A Survey of Learning Style Detection Method using Eye-Tracking and Machine Learning in Multimedia Learning

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***Abstract*—Current utilization of multimedia learning environment focuses on student-centered approach. This approach is based on a theory stating that learning styles affect individuals in information processing. Based on prior works, there are three main approaches to distinguish learning styles: conventional approach—such as interview and self-reporting, artificial-intelligence-based approach, and sensor-based approach. Unfortunately, there is no comparative analysis that addresses strengths and limitations of these approaches. Thus, there is no information on how and when to use these approaches appropriately. To address this limitation, we present a brief literature review of several studies in distinguishing learning styles, including their strengths and limitations. We also present insights on potential methods of detecting learning styles in multimedia learning based on eye movement data and machine learning algorithms. Our paper is useful as a guideline for developing intelligent e-learning systems based on eye tracking and machine learning.**

***Index Terms*—learning style, cognitive style, eye-tracking, multimedia learning, machine learning**

I. INTRODUCTION

Multimedia learning these days grows at a rapid speed. Multimedia learning includes multimedia presentations and e-learning that are conducted in diverse platforms [1]. E-learning as an information technology advancement supports teaching and learning activities by using computer and networks [2]. E-learning encourages mentors and teachers to reach broader users without any time and geographical constraint [3]. Recently, cognitive processes during multimedia learning open another viewpoint in research of multimedia platforms [4].

Mayer conjectured that the design of multimedia material supports individuals in learning [5]. Cognitive theory of multimedia learning focuses around information processing as cognitive models. Everybody has a unique originality in information processing. Each person's creative process yields individual diversity in learning and thinking process [6]. With regards to education, one approach to portray individual differences is through learning styles [7], [8].

Each student has various degrees of inspiration, mentalities, and reactions in learning. These distinctions influence their learning inclinations [9]. Learning style is characterized as trademark, quality and inclination of people in processing information [7]. Felder and Silverman's learning style model pays attention on students' preference in information processing and understanding [10].

Each incoming information is mentally processed in two different ways: verbally and visually. Based on four Felder and Silverman's dimensions, one significant aspect that affects people in learning is visual-verbal dimension [11], [12]. This dimension is also usually described as visualizer-verbalizer style. Visualizer style is discovered in people who generally think in pictures. On the opposite, verbalizer style is discovered in people who generally think in words. When an individual understands how to utilize textual and pictorial contents, the cognitive style of the visualizer and verbalizer can affect behavior, preferences, and learning results [8].

Cerebrum function during information processing is one of important factors in understanding learning styles [13]. The left side of cerebrum prefers learning in a sequential format and tends to be more analytic. Sequential format begins from the subtleties to get a handle on applied comprehension. In the interim, the right side of the cerebrum tends to be more holistic or encompassing general ideas [14]. In agreement with the dominance of sequential-left cerebrum or global-right cerebrum, Felder and Silverman's learning style model has a dimension of global and sequential learning styles identified with information understanding [15]. Contrast in learning style dimensions shows diverse learning procedures and various types of students collaboration in utilizing multimedia learning platforms [16].

Various approaches to distinguish learning styles have been proposed by several researchers. Conventional methodology is applied to determine learning styles from students. This methodology includes self-reporting, behavioral assessments, and interviews to investigate cognitive activities in multimedia learning. Unfortunately, these techniques are unable to capture temporal fluctuations in cognitive processes [5], [17].

Another methodology known as automatic detection is carried out to distinguish students' learning styles (i.e., artificial-intelligence-based approach). The learning style detection pro-

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cess is conducted by gathering data from students' interactions with a multimedia learning system during a specific period [18]. Computerized reasoning techniques based on artificial intelligence are then used to automate detection of learning styles.

The third methodology is sensor-based approach. Audio-visual sensors such as camera and microphone, even biometric sensor (heart rate, galvanic skin response, and EEG) are implemented in learning style detection. Initially, biometric sensors were limitedly used in the laboratory environment because of high-cost maintenance. However, recent technology advancement has provided low cost and highly compatible biometric sensors such as screen-mounted eye-trackers or simplified head-mounted EEG for widespread utilization [19]. Usage and analysis of eye movement data have burgeoned into a specific field related to human cognition, especially investigating individual differences based on learning style. Eye movement is related with human cognitive function [3], [20]. Eye movement data can be used to investigate individual gazes and attention toward multimedia content to understand the cognitive processes during learning experiments [20]–[22].

Compared with other audio-visual sensors, eye-tracker seems to be more effective and reliable to capture spatial and temporal information during differentiation of learning styles. However, eye-tracker data are limited, because not all eye-tracking metrics are useful to differentiate learning styles. In addition, commonly used heat maps from eye-tracking data require further interpretations from human experts. Unfortunately, there is no comparative analysis that covers these three methodologies—conventional approach, artificial-intelligence-based approach, and sensor-based approach—while highlighting their advantages and disadvantages.

To tackle this research gap, this paper proposes a brief literature review that covers development of learning style detection technologies, their advantages, and their limitations. This paper also provides an insight on data collection through eye-tracking, data preprocessing, and possibility of machine learning implementation on learning styles detection.

II. Learning Style Detection Methods

We used Google Scholar to manually gather articles and choose 15 papers related to our topic. Combinations of the following keywords were used: *multimedia learning, learning style, eye-tracking,* and *machine learning*. We choose papers that were published in academic journals or presented papers in international conferences up to 2019. Collected articles were grouped based on several sub-topics. There were two papers related with conventional approach and five papers related with AI-based approach. Four papers explained the usage of eye-tracking in learning style detection. Last, we reviewed four papers that utilized eye-tracking measures in machine learning to give insight into the new method to detect learning styles in multimedia learning.

A. Conventional approach

Kahtz and Kling [23] discovered the differences in learning preferences and similarities of students who had field-independent (FI) and field-dependent (FD) cognitive styles. Kahtz and Kling used computer-assisted instruction (CAI) programs designed for ornamental horticulture classes. In depth interviews were used as a mean to check students' experiences. Because of different topics and duration, the interviews were conducted in three separate rounds. Each round of interviews focused on a different topic. The first round explored their cognitive learning styles and experiences. The second and third round interviews involved participants in the way they responded to various information that was presented by focusing on the CAI program. These narratives produced abundant sources of information related to perceptions of the students in learning and teaching methods they preferred.

Identifying learning styles with this conventional methods was commonly performed through self-reporting, behavioral assessment, and interviews. In their research, Ang et al. investigated the relationship between global and sequential learning styles [24]. Specific objectives of this study were to explain sequential and global learning styles and to discover whether students' historical understanding and thinking were different from their learning styles. The participants of the study consisted of 40 secondary school students from a National School in Kedah State, Malaysia. Index of Learning Style Questionnaire (ILS) was used as a basic indicator. Moreover, a historical essay writing test was conducted to determine their historical thinking from four categories, such as chronological understanding, making interpretations, expressing opinions with a sense of empathy, and making rationalization. The results showed that there were significant differences between sequential students and global students in chronological understanding.

B. AI-based approach

AI-based approach detects learning styles by automatically gathering and predicting information from students' interactions with an online system. Student behavior is tracked by the system and collected during a certain period [18]. This technique gathers certain data into a holder called the user model. This approach has the potential to be more accurate while reducing the number of errors. This approach also encourages students to be more focused on learning because the process of detecting is done implicitly. Research by Graf et al. [25] introduced two main models within this approach: literature-based models and data-driven models.

1) Literature-based model: Literature-based model uses student behavior to get directions for their learning style preferences. The model applies a simple rule-based method for calculating learning styles from a number of suitable clues. This approach is similar to the method used to calculate learning styles in the Index of Learning Style (ILS) questionnaire. Generic in a sense, the approach applies to data collected from any course, due to the fact that Felder and Silverman's

Learning Style Model (FSLSM) was developed for learning in general.

Researches about cognitive style specifically look for behavioral differences based on cognitive style groups. Chen in his research investigated how a web-based learning program is used by students with different cognitive styles [16]. Analysis is performed on browsing data recorded in log files. Aiming at developing adapted web-based learning systems, this study created a design model to develop systems that fit the preferences associated with each cognitive style. Samples were taken from 105 participants who were third-level students majoring in Accounting Information System. The results of statistical analysis showed that participants with FD (Field-Dependence) and FI (Field-Independence) cognitive approaches had similar learning approaches but used different navigation features in the learning process. This study was still limited in using log files from the web and behavioral analysis using descriptive statistical methods.

Research by Graf et al. [25] analyzed the behavior of 127 students while attending object-oriented modeling lectures using Moodle Learning Management System (LMS). This examination used Felder and Silverman's learning styles (FSLSM) with the underlying phases of filling Index of Learning Style (ILS) questionnaire. The features in the LMS were chosen as the basic forming patterns for detecting learning styles. The most frequent patterns were added up and divided by the sum of all patterns. Meanwhile, Pham and Florea [26] used a system called POLCA to detect FSLSM learning styles in students. POLCA adapted learning materials for students. Learning objects were arranged and adapted to the four dimensions of learning styles. As long as participants was learning, their activities and ways of interacting were detected automatically. The results showed that this method could be used to detect learning styles with fairly good precision.

2) Data-driven model: Automatic detection of learning styles on data-driven models is carried out by AI classification algorithms that take user models as input and student learning style preferences as output. The advantage of this approach is that the model can be very accurate because of the use of real data. However, this approach is highly dependent on data availability. The representation of the data set is very important to build an accurate classification.

Garcïa et al. [27] used the Bayesian network algorithm to detect student learning styles. There were three Felder and Silverman's learning styles detected–Perception, Processing, and Understanding. The Bayesian network used two types of data tables including tables based on analysis of student activity log data and conditional probability tables (CPT). The results showed the effectiveness of the Bayesian network to identify learning styles based on student behavior.

The NBTree algorithm was used by Ozpolat and Akar [28] research to classify student learning styles based on their preference. The extracted data were based on personality factors such as learning styles, behavioral factors such as search history, and knowledge factors such as prior user knowledge. Experimental results using NBTree showed consistent ratio between learning styles that are detected automatically (AI-based approach) and learning styles obtained from traditional questionnaires (conventional approach). These results were consistent for some dimensions of Felder and Silverman's learning styles—73.3% of global-sequential and sensing-intuitive learning styles, 70% of active-reflective, and 53.3% of visual-verbal.

C. Sensor-based approach

Eye-tracking is one of commonly used sensor-based approaches to detect learning styles. Eye-tracking yields spatial information where visual attention is directed [29]. In addition, eye-tracking records temporal cognitive processes in real-time. Eye-tracker has been utilized to see how individuals process information as indicated by their learning and cognitive styles.

Mehigan and Pitt detected students' learning styles through biometric technology that was implemented in a mobile game-based learning [30]. They observed global-sequential learning styles and visual-verbal learning styles. This study used two measurements: accelerometer to measure the acceleration of mouse movements and an eye-tracker to measure eye movements.

Experimental results with the accelerometer showed that in the global-sequential learning style, sequential learners produced a vertical speed that was faster than global learners. However, sequential learners needed more time to arrive at the end of the page. In the verbal-visual learning style, visual learners spent more time in the drawing area than text while verbal learners spent more time in the text area than in images. Eye-tracking research showed that in a global-sequential learning style, global students produced faster eye movement speeds and lower fixation durations compared with sequential students. In the visual-verbal learning style, the visual learner showed a total fixation that was longer than the verbal learner, while the verbal learner showed a longer duration of the fixation than the visual learner.

Liu investigated field-independent (FI) and field-dependent (FD) cognitive style using eye-tracking technology to explore the contrasts between two cognitive styles in the efficiency of visual inquiry and performance in multimedia learning [31]. FI participants were found to be able to surpass FD participants based on post-test results. FI participants were better at identifying visual guides and shown by visual search patterns of different information formats. This study suggested an adaptable multimedia learning system where diverse types of media were afforded, which could be useful for users with different levels of information needs. The utilization of eye-tracking in this study captured how learners processed information according to their cognitive styles.

Tsianos et al. used eye-tracking to identify the behavior of hypermedia users and to validate cognitive styles as parameters of adaptive hypermedia personalization [32]. One of them was the verbal-imagery aspect that was the actual preference in the e-learning display. This aspect precisely identified the type of learner. Participants were 21 people and each person was classified as imager-verbal cognitive style using the CSA test

(Riding and Cheema's Cognitive Style Analysis). Afterwards, participants were asked to participate in an online learning course. During online learning, the eye movement data were recorded. The analyzed eye-tracking metrics were the ratio of eye fixation and tracking, number of fixations on the menu, and duration of the experiment. Results indicated that the cognitive style based on CSA theory was successfully validated using an eye-tracker. The eye-tracker metrics could be used to identify user types and revealed differences in style in information processing. These results are useful as personalization parameters.

Research by Koc-Januchta et al. [8] explored the distinctions between the visual-verbal cognitive style during multimedia learning. A total of 32 participants were classified based on their cognitive style using the Verbal-Visual Learning Style Rating questionnaire, Individual Differences questionnaire, and Santa Barbara Learning Style questionnaire. Participants were requested to study two different topics that represented knowledge of mechanical functions and conceptual knowledge. The choice of topic was chosen to identify patterns of eye movement in two types of contrasting knowledge. Participants' eye movements were recorded while studying both topics through stimulus consisted of combination of images and text. The eye-tracker data were processed into heat maps and were statistically compared. The results affirmed that the visual participants spent more time studying images than verbal participants, which were shown by different fixation duration. Verbal participants were more focused on studying the text. Focus on areas with important sources of information was inline with each participant's cognitive style (areas of images or text).

III. Eye-tracking and machine learning studies

There were some studies that combined sensor-based approach and machine learning. This aided effective data processing and is useful to develop a more sophisticated online learning system. Some research works applied this combined method toward case of human cognition and multimedia learning.

A study on the detection of cognitive imbalances using machine learning classification algorithms and eye movements data was conducted by Lagun et al. [33]. This study aimed to improve the accuracy of detection of mild cognitive impairment (MCI) using the characteristics of one's eye movements when performing the Visual Paired Comparison task. The eye-tracking metrics were novelty preference, fixation duration, re-fixations, saccade orientation, and pupillary diameter. Participants were divided into 3 groups: 30 people of normal group, 10 people with mild cognitive impairment, and 20 people with Alzheimer's disease. Participants were asked to do a Visual Paired Comparison task consisting of 20 experiments. Data obtained from the eye-tracker when working on tasks were used to train and to evaluate the Naïve Bayes, Logistic Regression, and Support Vector Machine (SVM) classification models. These algorithms were evaluated based on their accuracy, sensitivity, specificity, and the area under the ROC curve. The normal group and the MCI group had been successfully classified using SVM algorithm with 87% of accuracy, 97% of sensitivity, and 77% of specificity.

Shojaeizadeh et al. [34] utilized eye-tracking and machine learning in developing a task load detection system. The research aimed to develop a system that provided feedback or suggestions to ease cognitive efforts or to improve user's cognitive capabilities in decision making. Metrics used from eye-tracking were pupillary dilation, blink duration, saccade duration, and saccade amplitude. Participants were asked to solve complex cognitive problems in the form of 10 mathematical problems. The experimental group was given a time limit on the task because the time limitation increased participants' cognitive resources usage in task completion. The dataset was compiled from 48 participants. The classification algorithm were Random Forest—because of its ability to identify complex boundaries in the prediction model— and SVM that had been widely used as a classification model. Random Forest produced higher accuracy (69.6%) compared with SVM with an accuracy of 56% in the dataset with all features.

Eivazi and Bednarik [35] used eye-tracking to measure user's visual attention patterns and to understand behavior in problem-solving. A group of 14 participants was asked to complete 8-tiles puzzle game on a computer screen. The eye movements of each participant were recorded and a think-aloud method was applied. The think-aloud recordings were processed as a reference to cognitive processes that occurred during the experiment. The reference was used to categorize eye-tracking recorded during certain cognitive processes, such as 'planning' and 'concurrent moves'. The labeled eye-tracking data and machine learning model were applied to classify between a group with high performance and a group with low performance. SVM classifier was used for datasets that contained mean of fixation duration, sum of fixation duration, mean of path distance, total path distances, number of fixations, fixation rate, and visited rate. SVM yielded 87.5% of classification accuracy. This study showed that SVM is a potential classifier to be used with eye-tracking data.

A study by Lou et al. [36] also used SVM to identify literacy abilities based on eye movements. The eye movement data were analyzed from 61 participants who read multi-paragraph and multi-topic texts. The features from the eye-tracker data were forward fixation time, first pass time, second pass time, and regression path. The SVM was able to classify readers with high literacy abilities and readers with low literacy abilities with an accuracy of 80.3%.

IV. Discussion

Implementation of adaptive multimedia learning systems based on learning styles requires effective and efficient data processing. Therefore, to make the automatic learning style detection method applicable in the real world environment, good data sources and robust data processing methods must be considered.

The most fundamental stage in identifying learning styles using mixed methods is the process of acquiring data. Data acquisition in a learning style identification experiment has been supported by biometric technologies such as eye-tracking. Several aspects must be considered when experimenting using the eye-tracking sensor [37]. First, the participants in the study. Specific criteria for gender, educational background, age need to be considered. Second, the design of the tasks, the visual stimulus that will be given to each participant, and the estimated time for the task to be completed must be planned. Third, the eye-tracking sensor selection is important because each sensor has different characteristics and output. Some sensors have restrictions such as not being able to detect people who wear glasses. Last, the setting of the experimental environment, such as proportional distance of participants from the screen and the eye-tracker and lighting of the room.

Raw data collected from experiments require further data processing sequences. According to Han et al. [38], raw data are very vulnerable to noise, incomplete record, and inconsistencies. The following are some data processing techniques that are possibly applied, including:

- Cleansing data from outliers. Outliers can cause residuals in the data as well as producing wide intervals in the data. A method commonly used to eliminate outliers is the Boxplot [39] method.
- Performing data transformation to improve efficiency in data processing. Data transformation can be done by normalization, data scaling, and data aggregation. Minmax scaler, Standard scaler, Robust scaler are some examples of methods that can be applied in eye-tracking data [40].
- Reducing or changing dimensionality of the data. A high-dimensional dataset increases computation time. One common method in altering the dimensions of the data is the Principal Component Analysis [41].

Previous studies used eye-tracking data only as validation measurement in statistical descriptive methods or visual representations that required further interpretation from experts [8], [30], [31], [42]. However, recent studies of machine learning algorithms applied to eye-tracking data have opened new opportunities towards the learning style detection method. Several studies have used this combined method in the fields of human cognition and learning performance [33]–[36].

To classify learning styles using a machine learning approach, we need to consider the portion of the dataset used for training and testing. For example 70% data are used for training and the rest is used for testing. A cross-validation technique is possibly used if the size of dataset is rather small [43]. Furthermore, classification requires appropriate input attributes and output labels (discrete) in the dataset [43]. In creating our own dataset, we need to label the samples according to the groundtruth. Groundtruth must be valid and reliable, thus proven measurement tools must be adopted. In this case, the Index of Learning Style Questionnaire provides support as a reliable groundtruth in identifying the type of learning styles [44].

Various features or attributes cause the dataset to have high dimensionality. Each sample row may contain many attributes or characteristics. A large number of features can slow down the calculation process. Thus, handling high-dimensional data can be done by selecting the most relevant features or eliminating features that have less effect. Feature selection can be done by using the filter method that utilizes univariate correlation statistical tests (SelectKBest) or wrapper method that train a model using a subset of features in an iterative process until the optimum subset is found (SVM-Recursive Feature Selection) [45]–[47] method.

Classifiers selection affects the performance of the classification model that we build. We can use several classifiers that are commonly used in multi-disciplinary studies related to eye-tracking and machine learning, such as SVM [36], Logistic regression [33], Naïve Bayes [33], KNN [48], Decision Tree [49], Random Forest [33], and Neural Network (Multi-layer Perceptron) [50].

V. Conclusion

Learning style detection is necessary in development of intelligent multimedia learning system. There are various learning style detection methods with diverse data sources and processing techniques. In this paper, we describe some of the existing learning style detection methods. We also discuss several traits required in developing a learning style detection method. Good data source, valid and reliable data processing, choice of machine learning algorithms, and its parameters setting are necessary for developing a learning style detection method based on eye-tracking and machine learning.

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