HAND GESTURE RECOGNITION FOR HUMAN-ROBOT INTERACTION

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DEDICATION

This project report is dedicated to my dearest parents, who have always been my source of motivation and strength to embrace the challenges I meet. It is also dedicated to my mentor, sisters and friends who shared their words of advice and encouragement during my study.

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ABSTRACT

This project proposes an image segmentation method that improves the recognition rate of vision-based hand gesture recognition system on low-resolution images and occluded hand gestures. The solution is based on the idea that random walker-based segmentation could provide high quality segmentation despite weak object boundaries. The approach has several notable merits, namely high segmentation accuracy, fast editing and computation. A comprehensive verification using Matlab is carried out to determine the effectiveness of random walker method in segmenting occluded hand gesture images. The segmented images are then classified by artificial neural network and its performance is evaluated in terms of recognition rate and time. The result confirms that the proposed method is performs better than color-based segmentation, that is 5% higher recognition rate for the same dataset. The method proposed in this project can be integrated in vision-based recognition systems to widen the vocabulary of hand gestures recognition systems, recognizing both gestures with finger gaps as well as occluded gestures.

ABSTRAK

Kajian ini mencadangkan kaedah segmentasi imej yang dapat meningkatkan kadar pengiktirafan sistem pengiktirafan isyarat tangan berasaskan penglihatan pada imej resolusi rendah dan isyarat tangan yang berpaut. Kaedah tersebut adalah berdasarkan kepada idea bahawa segmentasi berasaskan *random walker* dapat memberi segmentasi yang berkualiti tinggi walaupun sempadan sesuatu objek adalah lemah. Pendekatan ini mempunyai beberapa merit yang ketara, iaitu ketepatan segmentasi tinggi, penyuntingan dan pengiraan pantas. *Matlab* dijalankan untuk mengesahkan keberkesanan kaedah *random walker* dalam segmentasi imej isyarat tangan berpaut. Imej bersegmen kemudian diklasifikasikan oleh rangkaian saraf buatan dan prestasinya dinilai dari segi kadar dan masa pengiktirafan. Hasilnya mengesahkan bahawa kaedah yang dicadangkan adalah lebih unggul daripada segmentasi warna, iaitu kadar pengiktirafan yang 5% lebih tinggi untuk dataset yang sama. Kaedah yang dicadangkan dalam kajian ini dapat diintegrasikan dalam sistem pengiktirafan berasaskan penglihatan untuk memperluaskan perbendaharaan kata sistem pengiktirafan isyarat tangan berasaskan penglihatan, mengiktiraf kedua-dua isyarat tangan dengan jurang jari serta isyarat tangan berpaut.

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LIST OF ABBREVIATIONS

ANFIS	-	Adaptive Network based Fuzzy Inference
ANN	-	Artificial Neural Network
CNN	-	Convolutional Neural Network
FV	-	Fisher Vector
KNN	-	K-nearest Neighbour
HRI	-	Human-robot Interaction
HOG	-	Histogram of Oriented Gradients
LBP	-	Local Binary Pattern
PCA	-	Principal Component Analysis
RBFNN	-	Radial Basis Function Neural Network
SDAE	-	Stacked Denoising Autoencoder
SIFT	-	Scale-invariant Feature Transform
SVM	-	Support Vector Machine
ToF	-	Time of Flight
W-KNN	-	Weighted K-nearest Neighbour

LIST OF SYMBOLS

B	-	Blue
CbCr	-	Chrominance
G	-	Green
H	-	Hue
N_h	-	Number of hidden neurons
R	-	Red
S	-	Saturation
V	-	Value
Y	-	Luminance

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CHAPTER 1

INTRODUCTION

1.1 Problem Background

Human-robot interaction (HRI) is an important field of research in the area of robotics nowadays. It is expected that the application of robots is going to extend beyond manufacturing industries and to be incorporated into daily environment [1]. Such incorporation requires effective and effortless communication between human and robot, such as voice recognition and gesture recognition. Vision-based hand gesture recognition system has been a global interest of research since last two decades. However, there are still a lot of challenges concerning gesture identification, which is also referred as feature extraction. The purpose of feature extraction is to obtain the most relevant information from original data and represent that information in a lower dimensionality space [2]. The precision of gesture identification is closely related to the choice of image segmentation method as it directly affects the accuracy and real-time of interaction between human and robot [3]. Besides, most existing recognition systems were developed in favor of hand gestures with gap between fingers. Recognizing occluded hand gestures remains a challenge in recognition systems, and therefore there is a need to develop a robust recognition algorithm that works well with occluded hand gestures.

In this study, a hand gesture recognition algorithm that is independent of finger gaps is presented. A hand gesture dataset consisting 10 classes of occluded hand gestures is chosen to be the subject of study. The images are pre-processed and the gestures are extracted through random walker-based segmentation. The hand gestures images are then recognized and classified by artificial neural network. The recognition algorithm is targeted to achieve a recognition rate of above 90%.

1.2 Problem Statement

Image segmentation is the most challenging step in vision-based gesture recognition [4]. Color segmentation is the most straightforward existing segmentation method as the process of segmentation only involves thresholding of color value. In skin color segmentation, user is required to define the thresholding range of skin color so that the recognition system is able to identify skin-colored image pixels and separate them from the background. However, this method is not universal as human skin color can be very diverse due to different ethnicities. Expanding the thresholding range for different skin tones has the possibility of including pixels that do not fall under skin color, thus resulting in inaccurate segmentation. Furthermore, presence of skin-colored objects in background would also reduce the segmentation accuracy. Thus, the choice of image segmentation method is crucial in recognition systems to ensure accurate segmentation.

Another popular approach is shape based recognition which is known for its simplicity and robustness. However, this approach is only suitable for hand gestures having finger gaps because it recognizes gestures mainly by significant hand feature such as detecting the number of fingers and finger widths [5]. This limits the vocabulary and control of recognition systems as there are many ways to express hand signs, including occluded hand gestures. Therefore further development on recognition approach should include occluded gestures as subject of study in order to expand the vocabulary of hand gestures recognition system and thus allow more diverse control.

Problem statements of this study can be summarized as below:

1) Inaccurate image segmentation is a huge factor of recognition errors.

2) Occluded hand gestures are difficult to be recognized, limiting the vocabulary and control of recognition systems.

1.3 Research Goal

Human-robot interaction is becoming an emerging field and researchers have been actively studying hand gestures recognition system as hand gestures can be used as command inputs to robots in various applications. The research goal in this field is to develop an efficient and robust hand gesture recognition system that allows the interaction between human and robot to be as natural as it is between humans. As a contribution towards this goal, the aim of this study is to develop a static hand gesture recognition algorithm that is able to recognize occluded hand gestures, which are part of human common expression. Recognition accuracy and computational time are two important criteria that define the efficiency of a gesture recognition system. In this study, the effectiveness of random walker-based image segmentation on hand gestures images and the resulted recognition accuracy and computational time of artificial neural network are to be explored in this study.

1.3.1 Objectives

The objectives of this study are :

(a) To perform image processing and random walker-based image segmentation on raw hand gesture images using Matlab.

(b) To classify the hand gestures images using artificial neural network.

(c) To achieve a recognition rate of above 90%.

1.3.2 Scope of Project

This project aims to develop a recognition algorithm that covers gesture identification and classification. In order to verify the effectiveness of the developed algorithm, a publicly available hand gesture database is used in this project because it is acknowledged that the databases are made in highly controlled environments to provide reliable verification [6]. This project employs the NUS hand posture dataset I which is widely used by academic researchers to test the recognition accuracy of hand gesture recognition algorithm [7][8][9]. It consists a total of 240 images and there are 10 classes of gestures, which all of them have a uniform background. In this project, Matlab is the platform for developing the recognition algorithm for its wide applications in the field of image processing and artificial intelligence. The Matlab toolboxes involved in this project includes image processing toolbox and graph analysis toolbox for image processing and random walker segmentation, as well as Neural Network Pattern Recognition application for classifying the segmentation outputs through a feedforward neural network. The scope of this project is limited to low resolution images and single hidden layer neural network due to the limited capability of computer hardware used in this project.

1.4 Report Outline

The preceding sections briefly summarized the contributions of the project report. This report consists of five chapters, and this section outlines each of the chapters.

Chapter 2 describes the main concepts relevant to hand gesture recognition system and the popular approaches in gesture identification and classification. An overview of related work in hand gesture recognition algorithms and research gap are also presented.

Chapter 3 describes the research methodology and the concept of proposed method. This chapter also presents detailed research activities and the choices of tools and platform.

Chapter 4 describes the results and discussion of the proposed work. Analytical proofs as well as simulation results are presented and discussed.

Chapter 5 concludes and recommends for future works.

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