A Review of an Invasive and Non-invasive Automatic Confusion Detection Techniques

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Abstract. Human mind confusion was found one of the primary causes of minimal execution in any type of everyday assignment that requires reasoning or during any learning process. Detecting confusion is important, and it plays a vital role in student e-learning environment. Detecting confusion by computerized machinery is challenging since it requires artificial intelligence methodology, and it has many advantages, which are highlighted in this work. The computerized confusion detection techniques are classified into two categories, sensor based and extraction of facial visual cues, in the paper, with elaborating on their details. The different confusion detection techniques that have been used in some previous research works with their classification technique, number of participants, accuracy and feature type were listed and compared to investigate the better technique, and recommendation was stated. This review would absolutely rapid researchers to supplement their efforts towards the expansion of automatic confusion detection systems.

Keywords— Confusion Detection; EEG; EMG; Eye movement; Facial expression extraction; classification.

1. Introduction

People examine confusion feeling when the received information does not make any sense causing uncertainty. Feeling confused occurs when an information does not match with what person believes/knows, or due to receiving vague information.

Meanwhile learning and studying process, e.g. classroom environment, many emotions are produced, and they have positive or negative effects on learning. Usually, confusion feeling takes place during learning process. So early studies by Pauli 1960 [1] involved in confusion and problem solving followed by Rozin [2], silvia [3] and Conati [4] studies, all concerned in confusion using different technique to explain this emotion. D’Mello [5] showed that confusion is an effective state that is highly relevant to learning and problem solving during device comprehension. Later for same year Andres [6] investigated the interplay between confusion and in-game behavior among students using Newton’s Playground (NP). Although it feels undesired, confusion holds many benefits since it has been proven advantageous for learning [7], such an attempt to induce confusion during learning was introduced by Lehman in [8,
As computerized machines and devices are invading the human daily life, the facial Confusion Detection System (CDS) has been investigated through many research works over the past years for many goals. Accordingly, artificial intelligence and machine learning techniques have been proposed and adopted. The automatic confusion detection systems/techniques elevate the intelligence level of any computerized system since it works on providing solution quickly for the confusion before the subject becomes frustrated or bored.

Facial recognition systems nowadays became ubiquitous and more powerful, which gave positive progress for deep learning techniques, technological advances and big data manipulation. This advancement has pursued from the development of face detection techniques and software [12], which allocate face features, such as “eye gaze, mouth smile … etc.” [13, 14] and compare them to unchanging posture/state according to certain model/mechanism, such as iris detection and 3-D head modelling [15]. However, confusion may not be an obvious emotion since there have been some facial cues related to other emotions as well as confusion, such as furrowing of the eyebrows and tightening of the eyelids [16], [17].

In this paper, several techniques for confusion detection are presented, and an overview of many methods used for confusion detection is given. Before detailing the types of confusion detection in section 3, next section demonstrates the advantage of such studies, while section 4 will provide a short review for some previous works, with their number of participants, classification techniques and accuracy achieved, and the listed works will be compared per the different confusion detection techniques to reach an overall final conclusion.

2. Advantage of confusion detection system (CDS)
In computer-aided classroom environment, despite its many advantages, it is difficult to achieve the opportunity to provide synchronous face-to-face human interaction. It is therefore difficult to reply with encouragement or guidance to students to support their progress when they are lost and become confused. Problems that lead to confusion through learning can be either productive or unproductive. It depends on the structure and relationship within a computer-aided learning environment between a set of variables. This include the type of learning activity, the area of learning and individual differences between students, such as how students interact with problems and their capacity for self-regulated learning. Several researchers have focused on this side in attempt to detect learner’s confusion as found in [18–20], also in Massive open online courses (MOOCs), where struggling students do sometimes ask for help by raising comments to the discussion forums. So establishing confusion detection system improve student retention in MOOCs as investigated in [21-25].

In more details, students will step into the confusion zone as long as they are properly involved, but they encounter the impasse to be confusing. On one hand, the student will have ample metacognitive knowledge if this happens in a productive manner, and will use skills to interpret the confusion as a signal to changing strategy. The state of disequilibrium will be successfully overcome, and there will be logical change, which lets students move on to another learning problem. In the other side, if the confusion remains permanent, then students may transfer into a sub-optimal confusion zone. When this occurs, the confusion becomes unproductive which leads to potential frustration and/or boredom [26]. Therefore, confusion detection systems can effectively increase student engagement within digital learning environment as Arguel discussed in [27, 28] and Richey in [29].

Another study shows that confusion reflects a loss of understanding or, in a dynamic environment, a loss of situation awareness (SA). Confusion that resulted from misunderstanding the instructions of operating a device can delay mastery, increase training costs, or, more critically, produce an operator who does not have the correct equipment understanding. SA is critical to successful monitoring and controlling an operational environment when it is crucial to understand performance threatens to maintain safety. For instance, loss of SA in air traffic controllers leads to an increased number of errors,
with potentially deadly consequences [30], and driver confusion status detection [31]. To summarize, CDS is very useful for interactive operational environments. Because of cognitive limitations and lower health literacy, many elderly patients have difficulty in understanding verbal medical instructions. Automatic detection of facial movements provides a nonintrusive basis for building technological tools supporting confusion detection in healthcare delivery applications on the Internet [32], also allows the detection of space confusion of people with Alzheimer disease [33].

3. Confusion detection techniques

Some of the confusion detection techniques will be reviewed in this section, with demonstrating their classification techniques, number of participants and the accuracy achieved. They have been classified into two categories, sensor based (invasive) and extraction of facial visual cues (non-invasive). The latter will also be classified according to the facial feature/area being tracked into two types: eye movement and facial expressions. In general, the confusion detection system stages are as shown in Figure 1 below.

![Figure 1. Confusion detection system configuration.](image)

3.1 Sensor based technique

Electromyography (EMG) and electroencephalogram (EEG) systems have been utilized in confusion detection techniques. These are considered invasive techniques to detect confusion since they require connecting sensors to the participants’ body during the experiments. One of the previous research works conducted by Durso investigated a confusion detection system using EMG. EMG works on sensing the electrical activity of the detectable facial musculature related to confusion. Twenty-four participants monitored with EMG while they listened to a confusing audio passage. The EMG system revealed confusion in 21 participants with accuracy of 87.5%. Although several participants did not confess feeling confused, their confusion attitude expressions differed from casual expressions extracted through the experiment. Accordingly, the EMG system was able to tell the difference, the system proved its efficiency in detecting confusion [30]. Another study by Ni investigated EEG signals where "Bidirectional LSTM Recurrent Neural Networks” were used to classify students’ confusion during observing (online course videos). The assumption considered that confused people EEG signals would be diverge from normal state signals. The findings showed that it is possible to build a model to recognize if a person is confused or not and analyze the continuous data. As confusion categorized to ‘true or false’, the two class classifier has been used in order to make use of “EEG data’s properties.” The accuracy achieved in that study was 73.3% [34]. Another work represented by Zhou for detecting confusion by employing EEG system. EEG-based Brain Computer Interface was the initial stage for confusion observation and interfering for learning process. 16 participants’ EEG data were recorded and processed. The obtained raw EEG data using Emotiv headset was proposed within fifteen seconds. The results revealed 71.36% accuracy [35]. For the EEG or EMG based confusion detection systems mentioned above, the system configuration was as shown in Figure 1.

3.2 Facial visual cues extraction technique

Tracking the eye movement and facial expressions extraction have been used as other confusion detection techniques.

3.2.1 Eye movement based technique
DeLucia presented a methodology for eye movements tracking to recognize user’s confusion during testing/using two fabricated devices, which were given them to finish the same assignments. However, the two devices were different in their individual ratings. Consequently, sophisticated and unsophisticated users managed 9 assignments with each device while measuring their performance and eye movements. The study yielded 15 unique eye movements, which provide database for improving predicting and identifying eye movement based confusion detection framework, and eventually, building products that help to avert confusion [36]. Another work represented by Pachman for confusion detection using eye tracking in digital learning environment (DLE) [37]. 14 participants dealt with 2 confusing visual digital puzzles. The participant’s eye trajectories were tracked and the data were recorded. His investigation used multiple measures like calculating the time that the eye trajectories are fixed; time elapsed to solve the puzzles, and self-rating participant evaluation. Amaël [38] proposed another work aimed to check if human computer contact will provide accurate indicators of the epistemic emotions of learners and, in particular, the level of confusion, using visual logic puzzles to construct complex problem-solving tasks, using visual logic puzzles to create complex problem-solving tasks. Where the number of puzzle clicks per interval could indeed be an indicator of confusion. Eye tracker and a computer used to record interaction with the puzzles from 31 participants. More recent study represent by Hucko [39] consisting of two modalities-mouse movements and user eye movements for confusion detection. Where the normal interaction between users and a real world web application were recorded for 60 participants, users prefer to click the confusion button 80 per cent for the entire duration of the application task.

3.2.2 Facial expression extraction based technique

Many techniques based on facial expressions extraction have been utilized for confusion detection due to simple and uncomplicated processing, which include less cost and higher accuracy. For these techniques, the general confusion detection system configuration that was shown in Figure 1 can be also applied with different type of input, image or video. A forecasting model introduced by Grafsgaard for detecting confusion combined dialogue moves, task performance, and facial expression by using Hidden Markov Models (HMMs) as the classifier [40]. The developed model incorporated student chat, task progress, and the facial expressions to predict confusion. The results of fourteen videos showed that predicting student confusion with HMMs can be presented by the Fourth Action Unit (AU4), shown Figure 2, according to the Facial Action Coding System (FACS). This outcome has combination of both essential inquiry of audience emotions and confusion prediction while tutoring. Using FACS AUs properly gives positive results since each AU is associated with a specific set of facial muscles. Accurate geometrical modeling and tracking of facial features leads to better recognition results.

![Figure 2. AU4 displayed by students [40].](image)

Other studies give the efficiency of employing facial expression extraction technique for confusion detection according to the number of participants. For instance, recent study by Shi [41] yielded effective results to recognize confusion for academic 82 students, using a method combining two classifiers, Convolutional Neural Network and Support Vector Machine (CNN-SVM), achieving an accuracy of 93.8%. For facial cues extraction confusion detection technique, different types of classifiers have been used and investigated for previous research works. The robustness and Precision of these classifiers
depend on the proposed system for each study and changing by one of most effective factors that effect on establishing a reliable confusion detection system, which is the number of participants that effect on the resulting accuracy as the number of participants increased. Examples of previous works that concerned in study the effective state detection in learning environment [42-47]. While the classifiers that most commonly used and achieved a considerable good accuracy are discussed by Nayak, Melgani, Hearst and Tomar who explained SVM type classifier [48-51], while Razavian and Bluche for CNN classifier type [52, 53], and Rabiner with HHM type classifier [54].

4. Comparison of the different confusion techniques
Many of the earlier works have gathered the datasets through interviews and online courses. The datasets used in previous works are not publicly available and are different from the collected data sets used in each work, and for this reason, there were difficulty in comparison. The comparisons were made depending on the participant’s number and the detection accuracy, since the comparison according to methods, which were employed, the algorithms, the classifiers, and features number is difficult to make. Now After demonstrating the two confusion techniques, sensors based and facial visual cues extraction, with their details and bifurcations, some previous studies are listed in Table 1 with their used classification technique, number of participants, accuracy and feature type for comparison purposes.

Table 1. List of previous confusion detection works.

| References | Confusion detection technique | Number of Participants | Accuracy | Feature type |
|------------|-------------------------------|------------------------|----------|--------------|
| [42]       | FEE a ( AT b)                | 34 p / 28 v            | 64%      | Feeling puzzled & struggling to understand |
| [44]       | FEE ( AT)                    | 28 p                   | N/A      | AU c 4, 7 and 12 |
| [43]       | FEE ( AT)                    | 7 p                    | 87%      | AU 4, 7 and 12 |
| [45]       | FEE ( AT)                    | 28 p                   | 76%      | Pressure features, emotion and judgement |
| [46]       | FEE ( AT)                    | 28 p                   | N/A      | Self judgement, BPMS d and Motion tracking system |
| [40]       | FEE (HMM classifier)         | 14 v                   | 86%      | AU4 |
| [30]       | EMG                           | 24 p                   | 87.5%    | EMG data |
| [55]       | FEE (CERT e)                 | 67 p                   | 85%      | AU4, AU7 |
| [47]       | FEE (CERT )                  | 99 p                   | N/A      | AU1, AU4 |
| [36]       | Tracking eye movement        | 20 p                   | N/A      | 15 different eye movement |
| [37]       | Tracking eye movement        | 14 p                   | N/A      | Gaze trajectories and fixations |
| [34]       | EEG (LSTM)                   | 10 p                   | 73.3%    | EEG signal |

References:
a - AT = Affect Tracking
b - CERT = Cognitive Engagement Recognition Technique
c - AU = Action Unit
d - BPMS = Biographical Profile of Motivation and Self-regulation
e - LSTM = Long Short-Term Memory

(All references are from the text provided.)
Table 1 listed 18 previous works on chronological order, from past to recent. Looking at the first research works that employed FEE using AutoTutor system to study the effective state for confusion detection in learning environment between the years (2004-2011) Craig [43] achieved the higher accuracy of 87% but with small participants’ number. Later by utilizing HMM [40] and CERT [55] classifiers in Grafsgaard works yielded 86% and 85% accuracy, respectively, while Sawyer [56] achieved 75.8% using tracking system called iMotions. Borges [57] work yielded 81% accuracy by using LSTM classifier and Shi [41] 93.8% with relatively high number of participants using a combined method of two classifier CNN-SVM. Accordingly, Shi’s technique is considered the better technique compared to other work. On the other hand, sensor-based technique introduced by Durso [30] using EMG technique achieved an accuracy of 87.5% while Zhou [35] utilizing EEG technique yielded an accuracy of 71.3%. The unique combination technique of Ni [34] by using EEG with LSTM classifier did not give higher accuracy level (73.3 %) compared to the other works. Since DeLucia [36] and Pachman [37] works, which concerned eye movement tracking method, have no accuracy evaluation, they cannot be considered for comparisons. While two other recent work proposed by Arguel [38] and Hucko [39] respectively, the latter one yielded an accuracy of 80%. The illustration of table 1 above states that the non-invasive techniques showed higher performance results compared to the invasive ones listed. However, invasive techniques may give inaccurate information because it requires connecting sensors to the participant’s body, which makes the participant confused/anxious during experiment. While this potentially can give false misreading sensor signals leading to confusion detection miss-predication, the non-invasive techniques has no restriction for the working environment, i.e. ordinary room state, with the presence of the camera. Thus, non-invasive techniques give more accurate results since they do not cause any side effect emotions that can adversely impact the experiment.

5. Conclusion
The advantages of detecting students’ confusion in student e-learning and interactive operational environments, along with health care application were discussed. The confusion detection techniques were categorized into two types whether they require invasion, by connecting electrical sensors, to the participants body or not, in a detailed discussion. Eighteen previous works which used different techniques were listed and compared. Comparing confusion detection accuracy for these works depending on the classification technique, number of participants, and feature type, it was found that the non-invasive techniques yielded better results. In addition, the invasive techniques accuracy evaluation can be tricky and not reliable since it is side affected by the state nervousness of the participant due to attaching body sensors.
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