A NOVEL APPROACH TO DATA MINING USING SIMPLIFIED SWARM OPTIMIZATION

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy in the School of Information Technologies at The University of Sydney

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ABSTRACT

Data mining has become an increasingly important approach to deal with the rapid growth of data collected and stored in databases. In data mining, data classification and feature selection are considered the two main factors that drive people when making decisions. However, existing traditional data classification and feature selection techniques used in data management are no longer enough for such massive data. This deficiency has prompted the need for a new intelligent data mining technique based on stochastic population-based optimization that could discover useful information from data.

In this thesis, a novel Simplified Swarm Optimization (SSO) algorithm is proposed as a rule-based classifier and for feature selection. SSO is a simplified Particle Swarm Optimization (PSO) that has a self-organising ability to emerge in highly distributed control problem space, and is flexible, robust and cost effective to solve complex computing environments. The proposed SSO classifier has been implemented to classify audio data. To the author's knowledge, this is the first time that SSO and PSO have been applied for audio classification.

Furthermore, two local search strategies, named Exchange Local Search (ELS) and Weighted Local Search (WLS), have been proposed to improve SSO performance. SSO-ELS has been implemented to classify the 13 benchmark datasets obtained from the UCI repository database. Meanwhile, SSO-WLS has been implemented in Anomaly-based Network Intrusion Detection System (A-NIDS). In A-NIDS, a novel hybrid SSO-based Rough Set (SSORS) for feature selection has also been proposed. The empirical analysis showed promising results with high classification accuracy rate achieved by all proposed techniques over audio data, UCI data and KDDCup 99 datasets. Therefore, the proposed SSO rule-based classifier with local search strategies has offered a new paradigm shift in solving complex problems in data mining which may not be able to be solved by other benchmark classifiers.

PUBLICATIONS

Refereed Journal Articles:

1. Wei-Chang Yeh, Noorhaniza Wahid, Yuk Ying Chung. “Effective Audio Classification Algorithm using Swarm-based Optimization Technique Approach”, submitted to Expert System with Applications (SCI journal with Impact Factor 2.908).
2. Wei-Chang Yeh, Noorhaniza Wahid, Yuk Ying Chung. “A Hybrid Network Intrusion Detection System using Simplified Swarm Optimization (SSO)”, submitted to Applied Soft Computing (SCI journal with Impact Factor 2.415).
3. Wei-Chang Yeh, Noorhaniza Wahid, Yuk Ying Chung. “A New Simplified Swarm Optimization (SSO) Data Mining Classification Algorithm”, submitted to Computers & Industrial Engineering (SCI journal with Impact Factor 1.057).

Refereed Conference Paper:

1. Noorhaniza Wahid, Yuk Ying Chung, Wei-Chang Yeh, Guang Liu, “Feature Selection Using a Novel Swarm Intelligence Algorithm with Rough Sets”, in the Proceedings of the 2010 International Conference on Data Mining (DMIN'10), pp. 294-300, 2010.

ABBREVIATIONS

Acronym	Expended term
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ADEL	Ankyloglossia with Deviation of the Epiglottis and Larynx
AI	Artificial Intelligence
AIS	Artificial Immune Systems
A-NIDS	Anomaly-based Network Intrusion Detection Systems
ANN	Artificial Neural Network
ARS	Average Rule Size
BPSO	Binary Particle Swarm Optimization
BW	Baum-Welch
CHD	Coronary Heart Disease
CLPSO	Comprehensive Learning PSO
CPSO	Constricted PSO
CPSO	Cooperative Particle Swarm Optimizer
DE	Differential Evolution
DFT	Discrete Fourier Transform
DoS	Denial of Service
DPSO	Discrete PSO
EAs	Evolutionary Algorithms
ELS	Exchange Local Search
EP	Evolutionary Programming
ES	Evolution Strategy
FCM	Fuzzy C-Means
FCPS-classifier	Fuzzy Controlled Particle Swarm-classifier
FDTs	Fuzzy Decision Trees
FIPS	Fully Informed Particle Swarm
FN	False Negatives
FP	False Positives
FPPSO	Feature Partitioning PSO
GA	Genetic Algorithm
GEPSVM	Generalized Eigenvalue Proximal SVM
GMM	Gaussian Mixture Model
GNB	General Naive Bayes
GP	Genetic Programming
GRBF	Gaussian RBF
HEHRS	Hierarchical Rule Sets
H-IDS	Host-based IDS

Acronym	Expended term
HMM	Hidden Markov Model
IA	Immune Algorithm
IDS	Intelligent Dynamic Swarm
IDSRS	Intelligent Dynamic Swarm with Rough Set
IkNN	Informative k Nearest Neighbor
IPS-classifier	Intelligent Particle Swarm-classifier
IS	Immune System
KDD	Knowledge Data Discovery
kNN	kNearest Neighbour
KPCM	Kernel-based Possibilistic C-Means
LCM	Linear time Closed itemset Miner
LDPSO	Linearly Decreasing PSO
LDWPSO	Linear Decreasing Weight PSO
LGP	Linear Genetic Programming
LMNN	Large Margin Nearest Neighbor
LPC	Linear Predictive Coding
MARS	Multivariate Adaptive Regression Splines
MFCC	Mel Frequency Cepstral Coefficient
MI	Mutual Information
MLP	MultiLayer Perceptron
MOPSO	Multi-Objective PSO
MSSE	Mean Sum Squared Error
NB	Naive Bayes
NFL	Nearest Feature Line
NIDS	Network Intrusion Detection Systems
NIP	Numerical Interval Pruning
NN	Neural Network
NN	Nearest Neighbor
OBSI	Octave Band Signal Intensities
P2PkNN	Peer-to-Peer kNN
PCA	Principal Component Analysis
PM	Partition Matrix
PSO	Particle Swarm Optimization
PSO-NCC	PSO-Nearest Centroid Classifier
PUNN	Product Unit Neural Network
QDE	Quantum-Inspired Differential Evolution
QPPs	Quadratic Programming Problems
R2L	Remote to Local
RBF	Radial Basis Function
RHMM	Reverse HMM
RJMCMC	Reversible Jump Markov Chain Monte Carlo

Acronym	Expended term
RSC	Rough Set Classification
RSC-PGA	Rough Set Classification Parallel Genetic Algorithm
RST	Rough Sets Theory
RWS	Roulette Wheel Selection
SA	Simulated Annealing
SI	Swarm Intelligence
SMO	Sequential Minimal Optimization
SNNB	Selective Neighborhood Naive Bayes
SOM	Self Organizing Maps
SR	Silence Ratio
SSO	Simplified Swarm Optimization
SSO-ELS	SSO with Exchange Local Search
SSO-WLS	SSO with Weighted Local Search
SVDF	Support Vector Decision Function
SVM	Support Vector Machine
TN	True Negatives
TP	True Positives
TSP	Traveling Salesman Problem
TSVM	Twin SVM
U2R	User to Root
WEKA	Waikato Environment for Knowledge Analysis
WFPPSO	Weighted Feature Partitioning PSO
WLS	Weighted Local Search
WSVM	Weighted Support Vector Machine

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CHAPTER 1. Background Information and Problem Statements

In the emerging age of digital information we are overwhelmed with data, while our capability to analyse and interpret such huge datasets lags behind. Furthermore, it has been estimated that every 20 months the amounts of data stored in the world's databases are doubled, which caused difficulties when trying to justify this figure in a quantitative sense [1]. Often, traditional data analysis, and interpretation of changing data, has become insufficient for data processing as the data volumes grow exponentially. In addition, due to the advancement of software capabilities and hardware tools that enable the automated data collection, as well as the decreasing trend in their cost, there has been a dramatic increase in the data being collected and stored in databases. Although in recent years information collection and storage has become easier and more inexpensive, great effort is required to extract relevant knowledge information from such large-scale databases. Therefore, a new generation of computational techniques and tools is required to support the extraction of useful knowledge from the rapidly growing volume of data. Hence, data mining becomes the reliable solution for elucidating the patterns that underlie it.

Data mining is the application of specific algorithms that has been widely used for extracting patterns or models from data. Two main aspects in data mining are data classification and feature selection. Data classification classifies a data item into one of several predefined categorical classes. Feature selection can be defined as a process of choosing a small subset of features from the original set of features which is necessary and sufficient to describe the target concept. Other than the well-known

classical data mining techniques, heuristic approaches based on swarm intelligence algorithms have gained more attention and have been adopted in data classification problems in order to find a good solution. This thesis proposes and presents some new data mining approaches based on a population-based optimization algorithm for various data classification problems. The second topic being discussed in this thesis is about feature selection, which presents a new hybrid rough set reduction approach to feature selection. At this stage, this thesis is concerned with finding new approaches in both topics that contribute to the best classification accuracy; computation time is not taken into consideration. In this chapter, section 1.1 presents a brief discussion on data mining from the perspective of Knowledge Data Discovery (KDD). In section 1.2, the motivation is described and the problem statement in this thesis is identified. Next, the objective and contribution of the thesis is stated in section 1.3, followed by the organisation of the thesis in section 1.4.

1.1. Data Mining

Data mining is the process of analysing data from different perspectives and summarising it into useful information. It blends traditional data analysis methods with sophisticated algorithms for processing large volumes of data. It has been widely used and unifies research in fields such as statistics, databases, machine learning and Artificial Intelligence (AI). Regarding that, data mining has been seen as an explosion of interest from both academia and industry to improve the process of visualising and understanding the pattern of the data. Data mining is the core part of the Knowledge Discovery in Database (KDD) process, which is essential to solve a problem in a specific domain [2]. Generally, KDD is the overall process of identifying valid, novel,

potentially useful and ultimately understandable patterns in data and converting it into useful information [3]. An overview of the steps constituting the KDD process is depicted in Figure 1.1.

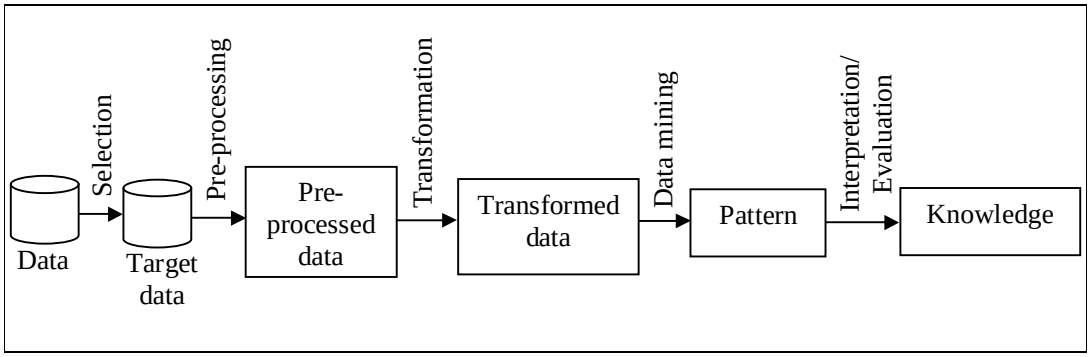

Figure 1.1. The processes of KDD [3]

Data mining in KDD applies a specific algorithm to extract meaningful knowledge so that the discovered knowledge can be applied in the related area to increase working efficiency and also to improve the quality of decision-making. Data mining involves several steps such as data integration from various databases, data pre-processing, and induction of a model using a learning algorithm. Based on the requirements of the problem domain, various techniques that expose diverse kinds of patterns from a given dataset have been implemented in data mining. The most common techniques learned in data mining include data classification, data clustering, association rule discovery, and outlier detection.

1.2. Motivation and Problem Statements

As mentioned earlier, data mining has been widely used to solve various kinds of data classification problems. However, data classification has turned out to be one of the most pervasive problems that encompasses many diverse applications in the data mining field. These problems have attracted more active research in order to find

efficient approaches to address them, and the outcome of the research is still unsatisfactory.

The ultimate goal of classification is to discriminate new data into the most likely of the specific categorical variable (the class) based on the induction model generated by the classifier. However, the classification problem has become very complicated and computationally infeasible when the number of possible different combinations of variables is so high. Hence, Swarm Intelligence (SI) algorithms are generally more suitable to solve these difficult problems because they are based on stochastic population-based approaches. In addition, they are also capable of avoiding becoming stuck in a local optimal and can find a global optimal solution [4].

Many data mining approaches have been proposed using stochastic population-based algorithms such as Particle Swarm Optimization (PSO), Immune Algorithm (IA), Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO). Nevertheless, there are problems in real-world that are NP-hard and combinatorial. Thus, evolutionary algorithm like PSO is generally more suitable to solve these difficult problems because of its stochastic nature. PSO is a well-known, biologically inspired computational search and optimization algorithm which is based on the social behaviours of bird flocks or schools of fish [5]. Because of its easy implementation, PSO has been successfully applied in many fields, particularly in optimization applications [6] and data mining [6-8]. This is due to its simplicity and efficiency when navigating a search space for optimal solutions. In terms of data mining, PSO has emerged as a promising technique to discover useful and interesting knowledge from databases [8]. Because of these advantages, the motivation of this thesis is to develop a new data mining technique based on the original PSO algorithm.

In many applications, people are dealing with massive data that contains multi-dimensional attributes such as network intrusion data, stock market data, medical data, weather forecast data and much more. Thus, data classification is faced with a problem when it has to generate rules with many attributes or features. Obviously, the time required to generate rules is proportional to the number of features. In addition, irrelevant and redundant features can reduce both the predictive accuracy and comprehensibility of the induced rule and degrade the classifier speed (due to its high dimensionality). Thus, selecting the most relevant features is necessary, and this strategy is implemented to simplify the rules and reduce its computational time while retaining the quality of classification, as it represents the original features set.

This thesis proposes and investigates the application of a new efficient population-based optimization algorithm for data mining based on the PSO algorithm. The new technique is referred as a Simplified Swarm Optimization (SSO) algorithm. Like PSO, SSO solves data mining problems by simulating the social interaction among agents or particles in their population, such as birds flocking or fish schooling. To deal with the problem of feature selection, a new hybrid swarm intelligence-based rough set theory for feature selection using SSO is proposed as a way to improve some performance criterion, such as accuracy of data classification. In this thesis, the author is concerned with introducing a new population-based optimization technique for data mining and feature selection that contributes to maximising the classification accuracy. Therefore, computation time is not taken into consideration.

Throughout this thesis, each algorithm was implemented using Java NetBeans IDE 6.1 on the following system: 1.8GHz Pentium (R) processor and 2GB RAM running in Windows XP Professional. Five traditional classifiers were involved in the

experiments for comparison with the proposed technique. Those benchmark classifiers were implemented from Waikato Environment for Knowledge Analysis (WEKA) [1]. The employed classifiers were set with their default parameters as set in WEKA.

1.3. Objectives and Contributions of the Thesis

This section outlines the main objectives and contributions to the area of data mining, particularly in feature selection and classification problems.

i. To develop and implement an efficient data classification technique based on an SSO algorithm to be implemented in audio datasets.
ii. To develop and implement a novel Exchange Local Search (ELS) strategy to improve the performance of the SSO rule-based classifier on various datasets.
iii. To develop and implement a new hybrid SSO-based Rough Set for feature selection and Weighted Local Search (WLS) strategy with SSO classifier to improve the Anomaly-based Network Intrusion Detection System (A-NIDS).

1.4. Outline of the Thesis

The remainder of this thesis is structured as follows:

"CHAPTER 2 Literature Review of Feature Selection and Data Mining" comprehensively presents two main topics that cover the foundations of feature selection and data mining. These topics provide a review of recent work that has been conducted in feature selection (with more emphasis on Rough set theory) and in data mining (with more emphasis on traditional classification techniques).

“CHAPTER 3 Data Mining using the Particle Swarm Optimization Algorithm” provides some introduction to four population-based optimization algorithms (with more emphasis on the PSO). This chapter also reviews the implementation of PSO algorithms for data mining purposes in various applications and problem domains. Four approaches have been highlighted in PSO-based classification including: PSO for Rule-based Classification Model, Nearest Neighbor Classification, PSO as Optimizer within Other Learning Algorithms, and Clustering with PSO Algorithms. Also, some PSO variants for data classification are discussed in this chapter.

“CHAPTER 4 Data Mining using Simplified Swarm Optimization Algorithm” presents the Simplified Swarm Optimization (SSO) algorithm that is based on traditional PSO for data mining. This is followed by the principle of the SSO algorithm; the SSO rule mining scheme; the SSO rule evaluation; and SSO rule pruning. The proposed algorithm is then applied to audio data and it is compared with Support Vector Machine (SVM) to investigate its competitiveness.

“CHAPTER 5 The Proposed SSO with Exchange Local Search for Data Classification” presents a proposed Exchange Local Search (ELS) strategy to be incorporated with SSO for data classification. To show the applicability of the proposed approach, SSO with ELS (SSO-ELS) is then applied to 13 datasets obtained from public sources such as the UCI repository database. The performance is compared with and without ELS for SSO and PSO, and four other traditional classifiers including SVM, J48, PART and kNearest Neighbor.

“CHAPTER 6 A Hybrid SSO-based Rough Set Reduction Method for Network Intrusion Detection Systems” introduces a proposed hybrid SSO-based rough set

reduction for features dimensionality reduction. This approach is specifically applied to solve the classification problem in Anomaly-based Network Intrusion Detection Systems (A-NIDS) due to its large amount of attributes. This is followed by the principle of the proposed SSO with Weighted Local Search (WLS) strategy for mining anomaly intrusion patterns. The experimental results, when compared with original SSO and PSO, and also with SVM and Naive Bayes, show the effectiveness of hybridizing SSO-WLS approaches for A-NIDS detection.

"CHAPTER 7 Conclusions and Future Work" contains a summary, conclusion, limitations and future direction of the research conducted in this thesis.

CHAPTER 2. Literature Review of Feature Selection and Data Mining

In recent years, the field of automated data mining has emerged as an important area of applied research when dealing with the voluminous data collected in various industries. This is due to the low cost and availability of larger storage devices. Thus, two major data mining tasks that must be solved are feature selection and classification. In this chapter, the investigation on several techniques of feature selection and data classification is continued, and comprehensive reviews on both topics are presented in section 2.1 and section 2.2. In this thesis, the new data mining algorithms based on the population-based optimization algorithm are proposed in Chapter 3.

2.1. Feature Selection Overview

Feature selection plays an important role in data pre-processing technique for data mining [2]. It is a process of finding a subset of features from the original set of features, and forming patterns in a given dataset to obtain the optimal one according to the given goal of processing and criterion. It reduces the number of features, removes irrelevant, redundant, or noisy data and brings immediate effects for applications: speeding up a data mining algorithm, improving mining performance such as classification accuracy, and improving results comprehensively.

In the context of classification, feature selection can be structured into three fractions: *filter* method, *wrapper* method and *embedded* method [9]. Filter methods rely on the intrinsic properties of the training data to select some features without involving any

learning algorithm. Each feature is ranked according to some univariate metric, and only the highest ranking features are used while the remaining low ranking features are eliminated. Afterwards, this subset of features is presented as input to the classification algorithm. Therefore, feature selection is allowed to be performed only once, and then different classifiers can be evaluated. A number of multivariate filter techniques were introduced to overcome univariate problems in filter methods.

Wrapper methods embed the model hypothesis search within the feature subset space. These methods begin by looking for the dependency from a suboptimal subset. Then this value is fed into the fitness function of the selected learning algorithm and evaluated in order to find the suitable features. These methods suffer from a high risk of overfitting and require huge computational cost.

Meanwhile, in the third category of feature selection, namely, embedded methods, the search for an optimal subset of features is built into the classifier construction, which can be seen as a search in the combined space of feature subsets and hypotheses. Thus, their function is seen as more specific to a given learning algorithm. Embedded methods are less computationally intensive than wrapper methods due to the internal interaction with the classification model during the feature selection process.

2.1.1. Feature Selection Problems

The feature selection problem is more or less a special case of a much broader problem of subset selection. Suppose a large set of M items $\{x_k,y_k\}$ where $k = 1, 2,\ldots.$, M consisting of n input variables $x_{k,i}$ where $i = 1, 2,\ldots., n$ and one output variable y_k is given from which we need to find a small m subset being optimal in a certain sense. Fitness function (F_i) is computed from the values $x_{k,i}$ and y_k , $k = 1, 2,\ldots., m$ to rank the

variables with a high F_i value. Then, the features with a high F_i value will be selected as the most relevant features. In statistical subset selection, being optimal usually means being most suitable for classification or data approximation. Although it may not be apparent, the subset selection problem may become prohibitive because of its computational complexity [10]. It is not possible to rank the items in our set simply according to their individual properties and select only the best. The item properties may depend strongly on each other and a subset of individually "bad" features may prove to be rather "good" because of positive interaction effects. Because of this uncertainty, the only apparent way of searching for optimal subsets is to evaluate all the 2^n possible item combinations.

Generally, feature selection is composed of two parts. First, there is a searching strategy that selects a feature subset. By searching all the feature subset, we shall ensure the number of $\binom{N}{M}$ where N is the original features, M is the feature subset, and $M < N$. If we optimized an M, we should be able to estimate the combination number of 2^N. Therefore, we must select a good searching strategy to evaluate quite a number of combinations because it is definitely inefficient to evaluate the whole feature sets. In addition, testing all subsets is a combinatorial NP-hard [11] problem that requires an exponential amount of computational time. Second, there is a fitness function that evaluates the feature subsets, returns their scores to the corresponding subsets and finally selects the best subset.

Feature selection has been used as a measure to decide the importance and necessity of features. Hence, a broad range of sub-optimal feature selection methods have been developed over the last decade to overcome its limitation. Previous research on

feature selection which employed a heuristic approach, such as hill-climbing methods, has proven more efficient when dealing with little noise and a small number of features [12, 13]. On the other hand, due to the reason that heuristic methods fail to find an optimal reduct [14], many researchers have shifted to metaheuristic approaches such as Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search, Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) [15].

Previous research has introduced various techniques of feature selection with the use of SI algorithms, either in single or hybrid approaches. Bello et al. [16] proposed a two-stage heuristic search performed by PSO and ACO in order to find the optimal feature subsets. In [17], the authors used chaotic BPSO with logistic map to determine the inertia weight to solve the feature selection problem. As a result, their approach has successfully reduced the computation time as well as improved the quality of reducts and classification accuracies. Moreover, several hybrid methods that used SI algorithms and rough sets for feature selection have been reported. Methods which combine ACO and rough set to find reducts with promising results were proposed by Ke et al. and Chen et al. in [15] and [18], respectively. Later, inspired from the work of Wang et al. [14], a new algorithm to find minimal rough set reducts by using modified PSO, namely, Intelligent Dynamic Swarm (IDS), was introduced by Bae et al. [19]. The experimental results from that work showed that IDS is efficient for rough set-based feature selection. In the next section, this study only limit to the concept of rough set theory for the purpose of the feature selection approach.

2.1.2. Rough Sets Theory

Rough sets theory (RST), which was proposed by Pawlak [20], has been successfully applied as a feature selection method to discover data dependencies and reduce the number of attributes contained in a dataset. It involves mathematical theory that is able to deal with imprecise, uncertain and vague information [21]. At the first stage of the feature selection procedure, rough set is used to reduce and clean data with minimal model assumption. Then the result is used as a basis for further analysis performed with our proposed method. Rough set has been proven as an efficient tool for feature selection as it does not require any preliminary or additional knowledge except for the supplied data.

Table 2.1. A decision table

Object	a_1	a_2	a_3	a_4
x_1	2	3	1	4
x_2	1	4	3	5
x_3	2	3	1	4
x_4	3	2	1	1
x_5	1	2	1	2
x_6	1	2	3	2
x_7	1	4	3	5
x_8	2	1	1	2
x_9	1	2	3	4
x_{10}	1	4	3	5

In rough set theory, the data is organised into a table called a decision table. Table 2.1 shows the structure of the table which consists of rows and columns. The rows of the decision table correspond to objects, and columns correspond to attributes. In the dataset, a class label indicates the class to which each row belongs. The class is called

the *decision attribute*, while the rest of the attributes are the *condition attributes*. Some basic concepts of rough set are explained below.

The information system of a decision table is defined as a tuple T = (U, A), where U is a non-empty set of finite objects (the universe) and A is a non-empty finite set of attributes. As in Table 2.1, the information table assigns an object *x* to the universe U with U = $\{x_1, x_2, \ldots, x_{10}\}$. Whereas each attribute or feature $a \in$ A is associated with a set $\forall a$ of its value denoted as A = $\{a_1, a_2, \ldots, a_4\}$. It is called the domain of *a*. The attribute set A can be partitioned into two subsets, *C* and *D*, which are called condition and decision attributes, respectively.

For a subset of attributes $R \subseteq$ A, the *R*-indiscernibility relation is denoted by *IND(R)*, is an equivalence relation defined as:

$$IND(R) = \{(x, y) \in U \times U : \forall a \in R, a(x) = a(y)\} \quad \text{Eq. 1}$$

where *a(x)* denotes the value of feature *a* of object *x*. If $(x,y) \in IND(R)$, *x* and *y* are said to be indiscernible with respect to *R*. The family of all equivalence classes of *IND(R)* is denoted by *U/IND(R)*. Each element in *U/IND(R)* is a set of indiscernible objects with respect to *R*. Equivalence classes *U/IND(C)* and *U/IND(D)* are called condition and decision classes. According to the objects from the example in Table 2.1, we consider the full set of attributes A = $\{a_1, a_2, a_3, a_4\}$ and the sets of *U/IND(R)* can be listed as *U/IND(R)* = $\{\{x_1, x_3\},\{x_2, x_7, x_{10}\},\{x_4\},\{x_5\},\{x_6\},\{x_8\},\{x_9\}\}$.

For any concept $X \subseteq U$ and attribute subset $R \subseteq$ A, *X* could be approximated by the *R*-lower approximation and *R*-upper approximation using the knowledge of *R*. The lower approximation of *X* is the set of elements of *U* that are surely in *X* is defined in

Eq. 2. The upper approximation of *X* is the set of elements of *U* that are possibly in *X* is defined as in Eq. 3.

$$\underline{R}(X) = \bigcup\{E \in U / IND(R) : E \subseteq X\} \quad \text{Eq. 2}$$

$$\overline{R}(X) = \bigcup\{E \in U / IND(R) : E \cap X \neq \phi\} \quad \text{Eq. 3}$$

Consider the target set X = $\{x_1, x_2, x_3, x_4\}$, therefore the *R*-lower approximation and *R*-upper approximation can be represented as $\underline{R}X = \{x_1, x_3, x_4\}$ and $\overline{R}X = \{x_1, x_3, x_4, x_2, x_7, x_{10}\}$, respectively. Let *R* and *S* be equivalence relations over *U*, then the positive, negative and boundary regions can be defined as:

$$POS_R(S) = \bigcup_{X \in U/S} \underline{R}X$$

$$NEG_R(S) = U - \bigcup_{X \in U/S} \overline{R}X$$

$$BND_R(S) = \bigcup_{X \in U/S} \overline{R}(X) - \bigcup_{X \in U/S} \underline{R}(X)$$

The positive region, $POS_R(S)$ is a set of objects of *U* that can be classified with certainty to classes *U/IND(S)* employing attributes of *R*. The negative region $NEG_R(S)$, is the set of all elements *U* that cannot be classified to classes of *U/S*. On the other hand, the boundary region $BND_R(S)$ is the set of all elements that can be possibly, but not certainly, classified in this way. If the boundary region is empty, that is, $\overline{R}(X) = \underline{R}(X)$, *X* is said to be *R*-definable or crisp. In the opposite case, if $BND_R(S) \neq \phi$, the *S* is referred to as *rough* (*indefinable*) set with respect to *R*.

Another important issue in data analysis is discovering dependencies between attributes. Let R and S be subsets of A. We will say that S depends on R in a degree k ($0 \leq k \leq 1$), denoted $R \Rightarrow_k S$ if

$$k = \gamma_R(S) = \frac{|POS_R(S)|}{|U|} \qquad \text{Eq. 4}$$

If $k = 1$, S depends totally on R, and if $k < 1$, S depends partially on R, and if $k = 0$, then S does not depend on R. In other words, S depends totally (partially) on R, if all (some) elements of the universe U can be surely classified to blocks of the partition U/S employing R [14]. Dependency degree k can be used as heuristic in greedy algorithms to compute feature reduction.

The reduction of attributes is achieved by comparing equivalence relations generated by a set of attributes. Let A = (U, C $\cup$ D) be a decision table where C is the set of condition features, and D is the set of decision features. The degree of dependency between condition and decision features, $\gamma_R(D)$, is called the equality of approximation of classification induced by the set of decision features [22]. The aim of feature reduction is to remove redundant features so that the reduced set provides the same quality of classification as the original set. A *reduct* is defined as a subset of minimal cardinality R_{min} of the conditional attribute set C in such a way that $R \subseteq C$ is said to be a D-reduct of C if $\gamma_R(D) = \gamma_C(D)$. A given decision table may have many feature reducts, thus the set of all reducts is defined in Eq. 5.

$$\mathrm{Re}d = \{R \subseteq C \mid \gamma_R(D) = \gamma_C(D) \forall B \subset R, \gamma_B(D) \neq \gamma_C(D)\} \qquad \text{Eq. 5}$$

For instance, suppose that $C = \{a_1, a_2, a_3, a_4\}$, $R_1 = \{a_2, a_3, a_4\}$ and $R_2 = \{a_1, a_2, a_4\}$. As a reduct is the minimal set of attributes preserving the positive region such that $\gamma_{R_1}(D) = \gamma_C(D)$ and $\gamma_{R_2}(D) = \gamma_C(D)$, then *Red* = $\{\{a_2, a_3, a_4\}, \{a_1, a_2, a_4\}\}$.

The intersection of all the sets in R_{min} is called the *core*. The core is the set of attributes that are contained by all reducts, defined as $CORE_D(C) = \cap RED_D(C)$ where $RED_D(C)$ is the *D*-reduct of *C*. In other words, the core is the set of attributes that cannot be removed without changing the positive region. This means that all attributes present in the core are indispensable. Therefore, from the above example of *Red*, we conclude that core (C) = $\{a_2, a_4\}$.

The applications of the rough set model in feature selection problems have demonstrated its usefulness in a wide range of techniques from rough set [12], fuzzy rough set [10], and neural network [23]. Recently, the use of the metaheuristic approach has been widely implemented and has significantly increased the ability of finding very high quality solutions to select more dominating features in order to perform the classification tasks optimally in the data mining process. For example, hybrid rough with GA [24] and Genetic Programming (GP) [25] was proposed by Wa'el et al. for choosing the most relevant features in a network intrusion dataset. Chen et al. [18] and Ke et al. [15] proposed a feature selection mechanism based on rough-Ant Colony Optimization (ACO). Inspired from the work of Wang et al. [14, 26], which used PSO to find optimal features subset based rough set reducts, Bae et al. [19] proposed a new discrete PSO called Intelligent Dynamic Swarm (IDS) with rough set (IDSRS) for feature reduction. Instead of successfully reducing the massive

number of features from the original set, IDSRS could improve the computation speed when compared with the original PSO.

2.2. Data Mining Overview

In practice, the two primary goals of data mining tend to be *prediction* and *description*. Prediction involves using some variables or fields in the dataset to predict unknown or future values of other variables of interest. On the other hand, description emphasises finding patterns describing the data that can be interpreted by humans. The goal of predictive data mining is to produce a model expressed as an executable code which can be used to perform data mining tasks such as classification, prediction or other similar tasks. On the other hand, the goal of descriptive data mining is to gain an understanding of the analysed system by uncovering patterns and relationships in large datasets. Thus, the goals of prediction and description are achieved by using data mining techniques to solve data mining problems by realising several data mining tasks such as data classification, estimation, prediction, and association rules. The following section particularly focuses on data classification, which is our main consideration in this thesis.

2.2.1. Classification Task in Data Mining

Data classification is the most studied task in data mining. It is a process of discovering a predictive learning function that classifies a set of data items into one of several predetermined classes. All these data are typically represented by matrices whose rows are associated with the *objects* (or records), while the columns are associated with many measures taken on each object. Such measures are often referred to as *variables* (or features). The relationship in each record is tied up by a

specific attribute called a class *attribute*. The goal of the classification algorithm is to induce a model so that it can classify any new instances into classes according to class values. Data classification can be divided into two categories: *unsupervised classification* and *supervised classification.*

i. ***Unsupervised classification***: A method of unsupervised classification uses only the matrix of dissimilarity. No information of the class of an object is provided to the method. The objective is then to build a set of groups where each group contains a set of sufficiently similar objects. The number of classes and their contents are not known at the beginning. In data mining, unsupervised classification is also known as *clustering* [1]. Clustering divides the data into groups of similar objects and each group consists of objects that are similar between themselves and dissimilar to objects of other groups. There are many clustering algorithms that exist such as hierarchical clustering, K-Means clustering, Fuzzy C-Means clustering and many more. The two most popular classes of clustering algorithms are K-Means and Fuzzy C-Means (FCM) [27].

ii. ***Supervised classification***: On the other hand, in a method of supervised classification, the objects are labelled and each value of the label represents a class. The objective of this method is to build hyperplanes separating the objects according to their class. Supervised classification is performed on a set of training examples. Each training example $\langle x_i, y_i \rangle$ is composed of a feature vector, x_i and a corresponding class label, y_i. The feature vector contains measurable characteristics of the object under consideration.

In this section we are interested in the problem of supervised classification, therefore, the application of unsupervised classification in data mining will not be discussed in further detail. Support Vector Machines, kNearest Neighbor, Decision Tree (i.e.: PART and J48) and Naive Bayes classifiers are in the group of supervised classification and they have been used as state-of-the-art benchmarking classifiers throughout this thesis. The next sections, section 2.2.2.1 to section 2.2.2.4, will briefly describe the basic principle for each of the supervised classifiers and their applications in data classification problems.

2.2.2. Traditional Data Classification Methods

2.2.2.1. Support Vector Machines Classifier

Support Vector Machines (SVMs) are a group of supervised learning methods that can be applied to classification or regression. Theoretically, SVM is a well-motivated algorithm that is based on the statistical learning proposed by Vapnik [28]. SVM has shown promising empirical good performance and successful application in many fields such as bioinformatics, text categorisation, speaker verification, handwritten digit recognition, face detection, engineering and science, financial market evaluation [29], pattern recognition [30], image recognition [31] and many more. SVM has received overwhelming attention as a classification technique from diverse research communities due to its suitability, and works very well with high-dimensional data as well as avoiding the curse of the dimensionality problem [32].

The emergence of SVM in data mining technology has improved the efficiency of data classification that helps people to make decisions. Nevertheless, in real data mining applications, real-life databases sometimes contain outliers or noise data that

lead to the degradation of the classification performance. In order to improve the outlier sensitivity problem of standard SVM for two-class data classification, Yang et al. [33] introduced Weighted Support Vector Machine (WSVM). Different weights generated by Kernel-based Possibilistic C-Means (KPCM) are assigned to different data points such that WSVM learns the decision surface according to the relative importance of the data point in the training set. Furthermore, the training example is usually non-fuzzy where the output is either 1 or 0. However, due to the noise and error of measurement, the training examples are usually uncertain (fuzzy) [34]. Ji et al. [35] introduced the concept of fuzzy linear separable and approximately fuzzy linear separable for training two-class classification. Other works that related to fuzzy training data sets are also presented by Kikuchi and Abe [36] and Lin and Wang [37].

Recently, Mangasarian and Wild [38] proposed Generalized Eigenvalue Proximal SVM (GEPSVM) to perform a binary classification by obtaining two non-parallel hyperplanes, one for each class. In this approach, datapoints of each class are clustered around the corresponding hyperplane. The new datapoints are assigned to a class based on its proximity to one of the two hyperplanes. This formulation leads to two generalised eigenvalue problems, whose solutions are obtained as eigenvectors corresponding to the smallest eigenvalues. In 2007, Twin SVM (TSVM), which is similar in spirit to GEPSVM, was proposed by Jayadeva et al. [39]. The proposed TSVM obtains two non-parallel hyperplanes by solving two novel formulations of Quadratic Programming Problems (QPPs). The idea is to solve two dual QPPs of smaller size rather than solving a single dual QPP with a large number of parameters in conventional SVM. Experimental results in [39] showed the effectiveness of TSVM over GEPSVM and standard SVM on UCI datasets.

SVM was originally designed for binary classification in order to construct an optimal or maximal hyperplane so that the margin of separation between the negative and positive dataset will be maximised. There are many hyperplanes that might classify the data. The best hyperplane is chosen based on the one that represents the largest separation, or margin, between the two classes. So we chose the hyperplane so that the distance from it to the nearest data point on each side is maximised. Figure 2.1 illustrates how SVM finds the unique hyperplane having the maximum margin of linearly separable classes of objects denoted with δ.

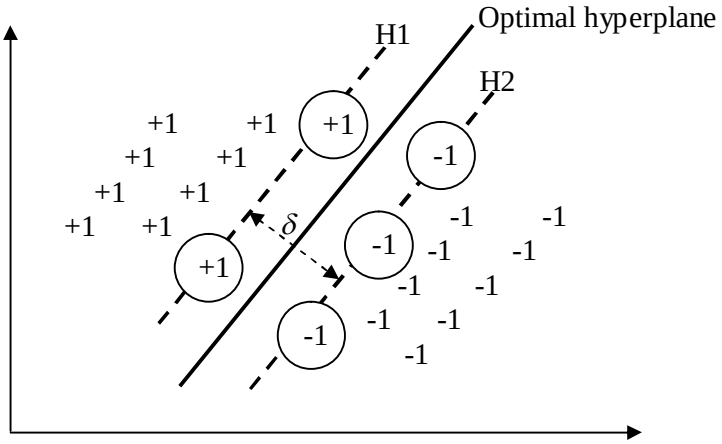

Figure 2.1. Maximum margin hyperplane denoted with δ for linearly separable case [40]

SVM works by mapping the input vectors into a higher dimensional feature space and then obtains the optimal separating hyperplane in the higher dimensional feature space. As depicted in Figure 2.1, two objects from class +1 – defined by the hyperplane H1 – and three objects from class -1 – defined by hyperplane H2 which were represented inside the circle – are called *support vectors*. For classification problems, SVM plots the training vectors in the high-dimensional feature space, and labels each vector by its class. SVM classifies data by determining a set of support

vectors, which are members of the set of training inputs that outline the maximum margin hyperplane in the feature space.

A binary classification problem to find a maximal margin classifier in SVM is presented as the following explanation. Suppose we are given some training data N where each training data is denoted by a pair of (x_i, c_i). Each x_i is a real number with $x_i = (x_{i1}, x_{i2}, \ldots, x_{id})^T$ corresponds to the attribute set for the i^{th} training data, and $i = (1, 2, \ldots, N)$. Each object x_i belongs to a class $c_i \in \{-1,+1\}$. Any hyperplane can be written in the following form:

$$w \cdot x_i + b = 0, \qquad \text{Eq. 6}$$

where w and b are parameters of the model. A training set of objects is linearly separable if at least one linear classifier exists defined by the pair (w,b), which correctly classifies all training data as shown in Figure 2.2.

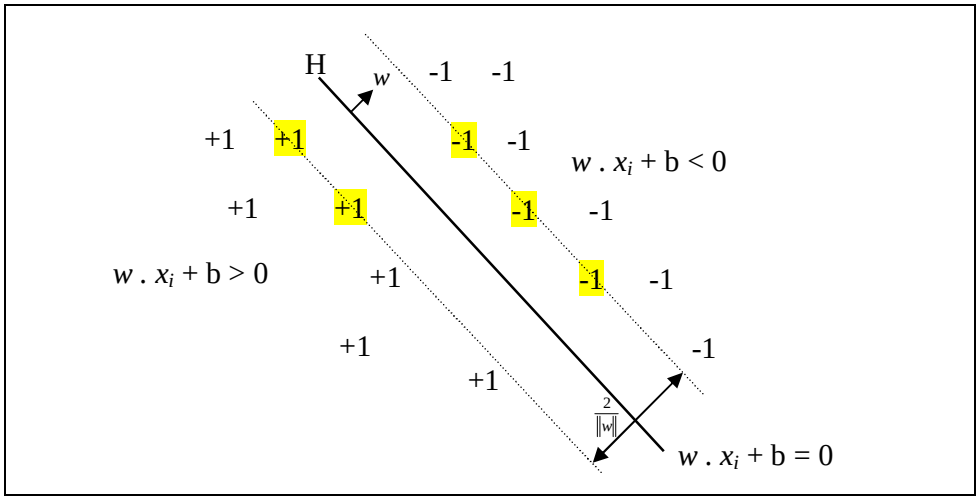

Figure 2.2. The classification hyperplane which defines two linear separable classes in +1 region and -1 region [40]

As the objective of training SVM is to find a pair of (w,b) with the largest margin, the parameters are subject to the following two constraints:

$$w \cdot x_i + b > 0, \text{ if } c_i = 1$$
$$w \cdot x_i + b < 0 \text{ if } c_i = -1 \qquad \text{Eq. 7}$$

In this case, w and b in Eq. 7 can be rewritten in a more compact form as below:

$$c_i(w \cdot x_i + b) \geq 1,\ i = 1, 2, \ldots, N \qquad \text{Eq. 8}$$

The margin separation between these two hyperplanes is defined by (w,b) is $\frac{2}{\|w\|}$ and therefore we want to minimise $\|w\|$, where $\|w\|$ is the norm of the vector w. However, it is difficult to solve the optimization problem as it depends on $\|w\|$ that involves square roots, which is known as a convex optimization problem. Hence, the Lagrange multiplier is used by substituting $\|w\|$ with $\frac{1}{2}\|w\|^2$ without changing the solution. Combining the Lagrange multiplier with Eq. 8 produces dual formulation of the optimization as in the following equation:

$$L_D = \sum_{i}^{N} \lambda_i - \frac{1}{2} \sum_{i,j=1} \lambda_i \lambda_j c_i c_j x_i . x_j \ , \qquad \text{Eq. 9}$$

where $\lambda_i \geq 0$ and under constraint $\sum_{I=1}^{N} c_i \lambda_i = 0$.

In a case of binary classification, SVM can easily find a hyperplane that separates two-dimensional objects which belong to two classes. However, in a real world problem, the dataset of interest usually cannot be separated with a linear classifier as shown in Figure 2.3(a). Therefore, SVM can solve this difficulty by implementing special non-linear functions to non-linearly map the input data to a high dimensional feature space as illustrated in Figure 2.3(b). These non-linear functions are called *kernels*, which are computed by feature functions denoted with ϕ. Here, the linear

REFERENCES

[1] I. H. Witten and E. Frank, *Data Mining: Practical Machine Learning Tools and Techniques*, Second ed. San Fransisco: Morgan Kaufmann, 2005.

[2] J. Han and M. Kamber, *Data Mining: Concepts and Techniques*. San Fransisco: Morgan Kaufmann, 2001.

[3] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, "The KDD Process for Extracting Useful Knowledge from Volumes of Data," *Communication of the ACM*, vol. 39, no. 11, pp. 27-34, Nov. 1996.

[4] C. Grosan, A. Abraham, and M. Chris, "Swarm Intelligence in Data Mining," In: A. Abraham, C. Grosan, and V. Ramos, (Eds) Studies in Computational Intelligence, vol. 34, pp. 1-20, Springer-Verlag: Berlin Heidelberg, 2006.

[5] R. C. Eberhart and Y. Shi, "Particle swarm optimization: developments, applications and resources," in *Proceedings of the 2001 Congress on Evolutionary Computation*, Seoul, South Korea, May 27-30, vol. 1, pp. 81-86, 2001.

[6] T. Sousa, A. Silva, and A. Neves, "Particle Swarm based Data Mining Algorithms for classification tasks," *Parallel Computing*, vol. 30, no. 5-6, pp. 767-783, May/June 2004.

[7] G. Chen, Q. Chen, and W. Guo, "A PSO-based approach to rule learning in network intrusion detection," In: B. Y. Cao (Ed) Advances in Soft Computing, vol. 40, pp. 666-673, Springer: Berlin-Heidelberg, 2007.

[8] S. H. Zahiri and S. A. Seyedin, "Swarm intelligence based classifiers," *Journal of the Franklin Institute*, vol. 344, no. 5, pp. 362-376, Aug. 2007.

[9] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *The Journal of Machine Learning Research*, vol. 3, pp. 1157 - 1182, Mar. 2003.

[10] R. Jensen and Q. Shen, "Fuzzy-Rough Sets Assisted Attribute Selection," *IEEE Transactions on Fuzzy Systems*, vol. 15, no. 1, pp. 73-89, Feb. 2007.

[11] H. Liu and L. Yu, "Toward integrating feature selection algorithms for classification and clustering," *IEEE Transactions on Knowledge and Data Engineering*, vol. 17, no. 4, pp. 491-502, Apr. 2005.

[12] K. Hu, Y. Lu, and C. Shi, "Feature ranking in rough sets," *AI Communications*, vol. 16, no. 1, pp. 41-50, May 2003.

[13] J. S. Deogun, S. K. Choubey, V. V. Raghavan, and H. Sever, "Feature selection and effective classifiers," *Journal of the American Society for Information Science,* vol. 49, no. 5, pp. 423-434, Apr. 1998.

[14] X. Wang, J. Yang, X. Teng, W. Xia, and R. Jensen, "Feature Selection Based on Rough Sets and Particle Swarm Optimization," *Pattern Recognition Letters,* vol. 28, no. 4, pp. 459-471, Mar. 2007.

[15] L. Ke, Z. Fenga, and Z. Rena, "An efficient ant colony optimization approach to attribute reduction in rough set theory " *Pattern Recognition Letters,* vol. 29, no. 9, pp. 1351-1357, July 2008.

[16] R. Bello, Y. Gomez, A. Nowe, and M. M. García, "Two step particle swarm optimization to solve the feature selection problem," in *Proceedings of The 7th International Conference on Intelligent Systems Design and Applications,* Rio de Janeiro, Brazil, Oct. 22-24, pp. 691-696, 2007.

[17] C. S. Yang, L. Y. Chuang, J. C. Li, and C. H. Yang, "Chaotic maps in binary particle swarm optimization for feature selection," in *Proceedings of the 2008 IEEE Conference on Soft Computing on Industrial Applications,* Muroran, Japan, June 25-27, pp. 107-112, 2008.

[18] Y. Chen, D. Miaoa, and R. Wanga, "A rough set approach to feature selection based on ant colony optimization," *Pattern Recognition Letters,* vol. 31, no. 3, pp. 226-233, Feb. 2010.

[19] C. Bae, W. C. Yeh, Y. Y. Chung, and S. L. Liu, "Feature selection with Intelligent Dynamic Swarm and Rough Set " *Expert Systems with Applications,* vol. 37, no. 10, pp. 7026-7032, Oct. 2010.

[20] Z. Pawlak, "Rough sets," *Internat. J. Comput. Inform. Sci,* vol. 11, no. 5, pp. 341-356, 1982.

[21] Z. Pawlak, *Rough Sets, Theoretical Aspects of Reasoning about Data*. Boston, MA: Kluwer Academic Publishers, 1991.

[22] Z. Pawlak, "Rough set approach to knowledge-based decision support," *European Journal of Operational Research,* vol. 99, no. 1, pp. 48-57, May 1997.

[23] L. Pan, H. Zheng, and L. Li, "A Hybrid Feature Selection Approach Based on the Bayesian Network Classifier and Rough Set," in *LNAI,* vol. 5009, pp. 707-714, Springer-Verlag: Berlin Heidelberg, 2008.

[24] M. M. Wa'el, H. N.Agiza, and E. Radwan, "Intrusion Detection Using Rough Sets based Parallel Genetic Algorithm Hybrid Model," in *Proceedings of the World Congress on Engineering and Computer Science 2009 (WCECS 2009),* San Francisco, USA, vol. II, 2009.

[25] M. M. Wa'el, H. N. Agiza, and E. Radwan, "Intrusion Detection Using Rough Set Parallel Genetic Programming Based Hybrid Model," *International Journal of Computer Science and Network Security,* vol. 9, no. 10, pp. 23-33, Oct. 2009.

[26] X. Wang, J. Yang, R. Jensen, and X. Liu, "Rough Set Feature Selection and Rule Induction for Prediction of Malignancy Degree in Brain Glioma," *Computer Methods and Programs in Biomedicine,* vol. 83, pp. 147-156, 2006.

[27] D. Karaboga and C. Ozturk, "Fuzzy clustering with artificial bee colony algorithm," *Scientific Research and Essays,* vol. 5, no. 14, pp. 1899-1902, July 2010.

[28] V. N. Vapnik, *Statistical Learning Theory*. New York: John Wiley, 1998.

[29] S. T. Li, W. Shiue, and M. H. Huang, "The evaluation of consumer loans using support vector machines," *Expert Systems with Applications,* vol. 30, no. 4, pp. 772–782, May 2006.

[30] Y. C. Wu, Y. S. Lee, and J. C. Yang, "Robust and efficient multiclass SVM models for phrase pattern recognition," *Pattern Recognition Letters,* vol. 41, no. 9, pp. 2874-2889, Sept. 2008.

[31] H. A. Park and K. R. Park, "Iris recognition based on score level fusion by using SVM," *Pattern Recognition Letters,* vol. 28, no. 15, pp. 2019-2028, Nov. 2007.

[32] P. N. Tan, M. Steinbach, and V. Kumar, *Introduction to Data Mining*: Pearson Addison Wesly, 2006.

[33] X. Yang, Q. Song, and Y. Wang, "A weighted support vector machine for data classification," *International Journal of Pattern Recognition and Artificial Intelligence,* vol. 21, no. 5, pp. 961-976, Aug. 2007.

[34] J. T. Jeng, C. C. Chuang, and S. F. Su, "Support vector interval regression networks for interval regression analysis," *Fuzzy Sets and Systems,* vol. 138, no. 2, pp. 283-300, Sept. 2003.

[35] A. b. Ji, J. h. Pang, and H. j. Qiu, "Support vector machine for classification based on fuzzy training data " *Expert Systems with Applications,* vol. 37, no. 4, pp. 3495-3498, Apr. 2010.

[36] T. Kikuchi and S. Abe, "Comparison between error correcting output codes and fuzzy support vector machines," *Pattern Recognition Letters,* vol. 26, pp. 1937-1945, 2005.

[37] C. Lin and S. Wang, "Training algorithms for fuzzy support vector machines with noisy data," *Pattern Recognition Letters,* vol. 25, no. 1647-1656, 2004.

[38] O. L. Mangasarian and E. W. Wild, "Multisurface proximal support vector classification via generalized eigenvalues.," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 28, no. 1, pp. 69-74, 2006.

[39] Jayadeva, R. Khemchandani, and S. Chandra, "Twin support vector machines for pattern classification," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 29, no. 5, pp. 905-910, 2007.

[40] O. Ivanciuc, "Applications of Support Vector Machines in Chemistry," *In: Reviews in Computational Chemistry,* vol. 23, pp. 291-400, 2007.

[41] S. W. Fei, M. J. Wang, Y. B. Miao, J. Tu, and C. L. Liu, "Particle swarm optimization-based support vector machine for forecasting dissolved gases content in power transformer oil," *Energy Conversion and Management,* vol. 50, no. 6, pp. 1604-1609, June 2009.

[42] M. K. Markey, G. D. Tourassi, and C. E. Floyd, "Decision tree classification of proteins identified by mass spectrometry of blood serum samples from people with and without lung cancer," *Proteomics,* vol. 3, pp. 1678-1679, 2003.

[43] M. A. Karaolis, J. A. Moutiris, D. Hadjipanayi, and C. S. Pattichis, "Assessment of the Risk Factors of Coronary Heart Events Based on Data Mining With Decision Trees," *IEEE Transactions on Information Technology in Biomedicine,* vol. 14, no. 3, pp. 559 - 566, 2010.

[44] D. E. van de Vlag and A. Stein, "Incorporating Uncertainty via Hierarchical Classification Using Fuzzy Decision Trees," *IEEE Transactions on Geoscience and Remote Sensing,* vol. 45, no. 1, pp. 237 - 245, 2007.

[45] P. C. Chang, C. Y. Fan, and W. Y. Dzan, "A CBR-based fuzzy decision tree approach for database classification," *Expert Systems with Applications,* vol. 37, no. 1, pp. 214-225, 2010.

[46] Y. Song, W. H. Wang, and F. J. Guo, "Feature extraction and Classification for Audio Information in News Video," in *Proceedings of the 2009 International Conference on Wavelet Analysis and Pattern Recognition*, Baoding, July 12-15, pp. 43-46, 2009.

[47] D. Tjondronegoro and Y. P. P. Chen, "Using decision-tree to automatically construct learned-heuristics for events classification in sports video," in *Proceedings of the IEEE International Conference on Multimedia and Expo, ICME 2006*, pp. 1465-1468, 2006.

[48] R. Jin and G. Agrawal, "Efficient decision tree construction on streaming data," in *Proceedings of the 9th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '03*, pp. 571-576, 2003.

[49] E. Frank and I. H. Witten, "Generating Accurate Rule Sets Without Global Optimization," in *Proceedings of the Fifteenth International Conference on Machine Learning*, pp. 144 - 151, 1998.

[50] J. R. Quinlan, *C4.5: Programs for Machine Learning*. San Mateo: Morgan Kaufmann, 1993.

[51] S. R. Safavian and D. Landgrebe, "A survey of decision tree classifier methodology," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 21, no. 3, pp. 660-674, May-June 1991.

[52] D. W. Aha, D. Kibler, and M. K. Albert, "Instance-Based Learning Algorithms," *Machine Learning*, vol. 6, pp. 37-66, 1991.

[53] T. M. Mitchell, *Machine Learning*: McGraw-Hill, 1997.

[54] Z. Xie, W. Hsu, Z. Liu, and M. Lee, "SNNB: A selective neighborhood based naive bayes for lazy learning," in *Proceedings of the Sixth Pacific-Asia Conference on KDD*, pp. 104–114, 2002.

[55] Y. Song, J. Huang, D. Zhou, H. Zha, and C. L. Giles, "IKNN: Informative K-Nearest Neighbor Pattern Classification," in LNCS, Knowledge Discovery in Databases: PKDD, vol. 4702, pp. 248-264, 2007.

[56] L. Baoli, Y. Shiwen, and L. Qin, "An improved k-nearest neighbor algorithm for text categorization," in *Proceedings of the 20th international conference on computer processing of oriental languages*, 2003.

[57] X. P. Yu and X. G. Yu, "Novel text classification based on K-nearest neighbor," in *Proceedings of the Sixth International Conference on Machine Learning and Cybernetics, ICMLC 2007*, vol. 6, pp. 3425-3430, 2007.

[58] K. Q. Weinberger and L. K. Saul, "Fast solvers and efficient implementations for distance metric learning," in *Proceedings of ACM International Conference*, vol. 307, pp. 1160–1167, 2008.

[59] G. H. John and P. Langley, "Estimating continuous distributions in Bayesian classifiers," in *Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence*, San Mateo, pp. 338-345, 1995.

[60] I. Rish, "An empirical study of the naive Bayes classifier," IBM Research Division, NY RC 22230 (W0111-014), Nov. 2, 2001.

[61] L. M. Wang, S. M. Yuan, L. Li, and H. J. Li, "Boosting Naive Bayes by active learning," in *Proceedings of 2004 International Conference on Machine Learning and Cybernetics, ICMLC' 04*, vol. 3, pp. 1383 - 1386, 2004.

[62] J. Yu, F. Cheng, H. Xiong, W. Qu, and X. Chen, "A Bayesian approach to support vector machines for the binary classification," *Neurocomputing*, vol. 72, pp. 177-185, 2008.

[63] S. B. Kim, K. S. Han, H. C. Rim, and S. H. Myaeng, "Some Effective Techniques for Naive Bayes Text Classification," *IEEE Transactions on Knowledge and Data Engineering*, vol. 18, no.11, pp. 1457-1466, Nov. 2006.

[64] M. L. Green and P. D. Karp, "A Bayesian method for identifying missing enzymes in predicted metabolic pathway databases," *BMC Bioinformatics*, vol. 5, no. 76, 2004.

[65] D. Karaboga and B. Basturk, "On the performance of artificial bee colony (ABC) algorithm," *Applied Soft Computing*, vol. 8, no. 1, pp. 687-697, Jan. 2008.

[66] D. Karaboga and B. Akay, "A comparative study of Artificial Bee Colony algorithm," *Applied Mathematics and Computation*, vol. 214, no. 1, pp. 108-132, Aug. 2009.

[67] C. Grosan and A. Abraham, "Hybrid Evolutionary Algorithms: Methodologies, Architectures, and Reviews," *Studies in Computational Intelligence (SCI)*, vol. 75, pp. 1–17, 2007.

[68] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From natural to Artificial systems*. New York: Oxford University Press, 1999.

[69] K. Shafi and H. A. Abbass, "Biologically-inspired Complex Adaptive Systems Approaches to Network Intrusion Detection," *Information Security Technical Report*, vol. 12, no. 4, pp. 209-217, 2007.

[70] M. Dorigo, M. Birattari, and T. Stutzle, "Ant Colony Optimization, Artificial Ants as a Computational Intelligence Technique," *IEEE Computational Intelligence Magazine*, vol. 1, no. 4, pp. 28-39, 2006.

[71] G. C. Luh and C. H. Chueh, "A multi-modal immune algorithm for the job-shop scheduling problem," *Information Sciences*, vol. 179, no. 10, pp. 1516 - 1532, Apr. 2009.

[72] D. Karaboga, "An idea based on honey bee swarm for numerical optimization," Technical Report TR06, Erciyes University, Engineering Faculty, Computer Engineering Department, 2005.

[73] G. Zhang, X. Shao, P. Li, and L. Gao, "An effective hybrid particle swarm optimization algorithm for multi-objective flexible job-shop scheduling problem," *Computers and Industrial Engineering*, vol. 56, no. 4, pp. 1309-1318, May 2009.

[74] H. Samarghandi, P. Taabayan, and F. F. Jahantigh, "A particle swarm optimization for the single row facility layout problem," *Computers and Industrial Engineering,* vol. 58, no. 4, pp. 529-534, May 2010.

[75] J. H. Holland, *Adaptation in Natural and Artificial Systems*. Ann Arbor, MI: University of Michigan Press, 1975.

[76] D. E. Goldberg, *Genetic algorithm in search optimization and machine learning*. Reading, MA: Addison-Wesley, 1989.

[77] M. A. Abed, A. N. Ismail, and Z. M. Hazi, "Pattern recognition Using Genetic Algorithm," *International Journal of Computer and Electrical Engineering,,* vol. 2, no. 3, pp. 1793-8163, June 2010.

[78] M. Wall. *Introduction to Genetic Algorithms*. Available: http://lancet.mit.edu/~mbwall/presentations/IntroToGAs/index.html, Access on: Aug. 16, 2010.

[79] M. Dorigo and G. D. Caro, "Ant Coloy Optimization: A New Meta-Heuristic," in *Proceedings of Congress of Evolutionary Computing*, pp. 1470-1477, 1999.

[80] W. C. Yeh, W. W. Chang, and Y. Y. Chung, "A new hybrid approach for mining breast cancer pattern using discrete particle swarm optimization and statistical method," *Expert System with Applications,* vol. 36, no. 4, pp. 8204 - 8211, May 2009.

[81] T. C. Chen and T. C. Hsu, "A GAs based approach for mining breast cancer pattern," *Expert System with Applications,* vol. 30, no. 4, pp. 674-681, May 2006.

[82] M. H. Tseng and H. C. Liao, "The genetic algorithm for breast tumor diagnosis - The case of DNA viruses," *Applied Soft Computing,* vol. 9, no. 2, pp. 703–710, Mar. 2009.

[83] M. H. Tseng, S. J. Chen, G. H. Hwang, and M. Y. Shen, "A genetic algorithm rule-based approach for land-cover classification," *ISPRS Journal of Photogrammetry & Remote Sensing,* vol. 63, no. 2, pp. 202-212, 2008.

[84] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics,* vol. 26, no. 1, pp. 29-41, Feb. 1996.

[85] Ant Colony Optimization. Available: http://en.wikipedia.org/wiki/Ant_colony_optimization, Access on: July 2010.

[86] M. Dorigo and T. Stützle, *The Ant Colony Optimization Metaheuristic: Algorithms, Applications, and Advances. Handbook of Metaheuristics,* 2002.

[87] D. Karaboga, "Artificial bee colony algorithm," *Scholarpedia, 5(3):6915,* 2010.

[88] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of the 1995 IEEE International Conference on Neural Networks. Part 4 (of 6)* Perth, Aust, Nov. 27 - Dec. 1, vol. 4, pp. 1942-1948, 1995.

[89] X. Li and A. P. Engelbrecht, "Particle Swarm Optimization - an introduction and its recent developments," in *GECCO 2007 Tutorial*, Access on: July 29, 2010.

[90] H. Liu, A. Abraham, and W. Zhang, "A fuzzy adaptive turbulent particle swarm optimisation," *International Journal of Innovative Computing and Applications*, vol. 1, no. 1, pp. 39-47, Apr. 2007.

[91] F. van den Bergh, "An Analysis of Particle Swarm Optimizers," PhD Thesis, Department of Computer Science, University of Pretoria, South Africa, 2002.

[92] D. W. van der Merwe and A. P. Engelbrecht, "Data clustering using particle swarm optimization," in *Proceedings of the 2003 Congress on Evolutionary Computation CEC '03*, vol. 1, pp. 215 - 220, 2003.

[93] R. Poli, J. Kennedy, and T. Blackwell, "Particle swarm optimization An overview," *Swarm Intelligence*, vol. 1, pp. 33-57, 2007.

[94] M. Montes de Oca, T. Stützle, M. Birattari, and M. Dorigo, "Frankenstein's PSO: A composite particle swarm optimization algorithm," *IEEE Transactions on Evolutionary Computation*, vol. 13, no. 5, pp. 1120–1132, 2009.

[95] J. Kennedy and R. C. Ebehart, "A discrete binary version of the particle swarm algorithm," in *Proceedings of the 1997 IEEE International Conference on Systems, Man, and Cybernetics. Part 5 (of 5)*, Orlando, FL, United States, Oct. 12-15, pp. 4104-4108, 1997.

[96] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in *Evolutionary computation Proceedings. IEEE World congress on computational intelligence*, pp. 69-73, 1998.

[97] M. Clerc and J. Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 1, pp. 58–73, 2002.

[98] R. Mendes, J. Kennedy, and J. Neves, "The fully informed particle swarm: simpler, maybe better," *IEEE Transactions on Evolutionary Computation*, vol. 8, no. 3, pp. 204–210, 2004.

[99] J. J. Liang, A. K. Qin, P. N. Suganthan, and S. Baskar, "Comprehensive learning particle swarm optimizer for global optimization of multimodal

functions," *IEEE Transactions on Evolutionary Computation,* vol. 10, no. 3, pp. 281–295, 2006.

[100] B. Alatas and E. Akin, "Multi-objective rule mining using genetic algorithms " *Knowledge-Based Systems,* vol. 22, no. 6, pp. 455-460, Aug. 2009.

[101] F. Du, W. Shi, L. Chen, Y. Deng, and Z. Zhu, "Infrared image segmentation with 2-D maximum entropy method based on particle swarm optimization (PSO)," *Pattern Recognition Letters,* vol. 26, no. 5, pp. 597-603, Apr. 2005.

[102] Z. Lian, X. Gu, and B. Jiao, "A similar particle swarm optimization algorithm for permutation flowshop scheduling to minimize makespan," *Applied Mathematics and Computation,* vol. 175, no. 1, pp. 773-785, Apr. 2006.

[103] I. D. Falco, A. D. Cioppa, and E. Tarantino, "Facing classification problems with Particle Swarm Optimization," *Applied Soft Computing,* vol. 7, no. 3, pp. 652-658, June 2007.

[104] Z. Chang and W. W. Ping, "An improved PSO-based rule extraction algorithm for intrusion detection," in *Proceedings of the 2009 International Conference on Computational Intelligence and Natural Computing*, Wuhan, China, June 6-7, pp. 56-58, 2009.

[105] A. Asuncion and D. J. Newman, UCI Machine Learning Repository. Available: http://www.ics.uci.edu/~mlearn/MLRepository.html, Access on: 2007

[106] S. X. Wu and W. Banzhaf, "The use of computational intelligence in intrusion detection systems: A review," *Applied Soft Computing Journal,* vol. 10, no. 1, pp. 1-35, Jan. 2010.

[107] T. Sousa, A. Neves, and A. Silva, "Swarm Optimisation as a New Tool for Data Mining," in *Proceedings of the International Parallel and Distributed Processing Symposium (IPDPS'03)*, Nice, France, Apr. 22-23, 2003.

[108] S. T. Li, C. C. Chen, and J. W. Li, "A multi-objective particle swarm optimization algorithm for rule discovery," in *Proceedings of the 3rd International Conference on Intelligent Information Hiding and Multimedia Signal Processing, IIHMSP 2007*, Kaohsiung, Taiwan, pp. 597-600, 2007.

[109] Z. Wang, X. Sun, and D. Zhang, "A PSO-based classification rule mining algorithm," in *LNCS*. vol. 4682 LNAI, pp. 377-384, Heidelberg: Springer Verlag, 2007.

[110] Z. Wang, X. Sun, and D. Zhang, "Classification Rule Mining Based on Particle Swarm Optimization," in LNCS, vol. 4062 LNAI, pp. 436-441, Springer-Verlag: Berlin Heidelberg, 2006.

[111] N. Holden and A. A. Freitas, "A hybrid PSO/ACO algorithm for discovering classification rules in data mining," *Journal of Artificial Evolution and Applications,* vol. 2008, Jan. 2008.

[112] N. P. Holden and A. A. Freitas, "A hybrid PSO/ACO algorithm for classification," in *Proceedings of the GECCO-2007 workshop on particle swarms: the second decade*, New York, pp. 2745–2750, 2007.

[113] N. Holden and A. Freitas, "A hybrid particle swarm/ant colony algorithm for the classification of hierarchical biological data," in *Proceedings of the IEEE Swarm intelligence Symposium (SIS '05)*, New York, pp. 100-107, 2005.

[114] R. S. Parpinelli, H. S. Lopes, and A. A. Freitas, "Data Mining With an Ant Colony Optimization Algorithm," *IEEE Transactions on Evolutionary Computiation,* vol. 6, no. 4, pp. 321-332, Aug. 2002.

[115] Z. Wang, Q. Zhang, and D. Zhang, "An IA-Based Classification Rule Mining Algorithm," in *Proceedings of the Eighth ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing,* Qingdao, China, July 30 - Aug. 1, vol. 3, pp. 309-313, 2007.

[116] H. Su, Y. Yang, and L. Zhao, "Classification rule discovery with DE/QDE algorithm," *Expert Systems with Applications,* vol. 37, no. 2, pp. 1216-1222, Mar. 2010.

[117] J. Zhou, T. Bai, J. Tian, and A. Zhang, "The study of SVM optimized by Culture Particle Swarm Optimization on predicting financial distress," in *Proceedings of IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Singapore, Dec. 8-11, pp. 1689 - 1693, 2008.

[118] J. Bai, X. Zhang, and Y. Guo, "Different inertia weight PSO algorithm optimizing SVM kernel parameters applied in a speech recognition system," in *Proceedings of the 2009 IEEE International Conference on Mechatronics and Automation (ICMA)*, Changchun, China, Aug. 9-12, pp. 4754 - 4759, 2009.

[119] S. W. Lin, Y. R. Shiue, S. C. Chen, and H. M. Cheng, "Applying enhanced data mining approaches in predicting bank performance: A case of Taiwanese commercial banks," *Expert Systems with Applications,* vol. 36, no. 9, pp. 11543-11551, Nov. 2009.

[120] Z. Zhou, "An improved ant colony optimization supervised by PSO," *Advanced Materials Research,* vol. 108-111, pp. 1354-1359, Progress in Measurement and Testing, vol. 108-111, no. 1, pp. 1354-1359, 2010.

[121] N. Holden and A. Freitas, "Hierarchical classification of protein function with ensembles of rules and particle swarm optimisation," *Soft Computing,* vol. 13, no. 3, pp. 259-272, 2009.

[122] M. Omran, A. Salman, and A. Engelbrecht, "Image Classification using Particle Swarm Optimization," in *Conference on Simulated Evolution and Learning*, vol. 1, pp. 370-374, 2002.

[123] M. Omran, A. Engelbrecht, and A. Salman, "Particle Swarm Optimization Method for Image Clustering," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 19, no. 3, pp. 297-322, 2005.

[124] X. Cui and T. Potok, "Document Clustering Analysis Based on Hybrid PSO+Kmeans Algorithm," *Journal of Computer Sciences (Special Issue)*, ISSN 1549-3636, pp. 27-33, 2005.

[125] L. Lifen and Z. Changming, "Alert clustering using integrated SOM/PSO," in *Proceedings of International Conference on Computer Design and Applications (ICCDA)*, vol. 2, pp. 571-574, 2010.

[126] O. Durán, N. Rodriguez, and L. A. Consalter, "Collaborative particle swarm optimization with a data mining technique for manufacturing cell design," *Expert Systems with Applications*, vol. 37, no.2, pp. 1563-1567, Mar. 2010.

[127] S. Paterlini and T. Krink, "Differential Evolution and Particle Swarm Optimization in Partitional Clustering," *Computational Statistics and Data Analysis*, vol. 50, no. 5, pp. 1220-1247, Mar. 2006.

[128] R. Xu, J. Xu, and D. C. Wunsch, "Clustering with differential evolution particle swarm optimization," in *Proceedings of IEEE Congress on Evolutionary Computation (CEC)*, pp. 1 - 8, 2010.

[129] J. Wang, J. Liang, J. Che, and D. Sun, "A Hybrid Evolutionary Algorithm Based on ACO and PSO for Real Estate Early Warning System," in *Proceedings of International Conference on Computer Science and Information Technology, ICCSIT '08*, pp. 167 - 171, 2008.

[130] F. van den Bergh and A. P. Engelbrecht, "Training Product Unit Networks using Cooperative Particle Swarm Optimisers," in *Proceedings of International Joint Conference on Neural Networks, IJCNN '01*, DC, USA, vol. 1, pp. 126 -131, 2001.

[131] H. Evans and M. Zhang, "Particle swarm optimisation for object classification," in *Proceedings of the 23rd International Conference Image and Vision Computing New Zealand, IVCNZ*, Christchurch, New Zealand, Nov. 26-28, 2008.

[132] W. C. Yeh, "A two-stage discrete particle swarm optimization for the problem of multiple multi-level redundancy allocation in series systems," *Expert System with Applications*, vol. 36, no. 5, pp. 9192-9200, July 2009.

[133] J. H. Ang, K. C. Tan, and A. A. Mamun, "An evolutionary memetic algorithm for rule extraction," *Expert System with Applications*, vol. 37, no. 2, pp. 1302-1315, 2009.

[134] E. S. Correa, A. A. Freitas, and C. G. Johnson, "A New Discrete Particle Swarm Algorithm Applied to Attribute Selection in a Bioinformatics Data Set," in *GECCO '06*, Seattle, Washington, USA, July 8-12, pp. 35-42, 2006.

[135] W. Pan, Y. Yao, Z. Liu, and W. Huang, "Audio Classification in a Weighted SVM," in *2007 International Symposium on Communications and Information Technologies (ISCIT 2007)*, pp. 468-472, 2007.

[136] J. Wang, Q. Wu, H. Deng, and Q. Yan, "Real-time speech/music classification with a hierarchical oblique decision tree," in *Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Las Vegas, NV, United States, Mar. 31- Apr. 4, pp. 2033-2036, 2008.

[137] G. Yu and J. J. Slotine, "Audio classification from time-frequency texture," in *Proceedings of 2009 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP 2009)*, Taipei, Taiwan, Apr. 19-24, pp. 1677-1680, 2009.

[138] C. Joder, S. Essid, and G. Richard, "Temporal Integration for Audio Classification With Application to Musical Instrument Classification," *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 17, no. 1, pp. 174-186, Jan. 2009.

[139] M. M. Mostafa and N. Billor, "Recognition of Western style musical genres using machine learning techniques," *Expert Systems with Applications*, vol. 36, no. 8, pp. 11378-11389, Oct. 2009.

[140] M. K. S. Khan and W. G. Al-Khatib, "Machine-learning based classification of speech and music," *Multimedia Systems*, vol. 12, no. 1, pp. 55–67, Apr. 2006.

[141] P. Dhanalakshmi, S. Palanivel, and V. Ramalingam, "Classification of Audio Signals using SVM and RBFNN," *Expert Systems with Applications*, vol. 36, pp. 6069-6075, 2009.

[142] J. Guo, Y. Chen, M. Zhu, S. Wang, and X. Liu, "An efficient support vector machine algorithm for solving multi-class pattern recognition problems," in *2010 International Conference on Computer Modeling and Simulation, ICCMS 2010*, Sanya, China, pp. 22-24, 2010.

[143] S. Z. Li, "Content-based audio classification and retrieval using the nearest feature line method," *IEEE Transactions on Speech and Audio Processing*, vol. 8, no. 5, pp. 619-625, Sept. 2000.

[144] T. Tada, T. Nagashima, and Y. Okada, "Rule-based Classification for Audio Data Based on Closed Itemset Mining," in *Proceedings of the International MultiConference of Engineers and Computer Scientist 2010*, Hong Kong, Mar. 17-19, 2010.

[145] C. C. Lin, S. H. Chen, T. K. Truong, and Y. Chang, "Audio Classification and Categorization Based on Wavelets and Support Vector Machine," *IEEE Transactions on Speech and Audio Processing*, vol. 13, no. 5, pp. 644-651, Sept. 2005.

[146] L. Lu, H. J. Zhang, and S. Z. Li, "Content-based audio classification and segmentation by using support vector machines," *Multimedia Systems*, vol. 8, no. 6, pp. 482-492, Apr. 2003.

[147] S. Essid, G. Richard, and B. David, "Musical instrument recognition by pairwise classification strategies," *IEEE Transactions on Audio, Speech and Language Processing*, vol. 14, no. 4, pp. 1401-1412, July 2006.

[148] V. Mitra and C. J. Wang, "Content based audio classification: a neural network approach," *Soft Computing*, vol. 12, pp. 639-646, 2008.

[149] A. Pikrakis, S. Theodoridis, and D. Kamarotos, "Classification of Musical Patterns Using Variable Duration Hidden Markov Models," *IEEE Transactions on Audio, Speech and Language Processing*, vol. 14, no. 5, pp. 1795-1807, Sept. 2006.

[150] X. He, Y. Shi, and X. Zhou, "An approach based on reverse hidden markov model for audio classification," in *1st International Conference on Information Science and Engineering, ICISE 2009*, Nanjing, China, Dec. 26-28, 2009.

[151] L. Xue, J. Yin, Z. Ji, and L. Jiang, "A particle swarm optimization for hidden Markov model training," in *8th International Conference on Signal Processing, ICSP 2006*, Guilin, China, Nov. 16-20, 2006.

[152] F. Yang, C. Zhang, and T. Sun, "Comparison of particle swarm optimization and genetic algorithm for HMM training," in *2008 19th International Conference on Pattern Recognition, ICPR 2008*, Tampa, FL, United States, Dec. 8-11, 2008.

[153] N. Najkar, F. Razzazi, and H. Sameti, "A novel approach to HMM-based speech recognition system using particle swarm optimization," in *BIC-TA 2009 - Proceedings, 2009 4th International Conference on Bio-Inspired Computing: Theories and Applications*, Beijing, China, Oct. 16-19, 2009.

[154] A. P. Schmidt and T. K. M. Stone, "Music Classification and Identification System," Retrieved June 2, 2010. From www.trevorstone.org/school/MusicRecognitionDatabase.pdf

[155] J. T. Foote, "Content-based retrieval of music and audio," in *Proceedings of SPIE - The International Society for Optical Engineering*, Dallas, TX, United States, 1997.

[156] "DSP Mini-Project: An Automatic Speaker Recognition System," Available: http://www.ifp.illinois.edu/~minhdo/teaching/speaker_recognition/speaker_recognition.html, 2010.

[157] C. Bae, Y. Y. Chung, M. A. M. Shukran, E. Choi, and W.-C. Yeh, "An intelligent classif ication algorithm for LifeLog multimedia applications," in *Proceeding of the IEEE International Workshop on Multimedia Signal Processing, MMSP 2008*, Cairns, Queensland, Australia, Oct. 8-10, pp. 558 - 562, 2008.

[158] E. Keogh and C. A. Ratanamahatana, "Exact indexing of dynamic time warping," *Knowledge and Information Systems*, vol. 7, no. 3, pp. 358 - 386, Mar. 2004.

[159] X. He, L. Guo, X. Zhou, and W. Luo, "Hybrid Support Vector Machine and General Model Approach for Audio Classification," In: D. Liu, (Ed.) LNCS, vol. 4493 LNCS, PART 3, pp. 434-440, Springer Verlag: Heidelberg, 2007.

[160] J. Platt, *Fast training of support vector machines using sequential minimal optimization*, B. Schoelkopf, C. Burges, and A. Smola, Advances in kernel methods - support vector learning. Cambridge, MA: MIT Press, 1988.

[161] A. Schaerf, "Local Search Techniques for Large High School Timetabling Problems," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 4, pp. 368-377, July 1999.

[162] M. Saniee Abadeh, J. Habibi, Z. Barzegar, and M. Sergi, "A parallel genetic local search algorithm for intrusion detection in computer networks," *Engineering Applications of Artificial Intelligence*, vol. 20, no. 8, pp. 1058-1069, Dec. 2007.

[163] J. Chen, Z. Qin, Y. Liu, and J. Lu, "Particle Swarm Optimization with Local Search," in *Proceedings of the International Conference on Neural Networks and Brain, ICNN&B '05*, Beijing, pp. 481 - 484, 2005.

[164] A. P. White, *Probabilistic Induction by Dynamic Path Generation in Vertual Trees*, M. A. Bramer (Ed.), Research and Development in Expert System III: Cambridge University Press, 1987.

[165] KDD99 Cup Dataset [Online]. Available: http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html, 1999.

[166] A. Abraham, C. Grosan, and C. M. Vide, "Evolutionary Design of Intrusion Detection Programs," *International Journal of Network Security*, vol. 4, no. 3, pp. 328-339, Mar. 2007.

[167] C. M. Chen, Y. L. Chen, and H. C. Lin, "An efficient network intrusion detection," *Computer Communications,* vol. 33, no. 4, pp. 477-484, Mar. 2010.

[168] S. Srinoy, "Intrusion Detection Model Based on Particle Swarm Optimization and Support Vector Machine," in *Proceedings of the 2007 IEEE Symposium on Computational Intelligence in Security and Defence Applications,* 2007.

[169] T. Verwoerd and R. Hunt, "Intrusion Detection Techniques and Approaches," *Computer Communications,* vol. 25, no. 15, pp. 1356-1365, Sept. 2002.

[170] W. H. Chen, S. H. Hsu, and H. P. Shen, "Application of SVM and ANN for intrusion detection," *Computers & Operations Research,* vol. 32, no. 10, pp. 2617-2634, Oct. 2005.

[171] D. E. Denning, "An Intrusin Detection Model," *IEEE Transactions on Software Engineering,* vol. SE-13, no. 2, pp. 222 - 232, Feb. 1987.

[172] M. Asaka, T. Onabura, T. Inoue, S. Okazawa, and S. Goto, "A new intrusion detection method based on discriminant analysis," *IEICE Transactions on Information and System,* vol. E84-D, no. 5, pp. 570-577, May 2001.

[173] W. Wang, X. H. Guan, and X. L. Zhang, "Processing of massive audit streams for real-time anomaly intrusion detection " *Computer Communications,* vol. 31, no. 1, pp. 58-72, Jan. 2008.

[174] P. G. Teodoro, J. D. Verdejo, G. M. Fernández, and E. Vázquez, "Anomaly-based network intrusion detection: Techniques, systems and challenges," *Computers and Security,* vol. 28, no. 1-2, pp. 18-28, Feb/Mar. 2009.

[175] W. W. Cohen, "Fast effective rule induction," in *Proceedings of the 12th International Conference on Machine Learning,* pp. 115-123, 1995.

[176] Y. Liao and V. R. Vemuri, "Use of k-nearest neighbor classifier for intrusion detection," *Computers and Security,* vol. 21, no. 5, pp. 439-448, 2002.

[177] Y. Li and L. Guo, "An active learning based TCM-KNN algorithm for supervised network intrusion detection," *Computers and Security,* vol. 26, no. 7-8, pp. 459-467, Dec. 2007.

[178] O. Depren, M. Topallar, E. Anarim, and M. K. Ciliz, "An intelligent intrusion detection system (IDS) for anomaly and misuse detection in computer networks," *Expert System with Applications,* vol. 29, pp. 713-722, 2005.

[179] Z. Zhang and H. Shen, "Application of online-training SVMs for real-time intrusion detection with different considerations," *Computer Communications,* vol. 28, vol. 12, pp. 1428-1442, July 2005.

[180] A. Zainal, M. A. Maarof, and S. M. Shamsuddin, "Feature Selection Using Rough-DPSO in Anomaly Intrusion Detection," in LNCS, vol. 4705 LNCS, pp. 512-524, Springer-Verlag: Berlin Heidelberg, 2007.

[181] S. Y. Wu and E. Yen, "Data mining-based intrusion detectors," *Expert Systems with Applications*, vol. 36, no. 3 PART 1, pp. 5605-5612, Apr. 2009.

[182] S. Mukkamala, A. Sung, and A. Abraham, "Intrusion detection using an ensemble of intelligent paradigms," *Journal of Network and Computer Applications*, vol. 28, no. 2, pp. 167-182, Apr. 2005.

[183] H. A. Nguyen and D. Choi, "Application of Data Mining to Network Intrusion Detection: Classifier Selection Model," in LNCS 5297, pp. 399-408, Springer-Verlag: Berlin Heidelberg, 2008.

[184] S. T. Powers and J. He, "A hybrid artificial immune system and Self Organising Map for network intrusion detection," *Information Sciences*, vol. 178, no. 15, pp. 3024-3042, Aug. 2008.

[185] L. H. Zhang, G. H. Zhang, L. Yu, J. Zhang, and Y. C. Bai, "Intrusion detection using rough set classification," *Journal of Zhejiang University Science*, vol. 5, no. 9, pp. 1076-1086, Sept. 2004.

[186] A. H. Sung and S. Mukkamala, "The Feature Selection and Intrusion Detection Problems," In: M. J. Maher, (Ed.) ASIAN 2004, LNCS, vol. 3321, pp. 468-482, M. J. Maher, Springer: Heidelberg, 2004.

[187] W. Hai-Bing and F. De-Sheng, "An intrusion detection system model based on particle swarm reduction," in *Proceedings of th 4th International Conference on Genetic and Evolutionary Computing, ICGEC 2010*, China, pp. 383-385, 2010.

[188] P. Srinivasulu, D. Nagaraju, P. R. Kumar, and K. N. Rao, "Classifying the Network Intrusion Attacks using Data Mining Classification Methods and their Performance Comparison," *Int Journal of Computer Science and Network Security*, vol. 9, no. 6, pp. 11-18, June 2009.

[189] S. Mukkamala, A. H. Sung, and A. Abraham, "Modeling Intrusion Detection System Using Linear Genetic Programming Approach," in LNCS, vol. 3029, pp. 633-642, Springer-Verlag: Berlin-Hiedelberg, 2004.

[190] B. Zhang, "Internet intrusion detection by autoassociative neural network," in *Proceedings of International Symposium on Information & Communications Technologies*, Malaysia, Dec. 2005.

[191] A. Abraham and R. Jain, "Soft Computing Models for Network Intrusion Detection Systems," Studies in Computational Intelligence, vol. 4, pp. 191-207, Springer-Verlag: Berlin-Heidelberg, 2005.

[192] A. N. Toosi and M. Kahani, "A new approach to intrusion detection based on an evolutionary soft computing model using neuro-fuzzy classifiers," *Computer Communications,* vol. 30, no. 10, pp. 2201-2212, July 2007.

[193] J. He, D. Long, and C. Chen, "An improved ant-based classifier for intrusion detection," in *Proceedings of the Third International Conference on Natural Computation*, Hainan, China, Aug. 24-27, pp. 819-823, 2007.

[194] S. Banerjee, C. Grosan, A. Abraham, and P. K. Mahanti, "Intrusion Detection on Sensor Networks Using Emotional Ants," *International Jounal of Applied Science and Computations,* vol. 12, no. 3, pp. 152-173, 2005.

[195] S. Kalyani and K. S. Swarup, "Classifier design for static security assessment using particle swarm optimization," *Applied Soft Computing,* vol. 11, no. 1, pp. 658-666, Jan. 2011.

[196] N. Wahid, Y. Y. Chung, W.-C. Yeh, and G. Liu, "Feature Selection Using a Novel Swarm Intelligence Algorithm with Rough Sets," in *Proceedings of The 2010 International Conference on Data Mining, DMIN 2010*, Las Vegas, Nevada, US, pp. 294-300, 2010.

[197] A Tutorial on Clustering Algorithms. Available: http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/index.html, Access on: Oct. 11, 2010