METAHEURISTIC APPROACH ON FEATURE EXTRACTION AND CLASSIFICATION ALGORITHM FOR HANDWRITTEN CHARACTER RECOGNITION

MUHAMMAD ‘ARIF BIN MOHAMAD

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Faculty of Engineering
Universiti Teknologi Malaysia

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DEDICATION

This thesis is special dedicated to my lovely family for their endless love, support and encouragement.

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ABSTRACT

Handwritten Character Recognition (HCR) is a process of converting handwritten text into machine readable form and it comprises three stages; pre-processing, feature extraction and classification. This study acknowledged the issues regarding HCR performances particularly at the feature extraction and classification stages. In relation to feature extraction stage, the problem identified is related to continuous and minimum chain code feature extraction at its starting and revisit points due to branches of handwritten character. As for the classification stage, the problems identified are related to the input feature for classification that results in low accuracy of classification and classification model particularly in Artificial Neural Network (ANN) learning problem. Thus, the aim of this study is to extract the continuous chain code feature for handwritten character along with minimising its length and then proceed to develop and enhance the ANN classification model based on the extracted chain code in order to identify the handwritten character better. Four phases were involved in accomplishing the aim of this study. First, thinning algorithm was applied to remove the redundancies of pixel in handwritten character binary image. Second, graph based-metaheuristic feature extraction algorithm was proposed to extract the continuous chain code feature of the handwritten character image while minimising the route length of the chain code. Graph theory was then utilised as a solution representation. Hence, two metaheuristic approaches were adopted; Harmony Search Algorithm (HSA) and Flower Pollination Algorithm (FPA). As a result, HSA graph-based metaheuristic feature extraction algorithm was proposed to extract the continuous chain code feature for handwritten character. Based on the experiment conducted, it was demonstrated that the HSA graph-based metaheuristic feature extraction algorithm showed better performance in generating the shortest route length of chain code with minimum computational time compared to FPA. Furthermore, based on the evaluation of previous works, the proposed algorithm showed notable performance in terms of shortest route length of chain code for extracting handwritten character. Third, a feature vector was derived to address the input feature issue. The derivation of feature vector based on proposed formation rule namely Local Value Formation Rule (LVFR) and Global Value Formation Rule (GVFR) was adopted to create the image features for classification purpose. ANN was applied to classify the handwritten character based on the derived feature vector. Fourth, a hybrid of Firefly Algorithm (FA) and ANN (FA-ANN) classification model was proposed to solve the ANN network learning issue. Confusion Matrix was generated to evaluate the performance of the model in terms of precision, sensitivity, specificity, F-score, accuracy and error rate. As a result, the proposed hybrid FA-ANN classification model is superior in classifying the handwritten characters compared to the proposed feature vector-based ANN with 1.59 percent incremental in terms of accuracy model. Furthermore, the proposed hybrid FA-ANN also exhibits better performances compared to previous related works on HCR.

ABSTRAK

Pengecaman Aksara Tulisan Tangan (HCR) adalah proses penukaran teks tulisan tangan ke bentuk yang boleh dibaca oleh mesin dan terdiri daripada tiga peringkat, iaitu prapemprosesan, pengekstrakan fetur dan klasifikasi. Kajian ini telah mengenal pasti masalah yang berkaitan dengan prestasi HCR khususnya pada peringkat pengekstrakan fetur dan klasifikasi. Pada peringkat pengekstrakan fetur, masalah yang dikenal pasti adalah berkaitan dengan mengekstrak kod rantai yang berterusan dan minimun yang berkait dengan isu titik mula dan titik berulang kesan daripada cawangan aksara tulisan tangan. Dalam fasa klasifikasi, masalah yang dikenal pasti adalah berkaitan dengan fetur input yang akan mengakibatkan ketepatan klasifikasi yang rendah dan model klasifikasi terutamanya isu pembelajaran dalan Rangkaian Neural Buatan (ANN). Oleh itu, matlamat kajian ini adalah untuk mengekstrak kod rantai berterusan bagi aksara tulisan tangan dengan meminimumkan panjangnya dan seterusnya membangun dan meningkatkan model klasifikasi ANN berdasarkan kod rantai yang telah diekstrak bagi mengecam aksara tulisan tangan dengan lebih baik. Terdapat empat fasa terlibat untuk mencapai matlamat kajian ini. Pertama, algoritma penipisan digunakan untuk menyingkirkan lebihan piksel dalam imej binari aksara tulisan tangan. Kedua, algoritma pengekstrakan fetur metaheuristik berasaskan graf dicadangkan untuk mengekstrak kod rantai berterusan di samping meminimumkan panjang laluan kod rantai bagi imej aksara tulisan tangan. Teori graf digunakan sebagai perwakilan penyelesaian. Dengan yang demikian, dua kaedah metaheuristik diadaptasi, iaitu Algoritma Carian Harmoni (HSA) dan Algoritma Pendebungaan Bunga (FPA). Hasilnya, algoritma pengekstrakan fetur metaheuristik berasaskan graf dicadangkan bagi mengekstrak kod rantai berterusan aksara tulisan tangan. Berdasarkan eksperimen, dapat dinyatakan bahawa algoritma pengekstrakan fetur metaheuristik HSA berdasarkan graf menunjukkan prestasi yang lebih baik dalam pengekstrakan panjang laluan terpendek kod rantai dan masa komputasi yang minima berbanding dengan FPA. Di samping itu, berdasarkan penilaian kerja terdahulu, algoritma yang dicadangkan menunjukkan prestasi yang lebih baik daripada segi panjang laluan terpendek kod rantai mengekstrak aksara tulisan tangan. Ketiga, vektor fetur diterbitkan berkaitan dengan isu fetur input. Penerbitan vektor fetur yang berasaskan peraturan pembentukan yang dicadangkan, iaitu Peraturan Pembentukan Nilai Tempatan (LVFR) dan Peraturan Pembentukan Nilai Global (GVFR) diadaptasi untuk menerbitkan fetur input untuk tujuan klasifikasi. Bagi tujuan klasifikasi, ANN digunakan untuk mengkelaskan aksara tulisan tangan berasaskan vektor fetur yang telah diterbitkan. Keempat, model klasifikasi hibrid antara Algoritma Kelip-Kelip (FA) dan ANN (FA-ANN) dicadangkan berkaitan dengan isu pembelajaran rangkaian ANN. Matriks Keliru telah dijana untuk menilai pencapaian model dari segi kepersisan, sensitiviti, spesifisiti, skor-F, ketepatan dan kadar ralat. Hasilnya, model klasifikasi hibrid FA-ANN yang dicadangkan didapati adalah lebih baik dalam mengklasifikasi aksara tulisan tangan berbanding dengan model klasifikasi vektor fetur berasakan ANN dengan 1.59 peratus kenaikan dari segi ketepatan model. Lagipun, model hibrid FA-ANN yang dicadangkan juga menunjukkan prestasi yang lebih baik berbanding dengan kerja terdahulu dalam HCR.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
CR	-	Character Recognition
FA	-	Firefly Algorithm
FA-ANN	-	Hybrid Firefly Algorithm with Artificial Neural Network
FCC	-	Freeman Chain Code
FN	-	False Negative
FP	-	False Positive
FPA	-	Flower Pollination Algorithm
GVFR	-	Global Rule Formation Vector
HCR	-	Handwritten Character Recognition
HCR	-	Handwritten Character Recognition
HSA	-	Harmony search Algorithm
LFV	-	Local Feature Vector
LGFV	-	Local Global Feature Vector
LVFR	-	Local Value Formation Rule
PR	-	Pattern Recognition
TN	-	True Negative
TP	-	True Positive

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Machine simulation of human function has been a very challenging research field since the advent of a digital computer (Chaudhuri *et al.*, 2017). It is always fascinating to be able to find ways of enabling a computer or machine to mimic a human function, like the ability to read, to write, to speak, to see things, and so on. Machine simulation of human reading is one of these areas (Babu, 2014). Human recognized characters easily and they repeat the character recognition process thousands of times every day. In our daily life, as we read papers and books, our brain continuously does the character recognition. We match it with our experience and memory, then based on that we react or take an action or infer some new things. So, this is our natural character recognition. How about recognizing characters with machine abilities?

Handwritten Character Recognition (HCR) is an area of character recognition which defines an ability of a machine to analyze patterns and identify the handwritten character. At present, handwritten characters are increasingly used in daily life. Handwritten information comes in a variety of different forms, including bills, manuscripts, documents, forms and photographed documents. Handwritten character recognition has wide application prospects, and there is great demand for it in industrial fields such as image recognition systems and handwritten text input devices as society develops and progresses (LeCun *et al.*, 2015). Development of HCR started in the early 1950s and its development advanced during 1970s and 1980s because of the advent of a lot of handwriting recognition applications (Chaudhuri *et al.*, 2017). After 1980, the character recognition system advanced rapidly in terms of algorithm and techniques because of the intensive research and development.

Despite the fact that the research in HCR has been studied extensively for more than five decades, but yet still an active and challenging area since many researchers have been engaged in this topic in present (Tiwari *et al.*, 2019; Cilia *et al.*, 2019 and Deepak Gowda *et al.*, 2019). Jain and Sharma (2018) stated, the variations in handwriting pose major challenge in developing accurate recognition system. Moreover, Konar and Kar (2018) had stated that handwritten character has the infinite variety of writing style from one person to another. Due to this wide range of variability, it is difficult to recognize a handwritten character by a machine. Therefore, this study observed that there is still scoping to work on HCR research area.

1.2 Background of Study

In general, there are three stages in HCR which are preprocessing, feature extraction and classification. First stage, preprocessing is a process of enhancing the image character, which should be used for further processing. Preprocessing is almost one of the basic steps in HCR. Usually, it is used to remove noise and different variations in the data. It may include binarization, noise reduction, data normalization and data compression. The purpose of preprocessing is to produce a clean character of handwritten character image that can be used directly and efficiently by the feature extraction stage.

Second stage, feature extraction is a process to produce several characteristics or features from the image character. Feature extraction related to extraction method to find the most representative information, which minimizes the within class pattern variability while enhancing the between class pattern variability (Li *et al.*, 2017). Based on literature review, two factors need to be considered in selection of feature extraction method which are simple and efficient. Wang *et al. (*2018) stated that, finding the features, it should be noted that in order to avoid extra complexity and to increase the accuracy of recognition, a more compact features is required. Furthermore, Mari and Raju (2015) stated, finding simple and efficient features for handwritten character recognition is still an active area of research.

Chain code by Freeman (1961) as one of the feature extraction method under geometrical and topological representation category, has been extensively applied for feature extraction purpose. This is due to its ease and minimal storage needs (Zalik *et al.*, 2018; Suliman *et al.*, 2010 Shaojie and Kai Kuang, 2000; Neuhoff and Castor, 1985). Furthermore, Dingli *et al. (*2018) stated that, chain code is widely used for descriptions of object borders in image processing, shape analysis and pattern recognition fields because of simple and compact form of data representation and its suitability for fast processing. Subsequently in HCR, literature had shown that chain code representation is still relevant in representing in HCR due to recent work on chain code for handwritten character by (Naik and Desai, 2019; Jangid and Srivastava, 2018; Dingli *et al. (*2018).

Unfortunately, the problem of chain code feature extraction process is the chain coding process would be very much on the way of the image would be traversed and the starting point of the traversing method (Nasien *et al.*, 2014). A start point of a character will produce a different chain code direction even though is the same image. Means, the starting node of chain code construction influences its length. Moreover, the problem become worse when involving handwritten character recognition since handwritten character usually contains branches on each character. This causes difficulty to decide which direction would the traverse continues and a revisit to previous visited node is often needed to visit all the nodes. Nasien *et al. (*2014) had suggested that one continuous route is needed to solve such problems, which cover all the nodes of the image. Chain code construction using one continuous route has not widely explored such a method would enable to extract and recognize such difficult characters and to find approximate solutions for chain code generation along with minimizing its length.

While as third stage of HCR, the intention of classification stage is a process to recognise the images of handwritten character by used the extracted features to recognize the feature class based on the properties in the features. Two important issues before building the classification procedure which are the data input for classification and classification method (Rao *et al.*, 2018). First, Rao *et al. (*2018) has stated, improper step during data input preparation will result to low accuracy and misguide output. The data input is related to feature vector as the feature vector is built from the extracted features in feature extraction stage. The performance of a classification is depending on the feature vector that contain the extracted features as provide data input for the classifier.

Second issue, classification method generally can be traced from template matching, statistical approach, and syntactic. Present, machine learning is introduced by many researchers to facilitate the process of solving classification of HCR. Machine learning techniques are applied due to the constraints of classification problems in recognising the conditions especially for procedures that involve complex data structures (Hasan *et al.*, 2012). Common machine learning methods that have been used by many researchers are Artificial Neural Network (ANN), Support Vector Machine (SVM), Genetic Algorithm (GA), Swarm Intelligence (SI) and Fuzzy Set. ANN is one of the most applied machine learning methods by researchers (Negnevitsky, 2005). Furthermore, Tautu and Leon (2011) had state that ANN seem to be the preferred solutions to the classification problem due to their proven accuracy in classifying new data.

The most difficult and important part for any types of neural network is learning (Russell and Norvig, 2016). For ANN, most applications have used standard or improved Back-Propagation (BP) algorithm as their training method (Samarasinghe, 2016). There are two important factors that give an impact to the modelling effect and precisions during the learning and training of BP. The factors are the initial interconnecting weights of the network and the modified quantities. Occasionally the interconnecting weights of BP are always stochastically and blindly produced. Therefore, to determine the initial interconnecting weights that are global is very difficult assignments. This might cause the network to run into partial optimisation and may decline the probability to obtain the best global solutions, (Zhang and Wang, 2008). The convergence velocity is always slow and sometimes the network does not even converge because of the Delta rule is always been used. The Delta rule is used to modify the interconnecting weights of BP. Hence, the weaknesses of BP that it has slow convergence rate and always been trapped in local minima. These weaknesses of are reasonable to be optimised and upgraded.

To sum up, basically the success rate of HCR is depending on entire stage which are preprocessing, feature extraction and classification stage. This study concentrates on feature extraction and classification stage only. As for preprocessing stage, the previous work is referred by applying the thinning process. So, the focus of this study on:

(a) Implementation of thinning process in preprocessing stage.

The implementation of thinning process is based on the previous work. This study only implemented the preprocessing stage by applying thinning process to handwritten character image in order to produced Thinned Binary Image (TBI). The TBI is then utilised as input for the next feature extraction stage.

(b) Feature extraction stage related to chain code feature extraction problem.

The two issues regarding in handling the chain code extraction of handwritten character which are starting point of chain code that influence the length of the extracted chain code; and branches of handwritten character that lead to the problem revisit to the previous visited nodes. These issues have motivated this study on construction of chain code using one continuous route which is such a method would enable to extract and recognize such difficult characters and to find approximate solutions for chain code generation along with minimizing its length. So, the focus in this study is on extraction of continuous chain code feature of handwritten character by propose graph-based metaheuristic feature extraction algorithm. The idea is, in order to carry out chain code feature extraction process, metaheuristic approach is utilised in chain code feature extraction process in order to find solutions for chain code generation along with searching the optimised chain code features in terms of minimising its length in relatively shorter computational time with shorter route length. Hence, graph theory is presented as solution representation for the proposed metaheuristic feature extraction approach. The importance of concept of the graph theory in the proposed metaheuristic approach, the starting point of chain code does not need to specify. To the best of our knowledge, the HSA and FPA have been not implemented for feature extraction problem yet.

(c) Classification stage related to derivation of feature vector and optimisation of ANN learning.

Derivation of a feature vector is a target of data input preparation for classification model as the data input will determined the classification performance. The focus in this study is on the derivation of feature vector based on the proposed formation rule. Then the feature vector-based ANN is develop aimed to validate the feature vector in recognizing the handwritten character. The purpose is to observe the relation between the number of features in feature vector and the result of classifying the handwritten character. Consequently, as classification problem in ANN learning, the focus in this study is on the ANN network learning is optimised by metaheuristic approach namely Firefly Algorithm (FA). This study explores the potential of FA as optimisation method to enhance the ANN classification model. The idea is that the created network of the ANN classification model is trained using the generated value of weight by FA approach in order to obtain an optimised network of the ANN classification model. At the time of writing, there are no researches on applying FA in ANN.

1.3 Problem Statement

So, there are two subjects considered to drive in this study related to feature extraction stage problem and classification stage problem. As feature extraction stage, the problem is related to continuous chain code construction in relation to the issues of starting point and revisit point due to branches of handwritten character would influences the length of extracted chain code. As for classification stage, the problems are related to the input feature for classification that would be resulting in low accuracy of classification and classification model particularly in ANN learning problem.

1.4 Research Question

The research question of this study can be stated as:

1. How to extract continuous chain code feature of handwritten character along minimising its length?
2. How to derive the feature vector as input for classification model based on extracted chain code feature?
3. How to validate the feature vector in influencing the classification of handwritten character?
4. How to enhance the ANN classification model of handwritten character?

1.5 Research Aim

The aim of this study is to extract the continuous chain code feature for handwritten character along minimising its length and then develop and enhance the ANN classification model based on the extracted chain code to recognize the handwritten character.

1.6 Research Objectives

To achieve the aim of this study, the objectives are defined below:

1. To develop Harmony Search Algorithm (HSA) and Flower Pollination Algorithm (FPA) Graph-Based Metaheuristic Feature Extraction Algorithm in extracting continuous chain code features of handwritten character image.

2. To propose formation rule for derivation of feature vector based on chain code features and image properties as input for classification model.

3. To develop Feature Vector-based Artificial Neural Network (ANN) classification model for handwritten character recognition.

4. To enhance the proposed feature vector-based ANN classification model by hybridising with Firefly Algorithm (FA-ANN).

1.7 Research Scopes

The scopes of the study are.

1. Data of handwritten character used for this study are from two databases sources which are Centre of Excellent for Document Analysis and Recognition (CEDAR) and National Institute of Standards and Technology (NIST).

2. Data of handwritten character consist of Uppercase (A-Z), Lowercase (a-z), Letter (mixture of uppercase/lowercase), Digit (0-9) and Characters (mixture of letter/digit).

3. As preprocessing stage, the established thinning algorithm is applied to produce Thinned Binary Image (TBI). For CEDAR dataset, method proposed by Engkamat (2005) is used, while *'bwmorph'* function is applied to NIST for the same thinning purpose.

4. Eight-directional of chain code is utilised, starts from 1 to 8 direction labelling.

1.8 Significant of Study

The findings of this study will contribute to the feature extraction and classification stage of handwritten character recognition. In relation to feature extraction stage, graph based-metaheuristic feature extraction algorithm is developed to generate chain code feature for handwritten character aim to find continuous route of chain code that covers all the nodes of the handwritten character image while satisfying the objective to minimise the route length of the chain code. On the other hand, in relative to classification stage, formation rule of derivation feature vector is proposed to derive feature vector aim to prepare input data to be fed to the classification model that influence the classification accuracy. Furthermore, hybrid FA-ANN is developed to optimise the ANN network learning process to enhance the ANN classification model to classify the handwritten character.

1.9 Thesis Organisation

This thesis is structured into eight chapters. The descriptions of each chapter are given as a brief introduction. The present chapter introduced the overview of the handwritten character recognition concern including the issues related to feature extraction problem and classification problem. Objectives and scopes of the research stated related to the issues, then followed by significant of the study.

Chapter 2 appraises the literature review. It discusses the related works for this study including introduction of pattern recognition and HCR, handwriting style and database, stage of HCR i.e. preprocessing stage, feature extraction stage, and classification stage. Metaheuristic approaches and performances measure are also included in this chapter. Chapter 3 grants the research methodology used to build up this study. This chapter presents the research framework, problem definition, data definition, preprocessing, development of graph-based metaheuristic feature extraction algorithms, derivation of feature vector and proposed feature vector-based ANN classification model, proposed hybrid FA-ANN classification model, evaluation, implementation and summary.

Chapter 4 explains the development of the proposed graph-based metaheuristic feature extraction algorithm to construct one continuous chain code feature for handwritten character. It describes the structure of the algorithms and its data structure, Harmony Search Algorithm, Flower Pollination Algorithm, testing algorithm procedure, result of the generating the chain code, evaluation and selection and followed by the summary. Chapter 5 describes the development of proposed feature vector-based Artificial Neural Network (ANN) classification model to classify the handwritten character based on the extracted chain code in previous chapter. It discussed the derivation of feature vector as input for classification model based on the proposed formation rule. Then, the development of feature vector-based ANN classification model, feasibility analysis, the classification results are reported in this chapter and followed by the summary. Chapter 6 briefs the development of proposed hybrid Firefly Algorithm and Artificial Neural Network (FA-ANN) classification model. It discusses introduction, experiment setup, parameter setting, training and testing procedure, validation, FA-ANN classification result and followed by summary.

Chapter 7 discuses result analysis and evaluation. It explains the analysis results of proposed graph-based metaheuristic feature extraction algorithm and proposed classification algorithms consists of feature vector-based ANN and hybrid FA-ANN classification model. Furthermore, evaluation of proposed works in this study with previous related works are discussed and followed by summary. Chapter 8 concludes the conclusion and future work. This chapter illustrates summary of study, benefit of study, contribution of study, conclusion and the suggestion for possible future work.

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