FEATURE SELECTION FOR TRADITIONAL MALAY MUSICAL INSTRUMENT SOUND CLASSIFICATION USING ROUGH SET

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ABSTRACT

With the growing volume of data and feature (attribute) schemes, feature selection has become a very vital aspect in many data mining tasks including musical instrument sounds classification problem. The purpose of feature selection is to alleviate the effect of the 'curse of dimensionality'. This problem normally deals with the irrelevant and redundant features. Using the whole set of features is also inefficient in terms of processing time and storage requirement. In addition, it may be difficult to interpret and may decrease the classification performance respectively. To solve the problem, various feature selection techniques have been proposed in this area of research. One of the potential techniques is based on the rough set theory. The theory of rough set proposed by Pawlak in 1980s is a mathematical tool for dealing with the vagueness and uncertainty data. The concepts of reduct and core in rough set are relevant in feature selection to identify the important features among the irrelevant and redundant ones. However, there are two common problems related to the existing rough set-based feature selection techniques which are no warranty to find an optimal reduction and high complexity in finding the optimal ones. Thus, in this study, an alternative feature selection technique based on rough set theory for traditional Malay musical instrument sounds classification was proposed. This technique was developed using rough set approximation based on the maximum degree of dependency of attributes. The idea of this technique was to choose the most significant features by ranking the relevant features based on the highest dependency of attributes and then removing the redundant features with the similar dependency value. In overall, the results showed that the proposed technique was able to select the 17 important features out of 37 full features (with 54% of reduction), achieve the average of 98.84% accuracy rate, and reduce the complexity of the process (where the time processing is less than 1 second) significantly.

ABSTRAK

Dengan peningkatan bilangan data dan skema ciri (atribut), pemilihan ciri telah menjadi aspek yang sangat penting dalam kebanyakan tugas pelombongan data termasuk masalah pengkelasan bunyi alat muzik. Tujuan pemilihan ciri adalah untuk mengurangkan kesan 'curse of dimensionality'. Masalah ini kebiasaannya berkaitan dengan ciri-ciri yang tidak relevan dan bertindan. Penggunaan keseluruhan ciri juga tidak efisien dari segi masa pemprosesan dan keperluan ruang penyimpanan. Selain itu, ia juga sukar untuk diterjemahkan dan boleh mengurangkan prestasi pengkelasan. Oleh itu, pelbagai teknik pemilihan ciri telah dicadangkan dalam bidang penyelidikan ini. Salah satu teknik yang berpotensi ialah teknik berasaskan teori set kasar. Teori set kasar yang dicadangkan oleh Pawlak pada tahun 1980an merupakan alat matematik yang digunakan untuk menguruskan kekaburan dan ketidakpastian data. Konsep 'reduct' dan 'core' dalam set kasar adalah relevan dalam pemilihan ciri bagi mengenalpasti ciri-ciri yang penting dikalangan ciri-ciri yang tidak relevan dan bertindan. Walaubagaimanapun, terdapat dua masalah yang berkaitan dengan teknik pemilihan berasaskan set kasar yang sedia ada iaitu tiada jaminan untuk memilih ciri-ciri yang paling optima dan melibatkan proses pemilihan yang sangat kompleks. Oleh yang demikian, dalam kajian ini, satu teknik pemilihan ciri alternatif yang berasaskan set kasar bagi pengkelasan bunyi alat muzik tradisional Melayu telah dicadangkan. Teknik ini dihasilkan dengan menggunakan anggaran set kasar berasaskan darjah kebergantungan maksima sesuatu ciri. Idea teknik ini adalah untuk memilih ciri-ciri yang paling signifikan dengan menyusun ciri-ciri yang relevan berdasarkan kebergantungan tertinggi bagi ciri-ciri tersebut dan kemudian membuang ciri-ciri bertindan yang mempunyai nilai kebergantungan yang sama. Secara keseluruhan, hasil keputusan menunjukkan teknik yang dicadangkan mampu memilih 17 atribut penting daripada 37 atribut penuh (dengan 54% kadar pengurangan), mencapai purata 98.84% kadar ketepatan serta mengurangkan kerumitan proses (masa pemprosesan kurang daripada 1 saat).

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M IR	-	Music Information Retrieval
MIDI	-	Musical Instrument Digital Interface
HPCP	-	Harmonic Pitch Class Profile
kB	-	Kilobyte
kHz	-	Kilohertz
IG	-	Information Gain
GR	-	Gain Ratio
SU	-	Symmetrical Uncertainty
PCA	-	Principal Component Analysis
IRMFSP	-	Inertia Ratio Maximization using Feature Space Projection
UIOWA	-	University of Iowa
MUMs	-	MacGill University Master Sample
RSAR	-	Rough Set Attribute Reduction
GA	-	Genetic Algorithm
DPLL	-	Davis-Logemann-Loveland
PSO	-	Particle Swarm Optimization
DPSO	-	Discrete Particle Swarm Optimization
FSDA	-	Feature Selection using Dependency Attribute
DPSORSFS	-	Dynamic Particle Swarm Optimization-Rough Set Feature Selection
MMR	-	Min-min Roughness
TR	-	Total Roughness
FSMMR	-	Feature Selection using Min-min Roughness

LIST OF SYMBOLS AND ABBREVIATIONS

FSTR	-	Feature Selection using Total Roughness
MFCC	-	Mel-frequency Cepstral Coefficients
MPEG	-	Moving Picture Experts Group
MPEG-7	-	Multimedia Content Description Interface
mel	-	Mel filter
f	-	Frequency of signal
ZCR	-	Zero-crossing rate
ZC	-	Zero-crossing
N	-	Number of samples in the frame
Fn	-	Value of the n-th sample of a frame
RMS	-	Root-mean-square
mag	-	Magnitude
S	-	Information system
U	-	Non-empty finite set of objects
u	-	Object
A	-	Non-empty finite set of attributes
V	-	Value of attribute
a	-	Attribute
B	-	Subset of A
f	-	Total function
D	-	Decision system
d	-	Decision attribute
$\|X\|$	-	Cardinality of X
X	-	Any subset of U

LIST OF SYMBOLS AND ABBREVIATIONS

t	-	Tuple
k	-	Degree of dependency attributes
$\cap$	-	Intersection
P	-	Probability Function
$\neq$	-	Inequality
$\forall$	-	Universal quantification
$\exists$	-	Existential quantification
$\subset$	-	Proper subset
$\subseteq$	-	Subset
IND	-	Indiscernibility
Red	-	Reduct
MLP	-	Multilayer Perceptron
SVM	-	Support Vector Machine
k-NN	-	*k*-Nearest Neighbours
RBF	-	Radial Basis Functions
PART	-	Partial decision tree
GMM	-	Gaussian Mixture Model
STFT	-	Short Time Fourier Transform
FFT	-	Fast Fourier Transform
DCT	-	Discrete Consine Transform
SFS	-	Sequential Forward Feature Selection
NMF	-	Non-negative Matrix Factorization
SNMF	-	Sparse NMF

LIST OF SYMBOLS AND ABBREVIATIONS

CDA	-	Canonical Discriminant Analysis
CFS	-	Correlation-based Feature Selection
RSOAR	-	Rough Set Ordinal Attribute Reduction
MDA	-	Maximum Dependency Attributes
NP-hard	-	Non-deterministic polynomial-time hard
ROSETTA	-	Rough Set Toolkit for Analysis of Data
RSES	-	Rough Set Exploration System
MSE	-	Mean-squared Error
BP	-	Backpropagation
LPC	-	Linear Prediction Coefficients
LPCC	-	LPC derived cepstrums
SP	-	Spectral Power
STE	-	Short Time Energy
LRM	-	Logistic Regression Model
LWL	-	Locally Weighted Learning
WEKA	-	Waikato Environment for Knowledge Analysis
DFT	-	Discrete Fourier Transform
LP	-	Linear Prediction
WAV/WAVE	-	Waveform Audio File Format
MP3	-	MPEG-1 or MPEG-2 Audio Layer III
CPU	-	Central Processing Unit

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LIST OF PUBLICATIONS

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CHAPTER 1

INTRODUCTION

1.1 Introduction

With the advances of digital signal processing and computational techniques, automatic musical instrument sounds classification has became an important aspect of music information retrieval (MIR). This area of research has numerous potential applications. For instance, recognizing and analyzing the content of the musical instrument sounds can lead to more knowledge about the different musical styles and can be further utilized for computer-assisted musical instrument tutoring (Ferguson, 2006; Percival, Wang & Tzanetakis, 2007). Furthermore, it can also be enhanced as a validation or quality control tool in musical instrument manufacturing. For that purpose, automatic musical instrument sounds classification plays an important role in tool development, especially as stepping stone in developing a wide variety of potential applications.

However, the implementation of musical instrument sounds classification still has limited practical usability. One of the problems is to handle a large number of sound databases and various types of feature (attribute) schemes available. It is well known that the dataset and features have a major influence in the success of classification task. Therefore, in achieving a better musical instrument sounds classification result, the first stage is to identify the right feature schemes used (Wicaksana, Hartono & Wei, 2006). For this reason, feature selection has become a very vital aspect in musical instrument sounds classification problems.

Several studies have been conducted regarding feature selection issues (Eronen, 2001; Liu & Wan, 2001; Fanelli *et al.*, 2004; Wicaksana *et al.*, 2006; Deng, Simmermacher & Cranefield, 2008). Most of these studies were conducted based on the Western musical instrument sounds. Currently, very little sound classification studies address on non-Western musical instruments, especially on traditional Malay musical instruments. However, adapting the existing approach for retrieval of Malay musical instruments contents might not be easy due to the differences in the feature schemes, amount of sound samples and recording environment. Wiezorkowska (1999) stated that the sound of musical instruments are different from each other depending on the musical articulation, the instrument itself, arrangement of recording equipment (such as microphones, MIDI controllers, and mixers), reverberation and many others factors. Golzari *et al.* (2008) also claimed that different musical instrument sounds may have different characteristic or behaviour. Gomez & Herrera (2008) discovered that there are differences in terms of tonal features (such as pitch distribution, pitch range, scale and gamut) between Western and non-Western musical sound. For example, they found that the HPCP (Harmonic Pitch Class Profile) features which represent the intensity of the different degrees of a diatonic major scale have larger values for Western music than non-Western music.

Thus, the goal of this research was to investigate the behaviour of traditional Malay musical instrument sounds and to identify the important features by introducing an alternative feature selection algorithm. To accomplish this, there were eight (8) main processes involved in this study namely data acquisition, sound editing, data representation, feature extraction, data discretization, data elimination, feature selection and feature validation via classification.

1.2 Research Motivation

In general, research in musical instrument sounds involved a huge amount of sound data and features. For example, one second of musical instrument sound for 22.1 kHz sampling frequency and mono recording consists of 41.5 kB of data. The common issue associated with large dataset is the ‘curse of dimensionality’, where there are too many features (dimensions) involved and it is difficult to identify which one is significant. Due to a large number of sound features available, how to select or combine them to achieve higher classification accuracy is important (Liu & Wan, 2001). In order to handle this problem, feature selection plays an important role. The purposes of the feature selection are to improve the classification accuracy, and to provide faster and robust classifier (Guyon & Elisseeff, 2003; Banerjee, Mitra & Anand, 2006). For that reason, various feature selection techniques have been proposed as highlighted in the literature by (Molina, Belanche & Nebot, 2002; Guyon & Elisseeff, 2003).

In musical instrument sounds classification problem, several feature selection techniques have been applied such as sequential forward (Liu & Wan, 2001), Information Gain (IG), Gain Ratio (GR), Symmetrical Uncertainty (SU), Principal Component Analysis (PCA) and Isomap (Deng *et al.*, 2008), subset selection algorithm with branch-bound search strategy (Benetos, Kotti & Kotropoulus, 2006), genetic algorithm (Mackay & Fujinaga, 2005; Essid, Richard & David, 2005a), Inertia Ratio Maximization using Feature Space Projection (IRMFSP) and class pairwise feature selection technique (Essid *et al.*, 2005a). Most of these studies obtained better accuracy in the classification performance after applying feature selection. However, benchmarking is still an open issue that needs further improvement (Guyon & Elisseeff, 2003; Deng *et al.*, 2008). For example, the data sources used in these studies are different and most of them are incorporated with the Western musical instrument sounds from University of Iowa (UIOWA) and McGill University Master Sample (MUMs CDs) recording. They found that the performance of the selected features is also influenced by the classifier used. This explains that the existing feature selection techniques applied in the various sound features may not affectively work in other condition. For example, even though the same PCA technique was applied by Kaminskyj & Czaszejko (2005) and Deng *et al.* (2008), the results varied in which the accuracy rate achieved by the former outperformed the latter due to the difference in data sources used. Therefore, it is exciting to explore other feature selection techniques with different types of musical instrument sounds in order to find the best alternative solution.

One of the potential techniques is based on the rough set theory. Several studies of feature selection using rough set in musical instrument sounds classification have been conducted (Wieczorkowska, 1999; Wieczorkowska, 2003a; Li *et al.*, 2005). The motivation of these studies is musical instrument sound data that deals with the inconsistency and uncertainty problems (Wieczorkowska, 1999). The uncertainty happens when the sound of different instruments can be similar, whereas the inconsistency occurs when the sound of one instrument changes drastically within the scale of the instrument. The theory of rough set proposed by Pawlak

(1982) is a mathematical tool for dealing with the vagueness, inconsistency and uncertainty data. Rough set theory is one of the useful tools for feature selection (Modrzejewski, 1993; Banerjee et al., 2006; Li *et al.*, 2006). Banerjee, *et al.* (2006) claimed that the concept of reduct and core in rough set is relevant in feature selection to identify the essential features among the non-redundant ones. In addition, the most important characteristic of rough set is no additional information required to identify data dependencies or to reduce the number of attributes contained in a dataset (Thuan, 2010; Kalyani & Karnan, 2012). These attractive characteristics of rough set in tackling the problem of irrelevant and redundancy in the large dataset have attracted researchers in wide areas of data mining domain to utilize rough set for feature selection (Kennedy & Eberhart, 1995).

However, there are two common problems related with the existing rough set-based feature selection techniques as discovered by Jensen (2005). First, there is no guarantee to find an optimal reduction such as in Rough Set Attribute Reduction (RSAR), Genetic Algorithm (GA) and dynamic reduct algorithms. Second, there are several techniques involved with huge complexity in finding the minimal reduction such as in dynamic reduct, Genetic Algorithm (GA) and Davis-Logemann-Loveland (DPLL-based) algorithms. Recently, many researchers have shifted to the alternative solution based on the evolutionary computation approach such as particle swarm optimization (PSO) (Kennedy & Eberhart, 1995) purposely to find an optimal reduct. One of the techniques applied in feature selection domain is the discrete particle swarm optimization (DPSO) (Zainal, Maarof & Shamsuddin, 2007; Yang *et al.*, 2008; Abdul-Rahman, Mohamed-Hussein & Bakar, 2010; Wahid *et al*., 2010). Even though it successfully provides better solution in finding the optimal reducts, it is more time-consuming as compared with conventional RSAR due to its non-deterministic nature (Jensen, 2005).

Therefore, it is essential to identify other alternative solution capable of improving the performance of the processing time (reducing complexity) and preserving the classification accuracy by finding the optimal features (reducts). Thus, in this study, an alternative feature selection technique based on rough set theory known as Feature Selection using Dependency Attribute (FSDA) for traditional Malay musical instrument sound was proposed. The technique was developed based on rough set approximation using maximum degree of dependency of attributes (MDA) proposed by Herawan, Mustafa & Abawajy (2010). The main idea of this work involved eliminating the irrelevant features and selecting the most significant features by ranking the relevant features based on the highest dependency of attributes on the dataset. Then, the redundant features with similar dependency value were deleted. The proposed technique was expected to improve the classification accuracy and reduce the processing time.

In order to evaluate the performance of the proposed technique, the existing rough-based feature selection techniques which are, Genetic Algorithm, Johnson, dynamic reduct and Dynamic Particle Swarm Optimization-Rough Set Feature Selection (DPSORSFS) (Wahid *et al.*, 2010) which have been successfully applied in other research area, were used to benchmark the proposed technique. The proposed technique (FSDA) was also designed to incorporate other two rough set techniques which are Min-min Roughness (MMR) (Parmar, Wu & Blackhurst, 2007) and Total Roughness (TR) (Mazlack *et al.*, 2000) which have been successfully employed in selecting clustering attribute and not yet being utilized in feature selection problem. The purpose was to investigate how it can be applied in feature selection problem. After that, the performances of these techniques were compared with the proposed technique (FSDA). Three parameters of evaluation were used which are the number of the selected features, the processing time and the classification accuracy. Several classifiers which are Rough Set, Multi-Layered Perceptron, Support Vector Machine, Naive Bayes, *k*-Nearest Neighbour (*k*-NN), PART, and J48 were employed to evaluate the performance of the proposed technique.

1.3 Research Objectives

The objectives of the study are:

(i) to propose an alternative feature selection technique using rough set theory,

(ii) to implement the proposed technique in (i) for traditional Malay musical instrument sounds problem,

(iii) to validate the performance of the selected feature schemes generated from (ii) using several classifiers which are Rough Set, Multi-Layered Perceptron, Support Vector Machine, Naive Bayes, *k*-Nearest Neighbour (*k*-NN), PART, and J48 classifiers and compare the result with other rough set-based feature selection technique.

1.4 Research Scopes

This study focuses on applying the Rough Set Theory to feature selection problem in musical instrument sounds domain purposely for traditional Malay musical instrument sounds. The scopes of this study concentrate on three (3) phases which are feature extraction, feature selection and feature validation via classification. In feature extraction phase, two (2) categories of feature schemes which are perception-based and Mel-Frequency Cepstral Coefficients (MFCC) are utilized in this study. The proposed feature selection technique is developed based on the rough set theory. The performance of the selected features is validated based on the number of the selected features, the processing time and the classification accuracy achieved in classifying the musical instrument sounds into four (4) families which are membranophone, idiophone, chordophone and aerophone. Rough Set, Multi-Layered Perceptron, Support Vector Machine, Naive Bayes, *k*-Nearest Neighbour (*k*-NN), PART, and J48 which have been widely used in many classification problems are used as classifier. Finally, the result is compared with other rough set-based feature selection techniques which are Feature Selection using Min-min Roughness (FSMMR), Feature Selection using Total Roughness (FSTR) and Dynamic Particle Swarm Optimization Feature Selection (DPSORSFS), Genetic Algorithm, Johnson Algorithm and dynamic reduct.

1.5 Thesis Outline

The rest of this thesis is structured as follows. Chapter 2: *Literature Review* presents the previous work of feature selection for musical instrument sounds classification. It starts with the overview of domain research which is traditional Malay musical instrument sounds. Then, the related works on musical instrument sounds classification process including data representation, feature extraction, feature selection and feature validation are highlighted. In addition, the preliminary of rough set theory is also explored in this chapter. In Chapter 3: *Research Framework*, the research framework of this study is presented. The research framework comprises two main phases which are pre-processing and post-processing phase. The development of the proposed technique for feature selection based on the rough set theory is then described in the Chapter 4: *Feature Selection using Maximum Degree of Dependency of Attributes (FSDA)*. After that, Chapter 5: *Experimental Design of FSDA for Traditional Malay Musical Instrument Sounds* presents the experimental setup of the proposed technique including the whole process involved in pre-processing and post-processing phases. The result addresses the first objective of this study. The performance of the proposed technique (FSDA) and other rough-based feature selection technique in terms of classification accuracy and processing time achieved are discussed in Chapter 6: *Results and Discussion.* The result obtained explained the effectiveness of the proposed technique and answered the second and third objectives. Finally, the conclusion of the study is presented in Chapter 7: *Conclusion and Future Work*, together with a discussion of research contribution and some directions for future work.

1.6 Summary

With the growing amount of digital audio feature schemes, feature selection has become very important aspect in extracting the implicit knowledge of the musical instrument content. A number of techniques have been applied in the past that differ in the features used to describe the importance of selection strategy. However, there has been no specific rule for the selection of feature schemes. Benchmarking is still an open issue that need further improvement. Thus, this study has significant importance in finding better mechanisms for feature selection problem for the traditional Malay musical instrument sounds. Following this introduction, Chapter 2 describes the background of the domain problem which is traditional Malay musical instrument sounds and reviews the related work on feature selection, rough set and the musical instrument classification.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The significant role that features play in musical instrument sounds classification makes them worthy of particular attention and endeavor. Extensive efforts in feature selection are very crucial to find the essential features by omitting unnecessary information or noise. The difficulty encountered within this area of research is the involvement of numerous musical instrument sounds and each of them has different pitch or timbre (quality of the sound) (Wieczorkowska, 2003a). It shows that different sounds may be similar to the other one, and sounds of the same instrument can be different (Wieczorkowska, 1999; Kostek & Czyzewski, 2001). Since each different sound has different pitch or timbre, the effectiveness of the existing feature selection algorithm is still subjective to the type of musical instrument sounds. Recently, almost all of the studies focused on Western musical instruments (Agostini, Longari & Pollastri, 2003; Wieczorkowska, 2003a; Hee-Suk & Doe-Hyun, 2005; Mackay & Fujinaga, 2005; Essid *et al.*, 2005a). As mentioned in Chapter 1, interest in the research of non-Western musical instruments is limited. Thus, this study attempted to explore other alternative feature selection technique for other domain problem which is traditional Malay musical instrument sounds.

Therefore, this chapter highlights several topics related to musical instrument sounds classification which are feature extraction schemes, feature selection techniques, and classification algorithms used to validate the performance of feature selection. The overview of rough set theory and the study of traditional Malay musical instrument are also discussed as the main focus of this research.

2.2 The Overview of Rough Set Theory

Pawlak (1982) introduced rough set theory to solve the problem of imprecise knowledge. Similarly to fuzzy set theory it is not an alternative to classical set theory but it is embedded in it. Fuzzy and rough sets are not competitively, but complementary to each other (Pawlak, 1985; Pawlak & Skowron, 2007). Rough set theory has attracted attention of many researchers and practitioners all over the world, who contributed essentially to its development and applications.

The original goal of the rough set theory is induction of approximations of concepts. The idea consists of approximation of a subset by a pair of two precise concepts called the *lower approximation* and *upper approximation*. Figure 2.1 illustrates a rough set concept with its approximations. Intuitively, the lower approximation of a set consists of all elements that surely belong to the set, whereas the upper approximation of the set composed of all elements that possibly belong to the set. The difference of the upper and the lower approximation is a *boundary region*. It consists of all elements that cannot be classified uniquely to the set or its complement, by employing available knowledge. Thus any rough set, in contrast to a crisp set, has a non-empty boundary region. Motivation for rough set theory has come from the need to represent a subset of a universe in terms of equivalence classes of a partition of the universe. In this section, the basic concepts of rough set theory in terms of data are presented.

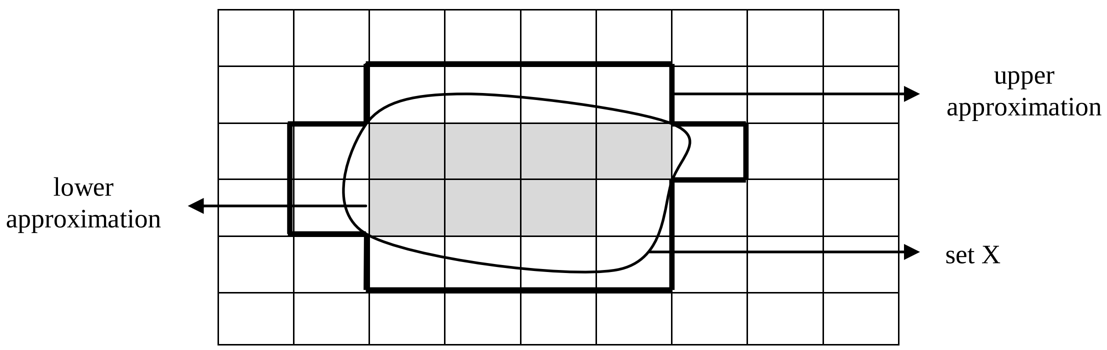

Figure 2.1: The lower and upper approximation of a rough set (Banerjee *et al.*, 2006)

2.2.1 Information System

Data are often presented as a table, columns of which are labeled by *attributes*, rows by *objects* of interest and entries of the table are *attribute values*. By an *information system*, a 4-tuple (quadruple) $S = (U, A, V, f)$, where U is a non-empty finite set of objects, A is a non-empty finite set of attributes, $V = \bigcup_{a \in A} V_a$, V_a is the domain (value set) of attribute a, $f : U \times A \rightarrow V$ is a total function such that $f(u, a) \in V_a$, for every $(u, a) \in U \times A$, called information (knowledge) function. An information system is also called a knowledge representation systems or an attribute-valued system and can be intuitively expressed in terms of an information table (refer to Table 2.1).

In many applications, there is an outcome of classification that is known. This *a posteriori* knowledge is expressed by one (or more) distinguished attribute called decision attribute; the process is known as supervised learning. An information system of this kind is called a decision system. A *decision system* is an information system of the form $D = (U, A \cup \{d\}, V, f)$, where $d \notin A$ is the *decision attribute*. The elements of *A* are called *condition attributes*. A simple example of decision system is given in Table 2.2.

Table 2.1: An information system

U	a_1	a_2	$\cdots$	a_k	$\cdots$	$a_{\lvert A \rvert}$
u_1	$f(u_1, a_1)$	$f(u_1, a_2)$	$\cdots$	$f(u_1, a_k)$	$\cdots$	$f(u_1, a_{\lvert A \rvert})$
u_2	$f(u_2, a_1)$	$f(u_2, a_2)$	$\cdots$	$f(u_2, a_k)$	$\cdots$	$f(u_2, a_{\lvert A \rvert})$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
$u_{\lvert U \rvert}$	$f(u_{\lvert U \rvert}, a_1)$	$f(u_{\lvert U \rvert}, a_2)$	$\cdots$	$f(u_{\lvert U \rvert}, a_k)$	$\cdots$	$f(u_{\lvert U \rvert}, a_{\lvert A \rvert})$

Example 2.1. Suppose there are given data about 6 students, as shown in Table 2.2.

Table 2.2: A decision system

Student	Analysis	Algebra	Statistics	Decision
1	bad	good	medium	accept
2	good	bad	medium	accept
3	good	good	good	accept
4	bad	good	bad	reject
5	good	bad	medium	reject
6	bad	good	good	accept

From Table 2.2, it has

$$U = \{1,2,3,4,5,6\},$$
$$A = \{\text{Analysis}, \text{Algebra}, \text{Statistics}\} = C \cup \{\text{Decision}\} = D,$$
$$V_{\text{Analysis}} = \{\text{bad}, \text{good}\},$$
$$V_{\text{Algebra}} = \{\text{bad}, \text{good}\},$$
$$V_{\text{Statistics}} = \{\text{bad}, \text{medium}, \text{good}\},$$
$$V_{\text{Decision}} = \{\text{accept}, \text{reject}\}.$$

A relational database may be considered as an information system in which rows are labelled by the objects (entities), columns are labelled by attributes and the entry in row u and column a has the value $f(u,a)$. It is noted that each map $f(u,a): U \times A \to V$ is a tuple $t_i = \left(f(u_i, a_1), f(u_i, a_2), f(u_i, a_3), \cdots, f(u_i, a_{|A|})\right)$, for $1 \le i \le |U|$, where $|X|$ is the cardinality of *X*. Note that the tuple *t* is not necessarily associated with entity uniquely (refer to students 2 and 5 in Table 2.2). In an information table, two distinct entities could have the same tuple representation (duplicated/redundant tuple), which is *not permissible* in relational databases. Thus, the concepts in information systems are a generalization of the same concepts in relational databases.

2.2.2 Indiscernibility Relation

From Table 2.2, note that students 2, 3 and 5 are indiscernible (similar or indistinguishable) with respect to the attribute Analysis. Meanwhile, students 3 and 6 are indiscernible with respect to attributes Algebra and Decision, and students 2 and 5 are indiscernible with respect to attributes Analysis, Algebra and Statistics. The starting point of rough set theory is the indiscernibility relation, which is generated by information about objects of interest. The indiscernibility relation is intended to express the fact that due to the lack of knowledge it is difficult to discern some objects employing the available information. That means, in general, it is unable to deal with single objects but clusters of indiscernible objects must be considered. Now the notion of indiscernibility relation between two objects can be defined precisely.

Definition 2.1. *Let $S=(U,A,V,f)$ be an information system and let B be any subset of A. Two elements $x,y\in U$ are said to be B-indiscernible (indiscernible by the set of attribute $B\subseteq A$ in S) if and only if $f(x,a)=f(y,a)$, for every $a\in B$.*

Obviously, every subset of *A* induces unique indiscernibility relation. Notice that, an indiscernibility relation induced by the set of attribute *B*, denoted by $IND(B)$, is an equivalence relation. It is well known that, an equivalence relation induces unique partition. The partition of *U* induced by $IND(B)$ in $S=(U,A,V,f)$ denoted by U/B and the equivalence class in the partition U/B containing $x\in U$, denoted by $[x]_B$.

Given arbitrary subset $X\subseteq U$, in general, *X* as union of some equivalence classes in *U* might be not presented. It means that, it may not be possible to describe *X* precisely in AS. *X* might be characterized by a pair of its approximations, called lower and upper approximations. It is here that the notion of rough set emerges.

2.2.3 Set Approximations

The indiscernibility relation is used next to define approximations, the basic concepts of rough set theory. The notions of lower and upper approximations of a set can be defined as follows:

Definition 2.2. *Let $S=(U,A,V,f)$ be an information system, let B be any subset of A and let X be any subset of U. The B-lower approximation of X, denoted by $\underline{B}(X)$ and B-upper approximations of X, denoted by $\overline{B}(X)$, respectively, are defined by*

$$\underline{B}(X)=\{x\in U \mid [x]_B\subseteq X\} \text{ and } \overline{B}(X)=\{x\in U \mid [x]_B\cap X\neq\phi\}.$$

The accuracy of approximation (accuracy of roughness) of any subset $X \subseteq U$ with respect to $B \subseteq A$, denoted $\alpha_B(X)$ is measured by:

$$\alpha_B(X) = \frac{|\underline{B}(X)|}{|\overline{B}(X)|}, \tag{2.1}$$

where $|X|$ denotes the cardinality of X. For empty set ϕ, $\alpha_B(\phi) = 1$ is defined. Obviously, $0 \le \alpha_B(X) \le 1$. If X is a union of some equivalence classes of U, then $\alpha_B(X) = 1$. Thus, the set X is *crisp* (precise) with respect to B. And, if X is not a union of some equivalence classes of U, then $\alpha_B(X) < 1$. Thus, the set X is *rough* (imprecise) with respect to B (Pawlak, 1985). This means that the higher the accuracy of approximation of any subset $X \subseteq U$ is, the more precise (the less imprecise) it is.

Example 2.2. Let us depict above notions by examples referring to Table 2.2. Consider the concept "Decision", i.e., the set $X(\text{Decision} = \text{accept}) = \{1,2,3,6\}$ and the set of attributes $C = \{\text{Analysis}, \text{Algebra}, \text{Statistics}\}$. The partition of U induced by $IND(C)$ is given by:

$$U / C = \{\{1\}, \{2,5\}, \{3\}, \{4\}, \{6\}\}.$$

The corresponding lower approximation and upper approximation of are as follows:

$$\underline{C}(X) = \{1,3,6\} \text{ and } \overline{C}(X) = \{1,2,3,5,6\}.$$

Thus, concept "Decision" is imprecise (rough). For this case, $\alpha_C(X) = \frac{3}{5}$ is obtained. It means that the concept "Decision" can be characterized partially, employing attributes Analysis, Algebra and Statistics.

Another important issue in database analysis is discovering dependencies between attributes. Intuitively, a set of attributes D depends totally on a set of attributes C, denoted $C \Rightarrow D$, if all values of attributes from D are uniquely determined by values of attributes from C. In other words, D depends totally on C, if there is a functional dependency between values of *D* and *C*. The formal definition of attributes dependency is given as follows.

Definition 2.3. *Let* $S = (U, A, V, f)$ *be an information system and let D and C be any subsets of A. Attribute D functionally depends on C , denoted* $C \Rightarrow D$*, if each value of D is associated exactly one value of C.*

2.2.4 Dependency of Attributes

Since information system is a generalization of a relational database, a generalization concept of dependency of attributes, called a partial dependency of attributes, is also needed.

Definition 2.4. *Let* $S = (U, A, V, f)$ *be an information system and let D and C be any subsets of A. The dependency attribute D on C in a degree k* $(0 \le k \le 1)$*, is denoted by* $C \Rightarrow_k D$*, where*

$$k = \gamma(C, D) = \frac{\sum_{X \in U/D} \left|\underline{C}(X)\right|}{|U|}. \tag{2.2}$$

Obviously, $0 \le k \le 1$. If all set X are crisp, then $k = 1$. The expression $\sum_{X \in U/D} \left|\underline{C}(X)\right|$, called a lower approximation of the partition U/D with respect to *C*, is the set of all elements of U that can be uniquely classified to blocks of the partition U/D, by means of *C*. *D* fully depends (in a degree of *k*) on *C* if $k = 1$. Otherwise, *D* is partially dependent on *C*. Thus, *D* fully (partially) depends on *C*, if all (some) elements of the universe U can be uniquely classified to equivalence classes of the partition U/D, employing *C*.

Example 2.3. From Table 2.2, there are no total dependencies whatsoever. If in Table 2.2, the value of the attribute Statistics for student 5 were "*bad*" instead of "*medium*", there would be a total dependency $\{\text{Statistics}\} \Rightarrow \{\text{Decision}\}$, because to each value of the attribute Statistics they would correspond unique value of the attribute Decision.

For example, for dependency $\{\text{Analysis}, \text{Algebra}, \text{Statistics}\} \Rightarrow \{\text{Decision}\}$, $k = \frac{4}{6} = \frac{2}{3}$ is obtained, because four out of six students can be uniquely classified as having Decision or not, employing attributes Analysis, Algebra and Statistics.

Note that, a table may be redundant in two ways. The first form of redundancy is easy to notice: some objects may have the same features. This is the case for tuples 2 and 3 of Table 2.2. A way of reducing data size is to store only one representative object for every set of so-called *indiscernible* tuples as in Definition 2.1. The second form of redundancy is more difficult to locate, especially in large data tables. Some columns of a table may be erased without affecting the classification power of the system. This concept can also be extended also to information systems, where the conditional and decision attributes are not distinguished. Using the entire attribute set for describing the property is time-consuming, and the constructed rules may be difficult to understand, to apply or to verify (Zhao *et al.*, 2007). In order to deal with this problem, attribute reduction is required. The objective of reduction is to reduce the number of attributes, and at the same time, preserving the property of information.

2.2.5 Reducts and Core

A reduct is a minimal set of attributes that preserve the indiscernibility relation. A core is the common parts of all reducts. In order to express the above idea more precisely, some preliminaries definitions are needed.

Definition 2.5. *Let $S = (U, A, V, f)$ be an information system and let B be any subsets of A and let a belongs to B. It is said that a is dispensable (superfluous) in B if $U/(B-\{b\}) = U/B$, otherwise a is indispensable in B.*

For further simplification of an information system, some dispensable attributes from the system can be eliminated in such a way that the objects in the table are still discernible as the original one.

Definition 2.6. *Let* $S = (U, A, V, f)$ *be an information system and let B be any subsets of A. B is called independent (orthogonal) set if all its attributes are indispensable.*

Definition 2.7. *Let* $S = (U, A, V, f)$ *be an information system and let B be any subsets of A. A subset* B^* *of B is a reduct of B if* B^* *is independent and* $U/B^* = U/B$.

Thus a reduct is a set of attributes that preserves partition. It means that a reduct is the minimal subset of attributes that enables the same classification of elements of the universe as the whole set of attributes. In other words, attributes that do not belong to a reduct are superfluous with regard to classification of elements of the universe. While computing equivalence classes is straightforward, the problem of finding minimal reducts in information systems is NP-hard. Reducts have several important properties. One of them is a core.

Definition 2.8. *Let* $S = (U, A, V, f)$ *be an information system and let B be any subsets of A. The intersection of all reducts is called the core of B, i.e.,*

$$\mathrm{Core}(B) = \bigcap \mathrm{Red}(B),$$

Thus, the *core* of *B* is the set of all indispensable attributes of *B*. Because the core is the intersection of all reducts, it is included in every reduct, where, each element of the core belongs to some reducts. Thus, in a sense, the core is the most important subset of attributes, because none of its elements can be removed without affecting the classification power of attributes.

Example 2.4. To illustrate the finding of reducts and core, the information system as shown in Table 2.3 is considered. The information system is modified from Example 2.2 as given by Pawlak (1983).

Table 2.3: A modified information system (Pawlak, 1983)

#	*A*	*B*	*C*	*D*
1	low	bad	loss	small
2	low	good	loss	large
3	high	good	loss	medium
4	high	good	loss	medium
5	low	good	profit	large

Let $X = \{A, B, C, D\}$, $X_1 = \{A, B, C\}$ and $X_2 = \{C, D\}$. These sets of attributes produce the following partitions, respectively:

$U / X = \{\{1\}, \{2\}, \{3,4\}, \{5\}\}, U / X_1 = \{\{1\}, \{2\}, \{3,4\}, \{5\}\}$ and $U / X_2 = \{\{1\}, \{2\}, \{3,4\}, \{5\}\}$,

Therefore, by Definition 2.5, the sets $\{D\}$ and $\{A, B\}$ are dispensable (superfluous). Referring to Definition 2.6, the sets X_1 and X_2 are independent (orthogonal). Hence, from Definition 2.7, conforming that X_1 and X_2 are reducts of X. Furthermore, from Definition 2.8, the intersection $X_1 \cap X_2 = \{C\}$ is the core of X.

From the overview of rough set theory, the concept of *reduct* and *core* is relevant to the feature selection in finding the most important features. The capability of this technique in solving the problem of feature selection in musical instrument sounds has been studied by Wieczorkowska (1999) and Li *et al.* (2005). In this study, this technique was applied to handle the issue of feature selection in traditional Malay musical instrument sound classification. Thus, several issues related to this topic are presented in the following section.

2.3 Conventional Musical Instrument Sounds Classification

Traditionally, almost all local musicologists recognize the musical instruments by their own knowledge gathered from the seminars, books or other references source. Some of them are capable of recognizing the instruments by the physical figures and sounds produced. This is made possible through their own experience and practice.

With the growing need of multimedia application in music field, the recognition based on physical is not practical because it only describes the structure of the instruments. Therefore, sound has a more realistic advantage to be manipulated for this purpose. However, identifying instruments from the sound is a very complicated problem especially when it occupies a complex fusion involving more than one playing at a time (Essid et al., 2005a). Besides, sound contains a vast amount of complex features that need to be implicitly discovered. With the conventional method through human (expert) capability, it is very inconvenient. This is because human perception can incorporate errors, due to partial misinterpretation, incorrect or inconsistent judgement of similar sound from different types of instruments, outside interference such as noise, or perceived bias (Ferguson, 2006).

Thus, with the advances of data mining and digital signal processing techniques, there is a significant need to develop automatic musical instrument sounds classification which able to enhance the process. Mackay & Fujinaga (2005) also claimed that automatic classification performance using machine learning produces better result compared to human capability due to time and cost restriction. The potential in analyzing music in original and non-intuitive ways also gives theoretical advantages that a human does not have.

2.4 Automatic Musical Instrument Sounds Classification

Automatic musical instrument sounds classification is a systematic approach that able to identify the complex features of the musical signals from the musical instruments database automatically. This is concerned as the first step in developing a wide variety of potential applications such as musical tutoring system, automatic music transcription, multimedia databases annotation and automatic pirated detection (Mackay & Fujinaga, 2005; Percival *et al.*, 2007; Deng *et al.*, 2008).

In literature, various algorithms and approaches have been used in solving each step of automatic musical instrument sounds classification such as in: (a) feature extraction phase there are onset duration, decay time, mean of spectral centroid and Mel-Frequency Cepstral Coefficients (MFCC) (Eronen, 2001), MPEG-7, perception-based (Deng *et al.*, 2008), and Short Time Fourier Transform (STFT) (Livingston & Shepard, 2005); (b) feature selection phase, there are Fisher discriminant algorithm (Joder, Essid & Richard, 2009), rough set-based technique (Wieczorkowska, 1999), sequential forward selection (Liu & Wan, 2001), and entropy-based techniques (Deng, Simmermacher & Cranefield, 2006); and

(c) classification, there are *k*-NN and Gaussian Mixture Model (GMM) (Eronen, 2001), Support Vector Machine (SVM), decision tree (J4.8) (Deng *et al.*, 2008), rough set and neural network (Li & Wang, 2004). However, there are still several remaining problem that need to be tackled in producing a good classification system (Herrera, Yeterian & Gouyon, 2002b; Wieczorkowska *et al.*, 2003b; Fuhrmann, 2012).

One of the issues highlighted by Fuhrmann (2012) is the recognition performance which usually degrades dramatically when different type of data and number of categories (classes) are applied. Hence, it is important to provide a quality dataset in pre-processing phase. Another crucial issue of automatic musical instrument sounds classification is to select the best feature schemes or properties (Liu & Wan, 2001; Mackay & Fujinaga, 2005; Deng *et al*., 2006). This is important because different musical instrument sounds have their own different behaviours or characteristics (Wieczorkowska, 1999; Kostek & Czyzewski, 2001; Golzari *et al.*, 2008). In addition, features are fed to pattern recognition framework as the input and are the basis in the lead of the classification process (Liu & Wan, 2001; Slezak *et al.*, 2002; Essid *et al*., 2005a; Janecek *et al*., 2008).

Thus, this research focused in investigating the issues of feature selection in automatic musical instrument sounds classification. In addition, a study of the existing algorithms for data representation, feature extraction and classification was also conducted. The purpose was to identify the suitable technique to be employed in this research in order to produce a good classification result.

2.4.1 Data Representation

In literature, the dataset used have an assortment of audio representation and sources (Liu & Wan, 2001; Piccoli *et al.*, 2003; Wieczorkowska, 2003a; Norowi, Doraisamy & Rahmat, 2005; Benetos *et al.*, 2006; Ding & Zhang, 2007; Lounghran *et al.*, 2008). It shows that different researchers have their own different ways to represent and obtain their data. In general, the difference is based on the length of audio file, sample size, audio format, audio type, size of sample rate (in Hertz) and filter technique used.

Benetos, Kotti & Kotropoulus (2006) used about 300 audio extracted from six (6) different instrument classes. The audio files were discretized at 44.1 kHz of sample rate with each file having duration of about 20 seconds. Eronen (2001) performed the experiment using 5286 samples of 29 Western orchestral instruments. Two different frame lengths for two different states (onset and steady) were examined. For the onset dataset, 20 ms length hamming-windowed frames with 25% overlap was used while the steady set used 40 ms frame length. The sample rate was 44.1 kHz. It can be seen that both of them used a uniformed length of audio file. Norowi, Doraisamy & Rahmat (2005) also recommended that a standard length for each data file is required to avoid poor classification result.

However, there were some researchers who used a certain length of audio files range. For instance, Liu & Wan (2001) employed an interval time between 0.1 second to around 10 seconds for each audio file. Every audio file was divided into hamming-windowed frames of 256 samples, with 50% overlaps. In this study, this method was adopted due to the limited sources problem (where some of the original data had a complete signal sound per cycle of less than one (1) second). On the contrary, Wicaksana et al. (2006) exploited combination of both approaches where the similar range was used for training and different range was used for testing.

Besides audio file length, there were also a variety of the samples frame size and filter techniques used in the past studies: 256 samples with hamming-windowed were used by Liu & Wan (2001) and Ding & Zhang (2007). 2048 samples with hanning-windowed by Piccoli et al. (2003) and 4096 samples by Wieczorkowska (2003a). There were assortments of sampling rate used in the previous work as well instead of only 44.1 kHz. For example, 16 kHz (Wieczorkowska, 2003a), 22 kHz (Piccoli *et al.*, 2003) and 32 kHz (Lounghran *et al.*, 2008). These variety of parameters used in the literature show that there were no standard benchmarking in determining the best parameter for data representation. This is because different dataset with different musical instruments were used in the previous work. Fuhrmann (2012) in his study described that the performance of classification system is also influenced by variability of the data used, the number of independent data sources, or any prior knowledge input to the system. This explains that the initial experiment in the early stage (data representation) of musical instrument sounds classification is vital to determine the reliability of data used.

2.4.2 Feature Extraction

In automatic musical instrument sounds classification, one of the challenges is the ability to distinguish between instrument sounds. The challenges become more difficult when the instruments are played in a group and involve a complex mixture of instruments. Thus, feature extraction plays an important role for this purpose.

The phrases of features are also known as *attributes* or *descriptors* (Banerjee *et al.*, 2006). Feature extraction is the process of obtaining digital representation (attributes) from the large amounts of information contains in music instrument, music genre and many other fields. Deng *et al.* (2006), explained that the extracted audio feature schemes can be used to interpret music with less human supervision. Furthermore, computational and learning cost have become major constraints in pattern recognition problem. Hence, by implementing feature extraction, these problems can be solved by reducing the amount of data required.

Various feature schemes have been identified and adopted by past research either by individual sets or combination of them. In audio signal processing, features can be obtained directly from the original signal, or from the process of transformations such as Fast Fourier Transform (FFT) or the Wavelet Transform (Banerjee *et al.*, 2006). Typically, these features consist of both spectral and temporal domain. Lounghran, *et al.* (2008) highlighted that the combination of both features domain is essential in order to provide an accurate description of sounds timbre. Some of the spectral features that have been widely used in the previous research are spectral range (bandwidth) (Ding & Zhang, 2007; Deng *et al.*, 2008), spectral centroid (brightness) (Ding & Zhang, 2007; Deng *et al.*, 2008; Gunasekaran & Revathy, 2008a), spectral rolloff (Ding & Zhang, 2007; Gunasekaran & Revathy, 2008a), spectral flux (Ding & Zhang, 2007; Deng *et al.*, 2008), and spectral kurtosis (Gunasekaran & Revathy, 2008a). The temporal features include zero crossing rate (Ding & Zhang, 2007; Deng *et al.*, 2008), energy (Ding & Zhang, 2007), root mean square (Deng *et al.*, 2008), and periodicity (Ding & Zhang, 2007). Other than these two domains of features, the other common feature used in this study was Mel-Frequency Cepstral Coefficients (MFCC). This feature derived from a type of cepstral representation of the audio. MFCC has been successfully in the audio processing research (such as speech processing, music genre and musical instrument sound) (Eronen, 2001; Ding & Zhang, 2007; Deng *et al.*, 2008).

Thus, in this research, two (2) different features categories proposed by Deng *et al.* (2008), which are Mel-Frequency Cepstral Coefficients (MFCC) features and perception-based features, were utilized. The perception-based category consists of both temporal and spectral features. There were six features in this category, which are zero crossing, zero-crossing rate, root-mean-square, spectral centroid, bandwidth and flux. For the MFCC, the first 13 coefficients have been found to be most useful in musical sounds features which also traditionally applied in speech processing (Ding & Zhang, 2007). The mean and standard deviation were calculated for each of the features for the classification purpose. The brief descriptions for each feature used are as follows:

2.4.2.1 Mel-Frequency Cepstral Coefficients

Mel-Frequency Cepstral Coefficients features (MFCC) have been used not only in musical instrument sounds classification but also in other audio processing area such as music genre and speech processing (Deng *et al.*, 2008; Loughran *et al.*, 2008). It has been proven that both temporal and spectral features are required for better recognition performance (Herrera *et al.*, 2000a; Lounghran *et al.*, 2008). MFCC is a spectral quality features, over the temporal duration of the note (Loughran *et al.*, 2008). This study was motivated by the effectiveness of MFCC in identifying different type of sound features (Eronen, 2001; Deng *et al.*, 2006; Loughran *et al.*, 2008; Joder *et al.*, 2009; Fuhrmann, 2012). The MFCC does not only effectively for Western musical instrument sound but also for non-Western musical instrument sound as applied by Gunasekaran & Revathy (2008a) and Weng, Lin & Jang (2009). For example, the average classifications achieved by power spectrum and MFCC are 59.37% and 93.13%, respectively (Weng *et al.*, 2009). This indicates that MFCC is one of the feasible features which can successfully classify the identical music content. For effective consideration, this feature was applied in this study.

To extract the MFCC features in this study, the steps derived in the study by Sigurdsson, Petersen & Lehn-Schioler (2006) were adapted. The input signal was first derived into frames. Here, the popular hamming-windowed was applied as a window function. Then, the Fast Fourier Transform (FFT) was used to obtain the power spectrum in each frame. The Mel filter bank was generated to scale the frequency logarithmically. The Mel filter bank is a collection of triangular bandpass filters characterized by the center frequencies. To calculate the center frequencies of the filter bank, a signal needs to be transformed from frequency (Hz) scale to *mel* scale with:

$$mel(f) = 2595 \log_{10}\left(1 + \frac{f}{700}\right) \tag{2.3}$$

where *f* corresponds to the frequency signal. The details procedures of Mel filter bank can be found in (Sigurdsson *et al.*, 2006). Finally, a Discrete Consine Transform (DCT) was performed to obtain the MFCC value from filter outputs. Here, the mean and standard deviation for the first 13 coefficients were extracted.

2.4.2.2 Perception-based

Perception-based features are extracted from multiple segments either in temporal-domain or spectral domain of a sample signal. This set of features is computed from human perceptual model (Gunasekaran & Revathy, 2008b). It represents the instrument sound samples in physiological way from human auditory nerve image (Deng *et al.*, 2008). Perception-based features also contain both spectral and temporal domain features which have significant influence towards classification performance as discussed in Sub Section 2.9.2. It consists of various features such as zero-crossing (ZCR), root-mean-square (RMS), spectral centroid and skewness.

In this study, a perception-based features used by Deng *et al.* (2008) was applied. This features schemes consist of 11 features extracted from ZCR, RMS, spectral centroid, flux, and bandwidth. For temporal features, zero-crossing rate (ZCR) was implemented with a concern for handling the additive noises (Gouyon, Pachet & Delerue, 2000). It can be used over large data sets to achieve satisfying discrimination between different input classes. The other temporal feature used was root-mean-square (RMS) which explains the energy distribution in each frame and channel over time. Finding by Panagiotakis & Tziritas (2005) for discriminating between music and speech signal shows that the combination of RMS and ZC increases the classification accuracy from 86% (with single RMS) to 95%.

For the spectral features, spectral centroid calculates the average frequency weighted by amplitude of a spectrum; bandwidth measures the magnitude-weighted

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