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On Digital Multimedia and Human Emotions Using EEG-Based Brain Computer Interface

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Abstract. An expanding attention regarding human emotion is a pressing motive towards the current research in neuroscience and artificial intelligent. People need to communicate by exchanging information through verbal or nonverbal communication via sound, visual gestures (facial expression or hand/body gestures). In today's society, digital multimedia is one of the essential elements in daily life activities that can emphasize communication and emotions adequately. People with severe motor disabilities have difficulties in communicating and showing their emotions directly. Therefore, brain computer interface (BCI) can be a helpful tool as an alternative and assistive communication tools for sharing emotional information. This paper has conducted a review analysis to present the current trend in using digital multimedia to express the human feelings for the latest five years. Twenty-nine studies were selected from IEEEXPlore, PubMed and ScienceDirect, and classified into three major categories: methodology, multimedia type and number of emotion classes. The results show the need for more case studies and games in this area. There is also a need to increase the quality and quantity of research in emotion using the electroencephalography (EEG).

Keywords. Brain computer interface, BCI, Human emotion, Digital multimedia, Electroencephalography, EEG, Review.

1. Introduction

Communication is one of the essential tools to deliver messages and exchange information. It can be either human to human communication or human to machines/devices interaction. Some people might not have full abilities or capabilities to communicate directly because they lost control of their voluntary muscles, such as people with severe motor injuries. Technologies have dependably been helpful instruments for this matter for collecting the information to communicate based on noninvasive brain waves using biosignals measurements such as *electroencephalogram* (EEG) [1] or *magnetoencephalogram* (MEG) [2]. Recently, brain computer interface (BCI) had risen as a popular field cross the multidisciplinary work. BCI system is moreover characteristically connected with the human brain because the brain is the primary and critical part that makes human system functioning [3]. Today's technologies even promise a variety of tools to help people with information. Progressively the video, audio, and text are widely used as tools for communication using BCI [4]. Other than that, the BCI can also be implemented in the real time environment and applications [5,6,7,8].

BCI is being mostly used in the rehabilitation process especially for people who had severe motor injuries. Previous research [9] showed that BCI can help people perform hand movements to communicate, and can restore the motor and sensory function for finger movement [10]. BCI can also be used in games for health-related project and communication. For instance, Brainio Bros 300 is a game that allow two players to communicate using BCI [11]. By playing this games, someone's intention, impression and action can be predicted. Emotions play an important contribution in communication. Emotions can imitate the human intention [12] to inform others about their feelings. The amygdala part in the brain is associated with emotion centrality, so emotion and brain have a connection to react to some of the events [13]. This happens especially when retrieving emotional events, whether they are pleasant or unpleasant ones [14]. Emotions play also essential parts in interaction, impression and decision-making. People tend to show their passion based on an emotional event. For example, people will be sad if someone is passed away. They can also be sad if they see a picture or image of people that already passed away. Digital multimedia can help to increase the way of human emotion [15] especially for the impaired people. Brainwave can be one of the tools that can be showing and detecting their emotion-based on digital multimedia, e.g. pictures, audio or text.

This paper aims to review the adaptation of digital multimedia with emotion based on BCI using only the EEG method. Based on the previous research by using EEG method is helpful, safe, and modest. The most significant EEG does not hurt the subject. It involves recording and analyzing the artifact of the brainwave. This survey of literature presents the fundamental foundation of emotion using the common digital multimedia in BCI such as pictures and videos. This paper aims also to investigate the current patterns of using digital multimedia for retrieving the emotion to propose further direction. The rest of the paper is organized as follows. EEG and emotion are explained in Section 2. While Section 3 describes the method used. Section 4 summarizes the results and discussion and conclusion are presented in Section 5 and 6, respectively

2. Emotion

Research on emotion recognition is rapidly increasing due to the era of artificial intelligent [16]. Many numbers of experiments have been done, and system have been designed for various application specifically for human to interact with computer or devices on an emotional level. The essential target of emotion recognition is to transform the signals and interpret the information and feelings. Emotion itself can be clustered into three categories which are: (i) arousal and valence; (ii) primary emotion; and (iii) secondary emotion. Arousal and valence for two-dimension to measure effective experiences. While the six primary emotions, the feelings that prompt in response to an event are happiness, sadness, disgust, fear, surprise and anger [17]. The secondary emotion is the reaction based on the primary emotion such as optimism, irritation or nervousness. For instance, if a student gets good marks in examination, s/he feels happy and because of this, s/he is more motivated to do well next time. Here, happiness is the primary emotion and motivation becomes the secondary emotion. Plutchik et al. [18] proposed the three-dimensional emotion that arranges the emotion in the circle where the inner circle is primary emotion while the outer circle, which is more complex, represents the level of intensity for each of the emotions. Example: the inner circle is grief and the outer circle is pensiveness.

EEG signals can relate to emotional changes and identify the current state of human emotion especially for the impaired people who cannot express their feelings. EEG is considered one of the crucial tools to detect emotion directly from the human brain [19]. From a psychological perspective, especially for autism patients, it is difficult to communicate and transfer the information to them. Hence, their emotion plays a significant contribution during transferrable knowledge and therapy. Additionally, observing their feelings can help people around them understand and fathom their behavior. Overwhelmingly, many researchers focusing on emotion recognition have applied the EEG for reading the stimulus [20,21]. Some of them used several machine-learning algorithms to classify the emotion based on EEG [22,23,24,25]. However, they used a survey to study the impact of multimedia EEG-based tools on recognizing emotions [26] but they did not provide further direction on multimedia contents.

Nowadays, multimedia plays a vital role in society, especially in communication, learning, entertainment or professional work. Barletta et al. [27] showed the invention to control the emotion while presenting the multimedia content. Byun et al. [28] using music to investigate the characteristic for the EEG pattern to analyze emotion and Tseng et al. [29] proposed the multimedia controller to choose music based on the prevailing emotion. Likewise, a video clip is used to interpret emotions while watching the video [30,31].

3. Method

This paper followed the guidelines by Preferred Reporting Items for Systematic Reviews and Meta- Analysis (PRISMA) specification [32]. The electronic search online database was performed to find candidate papers from the following database: PubMed, Science Direct and IEEE Xplore to locate publication dealing with emotion and multimedia in the BCI area using the EEG signal. The reason for searching papers from 2015 to 2019 is because we want to analyze the current trend in terms of digital multimedia. The primary keywords used were: “emotions” AND “EEG” AND “multimedia”. Only full text with the English language were selected. The search was limited to the title, abstract and keywords.

The main inclusion criteria were: (1) The healthy participants can be volunteers or a patient, (2) The tools to recognize the emotion must use the digital multimedia elements, (3) Using only the EEG method. The articles of the following exclusion criteria (EC) were not included in this paper: (1) expert opinion and book chapter; (2) physiological signal or biosignal as a task, such as focus on doing the exercise and physical movement to detect the emotion; and (3) not focusing on emotion as the final outcomes. A descriptive analysis table was built to extract significant information including the classes of emotions, methodology and multilmedia types. The categories of emotion did not focus on primary emotion but secondary emotion as well as the dimensional models of emotion. While the methodology was concerned about the type of research such as experiments, case study or questionnaire, other elements being considered in this paper were tools of digital multimedia.

4. Results

After retrieving all the articles from three digital databases, 218 articles were identified that included the searching keywords. Only 29 articles satisfied the inclusion criteria and were selected for review. The remaining articles were discarded because they fulfilled the exclusion criteria. The overall result of this paper is presented in Table I.

Figure 1 shows the diagram of selected studies. Uzun et al. [33] classified the emotion using multimedia but not with EEG as a conventional method, while [34] applied the EEG but focused on classifying the ethnic-based on music. Tech et al. [35] and Mothes et al. [36] experimented with the multimedia and EEG for depression for mental illness and healthy exercises, respectively.

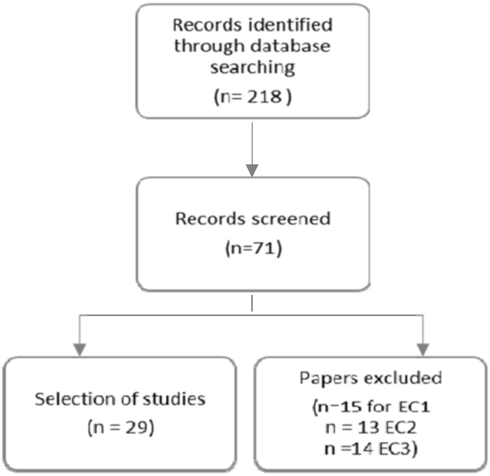

Figure 1. Flow diagram of study selection

Figure 2 shows the proportion of methodology being used in the selected articles. The majority of the selected articles (82%) used experiments to classify or recognize human emotion. Five articles combined both questionnaire with experiment. Only one paper used a case study in which the participant is a game player whose emotion is examined after the game and after killing enemies. The reason because to match the evaluation with the result using EEG since emotion can be very subjective and hard to identity.

Table 1. Characteristic and result of Included Articles.

Author	Methodology	Multimedia Type	Emotion class
Mohammadpour et al. [37]	Experiment	Pictures	fear, sad, frustrated, happy, pleasant and satisfied
Pan et al.[38]	Experiment	Pictures	happy and sad
Shahnaz et al. [39]	Experiment & Questionnaire	Music Video	valence, arousal, dominance and liking
Mehmood and Lee [40 ,41]	Experiment	Pictures	happy, calm, sad and scared
Raheel et al. [42]	Experiment	Mulsemedia	happy, relaxed, sad, and angry
Xing et al. [43]	Experiment	Video Clip	arousal and valence
Syahril [44]	Experiment	Video Clip	sad, fear, happiness and disgust.
Katsigiannis and Ramzan [45]	Experiment	Video Clip	valence, arousal, and dominance
Soleymani et al.[46]	Experiment	Video Clip	arousal and valence
Yoo and Hong [47]	Experiment	Pictures	arousal and valence
Ntalampiras et al [48]	Experiment	Music	arousal and valence
Abadi et al. [49]	Experiment	Music Video	valence, arousal, and dominance
Al Madi and Khan [50]	Experiment & Questionnaire	Video Clip Text	arousal and valence
Ding et al. [51]	Experiment	Video Clip	arousal and valence
Miranda-Correa and Patras [52]	Experiment & Questionnaire	Video Clip	arousal and valence
Antons et al. [53]	Experiment	Video Clip	valence, arousal, dominance, liking, quality
Raheel et al. [54]	Experiment	Video Clip	arousal and valence
Clerico et al. [55]	Experiment	Music Video	arousal, valence, dominance and liking
Han et al. [56]	Experiment & Questionnaire	Video Clip	arousal
Liang et al. [57]	Experiment	Video Clip	arousal, valence, dominance and liking
Kaur et al. [58]	Experiment	Video Clip	calm, anger and happiness
Qayyum et al. [59]	Experiment	Video Clip	happy sad, neutral, love, angry, surprise
Gauba et al. [60]	Experiment	Video Clip	valence
Riaz et al. [61]	Experiment	Pictures	arousal and valence
Kurbalija et al.[62]	Experiment	Speech Music	angry, fear, happy, neutral, sad, and surprise
Singhal et al. [63]	Experiment & Questionnaire	Video	happy, sad and neutral
Stein et al. [64]	Case study	Game	arousal and valence
Gupta and Falk [65]	Experiment	Music Video	arousal, valence, dominance and liking

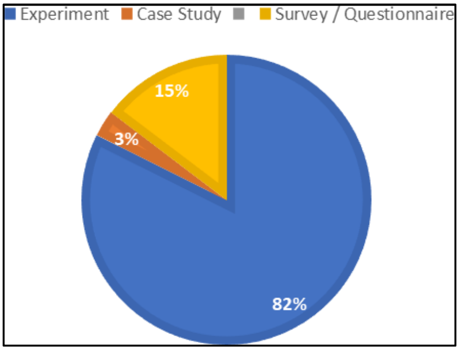

Figure 2. Methodology

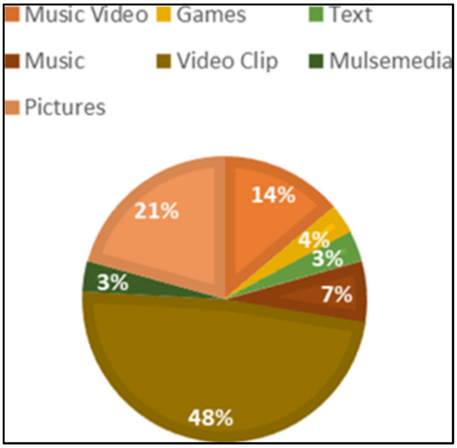

Figure 3. Multimedia Type

Figure 3 presents the multimedia types identified in all the selected studies. The majority of the human emotion based on digital multimedia are empirically evaluated using the video clips. Music videos and pictures were mainly conducted during the experiments. Text, games and mulsimedia were used in a few papers. Figure 4 illustrates the categories of emotion identified in the selected papers. The emotion was classified and recognized based on two class of model dimensional (arousal or valence), 4 class of model dimensional (arousal, valence, liking and dominance), primary emotion and combination within primary and secondary emotion. Many kinds of research focus on classifying the emotion within two classes that belong to arousal and valence. Additionally, other class such as only valence or only arousal also become the major contribution for human motion with 13% equally with two models dimensional. This class belongs to emotion that being classified or recognized using one emotion, which can be either valence or arousal, or classified the emotion into three categories: arousal, valence and dominance. The combination between primary and secondary emotion was identified only in 3% of the selected papers.

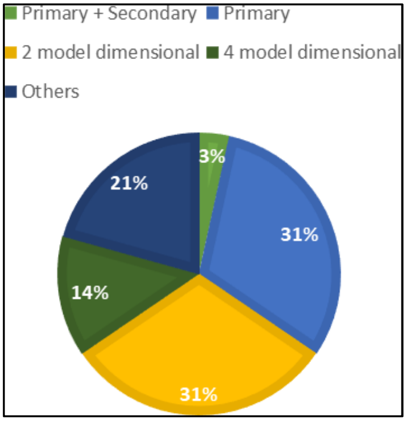

Figure 4. Emotion classification / recognition

5. Discussion

The study of emotions crosses disciplinary boundaries with the contribution and collaboration between medical, psychology, education, and entertainment. Human emotion is a research topic that has implications to be extended to future technologies with artificial intelligence [66]. Digital multimedia is now progressively used in every single aspect of human life. However, individual affection for multimedia elements can affect emotions and daily life performance. This paper investigated the current trend of different multimedia elements for the future direction to identify human emotion. Despite the fact that multimedia and emotion are becoming increasingly important, only 29 selected studies discussed the usage of digital multimedia that can erupt emotions. This might be due to the search keyword used since we used the general terms of “multimedia” rather than using the specific multimedia keyword such as “Games”, “Music” or “Video”. The majority of the selected studies used experiments to handle EEG and classify feelings.

The results showed also that video clips consisted of the majority of tools to perform emotion recognition [43,44,45,46,51,52,54]. This can be because video is the most popular digital multimedia, which includes audio and continuous images. In this case the emotion is triggered based on two media at the same time. Only [42] used mulsemedia combined with the action of smelling while watching the video during an experiment. Text [50] and games [64] are less favorable to be tested for human emotion. The reason might be because nowadays more people communicate with emoji or .gif rather than direct text. The quantity of the games as multimedia elements can be increased to identify the human emotions due to the demand. Most of people spend their free time playing video-games. Future games can be developed to control human emotion. In line with this paper, the emotion can be classified into few categories which can be extended to include more complex human emotions. More research is needed to study human emotion that relates to digital multimedia. In future work, we intend to conduct an EEG experiment in this topic.

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