Enhancing fuzzy inference system based criterion-referenced assessment with an analogical reasoning schema

Tze Ling Jee , *Kai Meng Tay *kmtay@feng.unimas.my Electronic Department, University Malaysia Sarawak

Abstract

In this paper, a fuzzy inference system (FIS) that incorporated with an analogical reasoning schema based criterion-referenced assessment (CRA) is proposed. The aim of CRA is to report students' achievement with reference to a set of objective reference points. Usually, scores were given to each task in order to eases the assessment as in common practice. A *total-score* is further obtained with a simple addition or weighted addition of these scores. Scoring rubric is an essential tool for subjectivity assessment. A search in literature reveals that the use of FIS in CRA is not new. It can be explained as an alternative approach how a *total-score* can be obtained. For a multiple input FIS based CRA, a large set of fuzzy rules are required. With the use of grid partition, the number of fuzzy rules required increases in an exponential manner and this phenomenon is known as the *curse of dimensionality* or *combinatorial rule explosion problem*. It is a tedious work in getting a full set of rules. The main objective of this paper is to propose a novel FIS based CRA schema that allow rules to be reduced. We suggest to adopt a systematic approach to select a set of rules (from the full rule base), and to incorporate an analogical reasoning schema to predict unknown consequent. An FIS based CRA procedure with an analogical reasoning schema is proposed and evaluated with a case study relating to students' laboratory project assessment is conducted in UNIMAS.

Keywords: Fuzzy inference system, Criterion-referenced assessment, Analogical reasoning schema

1. Introduction

Education assessment is an important yet complicated task for lecturers as it would influence students in their learning process outcomes directly [1]. Assessment in higher education can be done by using the criterion-referenced assessment (CRA) where CRA determines students' grades by comparing their achievements with a clearly stated criterion for learning outcomes and the standards for particular levels of performance are also clearly stated. It can be a simple pass-fail grading schema, a series of key criteria rather than as a single grade or percentage [2]. Hence, there is a possibility for all students within a particular group to get very high or very low grades depending on the individuals' performances against the established criteria and standards.

Fuzzy inference system (FIS) is also known as fuzzy rule based system, or fuzzy if-then model. FIS can be viewed as a method where a multiple-input model can be constructed in an easy manner [3]. One of the success key factors is the ability to incorporate human/expert knowledge where information is described by vague and imprecise statements. Furthermore, the behaviour of an FIS is also expressed in a language that could be easily interpreted by humans.

A search in literature reveals that many fuzzy logic based assessment models have been proposed. Indeed, some models are well accepted, especially by the society of fuzzy logic studies, as a potential application. Some articles on this topic are highly cited. For example, Biswas proposed a fuzzy set related method for students' answer scripts This approach was then further evaluation [4]. improved by Chen and Lee [5]. In [1], a fuzzy set approach was implemented to assess student-centered learning. Cin and Baba presented the use of fuzzy logic in English proficiency assessment [6]. Wang proposed to evaluate students' and Chen answerscripts based on extended fuzzy grade sheets [7].

FIS is implemented in CRA model as an alternative to simple addition or weighted addition for several reasons. (1) Criteria in rubric maybe qualitative rather than quantitative [8]. (2) Various combination of scores associated to each task may generate the same aggregated score; however, the performance of the students may be different. (3) Relative importance of each task may be different, depending on the learning outcome. FIS can be used as an alternative approach to model or to customize the relationship between the score of each task and aggregated score [9].

The process of collecting a full rule base for an FIS is rigorous. Various approaches have been proposed to overcome this issue, i.e., on how to select a set of important rules for an FIS modeling, and on how to handle incomplete rule base (i.e., analogical reasoning (AR) [10], similarity base reasoning [11] and fuzzy rule interpolation [12]). These lines of study are popular, and various works on this aspect has been reported. Various AR, similarity base reasoning and fuzzy rule interpolation techniques are developed to allow the missing rule from an incomplete rule base to be deduced. For example, in [13], a similarity based reasoning was used to reduce the rule base and to deduced new fuzzy rules. AR has been applied to many areas, likewise, analogical reasoning was applied in information retrieval for computer systems [14].

To the best of our knowledge, no works on the use of fuzzy rules selection and on handling of incomplete rule base in FIS based CRA is reported. Thus, we attempt to investigate on the use of these advance fuzzy logic techniques in FIS based CRA. The aim of this paper is to develop an FIS-based CRA with a reduced rule base. A rule selection technique and an AR are adopted and included to be part of the proposed FIS-based CRA procedure. The rule selection technique systematically highlights a set of rules that to be collected from lecturer. AR further predicts the unknown rule [10]. Our proposed procedure reduces the time required to collect a full set of rule base by collecting the selected rules only. Hence, it eases the FIS-based CRA procedure. The proposed FIS-based CRA procedure is then evaluated with a set of data/information collected from a laboratory project assessment conducted in UNIMAS.

2. The FIS-based CRA methodology

To ease the explanation of this methodology, the scoring rubrics are firstly presented. In this paper, students' projects were assessed based on three tasks, which were *system design* on the electronic circuitry, *system building* based on the designed circuitry and the *presentation skills*. Tables 1, 2 and 3 demonstrated the scoring rubrics used for the three tasks respectively. Holistic rubric was used for this case study.

| Rank | Linguistic | Criteria | |
|------|----------------|---|--|
| | Terms | | |
| 10 | Excellent | The circuit is complex (\geq 10 necessary ICs). All necessary components are included. Able to apply all learned knowledge in circuit design. Able to simulate and clearly explain the operation of designed circuit. | |
| 9~8 | Very good | The circuit is moderate (7~9 necessary ICs). Some components are not included. Able to apply most of the learned knowledge. Able to simulate and clearly explain the operation of the circuit. | |
| 7~6 | Good | The circuit is moderate (5~6 necessary ICs). Some unnecessary components are included. Able to apply most of the learned knowledge. Able to simulate the circuit and briefly explain circuit operation. | |
| 5~3 | Satisfactory | The circuit is simple (3~4 necessary ICs). Some unnecessary components are included. Apply moderate of the learned knowledge. Simulate only parts of circuit and briefly explain the circuit operation. | |
| 2~1 | Unsatisfactory | The circuit is simple $(1 \sim 2 \text{ necessary ICs})$. Some components are not included and unnecessary components are added. Only apply some of the learned knowledge. Unable to simulate and explain the operation of designed circuit. | |

Table 1. Scoring Rubric for System Design

| Table 2. | Scoring | Rubric | for System | Building |
|----------|---------|--------|------------|----------|
| | 0 | | ~ | 0 |

| Rank | Linguistic | Criteria | | |
|------|----------------|--|--|--|
| | Terms | | | |
| 10~9 | Excellent | PCB: Demonstrated excellent solder techniques (No cold solder joints, no bridge joints and | | |
| | | all components leads were soldered to the pad). Components are installed on the PCB | | |
| | | correctly. Circuit fully operated as expected. | | |
| | | Project board: All the components, jumpers and cables are well-arranged and tidy. Circuit | | |
| | | fully operated as expected. | | |
| 8~7 | Very good | PCB: Demonstrated good solder techniques (Some cold solder and bridge joints, some | | |
| | | components leads were not soldered to the pad). Components are installed on the PCB | | |
| | | correctly. Circuit operated as expected. | | |
| | | Project board: Most of the components, jumpers and cables are well-arranged and tidy. | | |
| | | Circuit operated as expected. | | |
| 6~5 | Good | PCB: Demonstrated good solder techniques. (Some cold solder and bridge joints, some | | |
| | | components lead were not soldered to the pad). Some components are not installed correctly. | | |
| | | Some parts of circuit malfunction. | | |
| | | Project board: The components are well-arranged but jumpers and cables are messy. Some | | |
| | | parts of the circuit malfunction. | | |
| 4~3 | Satisfactory | PCB: Demonstrated poor solder techniques (Many cold solder and bridge joints and many | | |
| | | components leads were not soldered to the pad). Some components are not installed correctly. | | |
| | | Most parts of circuit not function. | | |
| | | Project board: The arrangement of components, jumpers and cables are messy. Most parts of | | |
| | | the circuit malfunction. | | |
| 2~1 | Unsatisfactory | PCB: Demonstrated poor solder techniques. (Many cold solder and bridge joints and many | | |
| | | components leads were not soldered to the pad). Most of the components are not installed | | |
| | | correctly. The circuit totally not functions. | | |
| | | Project board: The arrangement of components, jumpers and cables are very messy. The | | |
| | | circuit totally not functions. | | |

| Rank | Linguistic Terms | Criteria |
|------|---------------------|--|
| 10 | Excellent | Information is presented in logical and interesting sequence. Full knowledge is demonstrated by answering all class questions with explanations and elaborations. Graphics explained and reinforced screen text and presentation. Used clear voice and correct, precise pronunciation of terms. |
| 9~8 | Very good | Information is presented in logical sequence. Eased with expected answers to all questions, but fails to elaborate. Graphics relate to text and presentation. Voice is clear. Pronounced most words correctly. Most audience members can hear presentation. |
| 7~6 | Good | Information is presented in logical sequence. Answers all simple questions, but fails to elaborate. Graphics relate to text and presentation. Voice is low; audience members have difficulty hearing presentation. Pronounced most words correctly. |
| 5~3 | Satisfactory | Jump around, difficult to follow presentation. Uncomfortable with information and is able to answer only simple questions. Used graphics that rarely support text and presentation. Voice is low. Pronounces terms incorrectly. |
| 2~1 | Unsatisfactory | Presentation cannot be understood because there is no sequence of information. Do not have grasp of information, cannot answer questions about subject. Used superfluous graphics or no graphics. Speak unclear, incorrectly pronounces terms, and speaks too quietly for audience in the back of class to hear. |

Figures 1 and 2 depict a plot of fuzzy membership functions for *system design* on the electronic circuitry and *system building* based on the designed circuitry. For example, score 6 to 7 in system design refers to criteria "*The circuit is moderate (5~6 necessary ICs). Some unnecessary*

components are included. Able to apply most of the learned knowledge. Able to simulate the circuit and briefly explain circuit operation." It can be represented as a membership function with label "Good" in Figure 1.



Fig 1. Membership Functions for System Design



Fig 2. Membership Functions for System Building

The relationship between the three tasks and the aggregated score could be represented with a set of If-Then rules where the aggregated score varied from 1 to 100. The aggregated score was represented by seven fuzzy membership functions which are "Very *Good*", "*Good*", "*Fair*", "*Weak*", "*Very weak*", and "*Unsatisfactory*" respectively. The full rule base was a total of 125 (5(*System Design*) × 5(*System Building*) × 5(*Presentation Skill*)). For example, Rules 1 and 2 showed a part of the rule base.

Rule 1

If System Design is **Good** and System Building is **Good** and Presentation Skill is **Unsatisfactory** then Total-Score is **Weak**

Rule 2

If System Design is Very Good and System Building is Very Good and Presentation Skill is Good then Total-Score is Good.

3. A Review on Analogical Reasoning (AR) Schema

AR can be divided into five steps [10]: (1) Choosing a Similarity Measure (SM), (2) Pattern matching, (3) Selecting a rule, (4) Deducing a consequent, (5) Combining consequents. The detail of AR algorithm is summarized in Figure 3.

In this paper, we explained a concept of predicting a set of empty rules n_{empty} using AR from a set of selected rules $n_{selected}$. $\mu_{R^{nempty}}$ represents the membership functions for the rules that are not selected, where as $\mu_{R^{n_{selected}}}$ represent the membership functions for the rules that are selected. $\mu_{R^{n_{empty}} \cap R^{n_{selected}}}$ shows the area of overlapping between $\mu_{R^{n_{empty}}}$ and $\mu_{R^{n_{selected}}}$.

Similarity Measure is defined as a measure transformed from a distance measure by using Similarity Measures:

$$SM = (1 + DM)^{-1}$$
 (1)

where Disconsistency measure:

$$DM = 1 - Sup\mu_{R^{n_{empty}} \cap R^{n_{selected}}}(x)$$
⁽²⁾

and

$$\mu_{R^{n_{empty}} \cap R^{n_{selected}}}(x) = \min \left[\mu_{R^{n_{empty}}}, \mu_{R^{n_{selected}}} \right]$$
(3)

Pattern matching is obtained through the use of a similarity measure between an antecedent and an observed fact of a rule where both may be stated as a combination of a set of linguistic variables and term. AR expressed that a rule is to be fired with the use of a Modification function that modifies the consequent of the rule, Deduced Consequent:

$$B^{n_{empty}} = MF(B^{n_{selected}})$$
⁽⁴⁾

If there is more than one deduced consequent presents at the end of the decision process, these consequents is calculated using weighted average method in order to obtain the final result.



Fig 3. AR algorithm [10]

4. The proposed FIS-based CRA incorporated with AR

Our proposed FIS-based CRA with AR methodology is summarized as in Figure 4. Our proposed methodology is as follow.

- (1) Define the purpose/learning objective and learning outcome.
- (2) Development of tasks for the project: *System Design* (*SD*), *System Building* (*SB*) and *Presentation skills* (*PS*).
- (3) Define the criterion for each task.
- (4) Development of scoring rubric for each task.
- (5) Development of the fuzzy membership functions for the three tasks: membership function for *SD*, *SB* and *PS* are μ_{SD} , μ_{SB} ,

and μ_{PS} respectively.

(6) $R^{n_{selected}}$ rules are systematically selected. $R^{n_{empty}}$ rules are to be predicted. Rule 1 is selected then Rule 2 will be left empty and Rule 3 is selected again.

- (7) The $R^{n_{selected}}$ selected rules are collected from expert.
- (8) The process is then continued with prediction of rules using AR.
 - a) DM is calculated using Equation (3)
 - b) *SM* is determined by Equation (2)
 - c) If *SM* is larger than the threshold τ_o , then the consequent for $R^{n_{empty}}$ is determined.
- (9) Construction of FIS-based CRA model with AR
- (10) Assessment for each task.
- (11) Aggregation of assessment scores are computed with Equation (5).

$$Score = \frac{\sum_{a=1}^{M_{SD}} \sum_{b=1}^{M_{SB}} \sum_{c=1}^{M_{PS}} \mu_{SD}^{a} \times \mu_{SB}^{b} \times \mu_{PS}^{c} \times B^{a,b,c}}{\sum_{a=1}^{M_{SD}} \sum_{b=1}^{M_{SB}} \sum_{c=1}^{M_{PS}} \mu_{SD}^{a} \times \mu_{SB}^{b} \times \mu_{PS}^{c}}$$
(5)



Fig 4. Authors' proposed FIS-based Criterion-referenced assessment with an Analogical Reasoning Procedure

5. Case Study and Experimental Results

An experiment was conducted to evaluate the proposed FIS-based CRA with an AR by using a case study involving second year university students; laboratory projects. For the project, students were required to use their creativity and technical skills to design and develop a digital electronic system based on the knowledge gained through the digital electronic and digital system applications subject.

Table 4 summarized the score for each task and the aggregated score using FIS-based CRA with an AR scheme. Column "Number" is the label of each student's project. In columns "*SD*", "*SB*' and "*PS*", the score for each task were shown. The "Fuzzy score" column represented the *total-score* of the lab project obtained using the FIS-based CRA with an AR. The "*Expert's knowledge*" column showed the linguistic term associated to each project. For example, student number 1 with SD = 4, SB = 4, PS = 6 obtained a *total-score* of 32.66%, which was deduced by a linguistic term of *weak* from the lecturer. For the student number 5 (SD = 6, SB = 8, PS = 5), the *total-score* is 43.65%. It was deduced by a linguistic term of 63.5% Weak, 36.5% Fair (which was predicted by AR).

Figure 5 depicts the surface plots for system design and presentation skill versus total score (Fuzzy score) at system building = 10, for FIS-based CRA with an AR.

| | Input scores | | | FIS-based CRA with Analogical Reasoning | | |
|--------|--------------|----|----|---|------------------------------------|--|
| Number | SD | SB | PS | Fuzzy score (%) | Expert's knowledge | |
| | | | | | Linguistic term | |
| 1 | 4 | 4 | 6 | 32.66 | Weak | |
| 2 | 5 | 4 | 6 | 33.53 | Weak | |
| 3 | 5 | 4 | 7 | 33.91 | Weak | |
| 4 | 7 | 4 | 6 | 37.37 | Weak | |
| 5 | 6 | 8 | 5 | 43.65 | 63.5% Weak, 36.5% Fair | |
| 6 | 5 | 5 | 7 | 44.95 | Weak | |
| 7 | 7 | 6 | 7 | 50.39 | Fair | |
| 8 | 5 | 7 | 7 | 51.37 | Fair | |
| 9 | 8 | 6 | 6 | 52.57 | 87.15% Fair, 12.85% Good | |
| 10 | 7 | 7 | 6 | 54.42 | 77.9% Fair, 22.1% Good | |
| 11 | 7 | 7 | 8 | 63.63 | 31.85% Fair, 68.15% Good | |
| 12 | 7 | 9 | 8 | 78.82 | Very Good | |
| 13 | 8 | 8 | 10 | 81.20 | Very Good | |
| 14 | 10 | 8 | 8 | 82.63 | 86.85% Very Good, 13.15% Excellent | |
| 15 | 10 | 9 | 8 | 95.68 | Excellent | |

Table 4. The Total-Scores using the proposed FIS-based CRA with a Analogical Reasoning schema



Fig 5. Surface Plot of SD and PS versus Total Score at SB = 10

6. Conclusion

An FIS based criterion-referenced assessment model with AR is presented and evaluated with a case study. Our proposed method was able to reduce the rule base for an FIS based CRA. Students' project can still be assessed with the proposed procedure. This maybe a more practical approach, as compared with the other FIS based CRA. The rules collected can be greatly reduced.

For future improvement, more experiments will be conducted.

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