Rule-Based Knowledge Representation for Modality Learning Style in AIWBES

Rahmah Mokhtar[1], Nor Azan Mat Zin[2], Siti Norul Huda Sheikh Abdullah[3]

Faculty of Information Science and Technology,
Universiti Kebangsaan Malaysia (UKM),
43650 UKM Bangi,Selangor, MALAYSIA
[1]rahmahnasri@gmail.com, [2] azan@ftsm.ukm.my, [3]mimi@ftsm.ukm.my

ABSTRACT

This paper is emphasizing rule-based knowledge representation in Adaptive Intelligent Web Based Education System (AIWBES). The knowledge was extracted from modality learning style expert based on Dunn & Dunn Model. From the expert point of view, the rules were built up by the researcher. The objective of this paper is to show how knowledge can be represented, producing the rule and replacing questionnaire for learning style prediction. The prototype namely K-Stailo was developed and tested by the researcher. The finding shows that rule-based knowledge representation can be accepted as questionnaire replacement for predicting modality learning style.

Keywords
Production Rule, Knowledge Representation, User model, modality learning style, AIWBES.

1.0 INTRODUCTION

Researches in adaptation through learning style had proved that adaptation of modality based learning style enhance the learning process among students (Triantafillow et al., 2004). In Adaptive Intelligent Web Base Education System (AIWBES) environment, adaptation was made via user model (Brusilovsky, 2003). From user model, the behavior, background, personal and learning style of the user can be detected by the system. Therefore in this research, the action of the user‘s browsing behavior will shows the modality learning style of each user. In other words through user’s action the system has a capability to predict user’s learning style.

Commonly, learning style questionnaire was used by Web Based Education System user model, as a tool for predicting user’s learning style. However, researches on online questionnaire resulted to problems e.g. users were not frank enough in answering the questionnaires (Draper, 1996; Parades & Rodriquez, 2004). Apart from that, the answering questionnaire session gave a hard time for users to complete them up. For example, there are questions related to their learning style. This would happen when they are not aware of their learning style (Merill, 2002) and they tend to leave the question unanswered or otherwise they tick all available answers.

Thus, the learning style built by the system became inaccurate (Draper, 1996; Parades and Rodriquez 2004). Mood and emotion of users did influence in the duration of answering the questions. The state of emotion like angriness, sadness, frustration and happiness contributed to the variation in output generation. We could also learn that learning style of an individual varies from one to another. This is normally caused by their upbringings which influenced their learning style and users desired to do trials before choosing the best mechanism to suit their learning style (Graf, 2007). This is lead to irrelevancy in existing style of learning therefore users are required to fill up the questionnaires in order to recapture the latest style of learning needed by users. The above explanation translated the importance to have dynamically and automatically user model in place thus style of learning can be dynamically determined through knowledge representation approach.

2.0 RULES AS KNOWLEDGE REPRESENTATION

Knowledge is theoretical or practical understanding of a subject or a domain (Negnevitsky, 2002.). A knowledge representation (KR) is most fundamentally a surrogate, a substitute for the thing itself, used to enable an entity to determine consequences by thinking rather than acting, i.e., by reasoning about the world rather than taking action in it; it is a fragmentary theory of intelligent reasoning, expressed in terms of three components: (i) the representation's fundamental conception of intelligent reasoning; (ii) the set of inferences the representation sanctions; and (iii) the set of inferences it recommends; a medium for pragmatically efficient computation, i.e., the computational environment in which thinking is accomplished. One contribution to this pragmatic efficiency is supplied by the guidance a representation provides for organizing information so as to facilitate making the recommended inferences and it is also a medium of human expression, i.e., a language in which we say things about the world (Davis, Shrobe & Szolovits 1993).

From the above statement we can see how representation plays the important role in the system. Representation can be made through four approach such as logic, semantic networks, frames and production rules (Martin, et al., 2009). Commonly, one of the most popular approaches to knowledge representation is to use production rules, sometimes called IF-THEN rules. The benefit of IF-THEN rules are that they are modular, each defining a relatively small and, at least in principle, independent piece of knowledge. New rules may be added and old ones deleted usually independently of other rules (Lewis, 2003). In this research, knowledge from learning style expert have been extracted and being formed as the production rules of knowledge representation.

Paradigm based on simple rule is very easy to understand. Any rule consists of two parts: the IF part, called the antecedent (premise or condition) and the THEN part called the consequent (conclusion or action). The basic syntax of a rule shown in figure 1:

IF <antecedent>

THEN <consequent>

Figure 1: Basic syntax of rule

In general, a rule can have multiple antecedents joined by the keywords AND (conjunction), OR (disjunction) or a combination of both.

3.0 RULE BASED USER MODEL SYSTEM

In a context of modality learning style prediction, rules have been made through expert knowledge on modality learning style which is visual, verbal and visual-verbal. Based on learning style feature made by learning style experts as stated in table 1 and user model for dynamic automatic detection of modality learning style namely, K-Stailo was built.

K-Stailo is a rule based user model system that has been built to predict user's learning style through production rules knowledge representation. Base on learning style feature the interface was designed in the form of user friendly interface. This can be referred to figure 2.

The user action is being detected by K-Stailo automatically. Implicitly, the user didn't realize that their actions have been observed by the system and their learning style was predicted. Subsequently, the system will match user's action to the rules made by modality learning style expert. K-Stailo rules which stated in figure 3, were used to predict user's learning style.

Table 1: Modality feature

<table>
<tr><th>VISUAL</th><th>VERBAL</th><th>VISUAL-VERBAL</th></tr>
<tr><td>Image orientation</td><td>Wordings orientation</td><td rowspan="6">Have both features equally</td></tr>
<tr><td>Well-verse in Ilustration</td><td>Well-verse in wordings</td></tr>
<tr><td>Interest in jigsaw puzzle</td><td>Interest in wording games like jigsaw puzzle</td></tr>
<tr><td>Understand visual</td><td>Understand complex semantic</td></tr>
<tr><td>Hardly to be taught off</td><td>Read own ideas</td></tr>
<tr><td>Manipulate and transforming images</td><td>Manipulate and transforming symbols</td></tr>
</table>

Figure 2: Modality representation interface

Rule 1
IF click_image THEN Ls_Modality Visual
Rule 2
IF click_words THEN Ls_Modality Verbal
Rule 3
IF click_>image THEN Ls_Modality Visual
Rule 4
IF click_>words THEN Ls_Modality Verbal
Rule 5
IF click_image=words THEN Sp-Modaliti VisualVerbal

Figure 3: Rules for cognitve learning style prediction

4.0 ANALYSIS

The test to 36 secondary school students in Selangor, Malaysia, has been done by the researcher. The objective of this test is to find out whether K-Stailo can be accepted as the replacement of learning style questionnaire. The students have been guided by the researcher throughout their surfing activity using K-Stailo. They were also been asked to fill in the Index of Learning Style questionnaires (ILS) for the purpose of similarity later on.

4.1 The Result

The total 36 data set was separated into 2, which 19 data is for training set and another 19 is for the test set. To find the similarity between K-Stailo and ILS, the researcher used precision formula 1 created by (Gracia et al., 2005) which:

$$Precision = \frac{\sum_{i=1}^{n} Sim\ (LS_{predicted,} LS_{questionnaire})}{n} \text{ X } 100 \qquad (1)$$

With, $\sum Sim$ or similarity function is similarity value, *Predicted LS* is learning style predicted by the system, *ILS questionnaire* is learning style value by ILS questionnaire and *n* is sum value of respondent. This formula has been applied by the researcher because ILS is the only accepted instrument and was being used by AIWBES researcher for learning style prediction (Gracia et al., 2005; Graf, 2007).

Sim function is being determined according to the similarity of simple rule base and ILS questionnaire, which if it given the same prediction, the value is 1, if it's average, the value is 0.5 and if the prediction is contrast, the value is 0. Based on *Sim function* value, the comparison in table 2 is listed. The graph of these differences can be referred to figure 4.

Table 2: Sim function for ILS and K-Stailo Prediction

Respondent	ILS	K-Stailo	∑Sim
1	Visual-verbal	Visual	0.5
2	Visual	Visual	1
3	Visual-verbal	Visual	0.5
4	Visual	Visual	1
5	Verbal	Verbal	1
6	Visual	Visual	1
7	Visual-verbal	Visual	0.5
8	Visual	Visual	1
9	Visual-verbal	Visual	0.5
10	Visual	Visual	1
11	Visual	Visual	1
12	Visual	Verbal	0
13	Visual	Visual	1
14	Visual	visual	1
15	Visual-verbal	Verbal	0.5
16	Visual	Visual	1
17	Visual-verbal	Visual	0.5
18	Visual	Verbal	0
19	Visual	Visual	1
			14.0

The formula 1 stated above was used to find the precision of K-Stailo.

$$Precision = \frac{14}{19} X\ 100$$

$$= 74\% \qquad (2)$$

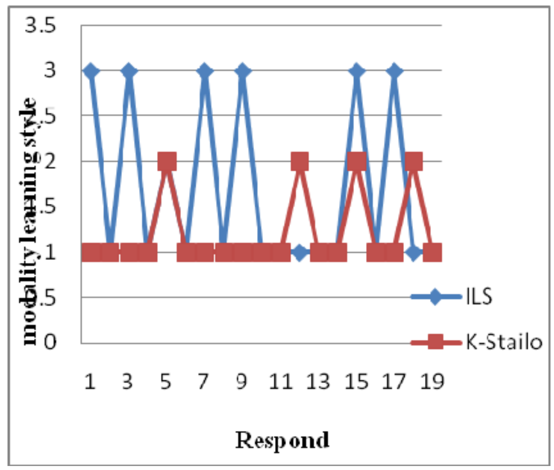

Figure 4: K-Stailo vs ILS comparison graph

The result of calculation in formula 2, shows that K-Stailo, produce 74% precision of similarity to ILS. According to Garcia 2005, more than 70% of precision is a high result for similarity between two approaches.

5.0 DISCUSSION

From the analysis discussed, the 74% of similarity precision between K-Stailo and ILS was a high number. Therefore, it can be accepted a proof figure that support the acceptance of knowledge representation technique in predicting modality learning style. Directly, K-Stailo, can be the replacement of ILS in predicting user's modality learning style.

6.0 CONCLUSION

This research discusses, the use of knowledge representation by production rule for modality learning style prediction. The prototype, namely K.Stailo was developed and tested in order to find the precision. The test to 36 secondary school student shows the total of 74% precision similarity between K-Stailo and ILS. This results support the usage of knowledge representation in AIWBES user model as the replacement of ILS which commonly used by AIWBES developer in predicting modality learning style.

REFERENCES

Brusilovsky, P. (2003). Adaptive and Intelligent Web-Based Educational System. *International Journal of Artificial Intelligence in Education,* 13:156-169.

Davis, R., Shrobe, H., & Szolovits, P. (1993) What is a Knowledge Representation? *AI Magazine*, 14(1):17-

33.

Draper, S.W. (1996). *Observing, Measuring or Evaluating Courseware: A Conceptual Introduction*. In G. Stoner (Ed.), Implementing Learning Technology, Learning Technology Dissemination Initiative, p.58-65.

Gracia, P.Amandi, A.Schiaffinos & Campo, M. (2005). *Evaluating Bayesian networks' precision for detecting students' learning style*. Computers & Education 49 (2007) 794-808.

Graf, Sabine,(2007). *Adaptivity in Learning Management Systems Focusing on Learning Styles*. Phd. Thesis. Faculty of Informatics. Vienna University of Technology,Vienna.

Lewis ,P.(2003). Knowledge representation : production rules for knowledge representation. 2003. www.ecs.soton.ac.uk.

Martin, M. et al. (2009). Knowledge representation and rule based system. Lecture notes. La, trobe university.

Merill, M.D. (2002). *Instructional Strategies and Learning Styles: Which Takes Precedence?* In R. Reiser & J. Dempsey (Eds.), Trends and Issues in Instructional Technology, *p*. 99-106. Columbus, OH, Prentice Hall.

Negnevitsky, M.(2002). *Artificial intelligence: a guide to intelligent system*. England:Pearson education limited.

Parades, P., & Rodriguez, P.(2004) . A Mixed Approach of Learning Styles in Adaptive Educational Hypermedia. *Advanced Technology for Learning*, *1* (4), 210-215.

Triantafillou, E., Pomportsis, A., Demetriadis, S. & Georgiadou, E. (2004). The value of adaptivity based on cognitive style:an empirical study. *British Journal of Educational Technology. 35*(1), 95-106.