



UNIVERSITI PUTRA MALAYSIA

**ROUGH NEURAL NETWORKS ARCHITECTURE FOR IMPROVING
GENERALIZATION IN PATTERN RECOGNITION**

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**ROUGH NEURAL NETWORKS ARCHITECTURE FOR IMPROVING
GENERALIZATION IN PATTERN RECOGNITION**

By

HANAN HASSAN ALI ADLAN

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia,
in Fulfilment of the Requirements for the Degree of Doctor of Philosophy**

December 2004



To
My Parents,
Brothers and Sisters
My Husband,
Husam and Alla



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in
Fulfilment of the requirement for the degree of Doctor of Philosophy

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Chairman: Associate Professor Abd Rahman Ramli, Ph.D.

Faculty: Engineering

Neural networks are found to be attractive trainable machines for pattern recognition. The capability of these models to accommodate wide variety and variability of conditions, and the ability to imitate brain functions, make them popular research area.

This research focuses on developing hybrid rough neural networks. These novel approaches are assumed to provide superior performance with respect to detection and automatic target recognition.



In this thesis, hybrid architectures of rough set theory and neural networks have been investigated, developed, and implemented. The first hybrid approach provides novel neural network referred to as Rough Shared weight Neural Networks (RSNN). It uses the concept of approximation based on rough neurons to feature extraction, and experiences the methodology of weight sharing. The network stages are a feature extraction network, and a classification network. The extraction network is composed of rough neurons that accounts for the upper and lower approximations and embeds a membership function to replace ordinary activation functions. The neural network learns the rough set's upper and lower approximations as feature extractors simultaneously with classification. The RSNN implements a novel approximation transform. The basic design for the network is provided together with the learning rules. The architecture provides a novel method to pattern recognition and is expected to be robust to any pattern recognition problem.

The second hybrid approach is a two stand alone subsystems, referred to as Rough Neural Networks (RNN). The extraction network extracts detectors that represent pattern's classes to be supplied to the classification network. It works as a filter for original distilled features based on equivalence relations and rough set reduction, while the second is responsible for classification of the outputs from the first system.

The two approaches were applied to image pattern recognition problems. The RSNN was applied to automatic target recognition problem. The data is Synthetic Aperture Radar (SAR) image scenes of tanks, and background. The RSNN provides a novel methodology for designing nonlinear filters without prior knowledge of the problem

domain. The RNN was used to detect patterns present in satellite image. A novel feature extraction algorithm was developed to extract the feature vectors. The algorithm enhances the recognition ability of the system compared to manual extraction and labeling of pattern classes. The performance of the rough backpropagation network is improved compared to backpropagation of the same architecture. The network has been designed to produce detection plane for the desired pattern.

The hybrid approaches developed in this thesis provide novel techniques to recognition static and dynamic representation of patterns. In both domains the rough set theory improved generalization of the neural networks paradigms. The methodologies are theoretically robust to any pattern recognition problem, and are proved practically for image environments.



Abstrak tesis dipersembahkan kepada Senat Universiti Putra Malaysia sebagai memenuhi syarat untuk penganugerahan Ijazah Doktor Falsafah

**SENIBINA RANGKAIAN NEURAL KASAR UNTUK MENINGKATKAN
PENYELURUHAN KEPADA PENGECAMAN CORAK**

Oleh

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Rangkaian neural didapati amat menarik untuk digunakan oleh mesin yang boleh dilatih untuk pengecaman corak. Kebolehan model ini untuk menangani julat kepelbagaian yang besar serta keadaan yang berbeza, dan juga kebolehan meniru fungsi otak, membuatkan ianya bidang penyelidikan yang popular.

Penyelidikan di dalam tesis ini memberikan fokus kepada pembangunan rangkaian neural kasar kacukan. Pendekatan yang baru ini dapat memberikan prestasi yang lebih baik untuk tujuan pengesanan dan pengecaman sasaran secara automatik.



Tesis ini menyiasat, membangun dan melaksanakan suatu senibina kacukan teori set kasar dan rangkaian neural. Pendekatan kacukan pertama menyediakan rangkaian neural yang baru yang dinamakan Rangkaian Neural Kasar Perkongsian Pemberat (BSNN). Ia menggunakan konsep penganggaran berdasarkan neuron kasar untuk penyesaran dan kaedah ciri perkongsian pemberat. Tahap rangkaian adalah rangkaian pengambilan ciri dan rangkaian klasifikasi. Rangkaian penyesaran mengandungi neuron kasar yang mewakili penganggaran atas dan bawah serta menggunakan fungsi keahlian untuk menggantikan fungsi aktif yang biasa. Rangkaian neural mempelajari penganggaran atas dan bawah sebagai penyesaran ciri secara bersama dengan pengelasan. RSNN melaksanakan pengubah penganggaran yang baru. Rekabentuk asas untuk rangkaian disertakan bersama peraturan pembelajaran. Senibina ini menyediakan kaedah baru untuk pengecaman corak dan adalah dijangka sesuai kepada sebarang masalah pengecaman corak.

Pendekatan ke dua ialah dua sistem sebahagian sendiri yang dinamakan Rangkaian Neural Kasar (RNN). Rangkaian menyesarkan pengesanan yang mewakili kelas corak untuk diberikan kepada rangkaian pengelasan. Ia bekerja sebagai penuras untuk pengambilan ciri asli berdasarkan kepada hubungan sama dan pengurangan set kasar, manakala yang ke dua bertanggungjawab untuk pengelasan keluaran daripada sistem yang pertama.

Ke dua-dua pendekatan diaplikasikan kepada masalah pengecaman corak imej. RSNN diaplikasikan kepada masalah pengecaman sasaran secara automatik. Data masukan ialah Radar Bukan Tiruan (SAR) yang mempunyai imej kereta kebal dan

latar belakang. RSNN menyediakan kaedah untuk merkabentuk penuras tidak lurus tanpa pengetahuan terdahulu untuk domain masalah. RNN adalah digunakan untuk mengesan corak yang terdapat di dalam imej satelit. Algoritma penyesaran ciri yang baru dibangunkan untuk menyesuaikan vektor ciri. Algoritma tersebut meningkatkan kebolehan mengesan berbanding dengan penyesaran dan penandaan kelas corak secara manual. Prestasi rangkaian kasar perambatan semula telah ditingkatkan berbanding senibina perambatan semula yang sama. Rangkaian telah direkabentuk untuk menghasilkan pelantar pengesanan untuk corak yang dikehendaki.

Pendekatan kacukan yang dibangunkan di dalam tesis menyediakan teknik baru untuk pengecaman corak yang statik dan dinamik. Set teori kasar meningkatkan keupayaan penyeluruhan paradigma rangkaian neural. Kaedah yang dibangunkan adalah bersesuaian secara teori kepada masalah pengecaman corak dan dibuktikan bersesuaian secara praktikal untuk digunakan kepada imej.

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I certify that an Examination Committee met on **27 of December 2004** to conduct the final examination of **Hanan Hassan Ali Adlan** on her **Doctor of Philosophy** thesis entitled “**Rough Neural Networks Architecture for Improving Generalization in Pattern Recognition**” in accordance with Universiti Pertanian Malaysia (Higher Degree) Act 1980 and Universiti Pertanian Malaysia (Higher Degree) Regularizations 1981. The Committee recommends that the candidate be awarded the relevant degree. Members of the Examination Committee are as follows:

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DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citation which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UPM or other institutions.

HANAN HASSAN ALI ADLAN

Date: 29 June 2004



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LIST OF APPREVIATIONS

ANN	Artificial Neural Networks.
FANNs	Feed forward Neural Networks.
SVMs	Support Vectors Machines.
SA	Simulated Annealing.
UCA	Unsupervised Classification Algorithm.
MCE	Minimum Classification Error.
BAB	Branch-and-Bound.
SFS	Sequential Forward Selection.
SBS	Sequential Backward Selection.
PTA(l, r)	“Plus l -take away r ” Selection.
GPTA(l, r)	Generalized “Plus l -take away r ” Selection.
SFFS	Sequential Forward Floating Search.
SBFS	Sequential Backward Floating Search.
GSFS(g)	Generalized Sequential Forward Selection.
GSBS(g)	Generalized Sequential Backward Selection.
PARA	Parallel Algorithm.
GA	Genetic Algorithm.
PCA	Principal Component Analysis.
ICA	Independent Component Analysis.
MDS	Multidimensional Scaling.
SOM	Self-Organizing Map.
MSE	Mean Squared Error.



FCM	Fuzzy c-Mean.
MST	Minimum Spanning Tree.
SL	Single Link.
CL	Complete Link.
ATR	Automatic Target Recognition.
AI	Artificial Intelligence.
VLSI	Very Large Sequential Integration.
PC	Personal Computer.
LVQ	Learning Vector Quantization.
EST	Eigen Space Separation Transformation.
MLP	Multi Layer Perceptron.
PCNN	Pulse Coupled Neural Net.
PCNNP	Pulse Coupled Neural Net Processor.
CFAR	Constant False Alarm Rate.
FAR	False Alarm Rate.
MACE	Minimum Average Correlation Energy.
SPNN	Self Partitioning Neural Network.
GWNN	Genetic Wavelet Neural Network.
SARTNN	Simplified Adaptive Resonance Theory Neural Network.
IART1	Improved Adaptive Resonance Theory 1.
SART1	Simplified Adaptive Resonance Theory 1.
ART1	Adaptive Resonance Theory 1.
ART2	Adaptive Resonance Theory 2.