GRANULAR MINING APPROACH FOR IDENTIFYING STUDENT'S LEARNING STYLE IN E-LEARNING ENVIRONMENT

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ABSTRACT

Pattern multiplicity of interaction in e-learning can be intelligently examined to diagnose students' learning style. This is important since a student's behaviour while learning online is among the significant parameters for adaptation in e-learning system. Currently, Felder Silverman (FS) is a common learning style model that is frequently used by many researchers. There are four learning style dimensions in FS model and most researches need to develop four classifiers to map the characteristics into the dimensions. Such approach is quite tedious in terms of data pre-processing and it also time consuming when it comes to classification. Therefore, this study improves the previous work by mapping the students' characteristics into Integrated Felder Silverman (IFS) learning style, by combining the four learning dimensions in FS model into sixteen learning styles. The most crucial problem for IFS model is the difficulties in identifying the significant pattern for the classifier that has high dimension and large number of classes. In this study, fifteen features have been identified as the granule learning features for learning style recognition based on the analysis resulting from questionnaire and log data. The granularity of the learning features is efficiently implemented using Rough Set Boolean Reasoning and Genetic Algorithm. However, Rough Set generates huge rules that are redundant and irrelevant. Hence, these rules need to be incrementally pruned to extract the most significant one. The rules are pruned by evaluating the rules support, the rules length and the rules coverage. The experiment shows that with only 12 per cents rules left, the classification accuracy is still significant and the rule coverage is also high. Comparative analysis of the performance between IFS classifier and the conventional four classifiers shows that the proposed IFS gives higher classification accuracy and rule coverage in identifying student's learning style.

ABSTRAK

Kepelbagaian corak interaksi pelajar dalam e-pembelajaran boleh diperiksa secara pintar bagi meramal gaya pembelajaran mereka. Ini adalah penting kerana kelakuan pelajar semasa belajar secara atas talian adalah antara parameter penting untuk diadaptasikan dalam sesuatu sistem e-pembelajaran. Pada masa ini, Felder Silverman (FS) adalah model gaya pembelajaran yang biasa digunakan oleh ramai penyelidik. Terdapat empat dimensi gaya pembelajaran dalam model FS dan kebanyakan penyelidik perlu membangunkan empat pengelas untuk memetakan ciri-ciri pelajar kepada dimensi FS tersebut. Pendekatan ini agak merumitkan dari segi pra-pemprosesan dan ianya mengambil masa yang lebih panjang semasa pengelasan. Oleh itu, kajian ini dapat menambah baik penyelidikan terdahulu dengan memetakan ciri-ciri pelajar kepada gaya pembelajaran Felder Silverman yang Bersepadu (IFS) menerusi gabungan pembelajaran empat dimensi dalam model FS menjadi 16 gaya pembelajaran. Masalah utama bagi model IFS adalah kesukaran dalam mengenal pasti corak penting bagi pengelas yang mempunyai banyak dimensi dan bilangan kelas yang besar. Lima belas ciri pelajar telah dikenal pasti sebagai butiran pembelajaran melalui penganalisaan soal selidik dan data log. Butiran ciri-ciri pembelajaran yang dilaksanakan menggunakan Set Taakulan Boolean kasar dan Algoritma Genetik, serta merupakan satu gabungan yang cekap. Walau bagaimanapun, Set kasar menjana peraturan yang berulang dan tidak relevan. Oleh itu, peraturan-peraturan ini perlu dicantas secara berperingkat untuk mengekstrak peraturan yang terpenting. Cantasan peraturan dilakukan dengan menilai sokongan peraturan, panjang peraturan dan liputan peraturan. Ujikaji menunjukkan dengan hanya 12 peratus peraturan yang tinggal, ketepatan pengelasan masih baik dan liputan peraturan juga tinggi. Analisis perbandingan prestasi antara pengelas IFS dan empat pengelas konvensional menunjukkan bahawa prestasi IFS adalah lebih tinggi dalam ketepatan pengelasan dan liputan peraturan bagi mengenal pasti gaya pembelajaran pelajar.

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LIST OF ABBREVIATIONS

AIVbG	-	Active Intuitive Verbal Global
AIVbSq	-	Active Intuitive Verbal Sequential
AIViG	-	Active Intuitive Visual Global
AIViSq	-	Active Intuitive Visual Sequential
ASVbG	-	Active Sensor Verbal Global
ASVbSq	-	Active Sensor Verbal Sequential
ASViG	-	Active Sensor Visual Global
ASViSq	-	Active Sensor Visual Sequential
BR	-	Boolean Reasoning
CE	-	Computer Engineering
CS	-	Computer Science
EDM	-	Educational Data Mining
EFB	-	Equal frequency Binning
FS	-	Felder Silverman
GA	-	Genetic Algorithm
IFS	-	Integrated Felder Siverman
ILS	-	Index of Learning Styles
IT	-	Information Technology
JA	-	Johnson Algorithm
LHS	-	Left Hand Side
LMS	-	Learning Management System
LSI	-	Learning Style Inventory
LSQ	-	Learning Style Questionnaire
MBTI	-	Myer-Briggs Type Indicator
MLP	-	Multi-layer perceptron

MOODLE	-	Modular Object-Oriented Dynamic Learning Environment
NN	-	Neural Network
RHS	-	Right Hand Side
RIVbG	-	Reflective Intuitive Verbal Global
RIVbSq	-	Reflective Intuitive Verbal Sequential
RIViG	-	Reflective Intuitive Visual Global l
RIViSq	-	Reflective Intuitive Visual Sequential
ROSETTA	-	Rough Set Toolkit for Analysis of Data
RSC	-	Rough Set Classifier
RSVbG	-	Reflective Sensor Verbal Global
RSVbSq	-	Reflective Sensor Verbal Sequential
RSViG	-	Reflective Sensor Visual Global
RSViSq	-	Reflective Sensor Visual Sequential
SPSS	-	Statistical Package for the Social Sciences
TEL	-	Technology Enhanced Learning
UTM	-	Universiti Teknologi Malaysia
WEKA	-	Waikato Environment Analysis

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CHAPTER 1

INTRODUCTION

1.1 Overview

Granular mining is a mining approach that explores the different level of mining phases. There are many methods in machine learning that cover the concept of granular mining. The most common methods are Fuzzy sets and Rough Sets. In Rough Sets, every phase of sub-tasks such as discretization, reduct and rule filtering needs to be examined extensively for the best classification accuracy. It is essential to implement an appropriate discretization method since performance of discretization methods differ significantly (Blajdo *et al.*, 2008). Hence, for Rough Set mining, it is important to cautiously choose the most suitable discretization and reduct technique since the chosen technique will greatly affect the classification accuracy.

Rough Sets also generate excessive amount of rules (Bose, 2006 and Li, 2007), whereby most of the rules are not significant and need to be filtered in order to choose only the essential rules. Existing works in Rough Set rule filtering involve filtering the insignificant rules based on the rule length and the rule support (Cheng *et al.*, 2011, Pai *et al.*, 2010 and Bose, 2006). The rule coverage and classification accuracy are the measurement to determine the reliability of the selected rules. However, Tsumoto (2002) stated that selecting rules with higher classification accuracy will result in small rule coverage. In contrast, selecting rules with higher coverage will result with rules with lower accuracy. Hence, during the rule filtering process it poses a challenge to get the most significant rules by observing the rule parameter such as the rule length, the rule support, the rule coverage and the effect to the classification accuracy.

This research provides in-depth studies on student's learning preferences and behavior while using e-learning system based on Felder Silverman (FS) learning dimensions. In e-learning environment, there is a correlation between the student's learning style and the choice of learning materials. Therefore, student's learning style can be observed through his web behavior which concerned on how user navigate, how user use the link and path provided, how user choose the type of learning material and the usage of the tool provided in the system. Previous studies need four classifiers to map the student's learning characteristics into four FS learning dimension. This approach is very tedious in preparing and pre-processing the data and it also quite time consuming for the four classifiers to be implemented.

In order to enhance the previous work, this study proposes granular mining approach to intelligently classify the student's learning style into integrated Felder Silverman (IFS) learning style based on patterns of student's behavior while learning in hypermedia environment. The student's most relevant attributes are analyzed and fed to only one classifier to develop the most significant classifier and rules discovery. Granularity searching using Rough Set Classifier is implemented to obtain significant features. To our understanding, none of the studies have been reported in implementing IFS features with significant rules for identifying learning styles. However, our focus will be more on extracting the significant rules for detecting the learning styles which is not being done previously by other researchers in this area. By focusing on different levels of granularity, one can obtain different levels of knowledge, as well as an in-depth understanding of the inherent knowledge structure of the mining phases.

1.2 Background of the Problem

Learning style has become a significant factor contributing in learner progress and many researchers agree that incorporating learning styles in education has potential to make learning easier for students and increases learning efficiency (Mampadi *et al.*, 2011; Popescu , 2010; Kinshuk *et al.*, 2009; Kazu, 2009; Brown, 2009 and Graf, 2008). The importance of learning style that can increase student's performance has led to the efforts in developing an adaptive learning system that adapt the course content based on the user features such as the student's learning style, background and preferences (Popescu, 2011, Graf, 2007, and Papanikolau *et al.*, 2003).

Early research has focused on student's learning style by using questionnaire to assess the student's learning characteristics (Wolf, 2003; Papanikolau *et al.*, 2003; Carver and Howard, 1999; Triantafillou *et. al*, 2002). However, the exploitation of questionnaires is time consuming and unreliable approach for acquiring learning style characteristics and may not be accurate (Villaverde *et al.*, 2006; Stash and de Bra, 2004; Kelley and Tangney, 2004). Most questionnaires are too long, hence, causing students to choose answers arbitrarily instead of thinking seriously about them. Even if the learning style has been determined, it's still cannot notify the real characteristics of the students while learning on-line. In addition, once the profile is generated, it becomes static and doesn't change regardless of user interaction. In on-line learning environment, the student's learning characteristics are changed accordingly when different tasks are provided.

Due to these problems, several studies have been conducted in detecting student's learning style that are based on the student's browsing behavior (Klasnja-Milicevic *et al.*, 2011, Popescu, 2010, Garcia *et al.*, 2007; Graf and Kinshuk, 2006; Yaannibelli *et. al*, 2006; Lo and Shu, 2005). This approach can be implemented successfully since the style of student's interaction with the system can be inferred accurately and can be used as attributes for adaptation purposes.

Various intelligent solutions have been used to represent student's learning style such as statistical analysis (Graf and Kinshuk, 2006), Neural Network (Lo and Shu, 2005; Villaverde *et al.*, 2006), Decision Tree (Cha *et al.*, 2006), Bayesian Networks (Garcia *et al.*, 2007), Naïve Bayes (Kelley and Tangney, 2004), Genetic Algorithm (Yaannibelli *et al.*, 2006) and AprioriAll (Klasnja-Milicevic *et al.*, 2011). However, all researchers develop four classifiers in order to classify the four FS dimension and the classification result for all classifiers are quite moderate as shown in Table 1.1. Therefore, a more powerful technique is needed for this domain in order to have more accurate learning style classification. Rough Set has its own strength in learning from data and generating rules that easier to interpret. To our knowledge, Rough Set method has never been used in providing significant rules of learning styles using FS.

Table 1.1 : Comparative result among researches in FS classification

FS Dimensions	**Cha *et al.*, (2006) Decision Tree**	**Garcia, (2007) Bayesian Network**	**Graf, (2007) Bayesian Network**	**Graf, (2007) Simple Rule**	**Popescu, (2010) Simple Rule**
Active/ Reflective	66.67	58	62.5	79.33	84.51
Sensor/ Intuitive	77.78	77	65	77.33	82.39
Visual/ Verbal	100	-	68.75	76.67	73.94
Sequential / Global	71.43	63	66.25	73.33	78.17

Rough Set theory, introduced by Zdzislaw Pawlak in the early 1980's is a mathematical tool to deal with vagueness and uncertainty (Pawlak, 1991). The methodology is concerned with the classificatory analysis of vague, uncertain or incomplete information or knowledge expressed in terms of data acquired from experience. Unlike other soft computing methods, Rough Set analysis requires no external parameters and uses only the information presented in the given data. However, Rough Set always generates a large number of rules (Bose, 2006 and Li, 2007), therefore, it is important to extract only the most significant rules for Rough Set classifier since it will be difficult for human to interpret the rules manually (Setiawan *et al.*, 2009 and Pai *et al.*, 2010). Rule filtering involve pruning the rules based on certain criteria, but which criteria to be implemented in rule filtering is still become an issue and need to have proper and careful investigation.

A variety of learning style model has been used to characterize learning styles for students. Among them are Felder Silverman learning style (Felder and Silverman, 1988), Kolb's theory of experiential learning (Kolb, 1984), Howard Gardner Multiple Intelligence (Gardner, 1993), Honey and Mumford (Honey and Mumford, 1986) and Dunn and Dunn model (Dunn and Dunn, 1978).

In this study, Felder Silverman learning style model has been chosen due to its successfulness in dealing with learning material adaptation, collaborative learning and traditional teaching (Felder and Silverman, 1998; Zywno, 2003; Carmo *et al.*, 2007). Furthermore, the development of the hypermedia learning system that incorporate learning components such as the navigation tool, the presentation of the learning material in graphics form, simulation, video, sound and help facilities can easily tailored to the FS learning style dimension. Carver (1999) and Graf (2007) considered FS as the most appropriate and feasible to be implemented for hypermedia courseware. Coffield *et al.* (2004) and Graf (2007) have studied several existing learning styles and concluded that currently there is no learning style that can be considered as the best learning style model, since every model have their own strength and characteristics. However, the learning dimensions in FS are parallel to other learning style models, for example, Active/Reflective is parallel with Kolb learning style and extravert/introvert in Myer-Briggs Type Indicator (MBTI).

Felder-Silverman learning style model was initially developed by Felder and Silverman in 1988 for engineering students. This model categorized a student's dominant learning style along a scale of four dimensions: active-reflective (how information is processed), sensing-intuitive (how information is perceived), visual-verbal (how information is presented) and global–sequential (how information is understood).

Felder and Solomon developed Index of Learning Styles (ILS) questionnaire to assess the student's learning style (Felder and Soloman, 1997). The objective of this questionnaire is to determine the dominant learning style of a student. This questionnaire can be accessed freely from website and is often used as instrument to identify learning style.

Figure 1.1 shows the learning style scale for FS dimensions. Once the student finished answering the questionnaire, his learning style will be identified. Every learning dimension has two poles. If the score in every dimension is between 1A to 11A, the learning style is active for processing dimension, sensor for perception dimension, visual for input dimension and sequential for understanding dimension. Meanwhile, if the score in every dimension is between 1B to 11B, the learning style is at the other poles, which are reflective for processing, intuitive for perception, verbal for input and global for understanding dimension.

If a student gets a score from 1 to 3 in any dimension, he/she has a mild preference and fairly balanced on the two dimensions. If the score is on scale 5 or 7, the student has moderate preference, and if the score is on scale 9 or 11 the student has a very strong preference for the dimension. The student with strong preferences for certain dimension must learn according to the environment that matches his learning style. He may have learning difficulty if he studies in the environments that are not suitable with his learning style.

ACTIVE	11A 9A 7A 5A 3A 1A 1B 3B 5B 7B 9B 11B	**REFLECTIVE**
SENSOR	11A 9A 7A 5A 3A 1A 1B 3B 5B 7B 9B 11B	**INTUITIVE**
VISUAL	11A 9A 7A 5A 3A 1A 1B 3B 5B 7B 9B 11B	**VERBAL**
SEQUENTIAL	11A 9A 7A 5A 3A 1A 1B 3B 5B 7B 9B 11B	**GLOBAL**

Figure 1.1 Felder Silverman learning style scales (Felder, 1996)

In this study, the Integrated Felder Silverman (IFS) is proposed that incorporate processing, perception, input and understanding learning styles in FS to be mapped into 16 (2^4) learning styles as shown in Table 1.2 (Klašnja-Milićević *et. al* , 2011; Graf and Kinshuk, 2007 and Felder, 1988). With this integration, the time consumption and the effort in diagnosing the learning styles will be lessen.

Table 1.2: Sixteen learning styles in IFS

IFS Learning Styles	**Label**
Active/Sensor/Visual/Sequential	ASViSq
Reflective/Sensor/Visual/Sequential	RSViSq
Active/Intuitive/Visual/Sequential	AIViSq
Reflective/Intuitive/Visual/Sequential	RIViSq
Active/Sensor/Verbal/Sequential	ASVbSq
Reflective/Sensor/Verbal/Sequential	RSVbSq
Active/Intuitive/Verbal/Sequential	AIVbSq
Reflective/Intuitive/Verbal/Sequential	RIVbSq
Active/Sensor/Visual/Global	ASViG
Reflective/Sensor/Visual/Global	RSViG
Active/Intuitive/Visual/Global	AIViG
Reflective/Intuitive/Visual/Global	RIViG
Active/Sensor/Verbal/Global	ASVbG
Reflective/Sensor/ Verbal/Global	RSVbG
Active/Intuitive/Verbal/Global	AIVbG
Reflective/Intuitive/Verbal/Global	RIVbG

1.3 Statement of the Problem

Student's learning characteristics and the choice of learning materials in e-learning environment have been used in previous research to classify student's learning style. However, it is still not clear of which behavior pattern are most significant for the classifier. Therefore, there is a need to granular the learning characteristics and adaptability could be instilled for making the learning styles more attractive and effective. Previous research need to conduct four classifiers to predict student's learning style into four FS learning dimensions. Thus it is desirable to integrate the FS four dimensions into 16 learning styles with only one classifier. However, this approach leads to large number of patterns and large number of classes for the classifier. Hence, the complexity of the classifier is increased and solved by the proposed granular mining approach. For better illustration, Figure 1.2 presents the problem scenario that leads to the problem statement of the study.

Hence, the primary research question in this study is given as:

"How to acquire the individual learning features granularly, and how it can be classified in order to intelligently and efficiently identify the learning styles using Rough Set?"

The secondary research questions that are needed to address the primary research question are written as:

i) Is there any significant difference between learning styles and the choice of learning materials in e-learning?

ii) Could information granulation of learning behavior and preferences being utilized to represent the most relevant learning features in e-learning for IFS learning styles?

iii) How accurate is Rough Set Theory in classifying student's learning styles into Felder Silverman model using four classifiers?

iv) How accurate is the proposed granular mining using Rough Set Theory in classifying student's learning styles into integrated Felder Silverman using one classifier and to discover rules?

v) How accurate is IFS classifiers in identifying the student's learning style compare to conventional approach?

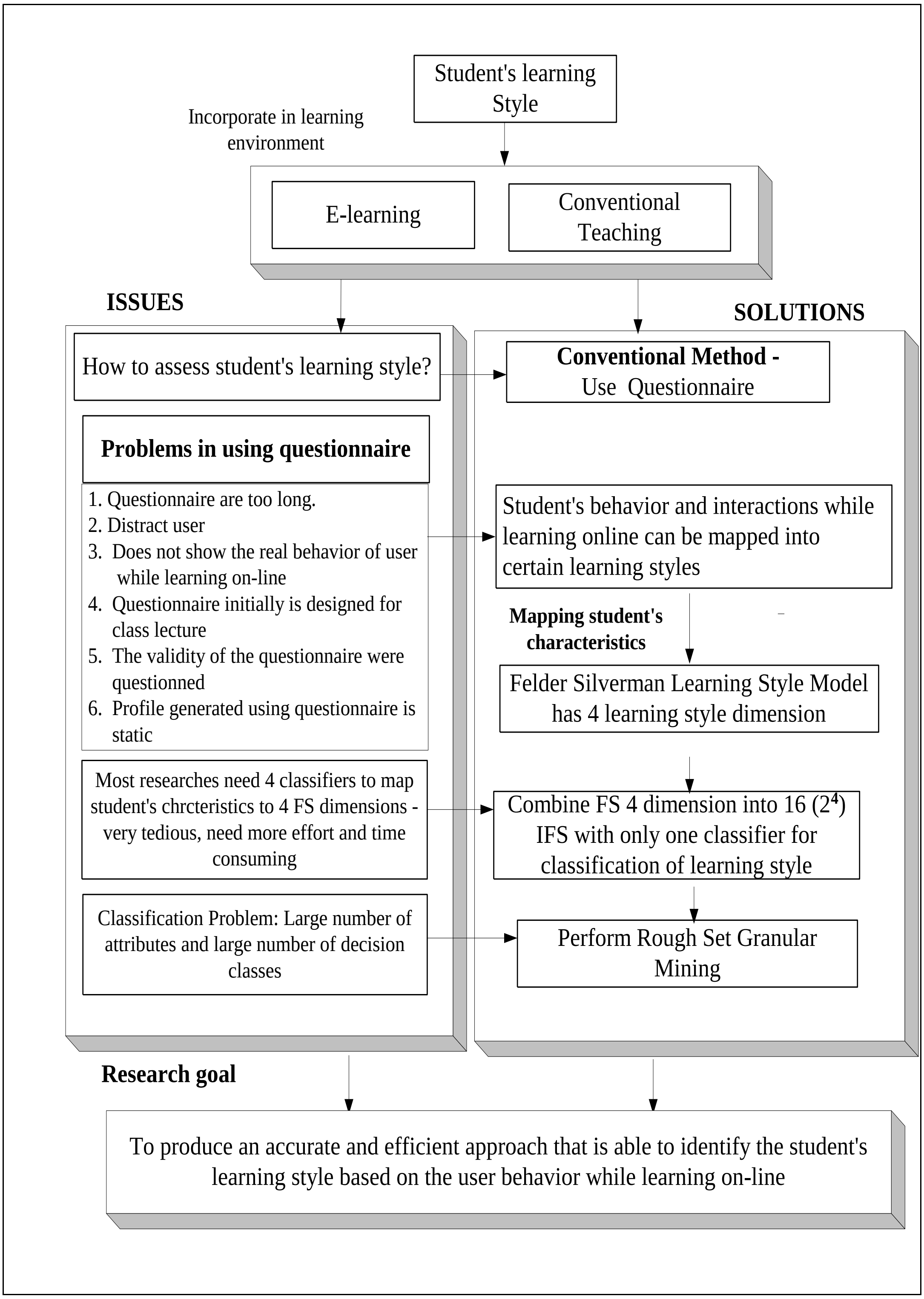

Figure 1.2 Scenario of the problems that lead to the proposed study

1.4 Objectives of the Study

The objectives of the study that need to be achieved are as follows:

i) To investigate and identify the granule learning features for FS learning dimensions. The sub objectives include:
   a. Features investigation for the conventional FS
   b. Integration and development of the proposed IFS features

ii) To investigate the performance of Rough Sets classifier in identifying four FS dimensions.

iii) To propose an approach based on Rough Set granular mining in order to extract compact IFS rules. The sub objectives include:
   a. To discretize IFS data for mining the granularity of the features
   b. To measure and quantify the significant parameters of IFS rules based on rule length, rule accuracy, rule strength and rule coverage.
   c. To investigate and compare the performance of Rough Sets in classifying IFS dimensions with four FS classifiers.

1.5 Importance of the Research

This research is an application based research and is important in terms of theoretical knowledge in Computer Science and practical of real application in e-learning domain. The following list several importance of the study:

i) The objective of this research is to identify the student's learning style based on the student's behavior pattern in e-learning environment. The finding of the significant patterns of the student's behavior while accessing e-learning and the approach of learning style classification are important in the development of adaptive learning systems that adapt the learning contents based on the student's learning style.

ii) Several classifiers need to be developed using conventional learning style identification approach. The integration of learning style dimensions can reduce the burden of the heavy work in the classification phases by implementing only one classifier for the learning style identification purpose.

iii) The granular mining approach using Rough Set is proposed in order to extract compact IFS rules. Every level of mining phases need to be explored extensively using various discretization and reduct techniques. In this domain, Boolean Reasoning and Genetic Algorithm give the highest classification accuracy compared to other discretization and reducts techniques. Pruning the rules incrementally based on the rule support and the rule length able to extract only significant rules with higher coverage and higher accuracy. The granular mining approach can be adopted and apply systematically in Rough Set rule mining in order to get the highest classification accuracy with only significant rules.

1.6 Research Methodology

This section describes briefly the research methodology implemented in this study. It consists of four main tasks in order to achieve the goal and objectives of this study as shown in Figure 1.3. In phase 1, an e-learning system that incorporates various designs of course contents, learning activities and learning strategies that are based on Felder Silverman Learning model is developed in Moodle environment. The system is specifically used for students learning Data Structure in Universiti Teknologi Malaysia (UTM). During learning, the students' interaction, characteristics and behavior are captured in log files provided by Moodle. In phase 2, the behavior and preferences of the students were analyzed implicitly, using questionnaire and explicitly by analyzing the data in the log. The analysis then is used to identify behavior patterns and to capture the granule information of the most relevant IFS features.

Phase 3 is to conduct Rough Set classification in identifying FS learning dimensions. Four classifiers have been developed in order to determine Rough sets performance in classifying the learning styles into active/reflective, sensor/intuitive, visual/verbal and global/sequential. In phase 4, granular mining using Rough sets is implemented to discover the most significant rules. Various discretization algoruthms and reduct techniques have been experimented using 10-fold cross validation technique. Finally, the extracted rules are filtered based on the rule's support, rule length and the combination of the two criteria. The performance of the rules are measured based on rule's accuracy and rule's coverage in order to get the most sufficient rules. Comparative analysis of Rough Sets performance on IFS classification with other classifiers is conducted in phase 5. The detail description of the research methodology is explained in Chapter 3.

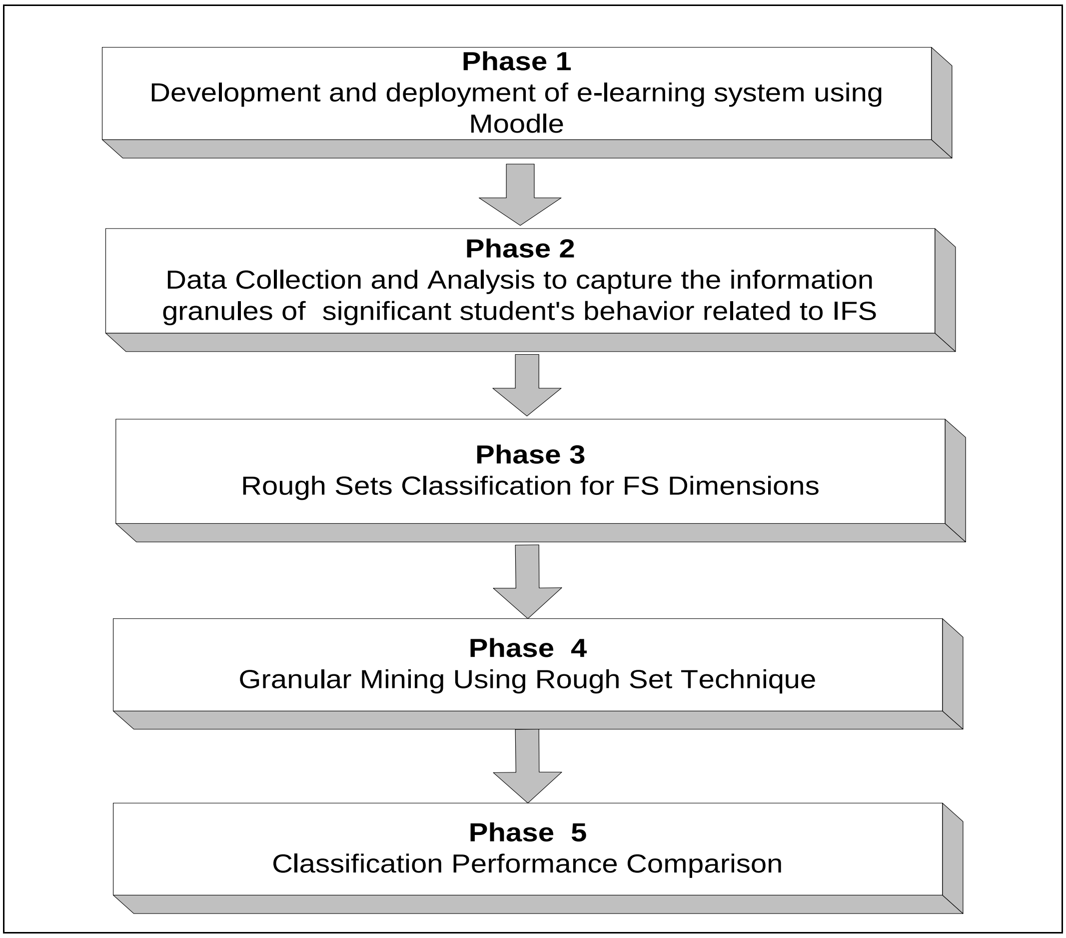

Figure 1.3 Research methodology implemented in this study

1.7 Contributions of the Study

The research contributions of the study are as follows:

i) Significant characteristics related to Felder Silverman learning dimension: active/reflective, sensor/intuitive, visual/verbal and sequential/global by analyzing student's preferences while using e-learning system developed using Moodle. These outcomes can be benefited by educators who wish to incorporate various learning materials in their e-learning presentations by associating the content with the student's learning style.

ii) Rules generated by Rough Sets for four FS classifiers.

iii) Rules Granularity by identifying the most significant rules based on the rule length, rule accuracy and rule strength.

Detailed explanation and discussions of the contributions are given in Chapter 7.

1.8 Scope of the Study

The scopes of the study are limited to the following:

i) The e-learning system that includes various teaching approaches is deployed using Moodle LMS provided by UTM.

ii) The students being selected as respondent for this study are UTM students who are taking Data Structure course. Their behavior while learning 3 topics in Data Structure are captured in Moodle web log file.

iii) This study focuses on the behavior and preferences of e-learning materials, and not on the student's emotion during learning.

iv) Only Felder Silverman learning style model is being considered since this model is the most preferred model among researches in learning style (Graf, 2008; Kazu, 2009; Brown, 2009 and Mampadi *et al.*, 2011).

v) The strong preferences of FS learning dimensions are considered for analyzing the learning characteristics of IFS since the student's with strong preferences in certain learning dimension might have difficulties in learning if the learning style is not supported by the teaching environment (Felder and Solomon, 1997).

vi) This study used the classifiers provided by WEKA and ROSETTA mining tool.

1.9 Definition of Terms

Several terms used extensively in the thesis will be described in this section.

i) **Learning styles**
The different ways of learners use to perceive, gather and process information.

ii) **Granular mining**
A mining approach whereby every level of mining phase will be examined thoroughly in order to find the best mining result.

iii) **Felder Silverman learning style model**
A learning style model developed by Felder and Siverman in 1998 that classify students into 4 dimensions; processing (active/reflective), perception (sensor/intuitive), input (visual,verbal) and understanding (sequential,global).

iv) **Integrated Felder Silverman learning style**

The proposed approach whereby the 4 dimensions of FS learning style model is combined to be represented into sixteen learning styles.

v) **Rule length**

Characteristic of a rule which represents the number of conditional attributes in the IF part of a rule.

vi) **Rule Support**

Characteristic of a rule which represents the number of record or instances in the training data that fully match with the property described by the If-Then condition.

vii) **Classification Accuracy**

The percentage of number of instances that correctly classified into the target class over the total population of data sample.

viii) **Discretization**

A process of dividing a range of continuous attributes into interval. It engages searching for cuts that determine the intervals and unifying the values over each interval. All values that lie within each interval are mapped to the same discrete value.

ix) **Reduct**

A term in Rough Set theory that generally defined as a minimal subset of attributes that can classify the same domain of objects as unambiguously as the original set of attributes.

1.10 Thesis Organization

The thesis consists of 7 chapters. Chapter 1 gives the introduction of the study, the background of the problem, the aim of the study, the objectives, the scope, thesis organization and ends with the thesis contributions. Chapter 2 presents the conducted literature review to probe and elaborate on related issues and solutions of the problem. Chapter 3 describes the research methodology employed in this study. The results of this study are discussed in Chapter 4, 5 and 6. Chapter 4 presents the student's behaviour and preferences analysis for on-line learning. The analysis in this study identifies the significant attributes for the purpose of classifying the student's learning styles. Chapter 5 explains the Rough Sets classification for Felder Silverman learning styles, while Chapter 6 describes the granular mining approach of Integrated Felder Silverman learning styles using Rough Sets classifier. Comparative studies with other classifiers are also discussed in Chapter 5 and 6. Chapter 7 ends with the summary and conclusion of the study.

1.11 Summary

This chapter has presented the ground work of the research in this study. It started with the overview of the problem, provided the background study of the problem that related to the problem domain and technique that lead to problem formulation, outlined the problem statement and listed the objectives and scopes of the study. A brief roadmap on the research methodology has also been provided in this chapter. The importance of the research and contributions of the study have been pointed out accordingly.

The next chapter will present the related literatures of the study by analyzing the problems and issues in conventional learning style classification approach. Rough Set mining approach and the research issues related to this technique will also be explored extensively in order to propose an approach that can enhance Rough Set performance.

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