TRADEMARK IMAGE CLASSIFICATION APPROACHES USING NEURAL NETWORK AND ROUGH SET THEORY

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DEDICATION

In loving memory of Allahyarham Haji Saad Yob, my beloved father for instilling the courage, commitment, dedication and strength to seek gold in everyone and in life events.

Especially for my precious jewels; Muhammad Izzuddin, Nur Izzati and Abdul Rahman

abide the golden principle of low promise and high delivery...

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ABSTRACT

The critical step in automatic trademark matching is to extract trademark features from the database automatically and reliably. However, the performance of existing algorithms rely heavily on the size of the database. It is essential to incorporate an efficient classification technique to partition the database in order to ensure the performance of an automatic trademark matching system is robust with respect to the increase in the database size. Two new approaches are proposed to classify trademark images. The approaches contain five major stages, namely: image acquisition, image preprocessing, feature extraction, data transformation and classification. Feature normalization and data discretization techniques are utilized to perform the data transformation phase. An Adaptive Multi Layer Perceptron (MLP) embedded with an enhanced Backpropagation (BP) algorithm and Rough Set Theory are applied to classify the images. Experimental results reveal that the Adaptive MLP embedded with the enhanced BP algorithm exhibits a faster convergence rate than the classical BP algorithm. In conclusion, the Adaptive MLP outperforms Rough Set Theory in terms of speed, accuracy and sample size.

ABSTRAK

Langkah kritikal dalam pemadanan imej logo ialah pengekstrakan fitur logo daripada pangkalan data secara otomatik dan pasti. Walaubagaimana pun algoritma yang sedia ada amat bergantung kepada saiz pangkalan data. Satu teknik klasifikasi yang efisien perlu disertakan untuk memetakan pangkalan data supaya prestasi suatu sistem pemadanan logo itu teguh daripada aspek peningkatan saiz pangkalan data. Dua pendekatan baru diperkenalkan untuk pengelasan imej logo. Pendekatan berkenaan mempunyai lima fasa yang terdiri daripada perolehan imej, prapemprosesan imej, pengekstrakan fitur, transformasi data dan pengelasan. Teknik pernormalan fitur dan pendiskretan data digunakan dalam fasa transformasi data. Perceptron Berbilang Lapis (MLP) Adaptif beserta algoritma pembelajaran pembaikan daripada algoritma Rambatan balik (BP) dan teori set kasar digunakan untuk mengelaskan imej. Hasil ujikaji mendedahkan bahawa MLP Adaptif mempunyai kadar penumpuan yang lebih pantas jika dibandingkan dengan algoritma BP asal. Kesimpulannya, MLP Adaptif menandingi teori set kabur dari segi kelajuan, ketepatan dan saiz sampel.

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LIST OF ABBREVIATIONS

2-D	-	Two Dimension
AM	-	Associative Memory
ANN	-	Artificial Neural Network
ART	-	Adaptive Resonance Theory
BAM	-	Biassociative Memory
BDD	-	Binary Decision Diagram
BFGS	-	Broyden-Fletcher-Goldfarb-Shanno
BP	-	Back Propagation
BSB	-	Brain-state-in-a-box
CNF	-	Conjunctive Normal Form
DNF	-	Disjunctive Normal Form
DS	-	Decision System
DT	-	Decision Table
G.M	-	Geometric Invariant Moment
LMS	-	Least Mean Square
LVQ	-	Linear Vector Quantization
MITI	-	Ministry of Trades and Industry
MLFF	-	Multilayer Feed Forward
MLP	-	Multi Layer Perceptron
MMSE	-	Minimum mean-square error
MRI	-	MADALINE Training
NN	-	Neural Network

NP-Complete	-	Non Polynomial Complete
NP-Hard	-	Non Polynomial Hard
RBF	-	Radial Basis Function
RNN	-	Recurrent Neural Network
RST-invariance	-	Rotation Scale Translation Invariance
SAT	-	Satisfiability
SOFM	-	Self-Organizing Feature Map
VLSI	-	Very Large Scale System Integration
Z.M	-	Zernike Moment

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GLOSSARY OF BASIC NEURAL NETWORK TERMINOLOGY

Term	Synonyms	Definition
activation function	excitation function, squashing function transfer function	a bounded function of infinite domain applied to the weighted and summed inputs to limit the amplitude of the output signal. For multi-layer networks this must be a continuously function.
architecture	model, paradigm, topology	the arrangement of nodes in a neural network. Different architectures vary in the arrangement, type and number of their connections and in their activation functions and types of learning algorithms.
bias	intercept, threshold	a weight parameter for an extra input whose activation is permanently set to +1
neuron	cell, node, neurode, unit, processing	a simple linear or nonlinear computing element that accepts one

	element	or more inputs, computes a function thereof and may direct the result to one or more other cells.
epoch	cycle	each repeated entry of the full set of training patterns
backpropagation	error-backpropagation, dynamic feedback, learning logic	a method for computing the error gradient, i.e. the derivatives of the error function with respect to the weights, for a feedforward network
error function	cost function, objective function, energy function, performance function	an expression which describes the difference between the computed and target output. Typically the mean squared error
fault tolerance	graceful degradation	processing continues even if some nodes or connections are damaged
feedforward	forward propagation, static	uni-directional transfer of information
function approximation	heteroassociation, prediction, forecasting	the prediction of output values on the basis of input values; includes both classification and regression
generalisation	inference, interpolation, prediction	ability to draw conclusions about highly complex new situations by making associations with previous

		experience of similar situations.
gradient descent	steepest descent, standard backpropagation	the iterative changes in the weights during training are proportional to the negative of the first derivative of the total error.
hyperbolic tangent function	bipolar sigmoid	$f(x) = \tanh\left(\frac{x}{2}\right) = \frac{1-e^{-x}}{1+e^{-x}}$ the bipolar sigmoid function is a type of hyperbolic tangent function which ranges from -1 to 1
learning algorithm	training algorithm, learning rule	the method by which the weights are adjusted during training.
linearly separable		data that can be separated by a straight in two dimensions or a hyperplane in n-dimensions.
logistic function		$f(x) = \frac{1}{1+e^{-ax}}$ the logistic function is a type of sigmoid function, that ranges from 0 to 1.
multilayer perceptron		a fully connected feedforward backpropagation neural network with at least one hidden layer
neural network	artificial neural	a class of flexible nonlinear

	network, neural net, connectionist model	regression and discriminant models, data reduction models and nonlinear dynamical systems consisting of an often large number nodes interconnected in often complex ways and often organized into layers.
overfitting	overlearning, overdetermination	construction or training of a network to fit the details of the training patterns rather than generalize well for new data.
overtraining		overfitting of the training patterns by continuing to train without the use of an appropriate validation set.
regression		prediction of the value of a continuous variable y from an input vector x.
sigmoid function		a strictly increasing function which exhibits smoothness and asymptotic properties, such as a logistic or hyperbolic tangent function.
targets outputs		the output values provided to the network in supervised learning
test set		a set of data that the neural network has not previously seen, which is used to test how well the neural

		network has learned to generalize
training	adaptation, estimation, learning, model fitting, optimisation	training is accomplished by using examples to adjust the weights on the connections in the neural network such that the network performs its task correctly. Learning is equivalent to the minimization of an error function.
training patterns	construction sample, example data, training cases, training data	the data set used to train the neural network.
validation set	test data, hold-out sample, cross-validation, verification.	a set of data used to test the performance of the network during training, but not used for modifying the weights of the network.
weights	parameters, strengths, synaptic weights	the network parameters that are determined iteratively by training.

CHAPTER 1

INTRODUCTION

1.1 Background

Trademark is a symbol in a form of an image used to publicize and indicating services or products of an organization or a company. Trademark symbols enable clients to identify the good products. The trademark symbol is legally registered representing the specific company or the organization. A registered trademark is protected through legal proceedings from imitation and misuse. Based on these aspects, it is a stringent requirement for trademark symbols to be uniquely different from other trademarks for legal reasons and in order not to mistakenly identify the company's identity (Soffer and Samet, 1998; Eakins *et al.*, 1996 ; Lam *et al.*, 1995).

Trademark offices in several countries in the world strive to ensure the uniqueness of all registered trademarks. There is a very challenging task due to ever increasing number of registered trademarks. Up to now, the number of trademark worldwide is over one million and is growing rapidly (Chan and King, 1999). The problem is further aggravated by the complexity and diversity of trademark patterns. Most trademark offices are not yet automated. Traditionally a database system is employed to a limited extent for such purpose, as they still need to use a paper based indexing method for searching the trademark image and Vienna Classification for filing and indexing (Lam *et al.*, 1995).

In Malaysia, trademarks are registered at the Ministry of Trades and Industry (MITI). Due to the increasing number of registered companies, of over 200 trademarks per month, it is becoming a difficult task of designing and registering new trademarks (Puteh *et al.*, 1998a). The current practice to classify trademarks is by keeping them in separate files according to specific class order and the classification process is performed manually. However, when the number of registered trademarks escalated to hundred thousands, the tasks become tedious, inefficient and furthermore redundancy may occur (Dzulkifli, 1997).

Other application of trademark classification is in document processing domain, a trademark is used for the purpose of indexing documents. Given a representative trademark (known or unknown), the database of documents is searched and all documents, which contain that trademark, will be extracted (Gori *et al.*, 2003; Neumann *et al.*,2002; Alwis, 2000; Sieden *et al.*,1997).

Another problem associated with the trademark image is its intrinsic nature that it is complex and highly occluded. In addition, the image consists of various shapes and design style. On top of that, the text in the image composes of different fonts and artistic style (Lam *et al.*, 1995). A suitable feature extraction algorithm is required to extricate the non-redundant features from the image before a classification process is done.

1.2 Statement of the Problem

In this study we intend to come up with an approach to provide insights into solving the feature extraction and classification of trademark images. The research question is:

How to produce an approach that is able to classify the trademark image robust, fast, accurate and efficient?

In order to answer the main issue raised above, the following issues need to be addressed as a pre-requisite:

a. What is the suitable technique to extract unique global features from the trademark image?

b. What is the suitable Neural Network architecture to be adopted for image classification?

c. It is well known that Back-Propagation learning algorithm suffers many drawbacks, such as low convergence rate and the problem of local minima. How can it be overcome?

d. How to perform image classification using Rough Set Theory?

e. Another problem with any learning algorithm is the curse of dimensionality associated with input data, since they slow down the learning process, what is the suggestion to reduce the dimension of the input data?

1.3 Aim

The goal of this study is to develop a trademark image classification approach that is robust, fast, accurate and efficient.

1.4 Objective

In order to achieve the above aim, listed below are the objectives of this thesis:

(a) To study the trademark image classification techniques and propose new approaches for classification of trademark images based on the conventional approach.

(b) To study the feature extraction process of trademark images and to produce new algorithms for feature extraction of global shape features belong to trademark images.

(c) To perform data transformation of the trademark image features using Feature Normalization Technique and Data Discretization.

(d) To compare the performance of the conventional trademark classification approach with the proposed approaches.

In order to realize the above goal and objectives, next section is dedicated to outline the research framework adopted in this study.

1.5 Research Framework

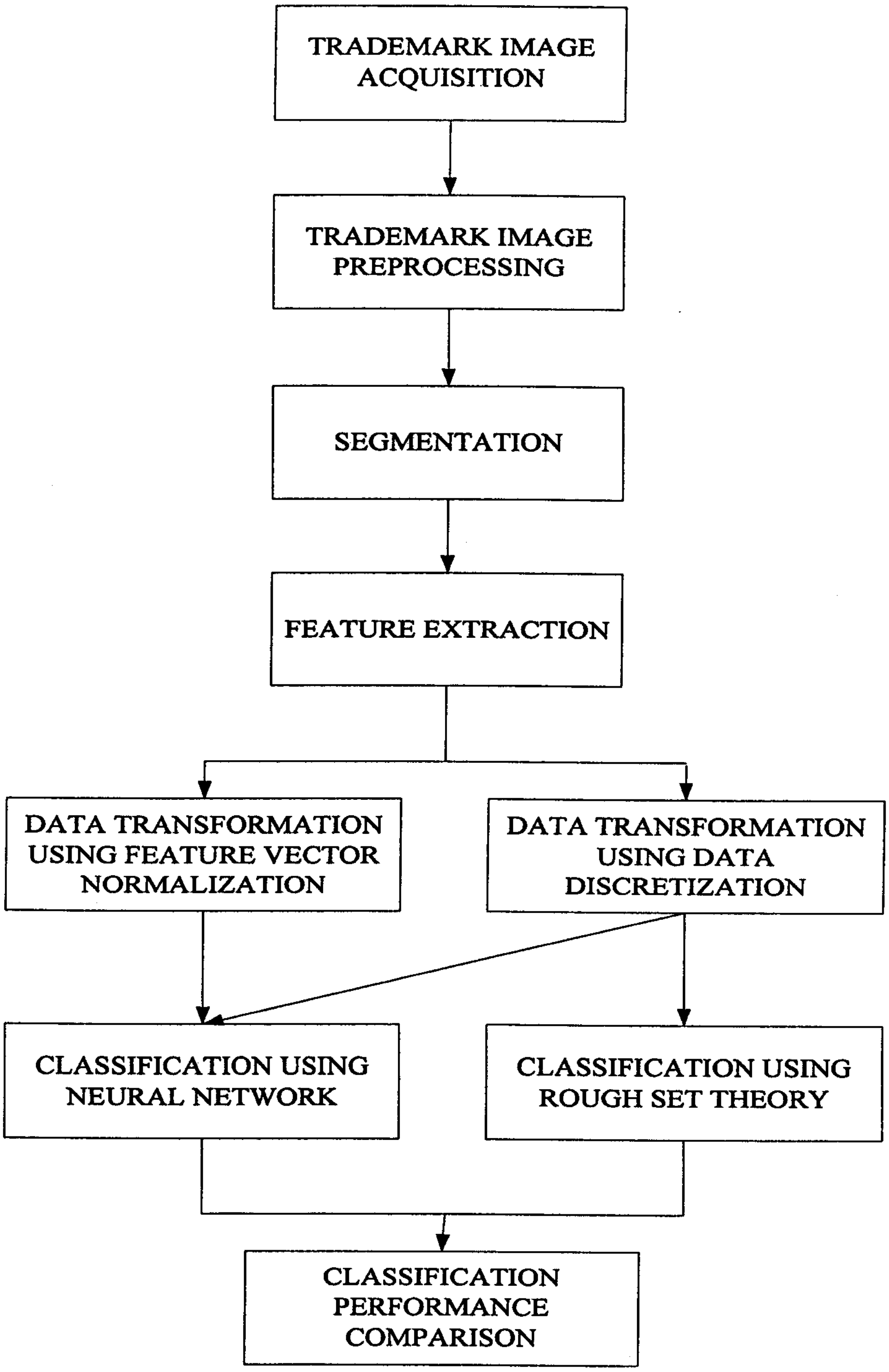

Figure 1.0: The Research Framework

Figure 1.0 depicts the Research Framework utilized in this study. In this study three trademark classification approaches are studied and the results obtained are compared in terms of robustness, speed, accuracy and efficiency. The first approach is based on the conventional image classification that consists of the following steps:

i. Trademark Image Acquisition
ii. Trademark Image Preprocessing
iii. Trademark Image Segmentation
iv. Feature Extraction
v. Classification Using Neural Network that implements standard Back Propagation learning algorithm

The second classification approach is an enhancement of the first approach by inserting a data transformation phase before classification. It consists of the following steps:

i. Trademark Image Acquisition
ii. Trademark Image Preprocessing
iii. Trademark Image Segmentation
iv. Feature Extraction
v. Data Transformation using Feature Vector Normalization and Data Discretization
vi. Classification Using Adaptive MLP Architecture with an enhanced Back-Propagation algorithm.

The third classification approach consists of the following steps:

i. Trademark Image Acquisition
ii. Trademark Image Preprocessing
iii. Trademark Image Segmentation
iv. Feature Extraction
v. Data Transformation using Data Discretization

vi. Classification Using Rough Set Theory

The main differences between second and third approaches are that in the second approach, the data transformation process is implemented using Feature Vectors normalization and data discretization. An adaptive MLP is used to perform classification. In the third approach however, the data transformation process is carried out using only data discretization method and classification is performed using Rough Set Theory.

In Trademark Image Acquisition, an optical trademark image is scanned to produce a continuous signal that is then sampled into a discrete form. Through preprocessing tasks, the contrast of the discrete image is enhanced and noise is removed. In segmentation, the resulting image from the preprocessing step is partitioned into its constituent objects using a thresholding technique. In feature extraction phase, suitable techniques will be used to obtain a set of condensed representative characteristics (or features) of an image for differentiating one class of objects from another that is RST-invariance.

The resulting feature vectors produced in the feature extraction phase are transformed into a suitable format before classification. Two different kinds of data transformation adopted here first is Features Normalization and second is Data Discretization. Feature Normalization refers to the rescaling of features to an appropriate range (for instance 0 to 1 or -1 to 1). The types of normalization techniques chosen to be studied are *unit range, linear scaling, improved linear scaling* and *simple normalization.* The techniques may yield zero values after the transformation, which is not preferable in NN training (Waseem, 2002). The *unit range* and *simple normalization* techniques are enhanced producing values within the range (0.1 – 0.9).

Discretization refers to the process of arranging the attribute values into group of similar values. There are two types of discretization; unsupervised and supervised. The unsupervised method relies on assumptions of the attribute values distribution. This method is suitable to objects that do not have class labels. The drawback of unsupervised method is that it is vulnerable to outliers that may drastically skew the range of the attribute values distribution. The supervised method is suitably applied to objects that have a class label. In our mission, we choose a disretization method based on the integration of Rough Set Theory and Boolean Reasoning proposed by Nguyen and Skowron (1996). The discretization process consists of three major steps:

a. Creation of a discernibility matrix
b. Finding a minimum set of cuts or the Prime Implicant.
c. Mapping the original attributes into appropriate regions.

Step (a) and (c) involve direct computation, however step (b) is categorized as NP-Hard problem in the literature (Nguyen and Nguyen, 1998). We proposed another heuristic in finding the minimum set of cuts.

As for the classification process, two methods are chosen; Neural Network and Rough Set Theory. Artificial Neural Network consists of a collection of algorithms that facilitates learning operated in either a single layer or a multi-layer architecture (Haykin, 1999). There are two types learning, supervised and unsupervised learning. With supervised learning, the network is trained based on a learning algorithm using samples with class labels, on the other hand, in unsupervised learning training is done on samples without class labels. In this study, an enhanced error-back propagation supervised learning implemented in an adaptive MLP architecture is adopted to classify trademark images due to its robustness, faster speed and producing accurate classification results.

Rough set theory is a new mathematical tool developed by Pawlak (1991) to perform classification using data represented in a form of a table. Rows represent objects under consideration and tuples represent attributes of the objects. In our study tuples represent Geometric Invariant Moment features or Zernike Moment features. The advantages of using rough set are that it does not require a priori or additional information regarding the objects, such as probability distribution or basic probability assignment as in other techniques. Rough set has been successfully applied in various domains, to name a few for instance in medicine, finance, telecommunication, vibration analysis, conflict resolution, intelligent agents, image analysis, pattern recognition, control theory, process industry and marketing (Pawlak, 1997). The steps adopted to perform trademark image classification are: computation of reducts, derivation of rules from reducts and classification.

1.6 Scope

The scope of this study is as follows:

(a) Trademark images samples are obtained from the Ministry of Trade and Industry Malaysia in a hard-copy form.

(b) The domain chosen for this study is a 1-D monochrome (or black-white) trademark images.

(c) Image Acquisition, noise removal and segmentation are performed using existing techniques.

(d) Image orientations considered in this study are scale (enlarged and reduced), angular (rotated to 90 degrees), positional (horizontal and vertical orientation), rippled to 160 degrees and twirled to -72 degrees.

(e) As for the purpose of classification a supervised Neural Network and Rough Set Theory are used.

1.7 Thesis Organization

The thesis consists of 9 chapters. Each chapter is briefly described as follows:

(a) Chapter 1 describes the background, statement of the problem, aim, objective, research framework, scope, thesis organization and ended with thesis contribution.

(b) Chapter 2 illustrates the trademark classification problem, image classification phases, literature review on existing trademark image classification, background study of BP, open issues of BP, BP improvements and concepts of rough set theory.

(c) Chapter 3 briefly describes the three approaches adopted to perform the trademark image classification.

(d) Chapter 4 describes the implementation of the Feature Extraction process. The results obtained are analysed and discussed.

(e) Chapter 5 presents Data Transformation phase that consists of Feature Normalization and Data Discretization. The implementations are explained and the results of the experiments are analysed and discussed.

(f) Chapter 6 illustrates the methodology, the implementation and results of trademark classification using the conventional and the Neural Network approaches.

(g) Chapter 7 describes the methodology, the implementation and results of trademark classification using Rough Set Theory.

(h) Chapter 8 compares and discusses the trademark image classification performances of the Neural Network and Rough Set Theory approaches.

(i) Chapter 9 ends with a conclusion

1.8 Thesis Contributions

1. Two new trademark classification approaches are proposed.
2. Two feature extraction algorithms. The first algorithm is based on Geometric Moment Invariant Functions and another algorithm is based on Zernike Moment technique.
3. Enhancements to two feature vectors normalization methods; the enhanced Linear Scaling to Unit Range and the enhanced Simple Normalization Method.
4. Improvement of the performance of the standard BP algorithm by introducing a higher-order activation function into the adaptive MLP architecture.
5. Expose the importance of discretized data in escalating the classification performance.
6. Reveal the actual performance of Rough Set Theory for classification of trademark images.
7. Disclose the classification performance of the proposed MLP architecture with an embedded higher-order activation function.