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Eye Tracking Analytics for Mental States Assessment – A Review*

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Abstract— **With the increasing demands on mutual understanding between human beings and advanced systems, objectively measuring and monitoring human mental states in a non-intrusive way has been a hot topic in recent days. Eye-tracking data has long been found to be a kind of suitable bio signals in measuring human mental states, as visual is the first channel of information collection and eye-tracking data shows the process of human-system interactions. Traditionally, many studies have been conducted to confirm the correlations between eye-tracking data and human mental states. Recently, with advanced artificial intelligence algorithms, the spatial and temporal patterns of eye-tracking data can detect human mental states. This study aims to explore and review eye-tracking parameters and state-of-art methods for mental states assessments. The study reveals that most of the studies focused on using statistical methods to process eye-tracking data. While novel methods, such as machine learning and deep learning are important aspects in strengthening eye-tracking analytics owing to their ability in dealing with dynamic and noisy data. Besides, novel features extracted from eye-tracking data, such as gaze-bin and entropy may greatly improve the performance in assessing human mental states.**

I. Introduction

With advanced manufacturing capability and ubiquitous sensors, smart objects, which can sense the dynamic environment and make context-dependent decisions surrounds human beings [1]. These smart objects have induced substantial changes in almost all aspects of our daily life, such as shopping, educations, and transportation. For example, online shopping websites, like Taobao and Amazon can provide customized recommendations based on our shopping and view history. The automation car can drive independently with computer visions to avoid the collision. In a word, the objects seem to be smart to understand their surrounding environment. The capability is also term as context-awareness. Recently, researchers tried to improve the context-awareness of smart objects and found out that human mental states are the most uncontrollable and most complex variables in the environment [2].

Mental states are the inner fundament of every affective and/or cognitive manifestation [3]. Mental states include fatigue [4], vigilance [5], workload [6], and attention [7]. In addition, affective state relates to the emotional state of the learner including uncertainty is regarded as a kind of mental state, too [8]. Too many influencing factors, such as culture difference, age, gender, experience, health, and personality affect the mental states of human beings [9]. Hence, recently, several studies have been conducted to assess and monitor dynamic human mental states in real-time [5][10]. These studies can provide foundations for enhancing the understanding of smart objects in human beings. Among these studies, eye-tracking-based human mental states assessment received considerable attention owing to the special attributes of the eye-tracking data [10].

Eye-tracking data are normally including eyelid movements, gaze movements, and pupil changes [11]. The gaze movements show where the users are looking at and how users interact with the world. Hence, gaze movements can serve as a window into the brain. Also, the eyelid movement and pupil changes can hardly be controlled by our mental model. Hence, the eye-tracking data can provide objective and accurate information. The correlations between eye-tracking data have long been studied. Though many studies have confirmed the significant correlations, simply setting a single threshold, or using linear regression cannot achieve performance in measuring human mental states [10]. Hence, researchers proposed to use some state-of-art methods, including machine learning and deep learning algorithms to deal with the eye-tracking data [12].

To fully understand the efficiency of using eye-tracking to assess human mental states, we conducted a literature review on the related journal papers published after 2009. The eye-tracking parameters, the analytical methods, and the mental states are fully analyzed. Currently, the concept of monitoring human mental states has only been investigated in the laboratory. There is still a long way to go to achieve the applications in practice. It is expected this holistic review can provide references for both practitioners and researchers.

This paper is organized as follows: Section 2 introduces the methods adopted for collecting and grouping articles. The eye-tracking parameters for mental states assessment are introduced in Section 3. The statistical analysis, machine learning-based methods, and deep learning methods are presented in Section 4 separately. We concluded this study in Section 5.

II. Methods

A. Paper selection

The literature source includes the Web of Science database and Scopus database from 2009 to 2021. Only journal articles are selected. Two stages were conducted to identify target papers. In the first stage, we defined three sets of keywords presented as follows: ‘‘eye OR eye movement OR

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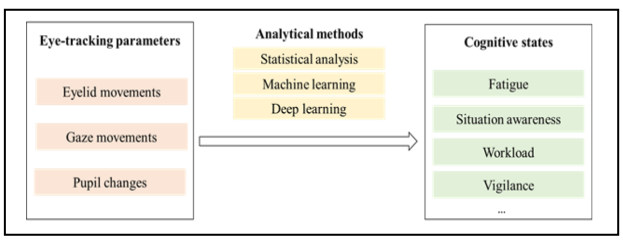
eye-tracking OR eye tracking OR gaze OR blink OR pupil" AND "detection OR monitor OR assessment'' AND ''mental states OR workload OR inattention OR fatigue''. Subsequently, these four sets of keywords were combined using the Boolean operator 'OR.' In the second stage, the authors manually and systematically select the articles that meet the following criteria: (1) did not focus on developing a mechanical eye tracker system, as the focus of this review is to examine the general trends of eye tracker application instead of eye tracker development; (2) used eye-tracking devices; (3) focused on human mental states; and (4) published in English. Finally, 81 papers were selected for this review.

B. *Coding procedure*

The content analysis consisted of two stages. In the first stage, the selected papers were preliminarily coded based on the data collected from different eye components. The human eye includes several components, such as the pupil, eyelid, eyeball, and iris [14]. The activities of these components can be recorded as bio-signals, such as eyelid movement, gaze movement, and pupil changes. Eyelid movement traces the open and close states of the eyelid. Gaze movement refers to eyeball activities. The pupil changes are the changes in pupil size. Thus, a coding scheme for analyzing the topics of the collected articles was developed as shown in Fig. 1. In the second stage, all papers were coded for the analytical methods adopted.

Figure 1. Structure of the review paper



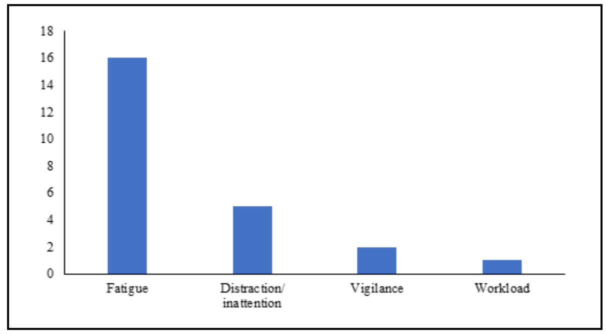
III. EYE-TRACKING DATA AND MENTAL STATES

The features extracted from different eye-tracking data, including eyelid movements, gaze movements, and pupil changes are discussed in the following sections.

A. *Eyelid Movements and Mental States*

Several muscles, such as skeletal eyelid muscles, the orbicularis oculi (OO) muscles, and smooth muscles control the eyelid movements. Environmental factors can stimulate these muscles controlled by different aspects of our brain. Hence, eyelid movements can be induced by various causes, such as fatigue, stress, electrical stimulation, and air puff [13][14][15]. These causes would induce significantly different eyelid movement patterns. For example, electrical stimulation would shortest eyelid movement, while spontaneous eyelid movement had a longer duration [16]. The difference in the eyelid movement patterns provides us chances to infer the causes of eyelid movement, including the human mental states. The eyelid movements can be collected by infrared camera [17][18], video surveillance[19][20], EOG [21], commercialized eye trackers [22][23], front-face-view camera [24], ODMS glasses [25], and so on. As shown in Fig. 2, most studies utilized eyelid movements for assessing human fatigue. While limited studies focused on using eyelid movements for inattention and vigilance [26][27]. Only one study tried to analyze blink duration and blink rate across different levels of mental workload [28].

Figure 2. Number of articles that using eyelid movements to assess mental states



B. *Gaze Movements and Mental States*

Gaze points refer to the instantaneous spatial locations, based on the visual axis, that corresponds to the stimulus. Each gaze points typically have three data points connected to them, an x and y coordinate, and a timestamp [29]. Gaze points are normally the raw outputs from an eye-tracking device. Many commercialized eye trackers can record the gaze points, such as SMI iView [30], Tobii X 120 [31], Eye Tribe [32], Smart Eye [33], Mobileye [34], and Face lab [35][36]. A single gaze point constitutes one raw sample of data captured by the eye tracking device. Multiple gaze points happen in a short span of time, resulting in a cluster, which is known as a fixation. The typical fixation duration is 100-300 milliseconds [37]. The quick and simultaneous eye movements between fixations are saccades [38].

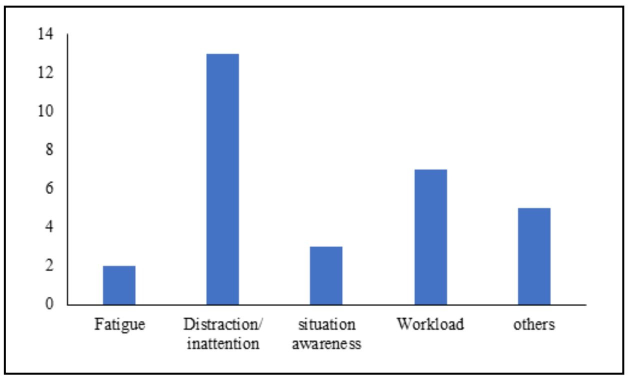
Fixations examine the instances where the eyes cease the scanning process of the environment and hold the central fovea vision in position to allow the subject to observe detailed information on the visual target. A saccade is a particular type of eye movement that involves a rapid movement of the fovea between points of interest [10][5]. Given the fast movements, the image that is captured by the retina is of reduced resolution. Therefore, while the human visual perception is guided by alternating between saccades and fixations, most of the information is captured during the fixation periods [10].

Most features extracted from gaze movements are parameters of fixations and saccades, such as fixation duration [36][39][40], fixation rate[41][31], fixation location coordinates [42][35], number of fixations [6], saccade peak velocity [43][44][45], saccade rate[46], saccade amplitude, saccade intrusion [47], and saccade duration [48]. Some parameters are obtained from the dynamic or static aggregations of fixations and saccades, such as fixation sequences [49], the length of scan path, heat maps [34], and glance duration [50][51]. Fixation sequences are generated based on fixation position and timing information [37]. This is essentially dependent on the area at which respondents are looking and how much time is spent at that particular location.

Besides the parameters of fixations and saccades, researchers tried to extract some parameters of raw gaze points [30], such as gaze rotation [52], dwell time [53], visual scanning entropy [53], gaze velocity entropy [10], gaze transition entropy, dwell time entropy [54][55], vertical and horizontal deviation of gaze [56]. Extracting these parameters does not require the eye-tracking parsing algorithms, which classify the gaze points into fixations and saccades. Hence, using the raw gaze movements as input can minimize the bias effects induced by the eye-tracking parsing algorithms [29].

Fig. 3 shows the number of articles on mental states assessment using gaze movements. It can be found that most studies utilized gaze movements to monitor or assess the inattention level of users. Comparing with eyelid movements, the gaze movements have relatively wider applications. They have been utilized to assess situation awareness [43], user intents [30], monitoring behaviors [57], and mental health [58].

Figure 3. The number of articles on mental states assessment using gaze movements



C. Pupil Changes and Mental States

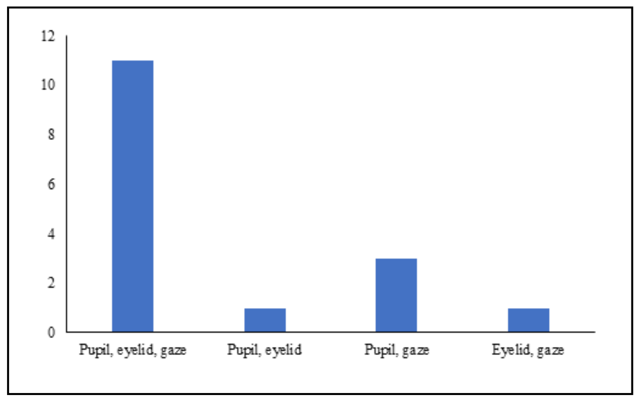
Pupil sizes can be classified into two categories: pupil dilation (increase in size) and pupil constriction (decrease in size). The changes in pupil size are primarily due to the change in light or stimulus material [37]. If lighting conditions can be controlled in an experiment setting, other attributes can be derived from this metric. Emotional arousal and mental workload are two commonly derived properties from the measurement of pupil constriction or dilation [59]. According to the literature collected, only 5 articles utilized pupil variations as the only indicators of mental states. The pupil diameters [59][60], changes in pupil diameters [61][62], and fractal dimension of pupil dilation [63] are calculated as indicators of mental states. In addition, these features have only been utilized for assessing mental workload and alertness.

D. Combined Eye-Tracking Parameters and Mental States

The information carried by different components of the eyes seems to be different. Hence, it is expected that the fusion of eye-tracking parameters can improve the performance in assessing mental states. Most studies combined the features from three aspects, including pupil, eyelid, and gaze movements. For example, a study utilized pupil diameter, blink rate, fixation rate, and saccadic rate as the inputs of Artificial Neural Networks for predicting mental workload in nuclear power plants [64]. Fusion data from the three source were mainly utilized for assessing mental workload [65][66][67][32][68][69] and fatigue [70][33][71]. The fusion of pupil and gaze movements has been utilized to assess fatigue [5], workload [72], and situation awareness [73]. The fusion of pupil and eyelid, eyelid, and gaze received relatively limited attention, as shown in Fig. 4.

According to the analysis conducted in Sections 3 to 6, we can find that the parameters obtained from different eye components seem to have been applied in different mental states assessment. In general, eyelid movements mainly contribute to human fatigue detection, as a fatigued person intends to close the eyes, resulting in long blink duration and high PERCLOS. The gaze movements reveal much more information about mental processes and human-machine interactions. Hence, gaze movements contribute to the studies on attention analysis, such as minding wandering, distraction, and situation awareness. The pupil size has a high correlation with stress and mental workload. Hence, we can find that pupil variations are normally applied in workload measurements.

Figure 4. The number of articles on mental states assessment using fused eye-tracking data



IV. Analytic Methods

According to the collected literature, three main methods were applied in assessing mental states with eye-tracking data, namely statistical analysis, machine learning, and deep learning. Besides these methods, some studies may develop a specific performance model, such as ACT-R model [74] and knowledge-based system [49] to assess mental states. The following section discusses the details of the three commonly used methods.

A. Statistical Analysis

Comparing with the other two methods, the statistical analysis has the longest history in the measurement of mental states with eye-tracking data. Statistical analysis, such as Analysis of variance (ANOVA), confidence interval, Receiver Operating Characteristic (ROC) curve analysis, and t-test/z-test [75][76][77]. Linear models can be used, however, non-linear models can better consider the multi-dimensional and temporal aspects of mental states. There has an increasing amount of research done on multi-variate models such as combining data from different eye components [72]. The statistical analysis reveals the correlations between the parameters extracted from the eye-tracking data and the mental states. For example, the number of fixations of harvester operators working in steep terrain conditions increased with the increasing mental workload [78]. A study based on statistical analysis reported that cognitive load significantly affected pupil diameter under the situation of low perceptual load. When the perceptual load was high, no significant effects on blink rate and pupil diameter [79].

B. Machine Learning

Though the statistical analysis has revealed the high correlations between eye-tracking data and mental states, the correlations are too complex to be directly used for mental states assessment. Recently, many machine learning algorithms have been applied to detect the potential patterns involved in the eye-tracking data [41][30]. With the features of adaptive learning, transfer learning, and active learning, the machine learning algorithms can deal with the inconsistency of the training and testing data sets. The most widely used machine learning algorithms including Support Vector Machine (SVM) [41][48][46][80][81], Random Forest (RF) [71][65], Decision Tree [70], Extreme Gradient Boosting [82][10], Bayesian Network (BN) [42][40], and Artificial Neural Networks (ANN) [30][64][67][66]. Among them, SVM is the most widely used machine learning in this field [83][26]. It minimizes the classification error by maximizing the margin between the closest observations from each class (i.e., support vectors) and the decision boundary.

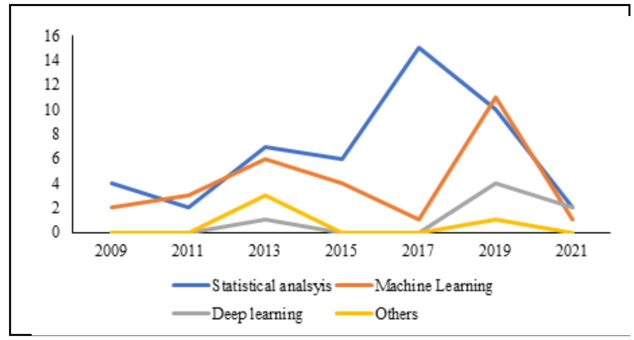
C. Deep Learning

The machine learning methods normally use various preprocess methods to select features as input. The process of feature selection often requires professional knowledge to achieve better performance. To address the manual and expert efforts required in machine learning, some studies proposed to use deep learning and raw eye-tracking data to assess mental states [84].

Deep Learning has already improved many fields, with computer vision being the main area for focus. Generally, recent studies have applied Hidden Markov Models [85], Convolutional Neural Networks (CNN) [86], and Long Short Term Memory [87] in measuring mental states with the eye-tracking data. Among them, CNN has received the most research attention. CNN has a deep network structure and includes convolution calculations. It has an input layer followed by several hidden layers, and then an output layer. The hidden layers are made up of a convolutional layer, pooling layer, and fully connected layer. Gradient descent algorithm is always used in CNN. Thus, it is necessary to normalize the input into the same interval to ensure efficiency. Recently, a study reported that the performance of attention-based CNN-LSTM on driver stress detection can achieve an average accuracy of 95.5%, which is much higher than most machine learning methods [87].

Fig. 5 shows the number of articles assessing mental states with eye-tracking data and different analytic methods. We can find that statistical analysis is the most popular way to analyze eye-tracking data. After 2017, both machine learning and deep learning are receiving research attention. It is expected that the artificial intelligence methods will enable efficient and accurate real-time measurements of mental states in near future.

Figure 5. The number of articles assessing mental states with eye-tracking data and different analytic methods



V. Conclusion

Eye-tracking data have long been proved to be valuable indicators of human mental states. This study discussed the parameters extracted from eye components movements and analytic methods with a focus on mental states assessment. A classification of different eye-tracking data and the corresponding mental states are presented. In addition, we summarize different analytics methods and their strength and limitations. This study revealed that novel artificial intelligence algorithms are important parts of the evolving eye tracking-based assessment of mental states owing to their strength in robust learning, adaptive learning, and self-learning.

This study only provides an overall review on the eye tracking-based assessment of mental states. Detailed analysis, such as the feature extraction and eye trackers devices is not presented. Nevertheless, this study might spark some new ideas for researchers and practitioners in this field.

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