



UNIVERSITI PUTRA MALAYSIA

**CLASSIFICATION OF TYPED CHARACTERS USING
BACKPROPAGATION NEURAL NETWORK**

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**CLASSIFICATION OF TYPED CHARACTERS USING BACKPROPAGATION
NEURAL NETWORK**

By

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in the Faculty of Engineering
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Dedicated to Family members and my sister's Family



Abstract of the thesis presented to the Senate of Universiti Putra Malaysia in the fulfilment of the requirement for the degree of Master of Science

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This thesis concentrates on classification of typed characters using a neural network. Recognition of typed or printed characters using intelligent methods like neural network has found much application in the recent decades. The ability of moment invariants to represent characters independent of position, size and orientation have caused them to be proposed as pattern sensitive features in classification and recognition of these characters. In this research, uppercase English characters is represented by invariant features derived using functions of regular moments, namely Hu invariants. Moments up to the third order have been used for the recognition of these typed characters. A single layer perceptron artificial neural network trained by the backpropagation algorithm is used to classify these characters into their respective categories. Experimental study conducted with three different fonts commonly used in word processing applications shows good classification results. Some suggestions for further work in this area have also been presented.



Abstrak tesis yang diserahkan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

CLASSIFICATION OF TYPED CHARACTER USING BACKPROPAGATION NEURAL NETWORK

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Tesis ini memberikan fokus kepada klasifikasi abjad yang ditaip dengan menggunakan rangkaian neural. Pengenalan abjad yang ditaip atau dicetak dengan menggunakan kaedah pintar seperti rangkaian neural banyak digunakan kebelakangan ini. Kebolehan invarian momen untuk mewakili abjad tanpa bergantung kepada kedudukan, saiz dan orientasi menyebabkan ia dianggap sebagai sensitif kepada corak dalam klasifikasi dan pengenalan abjad-abjad ini. Dalam kajian ini, abjad rumi huruf besar diwakili oleh huruf invarian yang diterbitkan menggunakan fungsi 'Regular Momen' yang dinamakan invarian Hu. Momen sehingga ke tertib ketiga telah digunakan untuk pengenalan abjad abjad yang ditaip ini. Satu lapisan perseptron rangkaian neural buatan yang dilatih dengan algoritma backpropagation digunakan untuk mengklasifikasikan abjad-abjad ini ke dalam kategori masing-masing. Kajian yang dilakukan dengan menggunakan tiga bentuk huruf berlainan yang biasanya digunakan dalam pemproses perkataan telah menunjukkan keputusan klasifikasi yang baik. Beberapa cadangan untuk kajian lanjut dalam bidang ini juga telah di sertakan.



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LIST OF SYMBOLS AND ABBREVIATIONS

| | | |
|------------------|---|--|
| ANN | : | Artificial Neural Network |
| ASCII | : | American Standard Code Information Interchange |
| B | : | Bias input to the hidden unit |
| b | : | connection weights of hidden unit |
| BP | : | Backpropagation |
| CAIRO | : | Center for Artificial Intelligence and Robotics of Universiti Technology Malaysia |
| CCD | : | charge- coupled device |
| E _{min} | : | minimum error |
| f(x) | : | binary sigmoid function |
| f(Z(i/p)) | : | continuous function |
| g(x) | : | continuous function |
| HMI | : | Hu Moment Invariants |
| IC | : | Image classification |
| MLP | : | Multi Layer Perceptron |
| NN | : | Neural Network |
| OCR | : | Optical character recognition |
| O _i | : | input neurons, i=1,2...n |

| | | |
|--------------------------|---|---|
| O_j | : | hidden neurons, $j=1,2,\dots p$ |
| O_k | : | output neurons, $k=1,2,\dots q$ |
| PDP | : | Parallel Distributed Processing |
| PBM | : | Portable Bit map |
| TNR | : | Time New Roman |
| t_k | : | target output, $k=1,2,\dots q$ |
| v_1, v_2 | : | connection weights between hidden and output unit |
| w_1, w_2 and w_3 | : | connection weights between input and hidden unit |
| W_{ji} | : | weight of the connection from O_i to O_j , $i=1,2,\dots n$ and $j=1,2,\dots p$ |
| W_{kj} | : | weight of the connection from O_j to O_k , $k=1,2,\dots q$ and $j=1,2,\dots p$ |
| $X_1, X_2,$ and X_3 | : | Input neurons that form the input unit |
| x_1, x_2, x_3 | : | Input activation level |
| Z | : | hidden layer neuron that forms the hidden unit |
| Y_1, Y_2 | : | Output neurons that form the output unit |
| Y_1 (i/p), Y_2 (i/p) | : | input to neurons Y_1 and Y_2 |
| Y_1 (o/p), Y_2 (o/p) | : | output to neurons Y_1, Y_2 |
| y_1, y_2 | : | output activation level |
| z | : | hidden layer activation level |

| | | |
|----------------------|---|---|
| $Z (i/p)$ | : | net weight to the neuron Z |
| $Z (o/p)$ | : | output of the neuron Z |
| θ_j | : | Bias on hidden unit $O_j, j=1,2\dots p$ |
| θ_k | : | Bias on output unit $O_k, k=1,2\dots q$ |
| η | : | Learning rate |
| α | : | Momentum term |
| δ_k, δ_j | : | error signal due to an error at the output unit O_k and from output layer to the hidden unit O_j |
| ΔW_{kj} | : | weight correction term for W_{kj} |
| ΔW_{ji} | : | weight correction term for W_{ji} |

CHAPTER ONE

INTRODUCTION

1.1 Classification of Typed Characters using BP Neural Network

Automatic classifications of typed or printed characters have found very important applications in the recent years like Optical Character Recognition (OCR) for automatic postal code sorting, document processing and vehicle registration number identification system. In this work, the classification or recognition of typed English alphabets is concentrated.

A major difficulty in this work lies in classifying characters independent of position, size, and orientation. The invariant capabilities of functions of regular moments are utilized. A number of modifications are made to the original regular moments to make them completely invariant to position, size and orientation as suggested by Hu in 1961 [1].

In general, pattern recognition systems receive raw data, which are preprocessed and features are extracted and classified. The thesis starts with the stage of data set creation i.e. creating rotated, scaled, translated English alphabets in the computer. Next, we move on to invariant feature extraction using regular moment functions. The extracted features are then used in the classification stage where the alphabets are classified according to their categories with an artificial neural network (ANN). ANN is chosen due to its ability to incorporate “intelligence” in the classification process [2,3]. This is where the ANN comes in useful since it can improve

classification although with approximate invariance provided it is trained properly. A multilayer perceptron trained by the backpropagation algorithm is used in the thesis. This particular ANN is chosen since many researchers in the field of character recognition have opted for this type of ANN structure. Figure 1.1 shows the general flow of the methodology of the thesis.

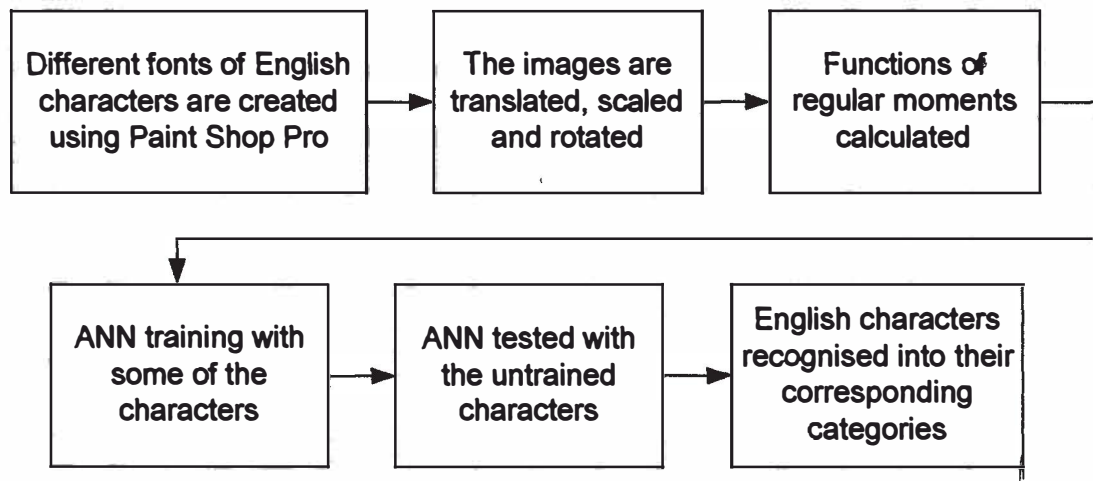


Figure 1.1: General flow of the Project.

Some of the areas, which can benefit indirectly from the thesis project, are document processing like in the government departments and Optical Character Recognition (OCR), which is especially useful for converting scanned text image into documents like the archival of books and journals.

1.2 Objectives of the Project

The objective of the thesis is to classify the typed uppercase English alphabets that are scaled, translated and rotated using Backpropagation Neural Network. The characters are represented by Hu moment invariant features, a type of regular

moment that are invariant to scaling, rotation and translation. In addition using Hu moment invariants, the input size is reduced.

1.3 Organization of the Thesis

The thesis is divided into five chapters. Chapter One gives the introduction. Chapter Two provides a general background review to the topic. This chapter consists of four main sections. The first section introduces imaging systems. The next section discusses the regular moments with focus on Hu Moment Invariants (HMI). The mathematical foundations behind the moments and their development to achieve invariance to translation, scaling and rotation are also covered in this section. The third section involves the discussion on the ANN classifier. The final section of this chapter gives a brief discussion of some possible applications of pattern recognition.

Chapter Three describes the methodology followed in this thesis. Chapter Four discusses the experimental study and the results obtained from the proposed system. It also contains the results obtained from computer simulations using C language. Chapter Five concludes the thesis. In addition, it also comprises some suggestions of possible areas of improvements that can be done in the future.

CHAPTER TWO

BACKGROUND AND LITERATURE REVIEW

2.1 Literature Review

The use of moment based methods for pattern recognition has received considerable attention. The method of moments is used to recognize targets of interest, such as aircraft and ship identification. Moments and functions of moments have been utilized as pattern features in a number of applications to achieve invariant recognition of two-dimensional image patterns. Hu first introduced moment invariants in 1961, based on methods of algebraic invariants.

Conventional regular moment functions have been proposed as pattern sensitive features in image classification and recognition applications. But conventional regular moments remain no longer invariant when the image is scaled unequally in the x- and y- axis directions NN and a Fuzzy ARTMAP is used to classify these images into their respective classes [4]. Regular moment functions are very sensitive to noise especially the higher order moments. The new moment invariants [5] that solve the symmetrical problem faced with regular moment functions and in addition, it is also shown that these new moments are less sensitive to noise and digitization error than both of the regular moment functions derived by Hu.

The initial results of an initiative to construct a system for automatically identifying structural features and applying Standard Generalized Markup Language (SGML) tagging, based on the Text Encoding Initiative Document Type Definition (TEI

DTD), to text captured from print documents via optical character recognition (OCR) is been presented [6].

Classification of printed or digitized gujarati characters were done by using classifiers with regular and invariant moments [7]. Moment descriptors have been developed as features in pattern recognition since the moment method was first introduced. New moment features for Chinese character recognition is proposed. These provide significant improvements in terms of Chinese character recognition, especially for those characters that are very close in shape [8]. Automatic recognition of Arabic printed text using an artificial neural network is one of the work done in this area [9]. An efficient neural classifier is used to solve the handwritten Chinese character recognition problem as well as other pattern recognition problems of large scale. Experiments are conducted to evaluate the performance of the proposed approach and results are promising [10-12].

The three fundamental problems encountered in image classification are data acquisition, feature extraction and classification.

2.2 Data Acquisition

Data acquisition is a process of converting a scene into an array of numbers that can be manipulated by the computer. Sensor signals are 'digitized' i.e., converted to an array of numerical values, each value representing a small area of the scene. The digitized values are called picture elements or 'pixels' in short and are stored in computer memory for further processing [13].

2.3 Feature Extraction

Feature extraction is the representation of a character by a set of numerical features to remove redundancy from the data and reduce its dimensions. The selected feature set must possess much of the useful information (in the sense of discriminability) present in the original data.

Selection of "good" features is a crucial step in the process, since the next stages look only on these features and further action on them. Good features satisfy the requirements below:

- **Small interclass variance** - The numerical values of slightly different shapes with similar general characteristics should be closer.
- **Large interclass variance** - different class features should be quite different numerically.

In addition, a flexible recognition system must be able to recognize the images regardless of its size, orientation and location in the field of view. Functions of regular moment satisfy all these properties and therefore suitable to be used in the feature extraction stage.

2.3.1 Moments and moment invariant

The use of invariants in computer vision has been motivated by the studies. These studies indicate that invariants construction belongs to pre-attentive stage in human visual system. This could explain why we can so easily recognize objects in different illumination conditions, from different viewpoints and viewing distances. Although it is not directly known how the human visual system extracts and utilizes

invariants, the inevitable performance of the human visual system has been an adequate reason to attempt to use invariants in recognition applications.

Numerous papers have introduced invariants and reported their application to a variety of tasks [14-18]. Invariants have been used in character recognition, fingerprint identification, indexing image databases, texture characterization, and recognition under blur, to mention a few.

Character recognition is a classical pattern recognition task, which has become increasingly important along with the evolution of palm top computers. As an indication of popularity, a search for IEL (IEEE/IEE Electronic library) electronic library (years 1988-1999) would find over 500 papers that share the term character recognition in their titles. Additionally, character recognition often serves as a standard application against which pattern recognition methods are tested.

The term character recognition covers actually a wide range of totally different pattern recognition applications. The characters in question are the English letters A-Z and the task is to recognize their deformed versions using only the original character images.

Moment invariant functions are a set of non-linear functions based on geometrical moments, which are invariant to translation, scaling and orientation. Hu in 1961 was the first to introduce the moment invariants. He derived a set of invariants based on combinations of regular moments using algebraic invariants. Extensive work on these invariants were performed by Palaniappan et. al. [5,18] to classify typed

characters. Dudani *et al.* applied these invariants to aircraft identification. Wong and Hall used them to match radar images to optical images. Khotanzad and Hong [19] utilized them in texture classification.

The term "invariant" denotes an image or a character, which remains unchanged if that image or shape undergoes one or more combination of the following changes:

- Change in size (scale)
- Change in position (translation)
- Change in orientation (rotation)

In addition to being invariant to the above changes, using moment functions also reduces the number of inputs to the ANN, therefore speeding up the process of training the network, which allows a larger number of patterns for training. Moreover the problems with the computer memory allocations are also reduced. By using moment invariants the input features are fewer than the total image size.

2.3.2 Properties of Moments

The regular moments are defined as:

$$m_{pq} = \int_{-\alpha}^{\alpha} \int_{-\alpha}^{\alpha} x^p y^q f(x, y) dx dy, \quad (2.1)$$

Where m_{pq} is the two-dimensional moment of a continuous function $f(x, y)$. The order of the moment is $(p+q)$ for $p, q = 0, 1, 2, \dots$. For a two-dimensional digital $M \times M$ character, equation (2.1) becomes

$$m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} x^p y^q f(x, y) \quad \text{for } p, q = 0, 1, 2, \dots, M. \quad (2.2)$$