewed used cross-validation to select the value of k, while the other omitted how it was chosen. The value of k varies from work to work (and in some cases from emotion to emotion), as expected, since this value will depend on the task at hand, and ranges from 2 to 13. All the papers that specified the distance metric used the Euclidean distance. In Fan et al. [21], the authors used Nested Cross-Validation to pick not only the value of k (1, 3, 9 or 27, in their case) and the distance metric (Manhattan or Euclidean), but also the weighted scheme (uniform-weighted or distance-weighted).

In most works, the authors develop more than one classifier, compare their results and pick the best one. Across the different works, the KNN classifiers are compared to Support Vector Machines (SVM) ([19], [18] and [26]), Linear Discriminant Classifiers (LDC) ([25]), Quadratic Discriminant Classifiers (QDC) ([19], [18] and [25]), Mahanalobis ([19]) and Probabilistic Neural Networks (PNN) ([16]) and the KNN classifier always achieves a better performance.

In Khosrowabadi et al. [20], the authors propose a boundary detection method to label the extracted features which used Self Organising Maps (SOM) for boundary detection. Using this model, they were able to increase the performance of the KNN classifier when compared to one using data labeled by crisp boundary selection.

Finally, in Ullah et al. [22], the authors use the KNN method in a different way. Instead of having one classifier using the data from all the EEG channels, they train one KNN model per EEG channel and combine the results at score level using the sum rule of score fusion. This is, however, outperformed by a K-SVM classifier which uses all the channels.

4 Summary & Conclusion

4.1 Summary

Most of the works report on the number of participants used to record EEG data, and their gender. Only a small number of studies were conducted with a number of participants that is considered statistically significant (30) and a fair gender distribution, with most studies being conducted on data from male subjects.

Images and videos were the main stimuli used to elicit emotions There is no consensus on the set of emotions being categorised, in both the type of representation used (categorical or dimensional) and the number of emotions to be recognised. Furthermore, the type of model being built (inter- or intrasubject) varies across the works.

The device used to collect data, as well as the sampling frequencies, sets of electrodes and the placement system being used varies from work to work. Even though there were several different feature extraction methods being used, most authors used brain waves as features. Artifact removal techniques are usually applied to improve the quality of the EEG signals collected. One common problem in the literature is the lack of explanations about the relationship between the features extracted and the emotions being recognised, which inhibits the readers comprehension of the results.

Generally, there is little detail about the parameters of the classifier as well as the methods used for feature extraction. This makes it so that the results are harder to reproduce and interpret. In the works where the KNN model was compared to other classifiers, it usually outperformed them.

4.2 Conclusion

In this review, I presented an overview of works that propose KNN methods for EEG-based emotional recognition. The main problems found were due to the authors not following some of the best practices proposed by Alarcão et al. [8]. Following these steps would allow the authors to achieve more reproducible and high quality results. Finally, it is important that future research, not only follows this set of best practices, but also focus on intersubject models, as these have a higher applicability.

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