A Proposed Model for Detecting Learning Styles Based on Agent Learning

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Abstract—**A learning style is an issue related to learners. In one way or the other, learning styles could assist learners in their learning activities. If the learners ignore their learning styles, it may influence their effort in understanding teaching materials. To overcome these problems, a model for reliable automatic learning style detection is needed. Currently, there are two approaches in automatically detecting learning styles: data driven and literature based. Learners, especially those with changing learning styles, have difficulties in adopting these two approaches since they are not adaptive, dynamic and responsive (ADR). To solve the above problems, a model using agent learning approach is proposed. Agent learning performs four phased activities, i.e. initialization, learning, matching and recommendations to decide which learning styles are used by the students. Furthermore, the system will provide teaching materials which are appropriate for the detected learning style. The detection process is performed automatically by combining data-driven and literature-based approaches. The detected learning style used for this research is VARK (Visual, Auditory, Read/Write, and Kinesthetic). This learning style detection model is expected to optimize the learners in adhering with the online learning.**

Index Terms—**detection model, VARK, reinforcement learning.**

I. INTRODUCTION

Learning style can be defined as ways used properly by the learners to improve their concentration in learning through the learning behaviour, such as reading, viewing, listening and imitating [1]. Research related to the detection of learning styles in the online learning systems is rapidly developed. There are two approaches of learning style detection models: conventional and automatic one [2]. The conventional detection model of learning styles uses questionnaires to find out about the learning style. the automatic detection model of learning styles is divided into two methods: data driven and literature based.

The learning styles detection model using data-driven method applies the method of artificial intelligence (AI) in the detection process, such as NbTree AI [3], the Bayesian Model [4] and the Decision Tree-Hidden Markov [5].the literature based learning styles detection model uses the access result of the learners toward the available teaching materials.

Therefore, the learning styles which are usually detected in the data driven or literature based research use Felder Silverman Learning Style Model (FSLSM) [6]. This learning style focuses on how students adhere with the learning process. The learning done has not shown the relationship of learning styles and the learning materials clearly. To show the relation between learning style and the proper learning material, we can use learning style of Visual, Auditory, Read/Write, and Kinaesthetic (VARK). This is because the VARK learning style uses teaching materials as the characteristic of the individual learning style.

The model proposed to detect the optimal learning style is based on the teaching materials available by combining the data-driven and literature-based approach. This is called hybrid detection. Hybrid detection features the Adaptive, Dynamic and Responsive (ADR) system. The data-driven method uses reinforcement learning (RL), while the literature-based method accesses log data of the teaching material which is frequently used by learners.

This paper is divided into four sections: Section 1. Background, 2. Literature Review, 3. Proposed learning Model, 4. Discussion.

II. LITERATURE REVIEW

A. Learning Style

There are several identified learning styles: Kolb's learning styles model [7], Honey and Mumford's learning styles model [8], Felder Silverman's learning style model [6] and VARK based learning styles [9]. Kolb's model is made up of four cycles of learner behavior in gaining new knowledge. The first cycle begins with Concrete Experience (CE), which is an activity conducted directly by learners in attempt to find a solution to the problem. Kolb called this process *feeling*. To ensure that the acquired knowledge is the answer of the problems, the learner needs to re-observe his experience. This is called Reflective Observation (RO). In this process, learners directly observe through visual means. This visual observation is known as *watching* by Kolb. The next process of the visual observation result or watching is a concept known as Abstract Conceptualization (AC). The narration of knowledge obtained from CE and RO is then written in AC. Kolb called this learning style *thinking*. And the final step is Active Experimentation (AE), which is a direct activity process to ensure the return of the experience (*feeling*), observation (*watching*), and concept (*thinking*). This step is known as *doing*.

From those 4 learner cycles, Kolb combines both cycles into 4 learning styles which are known as Kolb's Learning Style, they are: Diverging, a learning style which uses experience (*feeling*) and observation (*watching*) approaches. Learners with Diverging Learning Style prefer working in groups and they are able to solve the problem by looking at it from different angles. The teaching materials used in the diverging learning style are text and visual ones. This is in contrast to Assimilating Learning Style which combines observation (watching) and concepts (thinking), as this type of learners prefers something in the form of a concept or idea. Their favourite teaching materials are text books, journals, and other reading materials. On the other hand, the Converging Learning Style (AC/AE) combines Doing and Thinking, so learners prefer carrying out something (practice) to concepts. The suitable teaching materials for this kind of learners are practicum and discussion (kinaesthetic). The final learning style in Kolb's model is Accommodating (CE/AE), which is a learning style that combines Doing and Feeling [7]. Learners with this kind of learning style prefer doing something directly using their intuition. Suitable teaching material for this kind of learning style is case studies (kinaesthetic). The introduction process of learning styles in Kolb's model is through questionnaires, known as the Learning Style Inventory (LSI) which contains 12 questions.

Kolb's learning styles is the embryo of Honey and Mumford's learning styles. It adopts Kolb's learning style by dividing the learning style into 4 types, which are: Activist, Reflector, Theory and Pragmatics [10]. Therefore, the relationship between Kolb's and Honey and Mumford's learning styles can be seen in Table 1.

TABLE I.
COMPARISON BETWEEN KOLB'S AND HONEY AND MUMFORD'S LEARNING STYLES

Honey and Mumford	Kolb
Activist	Accommodating
Reflector	Diverging
Theorist	Assimilating
Pragmatics	Converging

The Honey and Mumford's Activist learning style theory is similar to Kolb's Accommodating learning style. Activist learners prefer learning activities that involve directly accessing the teaching materials or known as kinesthetic. The Activist learners do not enjoy the process of reading, writing and listening as much. Unlike Reflector learning style, which is similar to the Diverging learning style of Kolb, the Activist prefers observation to gain knowledge. The Reflector learner type applies a great deal of consideration and tends to learn through the process of visually seeing, reading and hearing. Another learning style is the Theorist, who prefers the learning process to be conceptually derived from the theory of multiple books. More in-depth and structured knowledge is gained. And the final learning style is Pragmatics, which is where the learners gain knowledge by discussing a topic and then associating it with existing theory. Pragmatic learners generally prefer learning from discussion forums, listening and engaging directly (kinesthetic). To perform the detection process of Honey and Mumford's model of learning styles, questionnaires (LSQ) containing 40-80 questions are used.

Another well-known model is the Felder Silverman Learning Style Model (FSLSM). The FSLSM looks at learner behavior by combining two diametrically opposed types with one another. Merger is used in the FSLSM to generate learning styles. The FSLSM's learning styles [1] consist of several parts: perception (sensory/intuitive), input (visual/auditory), organization (deductive/inductive), processing (active/reflective) and understanding (sequential/global). The first part is known as Perception learning style, which is subdivided into sensory and intuitive. The sensory learning style means using facts/examples by visual, textual and aural means. This is contrasted to the Intuitive which uses a concept in the abstract or written form. The FSLSM's second style is based on input, which is subdivided into visual and auditory. According to research [6], the visual learner likes teaching materials in the form of drawings, diagrams and flowcharts while the auditory learner likes writing (text) and description (audio). The third type of learning style represented in the FSLSM is organization, which is an approach used by thinking learners. The deductive process of learning involves relating the general to specific patterns of thinking while the inductive process relates the particular to the general. In this process, a visual example is required to illustrate both processes. The fourth learning style is called processing, which is divided into active and reflective approaches to the process, indicated by the absence of active learners in discussion forums that are used in online learning. The fifth learning style, namely understanding, is a learning process which is appropriately sequentially structured and has a gradually global pattern in which the learning does not follow stages. Questionnaires are used to detect learning styles when adopting the FSLSM, referred to as the Index Learning Style (ILS) containing 44 questions.

The final learning style discussed is the VARK model: visual, audio, read/write and kinesthetic. The VARK learning style uses an approach to teaching and learning materials which integrates all previous learning styles: Kolb's, Honey and Mumford's and Felder Silverman's models. The VARK learning style model has the following characteristics: (a) visual information that is usually depicted in charts, graphs, flow charts, symbols, arrows and hierarchies of teaching materials; (b) audio information that is represented by tutorials, verbal material, cassettes, group discussions, talking and discussing issues in online media; (c) read/write learning style, in which each input and output is text-based, such as e-books, e-journals, e-paper and the e-library; and (d) kinesthetic, which has characteristics based on experience or practice through the learner interaction with teaching materials to gain an understanding. Because VARK learning style has a very high relevance with the content of teaching material, this research uses VARK as learning style.

B. Detection Process in Learning Styles

The detection process is divided into the data-driven method and literature-based method.

1) Data-driven method

The data-driven approach is a method that uses Artificial Intelligence (AI). Several studies which have been conducted using AI to detect FSLSM learning styles are Bayesian Networks [4], NbTree Classification [3], the Decision Tree and Hidden Markov [5] and Reinforcement Learning [11]. Research into Bayesian Networks [4] uses data from students' log chats, forums and processing. Based on that log data, Bayesian Networks split two independent tables based on the analysis result of the log data and dependent conditional probability table. There are three learning styles that Felder Silverman detected: Perception, Processing and Understanding [4].

Another study which detects FSLSM learning styles using the NbTree Classification to extract the learning style of the learner by building the learner's profile through Learner Selected Data Objects (LSDO) [3]. Furthermore,

TABLE II.
COMPARISON OF PREVIOUS RESEARCH

	E Ozpolat et al [3]	**Garcia et al [4]**	**Ahmad et al [12]**	**PQ Dung et al [13]**	**Graf [2]**
Year	2009	2007	2013	2012	2007
Sample	25 students	27 students	20 students	44 students	127 students
Approach	Data Driven	Data Driven	Literature Based	Literature Based	Literature Based
Method	NB Tree Classification	Bayesian	Behaviors Pattern	Behaviors	Behaviors Pattern
Target Study	Engineering Education	AI	Interactive Multimedia	AII	Object Oriented Modelling
Assessment Method	Learning Model: ILS	BN Model: ILS	Behaviour: ILS	Learning Object: ILS	
Precision	67.7%		75%-83%		
Dimension					
Ac/Ref	70%	77%	75%	72.73%	79.33%
Sen/Int	73.33%	63%		70.15%	
Glo/Sec	73.33%	58%		79.54%	
Vis/Ver	53%	-		65.91%	

LSDO is classified into a learner profile. Once classified, the learning styles in the FSLSM are obtained (perception, input, organization and processing).

Another study adopted the detection model approach; which is the Hidden Markov and Decision Tree model [5]. The study provided learners with questionnaires . The results of the questionnaire were examined to determine the Level of Preference (LOP). The result of LOP was further processed using the NbTree Classification to obtain a classification based on learning styles. The results of the classification were then processed using the Hidden Markov model to obtain the FSLSM learning styles.

2) Literature-based method

Another detection model is a literature-based method, which uses traditional rules designed by the researchers, in terms of log data on a learner's interaction with teaching materials. Some logs taken are related to the outline, example, content, exercise and forums [12], [2] and [13].

Table II is a comparison of research that has been conducted to detect learning styles by using data-driven and literature-based methods.

C. Reinforcement Learning (RL)

RL is a machine intelligence approach that combines two disciplines, i.e. dynamic programming and supervised learning [11] [14] [15]. Dynamic programming uses mathematical models to solve conventional problems and control. The problems in dynamic programming occur in addressing (address).

While supervised learning is a common method used for training parameters, such as the neural network function. Supervised learning requires input and output as a function of learning. RL methods work to find an action (action) that corresponds to the problems encountered, to obtain the maximum reward.

RL needs to pay attention to three factors: the environment, reinforcement function and value function. With respect to the environment, the focus is on how to study it to generate the maximum value, while reinforcement function pays more attention to the value of the state/action to generate a reward [16]. Recently, the value function has concentrated more on the policy required by the system.

Figure 1 shows the model of RL.

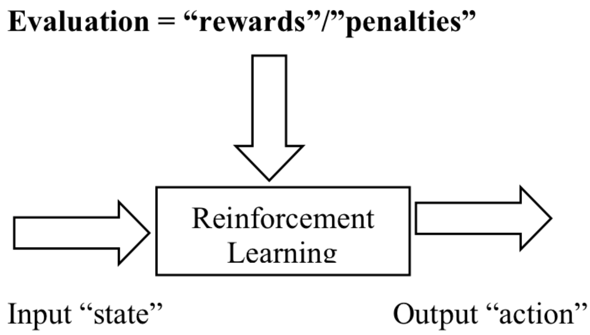

Figure 1. RL

III. PROPOSED MODEL

This paper proposes a detection model of learning styles with Adaptive, Dynamic, and Responsive (ADR) approach. Adaptive means capable to adapting to the learner's wishes to find teaching materials that match their learning style. The learning styles used is VARK. The VARK learning style is a representation of teaching materials. This process uses a model representation of ontology [17] so the learner will obtain the reference to teaching material according to the learning style. Dynamic refers to the ability of the system to adjust with learners' ability, so that they can maintain their motivation [18] in following their study. This is performed by always providing evaluation sessions for each study session, to determine whether the learning targets have been achieved or not. Responsive means using chat, discussions and emails with a direct response to the professor. Figure 1 shows the design of the learning styles detection model proposed.

The following is an explanation of the proposed model in Figure 2 and architecture for ADR.

A. Initialization Phase

Initialization phase begins with providing identity of each teaching material. The identity of the teaching material is divided into four types:

- Video: file materials with the extension of flv, mp4, dat. These files contain graphics, videos and animation.
- Audio: materials with the extension of mp3, aac. The stored files are the recorded voice of the professor who delivered the learning materials.

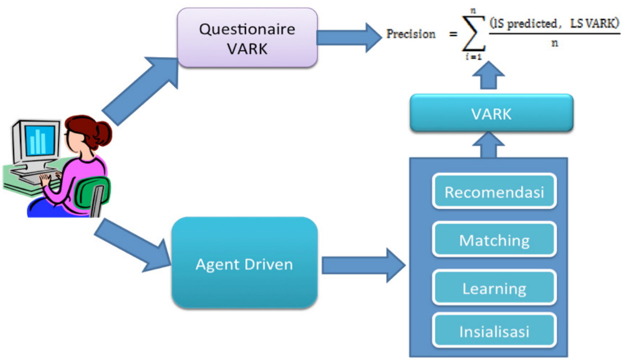

Figure 2. Architecture for ADR

- Read: materials with the extension of pdf, ppt and doc. The materials are offered in the form of lab modules, e-books and journals.
- Kinaesthetic: materials with the extension of pdf or use of the facilities located in Moodle forums.

Once the identity is given to the teaching materials, the duration of the access to the teaching materials is calculated rather than the frequency of the visits to the teaching materials, as in the NAM study [19]. In this proposed model, the teaching materials are not only available in the internal and external LMS, but there is also a need to be able to interact with the teaching materials outside the LMS using the ontology model [17].

B. *Learning Phase*

In the learning phase, activities performed are providing feedback to the learners related to the teaching materials that have been accessed. After the teaching materials have been accessed, they are processed, and the learners receive a question from the system. There are two questions that are delivered to the learners with a scoring system, as follows:

- Are the teaching materials not suitable (-10)
- Are the teaching materials suitable (10).

If the teaching materials are not suitable, the agent will not give recommendation of the teaching materials. However, if the teaching materials are suitable, the agent then provides recommendations for the teaching materials. This concept is known as RL. In RL, there is s = state, a = action and reward.

State: the process of accessing the teaching materials, the process of accessing the video, the process of discussion forums and the process of exams.

Action: the process of reading materials, the process of searching for videos related to the teaching materials, the process of replying the discussion and the process of exam results.

Reward: Suitable + 10

Not suitable -10

C. *Matching Phase*

The Matching phase starts with matching the teaching materials detection results in phase 1 with the learning style that was detected in phase 2. Learning styles which were detected in phase 1 with behaviour approach are compared to the learning styles in phase 2 with RL. If the results state that the learning style that was detected in phase 1 is the same with the teaching materials in phase 2, the system will recommend the teaching materials which are in line with the learning styles in the subsequent learning.

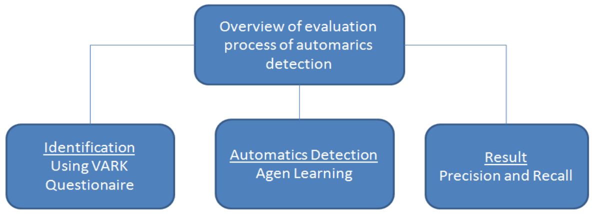

Figure 3. Model Evaluation

D. *Recommendation Phase*

In this phase, the system provides teaching materials recommendation which is appropriate to the learning styles that have been detected in the previous phase. Recommendations of these teaching materials use the semantic web method. It is expected that the result of the hybrid detection model, that is the combination of data-driven and literature based detections, can be compared with the detection result using questionnaires.

Questionnaires given are directly adopted from VARK inventory (www.vark-lern.com). The learners will receive their learning styles after completing 16 questions. Learning styles obtained will be stored in the database and classified as Group 1.

While in Group 2, the detection process of learning styles requires hybrid detection. Hybrid detection uses data-driven and literature based RL based upon the duration of the visits of the learners in accessing the teaching materials in the LMS Moodle.

The evaluation of this learning style detection model uses comparison of the learning style detection with questionnaires and the results of the evaluation and learner interaction. Figure 3 illustrates the performance evaluation model of proposed learning styles detection:

The evaluation process is divided into three phases:

- Identification: detecting the learning styles by using VARK questionnaires before the learning process begins. The results of these questionnaires show the learners which dominant learning style they have.
- Automatics detection: detecting the learning style using agent driven approach.
- Result: becoming a part that will compare the results of the questionnaires with the detection results of the learning styles to see the results of the pre-test, post-test and teaching materials. Next, the precision and recall will be achieved using the formula below.

$$\text{Precision} \quad = \sum_{i=1}^{n} \frac{(\text{IS predicted},\ \text{LS VARK})}{\text{n}} \ .\ \text{participant}$$

IV. CONCLUSION

The learning styles detection model generated helps in detecting learning styles using the agent learning approach. This approach is capable of detecting a more accurate learning style because it is combining the data-driven and literature-based methods which results in a learning agent with higher accuracy compared with previous detection models. It is hoped that this model will also maintain the morale and motivation of the learners in participating in online learning.

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