ARTICLE IN PRESS

Ain Shams Engineering Journal (2016) xxx, xxx–xxx

Ain Shams University

Ain Shams Engineering Journal

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ELECTRICAL ENGINEERING

Learning style detection based on cognitive skills to support adaptive learning environment – A reinforcement approach

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Received 10 August 2015; revised 1 April 2016; accepted 24 April 2016

KEYWORDS

Learning style;
Adaptive learning;
Cognitive skills;
Reinforcement approach

Abstract Presently, Learning Style Detection (LSD) has acquired a greater interest in the adaptive learning environment of any academic system. The existing methods of learning environment have facility such as content management and learner data analysis. The learning style detection based on learner's capability, assessment based on mental processing skill and knowledge improvement has not been addressed completely in these systems. Hence, this research works mainly emphasize on creating a reinforcement model for adaptive learning environment based on the Cognitive Skill (CS) of the learners. The model approaches the issues in threefolds; the first is to detect the Learning Style (LS) based on the cognitive skills of a learner dynamically. The second focus is on mapping cognitive skill, Bloom's taxonomy with the Learning Object (LO). The third focus is to create a reinforcement model to keep track and provide feedback on the knowledge competency level improvement.

1. Introduction

Learners have different ways to acquire knowledge on any theme. Adaptive learning is one of the methods intended for the acquisition of knowledge in a dynamic way [1]. It supports a computer-based educational system that adjusts the presentation of content in response to learner performance. Basically, adaptive learning includes three core elements such as content or Learning Object (LO) model, Learner Model and Instructional (LO delivery) Model. The content model refers to presentation style of a topic or domain content with learning outcome. It includes a learning sequence to be carried out in achieving the learning outcome. The sequence or learning path would vary based on learner's performance. The Learner Model targets in detecting the way of learning called Learning Style. The Learning Style focuses on individual learning capabilities, learning path, preferred learning content and performance [2]. The learning capability and performance are mostly predicted based on the mental processing which dwells in each individual as cognitive skill. Cognitive skills, a

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Peer review under responsibility of Ain Shams University.

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http://dx.doi.org/10.1016/j.asej.2016.04.012
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psychological concept are the vital tools that facilitate one to successfully think, prioritize, design, understand, visualize, remember, create suitable associations, and solve problems. It includes a variety of information processing abilities that change the way a learner acquires knowledge. Since cognitive skill can be developed and strengthened through various programs and exercises, the academic performance is much influenced by them. Information processing skills such as memory, concentration, perception and logical thinking are considered in this paper as a part of Learning Style Detection since strong cognitive skills lead to very good learning capability [3]. Finally the Instructional model concentrates in selecting a specific LO to specific learner at specific time. It uses the information gained through the content and learner model to deliver a precise LO. Incorporating all the core elements in single model an adaptive environment to support a reinforcement model for knowledge improvement is targeted in this research.

2. Related work

In order to understand the current scenario of the area of investigation, a study is performed on the already proposed methodologies. The summary of the study is tabulated in Table 1.

3. Proposed methodology

The developed framework to detect learning style of an individual consisted of three major phases as shown in Fig. 1. The framework includes,

- Learner model
- Learning object model
- Adaptation model

3.1. Learner model

The learner model is intended to identify the type of the individuals based on the cognitive skills possessed by them. Past research shows that cognitive skill in human being is classified as memory, concentration, perception and logical thinking. In order to pursue engineering education all these four skills are highly essential. However, each individual tend to possess various proportions of these skills. In order to impart the minimum competency of subject knowledge, it is desired to provide the learners with the materials that they can easily follow to assimilate the knowledge. Hence to provide the suitable materials, initially the users are categorized into four groups based on their cognitive skill. For performing the categorization, the responses received from them on undertaking the **Multiple Choice Questions** (MCQs) are considered.

Earlier, the questionnaires required for this assessment is stored in a Learning Environment Repository. With the help of a Learning Management System (LMS), the performance of each individual is recorded and results are retrieved in a structure format for further analysis. The following procedure is adopted to carry out the analysis.

Begin
For each S_i
For each CS_j
Assess student's performance and grade S_Score
End for
Rescale the score based on cognitive skill weightage
Normalize the Scores of all students as S_NScore
Compute the Average_score for each CS_j
For each Si
Check if (S_Nscore < Average_score) and (S_Nscore <= Average_score – C)
then assign Si to Class = 1
Elseif (S_Nscore >= Average_score – C and S_NScore <= Average_score + C)
then assign Si to Class = 2
Else assign Si to Class = 3

Initially, MCQs on the chosen course are segregated based on the required cognitive skill. The questionnaire was prepared based on the opinion survey of Bloom's taxonomy verb actions and a possible cognitive skill. Each student of the class is allowed to take up the initial screening test and an absolute grading is awarded. Assuming the normal human's cognitive skill composition as memory 15%, concentration 20%, perception 25% and Logical Thinking 40%, the scores of each student under the different cognitive skills are scaled. To analyse the factors uniformly, the scores are normalized.

3.1.1. Score normalization

The scaled scores of each student are normalized using the one technique called Min–Max Normalization. Min–Max Normalization transforms a value A to B which fits in the range $[M, N]$. It is given by the formula below:

$$B = \left(\frac{(A - \textit{minimum value of } A)}{(\textit{maximum value of } A - \textit{minimum value of } A)}\right) * (N - M) + M$$

The normalization performs a linear transformation of original scores and fits the scores in the range of 0–1. Hence, for the further processing, data range uniformity is obtained. After having the data normalization, the mean score for each cognitive skill CS_j is computed. Further the user classification is performed based on the following conditions:

if (S_Nscore < Average_score) and (S_Nscore <= Average_score – C) then S_i = Class 1
if (S_Nscore >= Average_score – C and S_NScore <= Average_score + C) then S_i = Class 2
Else assign Si to Class 3.

Where Class 1 is S_{low}, Class 2 is S_{med} and Class 3 is S_{high}.

Class 1 represents the users with low level of competency in the corresponding cognitive skill. Similarly Class 2 and Class 3 represent average level of competency and high level of competency in the cognitive skill. Considering the above mentioned conditions, the users are classified. According to the class, the materials are designed to improve one's competency level.

Table 1 Summary of the related work.

Work done by	Approach	Technology	Key points	Assessment methods	Precision/accuracy	Cognitive skill focussed
[4]	Data-driven	Browser-based system with rules	Processing dimension	67 students – ILS (Training) 7 students – **iLessons**	71% – Processing	Perception, concentration
[5]	Data-driven	Bayesian networks	Detection only	27 Systems engineering students – AI – **SAVER**	58% – Processing 77% – Perception 63% – Understanding	Perception, concentration
[6]	Data-driven	Bayesian networks	Detection and suggestions	42 Systems engineering students – AI – **SAVER** with **eTeacher**	83% feedback received was positive	Perception, concentration
[7]	Literature-based	Simple rules on Matching Hints	LMS Independent; Better results than data-driven approach	127 students – Info. Sys. & Comp. Sci. – Austria Univ. – Object Oriented Modeling – Moodle LMS	77.33% – Input 79.33% – Processing 76.67% – Perception 73.33% – Understanding	Perception, concentration
[8]	Data-driven	NBTree classification with Binary Relevance Classifier	Detection and suggestion; Uses only data objects selected by the user; LMS independent	10 graduate student (Training) 30 graduate students (Testing) – **PoSTech**	53.3% – Input 70% – Processing 73.3% – Perception and Understanding	Perception, concentration
[9]	Data-driven	Enhanced k-NN Clustering with GA	k-NN – Pre-Contrast and Post-Comparison Reduced no. of behavioural features	IRIS dataset by UCI 117 students – **SCORM-compatible Java-based LMS**	Increasing accuracy	-NA-
[10]	Data-driven	Browser-based System with Rules for Reasoning	More dimensions; Improved rules; Unknown category	67 students – ILS (Training) 7 students – same research task – **iLessons**	82% – Input 81% – Processing 69% – Understanding	Perception, concentration
[11]	Literature-based	Simple rules on Matching Hints	Processing dimension; 6 features considered	27 students – Comp. Educ. – Derivatives – **Moodle LMS**	79.63% – Processing	Perception
[12,13]	Data-driven	Fuzzy Logic	Bell-shaped Membership function; Better classification for Unknown	Comp. Sci. & Engr. – Anna Univ. – C-language	-NA-	-NA-
[14]	Literature-based	Simple rules on Matching Hints	LMS Independent; Parameters – No. of visits and Time spent	44 UG students – Comp. Sci. – Politechnica Univ., Bucharest – AI course – Web-based LMS **POLCA**	70.15% – Input 72.73% – Processing 70.15% – Perception 65.91% – Understanding	Perception, concentration
[15]	Literature-based	Fuzzy rules	LMS Independent McCarthy Model	LSI by Marlene LeFever	Increased Efficiency	Perception

Following Table 2 shows, the sample measures for fifteen learners that are obtained for the mentioned process of user classification.

According to the sample data collected, it was observed the mean score of cognitive skill Memory as [0.75] and Concentration as [0.63], perception as [0.54] and Logical Thinking as [0.43]. Using these measures, it was found that 110 numbers of students were categorized for each cognitive skill as low, average and high.

3.2. Learning object (LO) model

Once the learner's basic cognitive skill is determined, the learners are to be provided with the appropriate learning objects to improve the level of competency. As there exists no strong binding for the cognitive skill and learning objects, an opinion survey is conducted to draw a mapping between them. Using ANOVA, the influential learning objects for improving each cognitive skill are determined. To perform the analysis, input collected from more than hundred (100) learners is segregated into four groups based on their age and experience in the domain. Tables 3–6 show the composition of response from the groups for the Cognitive skill Memory and variance analysis. Similarly for all the other three CS, responses are categorized.

3.2.1. Bloom's taxonomy and action verbs

Bloom's taxonomy is a way of characterizing any questions of an education system. It refers to a classification of the different objectives that is set for learners with learning objectives. A goal of Bloom's taxonomy was to motivate educators to focus on all the dimensions to create a holistic approach on the education system [16]. The revised Bloom's Taxonomy (BT) and associated action verbs are shown in Fig. 2.

A survey instrument for establishing an association between Bloom's Taxonomy and Learning Object is created.

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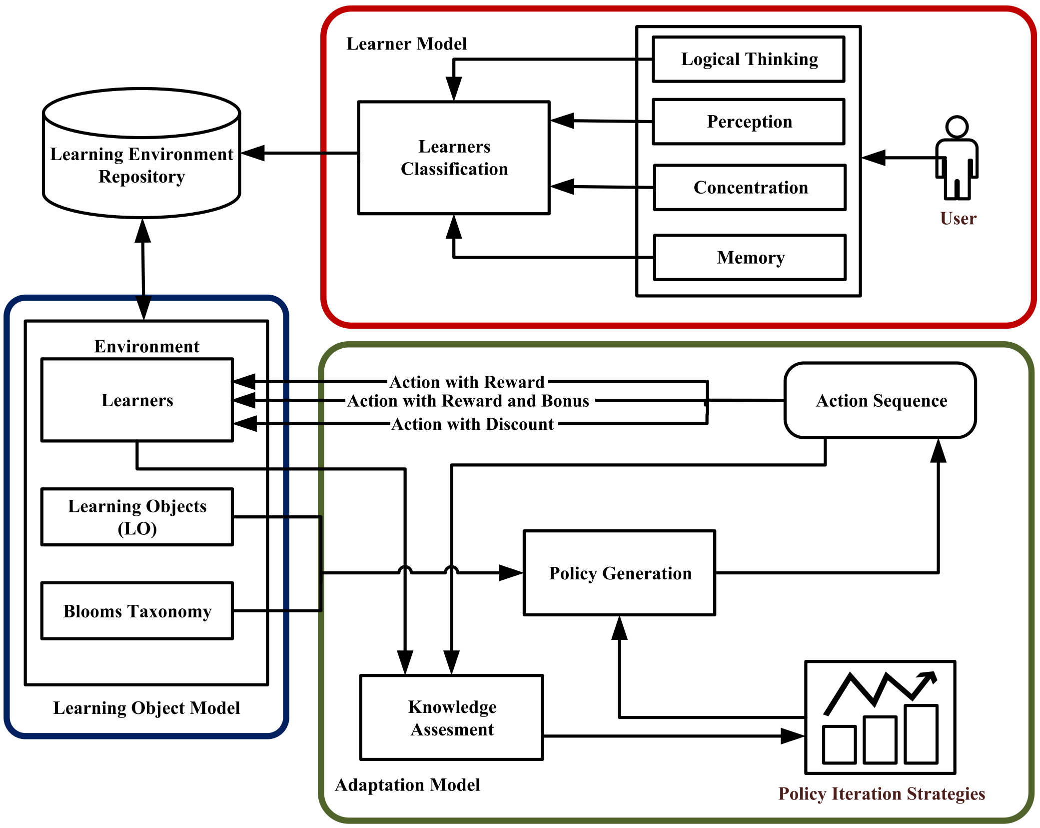

Figure 1 Framework for learning style detection based on cognitive skills.

Table 2 Learner's classification based on cognitive skill level.

RegNo	Observed values				Normalized values				Classified values			
	Mem	Con	Per	LT	Mem	Con	Per	LT	Mem	Con	Per	LT
L1	8	8	7	6	0.6	0.71	0.58	0.5	S_{low}	S_{high}	S_{med}	S_{med}
L2	10	8	6	3	1	0.71	0.29	0.13	S_{high}	S_{high}	S_{low}	S_{low}
L3	10	8	8	7	1	0.71	0.67	0.63	S_{high}	S_{high}	S_{med}	S_{high}
L4	10	8	8	7	1	0.71	0.67	0.63	S_{high}	S_{high}	S_{med}	S_{high}
L5	9	8	7	6	0.8	0.71	0.58	0.5	S_{med}	S_{high}	S_{med}	S_{med}
L6	9	8	8	7	0.8	0.71	0.67	0.63	S_{med}	S_{high}	S_{med}	S_{high}
L7	9	7	7	6	0.8	0.57	0.48	0.5	S_{med}	S_{low}	S_{low}	S_{med}
L8	10	7	8	8	1	0.57	0.67	0.75	S_{high}	S_{low}	S_{med}	S_{high}
L9	10	7	8	9	1	0.57	0.77	0.88	S_{high}	S_{low}	S_{high}	S_{high}
L10	10	9	8	7	1	0.86	0.77	0.63	S_{high}	S_{high}	S_{high}	S_{high}
L11	9	6	8	9	0.8	0.43	0.67	0.88	S_{med}	S_{low}	S_{med}	S_{high}
L12	10	7	6	4	1	0.57	0.29	0.25	S_{high}	S_{low}	S_{low}	S_{low}
L13	10	9	8	6	1	0.86	0.67	0.5	S_{high}	S_{high}	S_{med}	S_{med}
L14	10	7	7	7	1	0.57	0.58	0.63	S_{high}	S_{low}	S_{med}	S_{high}
L15	9	6	7	7	0.8	0.43	0.48	0.63	S_{med}	S_{low}	S_{low}	S_{high}

L – Learner, Mem – Memory, Con – Concentration, Per – Perception, LT – Logical Thinking.

The survey is expected to cover the opinion of the different learners towards the BT actions such as remembering, understanding, applying, analysing, evaluating, creating and LOs. Around 107 learners have provided the response. The learners were expected to give all possible LOs suitable for assessing with respect to Lower Order Thinking (LOT), Middle Order Thinking (MOT) and Higher Order Thinking (HOT). According to the Bloom's taxonomy, lower order thinking deals with the remembering and understanding actions. These two actions expect the learners to recall relevant knowledge to make sense accordingly to carrying out any process. The middle order thinking includes application and analysis where the learners apply the understood knowledge in various domains and application either fully or partially. Finally, the higher

Table 3 Composition of response for cognitive skill – memory.

Group category	Simulation	Case study	Diagram	Chart	Text	Audio	Video	Total
1	3	3	4	3	8	5	8	34
2	2	3	4	3	11	5	6	34
3	2	2	3	2	9	6	9	33
4	2	2	5	1	7	8	7	32

Table 4 Variance analysis for cognitive skill – memory.

Groups	Count-r	Sum	Average	Variance	% of influence
Simulation	4	9	2.25	0.25	2.86
Case study	4	10	2.5	0.33	3.81
Diagram	4	16	4	0.66	7.62
Chart	4	9	2.25	0.91	10.48
Text	4	35	8.75	2.91	**33.33**
Audio	4	24	6	2	**22.86**
Video	4	30	7.5	1.67	**19.05**

Table 5 Summary of variance analysis for cognitive skill – memory.

Source of variation	SS	df	MS	*F*	*P*-value	*F* crit
ANOVA						
Between groups	173	6	28.83	23.07	3.1805E−08	2.57
Within groups	26.25	21	1.25			

Table 6 Influential learning objects for each cognitive skill.

Cognitive skill	LO1	LO2	LO3
Memory	Text	Audio	Video
Concentration	Diagram	Chart	Case studies
Perception	Video	Diagram	Simulation
Logical thinking	Simulation	Case studies	Chart

order thinking deals with making judgement to evaluate based on the set of rules and principles that are gained out of LOT and MOT actions. Also, HOT focuses on the creating innovative process or product by utilizing the fundamental and application knowledge gained through the different set of actions comprising LOT and MOT. Thus using the opinion survey a binding is established to state the possible learning objects that might help in improving the skills in the prescribed level of competency as shown in Tables 7 and 8.

3.3. Adaptation model

The Adaptation model of the framework focuses on the assessment process and Reinforcement model, to facilitate improvement in learner's competency level of each CS. The elements of adaptation model considered in this research are shown in Fig. 3.

To initiate the assessment process, it is desired to test the learners frequently by providing appropriate learning objects. To evaluate the same in the education system, it is essential to identify the type of questionnaire to be questioned for determining the competency. For this purpose, the existing standard method of questioning in engineering education – Bloom's taxonomy is considered. Hence, another mapping between learning object and possible Bloom's action is derived from the opinion survey.

3.3.1. Reinforcement modelling

According to Sutton and Barto [17], reinforcement learning is learning of 'what to do' to map situations to actions to maximize a numerical reward signal. Here, the learner is not told which actions to take, instead must discover which actions yield the most reward by trying them. The model encompasses four main sub elements such as a policy, a reward function, a value function, and a model of the environment. The policy indicates a decision-making function in an environment and it is a mapping from perceived states of the environment to actions to be taken when in those states. A reward function defines the goal in a reinforcement learning to map each perceived state (or state-action pair) of the environment a reward, indicating the inherent desirability of that state. A value function specifies the total amount of reward can be expected to get accumulated from that state for the further decision making. The final element of the reinforcement learning is a model of the environment that mimics the behaviour of the environment.

3.3.2. Reinforcement learning for modelling education system

In general, the education system focuses on assessing the competency level of learners/students. In order to stay in or to improve the level of competency, the learners generally choose different methods of learning style with different types of LOs. Unfortunately, if the LO is not suitable for their dominant CS, performance degradation or no improvement on skill would occur. Eventually, this may lead to decreased level of competency or may create disinterest towards the course. Hence, it is required to choose appropriate LOs to achieve the level of competency.

As a follow-up, in this framework, Los determination is done. To check further, if the identified LO performed well, it is desired to assess the competency level. Hence, a reinforcement learning model is created to check whether the adopted learning style and Los helped in the improvement of competency level. Therefore, the four elements of RL are defined as follows:

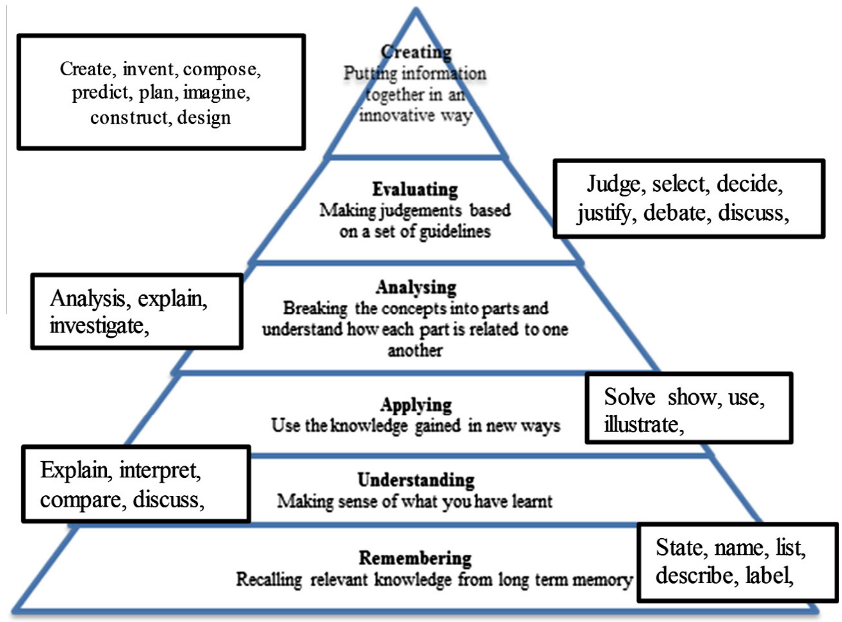

Figure 2 Bloom's taxonomy and action verbs.

Table 7 Opinion survey data for mapping LOs with Bloom's taxonomy actions.

LO/BT	LOT			MOT			HOT		
	R	U	Av	Ap	An	Av	E	C	Av
Simulation	19	46	18.69	59	62	56.54	36	45	37.85
Case study	21	47	30.84	38	70	50.47	40	26	30.84
Diagram	45	58	39.72	32	47	36.92	29	37	30.84
Chart	40	54	41.59	33	60	43.46	47	32	36.92
Text	49	68	50.00	29	34	29.44	20	34	25.23
Audio	58	64	58.88	31	29	28.04	18	26	20.56
Video	68	72	31.78	40	42	38.32	25	26	23.83

R – Remembering, U – Understanding, Ap – Applying, An – Analysing, E – Evaluating, C – Creating, Av – Average.

Table 8 Mapping between LO and knowledge competency level.

Learning object	LOT	MOT	HOT
Simulation		X	X
Case studies		X	X
Diagram	X		X
Chart	X	X	X
Text	X		
Audio	X		
Video		X	

3.3.3. Environment

An environment in AI defines a surroundings or conditions on which an agent or living things perform. In the case of an education system, it involves learners, their capability, course and course materials and finally the level of competency attained forms the environment. Therefore, the entire decision-making process involves the criteria such as Student's capability, Type of Course Material, and Level of Competency. The environment for this domain appears to be episodic and dynamic, as each learner would have different levels of CS for different types of courses.

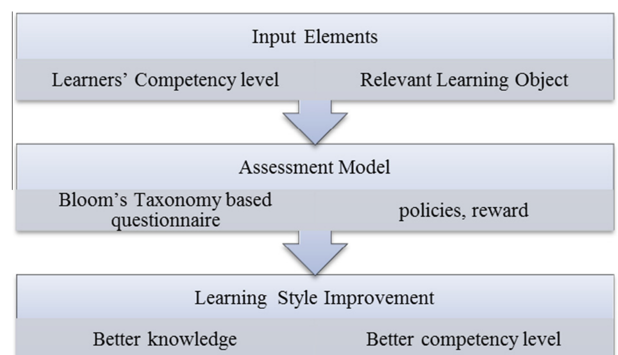

Figure 3 Elements of adaptation model.

3.3.4. Policy

The policy of RL indicates the way of mapping performed between the perceived states of environment and associated actions. According to the task performed, state ('S') are defined as follows:

States 'S' = $\{M_i, C_i, P_i, LT_i\}$,

where

M – CS_Memory
C – CS_Concentration
P – CS_Perception
LT – CS_LogicalThinking and i = {low, medium, high}

Actions 'A' = {take_simulation, perform_casestudy, use_chart, use_diagram, read_text, listen_audio, watch_video}

Policy, $\pi = \{$
$\{s_{low} \rightarrow s_{medium,}\ s_{medium} \rightarrow s_{high}\} => $ reward, r;
$s_{low} \rightarrow s_{high} =>$ reward with bonus, r_b;
$\{s_{high} \rightarrow s_{medium,}\ s_{medium} \rightarrow s_{low}\} =>$ negative reward, r_n
$\}$

Initially, in order to formulate the action sequence, from the opinion survey, actions are identified and a rule base is formulated using fuzzy based rule system. The rule base is created to assign appropriate CM based on the CS possessed by the learners for the specified domain. Due to the episodic and dynamic nature of the environment, the assignment of CM may vary from learner to learner and for the different courses. Hence, fuzzy rules are generated so that the assignment of CM is altered easily to the existing environment status.

3.3.5. *Fuzzy inference system for action sequence formulation*

A Fuzzy Inference System (FIS) is a way of mapping an input space to an output space using fuzzy logic. It uses a collection of fuzzy membership functions and rules, instead to reason about data. The set of rules in a fuzzy expert system is known as *knowledge base*. The rules in FIS are fuzzy production rules of the form:

"*if p then q*, where p and q are conditional facts"

3.3.5.1. Fuzzy rule base construction. In general, a rule based system is designed with group of facts, if then rules, and an interpreter controlling the application of rules specified in the facts. The group of facts are represented as fuzzy set as defined below:

A fuzzy set 'A' in X defined as a set of ordered pairs.

$A = \{(x, \mu_A(x)) \| x \in X\}$,

where $\mu_A(x)$ is called the member function (MF) for the fuzzy set. The MF maps each element of X to a membership grade between zero and one.

By using the memberships derived from the fuzzy sets, rules are formulated as conditional statements of the generic form:

'*if x is A then y is B*'

where if part of the rule 'x is A' is called the antecedent or premise, the part of the rule 'y is B' called consequent or conclusion.

Applying these principles, a fuzzy rule base is constructed for predicting the types learning objects in lieu with the cognitive skill of the learners.

3.3.5.2. Rule base construction for the selected domain. The purpose of the rule base constructed using the principles stated in the previous section was to generate policies dynamically. Using Sugeno fuzzy inference system, a model is created. The model is targeted to generate policies to suggest suitable learning objects according to the cognitive skill of the learners. Initially, model is created with four inputs stating the considered cognitive skills such as memory, concentration, perception and logical thinking. The created fuzzy inference system is shown in Fig. 4.

Three membership functions such as low, medium and high are defined. The ranges for the member functions are obtained dynamically from the learner's cognitive status.

Using the scores obtained by the learner's, the categorization is made. The average score under each cognitive skill category is considered to be middle point (mean) in splitting the range as low, medium and high. Hence, the scores less than Value (predecessor (mean) – 0.1)) are considered as low range, while the value (successor (mean – 0.1)) is considered as starting point for high range. The values between low and high range are treated to be medium range. Membership functions such as low, med and high are created for each of the cognitive skill and are assigned with the range determined. A sample membership functions created for cognitive skill are shown in Fig. 5.

For each range, the appropriate learning objects, as obtained from opinion survey are mapped. Therefore for each learners based on their level of cognitive skills, learning objects are suggested. In order to generate the different sequence of learning objects, the fuzzy model is used. A rule base for fuzzy inference is created for all combination of cognitive skills and accordingly the developed fuzzy model is expected to generate policies.

The rule base created is illustrated in Fig. 6.

The fuzzy rules along with the output learning objects are shown in the Fig. 7.

By using the created model several policies are generated to be supplied to the learners. For instance, the learners who are detected with low memory are given with the learning objects with a composition of video, audio and text. This is inferred from the rule base as shown in Fig. 8. At the same time for the learners with medium or high memory skill, a change in the composition of Learning Objects Video, Audio and Text is required as shown in the Figs. 9 and 10.

From the policy generated using the rule base, for the memory skill being medium, the suggested learning objects are similar to low level, yet the proportion of composition for text and audio content is considerably greater than for low memory level. Similarly, for learners having good memory skill, it is suggested to increase text content proportionately when compared to other two learning objects Audio and video.

Though there is a variation in memory skill level, it is indeed required a good level of concentration skill. Therefore, when concentration alone treated as low, medium and high for learners, the learning objects recommended are Chart, Diagram and Case studies. The exact level of each digital object is inferred from the fuzzy output.

The policies thus formulated for reinforcement model in terms of rules are listed below:

- If (Memory is low) then (Text is low) (Audio is med) (Video is high)
- If (Memory is med) then (Text is med) (Audio is high) (Video is high)
- If (Memory is high) then (Text is high) (Audio is med) (Video is low)
- If (Concentration is low) then (Chart is med) (diagram is high) (Case Study is low)
- If (Concentration is med) then (Chart is high) (diagram is med) (Case Study is high)

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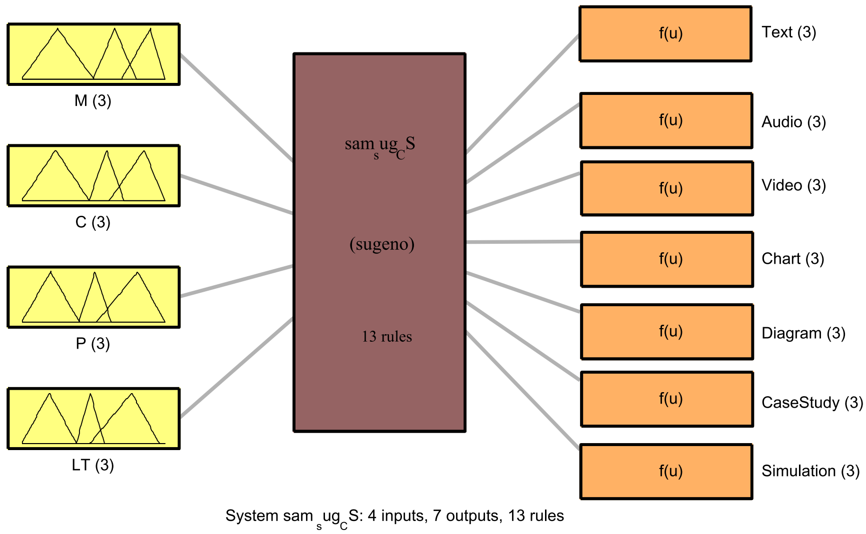


Figure 4 Fuzzy inference system.

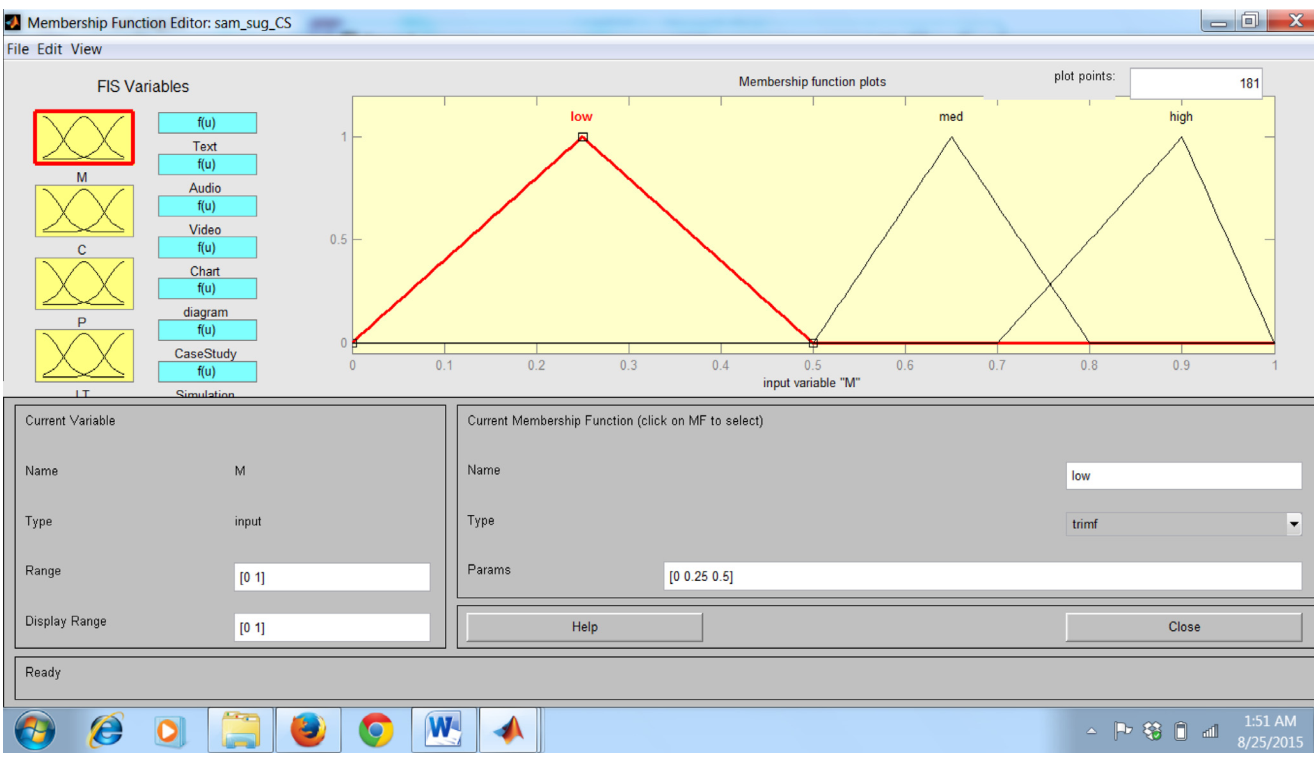


Figure 5 Sample membership functions for a cognitive skill.

- If (Concentration is high) then (Chart is med) (diagram is low) (Case Study is high)
- If (Perception is low) then (Video is med) (diagram is high) (Simulation is low)
- If (Perception is med) then (Video is high) (diagram is med) (Simulation is high)
- If (Perception is high) then (Video is med) (diagram is low) (Simulation is high)
- If (Logical Thinking is low) then (Chart is high) (Case Study is med) (Simulation is low)
- If (Logical Thinking is med) then (Chart is med) (Case Study is high) (Simulation is high)
- If (Logical Thinking is high) then (Chart is low) (Case Study is med) (Simulation is high)
- If (Memory is low) and (Concentration is low) and (Perception is low) and (Logical Thinking is low) then (Text is low) (Audio is med) (Video is high)

With the help of the generated policies, action sequences are generated for each learner. After having assigned with the

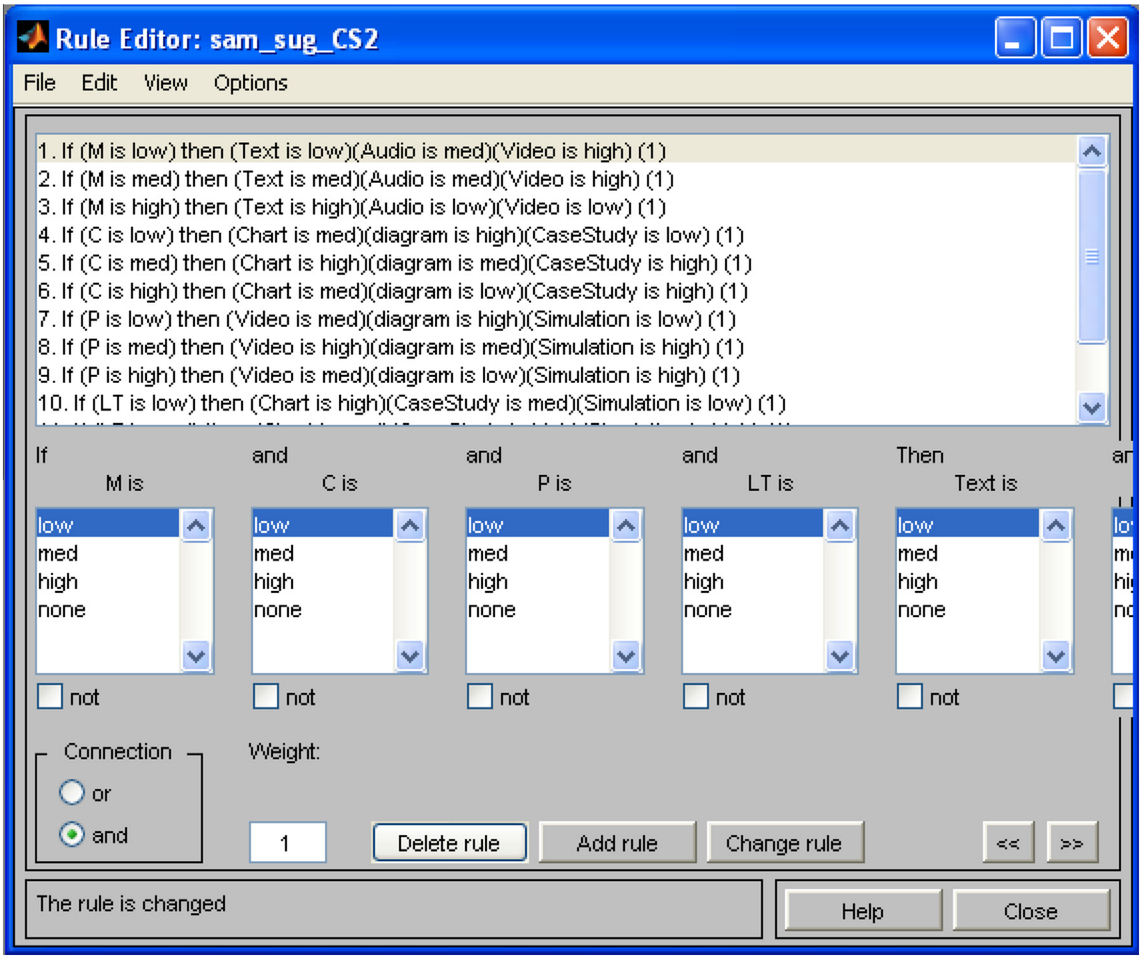


Figure 6 Fuzzy rule base.

suggested LOs, the learners are allowed to assimilate the LOs to gain known. A sufficient time period is provided to the learners followed by which assessment process is carried out. The assessment process is initiated with the questionnaires that are relevant to test the knowledge improvement through the improvement in the cognitive skill. Hence the questionnaires are set using the LOT, MOT and HOT action verbs of Blooms taxonomy. The responses for these cognitive skill based questions of the domain are evaluated and are rewarded accordingly as per the defined reward function of reinforcement model. The cycle is repeated, henceforth the assessment carried out in trial and error basis to determine the level of knowledge improvement.

With this, the reinforcement learning scenarios are described by states, actions, rewards and policies.

In order to execute the process two major algorithms such as Q-Learning Algorithm and SARSA (*State-Action-Reward-State-Action)* Algorithm may be employed [18–20].

3.3.6. State-action-reward-state-action process

SARSA algorithm is an improvement on the Q-learning algorithm which is a form of model-free reinforcement learning. The problem domain consists of an agent, its various states S, and a set of actions per state A. The agent can move from one state to another by performing some action a ϵ A. The transition, i.e. the next state gives a reward to the agent. The goal of the agent is to maximize the total reward. This is achieved by optimizing the actions for each state. Hence, there exists a function Q that calculates the quality of each state-action combination. Initially Q returns a fixed value. Subsequently, during each step when the agent is rewarded, new values are calculated and updated. The rule that updates the *Q*-value depends on the current state (s_t), the action the agent choses (a_t), and the reward (r). The next state that agent would fall after taking action is (s_{t+1}). The action at that state (s_{t+1}) is a_{t+1}. Thus the SARSA methodology is represented as

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[R(s_t, a_t) + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$$

where

$\leftarrow$ – Updating the old value
t – Current interaction
t + 1 – Next interaction
$Q(s_t, a_t)$ – The Q-values of the current interaction.
$R(s_t, a_t)$ – Reward obtained for performing action a_t in s_t
α – Learning rate ($0 \leqslant \alpha \leqslant 1$)
γ – Discount factor that decides the importance of future rewards ($0 \leqslant \gamma < 1$)

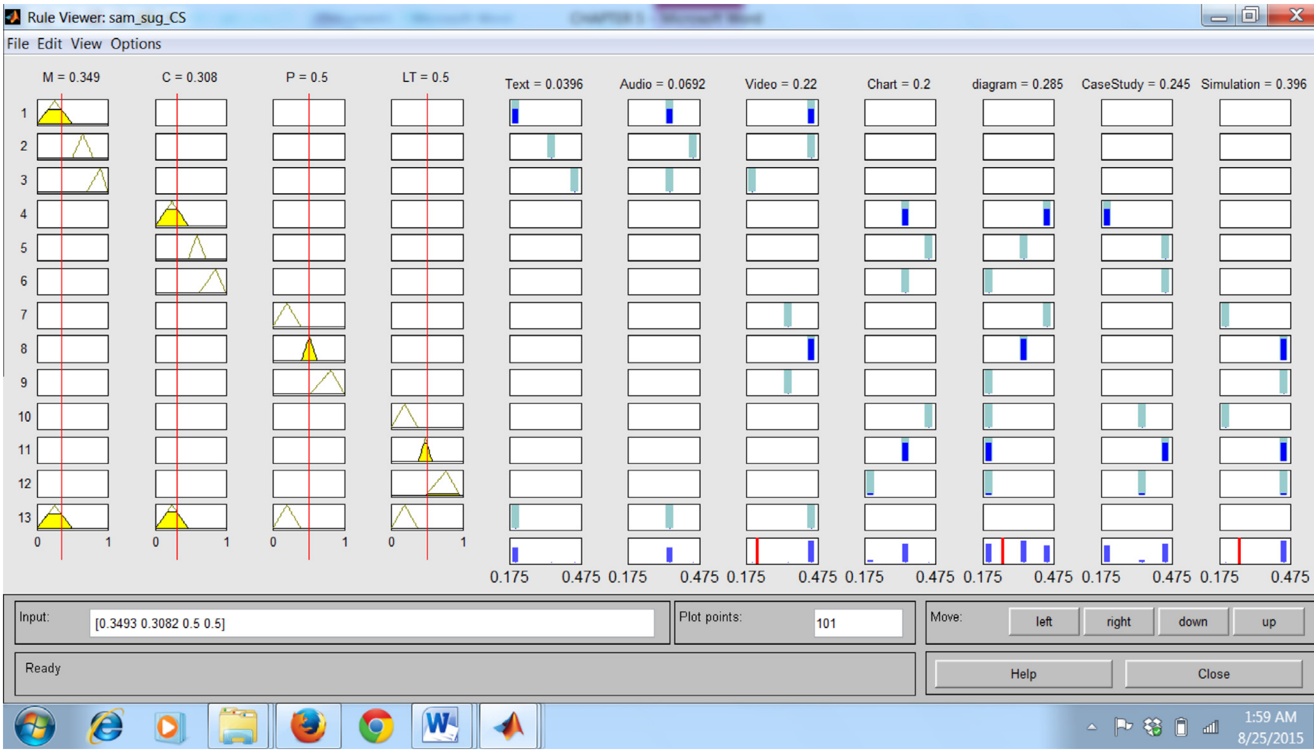


Figure 7 Fuzzy rules with output learning object.

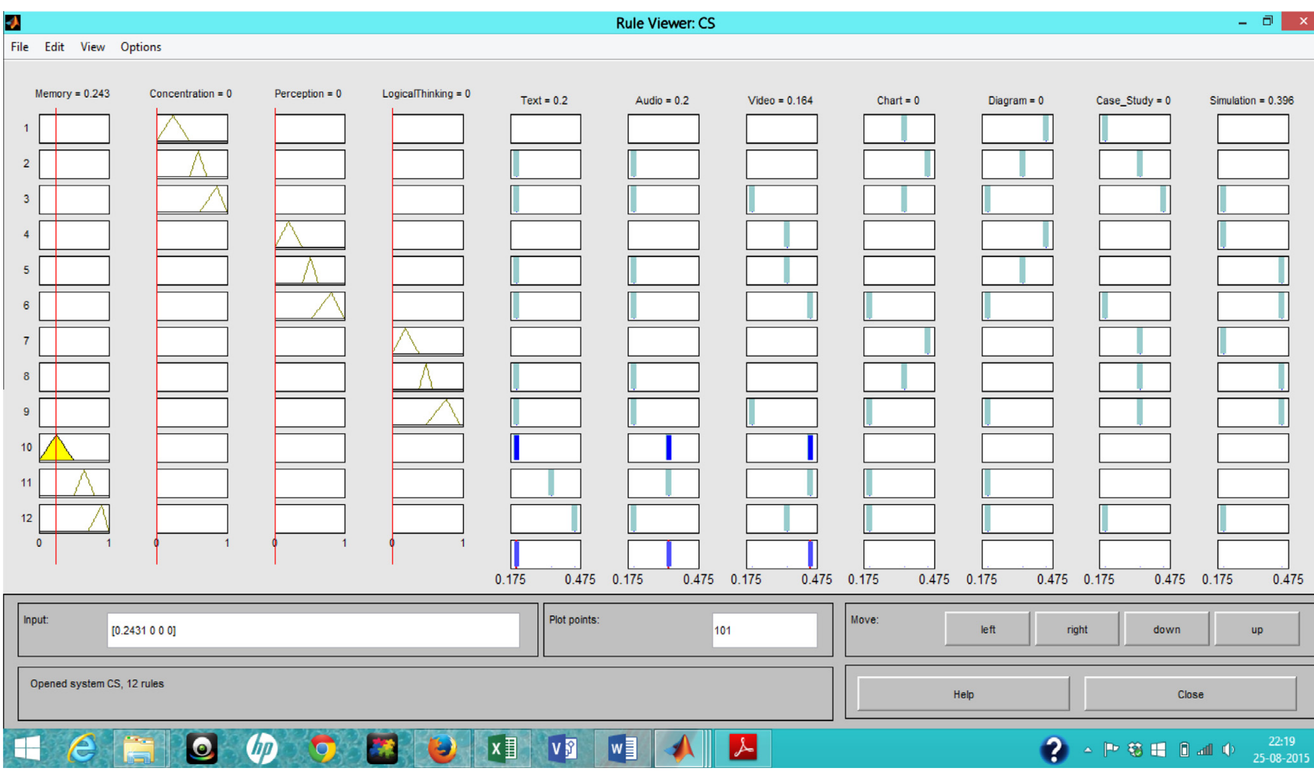


Figure 8 LO composition for low level in Memory CS.

The action sequence is decided based on the defined policies. The policy selection process is not always selecting the action that results in the maximum Q-value as this will lead to a phenomenon of "local maxima". Instead, it is determined on a factor epsilon ε which determines the extent to which the actions are randomized. The constraints that are applied on

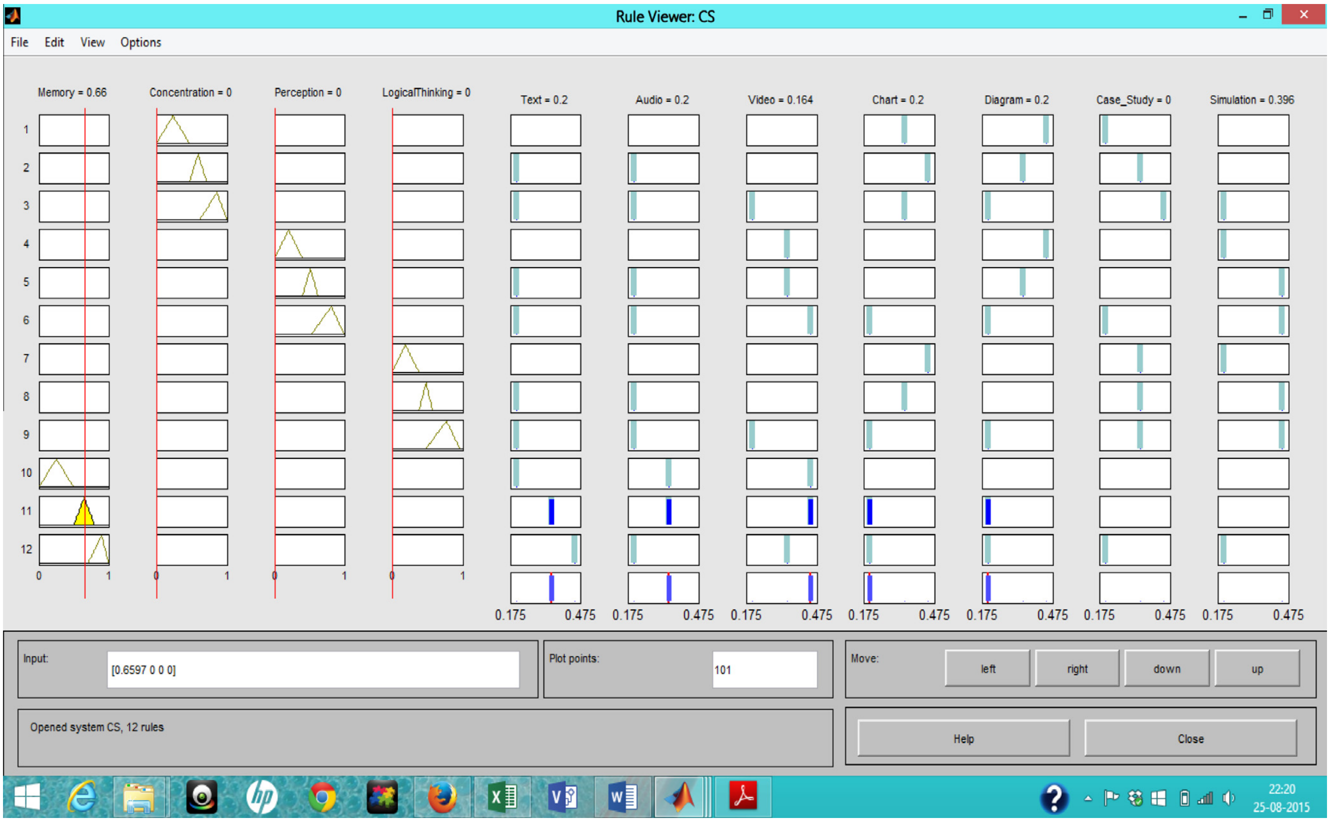


Figure 9 LO composition for medium level in Memory CS.

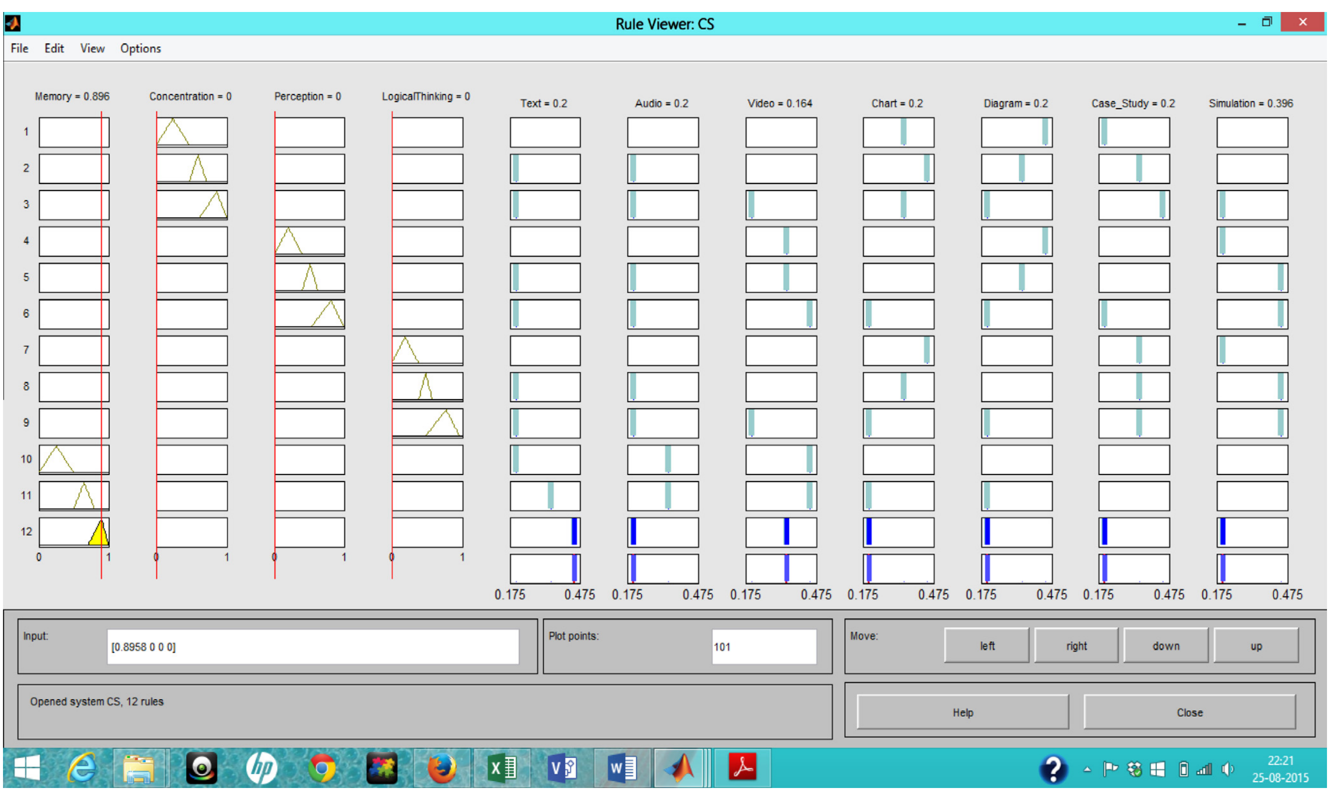


Figure 10 LO composition for high level in Memory CS.

Please cite this article in press as: Balasubramanian V, Margret Anouncia S, Learning style detection based on cognitive skills to support adaptive learning environment – A reinforcement approach, Ain Shams Eng J (2016), http://dx.doi.org/10.1016/j.asej.2016.04.012

the methodology to decide the improvement level are as follows:

$$\text{if } \gamma = 0, \text{ then } Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[R(s_t, a_t) - Q(s_t, a_t)]$$
$$=> \text{update with reward and Q value of current state.}$$
$$\text{if } \alpha = 0, \text{ then } Q(s_t, a_t) \leftarrow Q(s_t, a_t)$$
$$=> \text{no learning takes place}$$
$$\text{if } \alpha = 1, \text{ then } Q(s_t, a_t) \leftarrow Q(s_t, a_t) + R(s_t, a_t) - Q(s_t, a_t) \leftarrow R(s_t, a_t)$$
$$=> \text{reward only}$$
$$\text{if } \gamma = 1, \alpha = 1, \text{ then } Q(s_t, a_t) \leftarrow Q(s_t, a_t) + R(s_t, a_t) + Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t) \leftarrow R(s_t, a_t) + Q(s_{t+1}, a_{t+1})$$
$$=> \text{sum of reward and Q value of next state}$$

4. Results and discussions

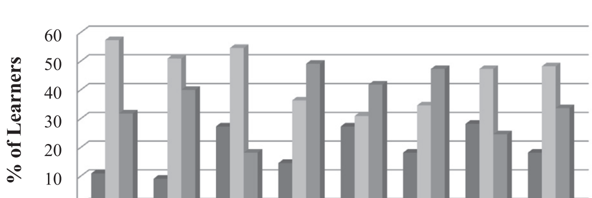
The framework developed is evaluated by considering 110 postgraduate students. Initially, a set of questions on a web related course is identified to assess the four different cognitive skills viz., memory, concentration, perception and logical thinking. For easy monitoring, follow-up of the assessment process, a batch of postgraduate students is considered. The questionaries are prepared by the course expertise and are verified to align with the mentioned cognitive skills based on the action verbs provided by the standard practice Bloom's Taxonomy [16].

A comparison of Assessment A-I and A-III is illustrated in Fig. 11.

It was noted from the Assessment A-I performance that, around 11% of learners ended up with poor memory skills while 57% learners of same level possessed moderate level of memory and 32% showed good memory skill. As far as concentration is concerned, in the chosen group, 27% had low level of concentration and 19% reported high level of concentration. For perception only 42% demonstrated high level. In case of logical thinking, a highly essential Cognitive Skill (CSs) for engineering education, majority of learners (75%) possessed only medium level and low level.

The same set of students is provided with suitable learning objects based on the identified policy. Students are assessed twice for the improvement with a time gap of a month between each assessment. From the third assessment, it is observed that cognitive skill memory showed a significant improvement in high level competency of memory with an increase of around 8%. At the same time there appears a decrease of around 1% in low level competency. Considering the cognitive skill concentration, it is seen that there is a considerable level of decrease in the low level competency of Concentration while the higher level showed an improvement in the subsequent assessment process. The cognitive skill perception provided a fuzzy outcome where significance is not seen very much. However, in terms of number of medium level learners there is a notable increase in value for the succeeding assessments. Finally, the logical thinking value in the final assessment appeared to be very much significant.

Hence from the observation, it is evident that the assigning suitable learning object based on the learner's cognitive skill has good impact on the learning style as well on the knowledge level improvement.



	Memory A-I	Memory A-III	Concentration A-I	Concentration A-III	Perception A-I	Perception A-III	Logical Thinking A-I	Logical Thinking A-III
Low	10.91	9.09	27.27	14.55	27.27	18.18	28.18	18.18
Medium	57.27	50.91	54.55	36.36	30.91	34.55	47.27	48.18
High	31.82	40	18.18	49.09	41.82	47.27	24.55	33.64

Figure 11 Three level assessments.

5. Conclusion and future work

A Framework for Learning Style Detection based on Cognitive skills is designed and implemented. The evaluation of the same is performed by segregating the learners into four groups based on their leading cognitive skill. For the first level of experimentation, the first two cognitive skills namely memory and concentration are focused. An opinion survey is conducted to relate the cognitive skill, learning style and the standard assessment technique – Blooms taxonomy. The survey yielded an insight into how best each of these factors could be related and hence suitable learning objects for each of cognitive skill improvement are identified through the policies derived through fuzzy inference. To prove the effectiveness of framework, assessment process is repeated twice. The scores of learners in the ensuing levels of assessment showed eloquent improvement in competency level. Thus the study correlated the cognitive skill with learning style for the knowledge improvement and hence proved, and the learning style detection based on cognitive skill would serve as a favourable methodology for knowledge improvement.

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Please cite this article in press as: Balasubramanian V, Margret Anouncia S, Learning style detection based on cognitive skills to support adaptive learning environment – A reinforcement approach, Ain Shams Eng J (2016), http://dx.doi.org/10.1016/j.asej.2016.04.012