

A HYBRID APPROACH TO EDGE DETECTION USING FUZZY SETS AND
CELLULAR LEARNING AUTOMATA

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To my beloved parents, thank you for always being there for me, supporting me and encouraging me to be the best that I can be.

ABSTRACT

Edge detection technique has a key role in machine vision and image understanding systems. In machine vision motion track and measurement system based on discrete feature, the exact feature edge orientation in the image is the precondition of the successful completion of the vision measurement task. Edge detection is one of the most commonly used operations in image analysis and digital image processing. Many studies have been conducted to enhance the edge detection algorithms in various domains. In this thesis, a robust edge detection method based on Fuzzy Sets and Cellular Learning Automata (CLA) is proposed. The proposed method includes two steps: (a) extracting the edges and (b) enhancing them by removing unwanted edges and eliminating false edges caused by noise. The performance of the proposed edge detector is tested on various test images with different sizes. The results are compared with Canny and Sobel edge detection methods. Simulation results reveal that the proposed Fuzzy-CLA method can detect edges more smoothly in a shorter amount of time compared to the other edge detectors.

ABSTRAK

Teknik pengesanan pinggir memainkan peranan yang penting dalam sistem visi mesin dan pemahaman imej. Dalam pergerakan menjejaki visi mesin dan sistem pengukuran berdasarkan fitur diskret, orientasi tepat bagi pinggir fitur adalah prasyarat kepada kesempurnaan bagi tugas visi pengukuran. Pengesanan pinggir adalah salah satu operasi sepunya yang banyak digunakan dalam operasi menganalisa gambar, adan kaedah ini lazim digunakan dalam pemprosesan imej. Terdapat banyak kajian setara yang telah dijalankan bagi menambak kaedah mengesan pinggir dalam pelbagai domain. Kajian ini mencadangkan kaedah pengesanan pinggir yang tegar berdasarkan Set Kabur dan Pembelajaran Automata Selular (PAS). Kaedah cadangan ini meliputi dua langkah: (a) penyarian pinggiran dan (b) meningkatkan pinggiran tersari dengan menghapuskan pinggir yang tidak diingini dan membuang pinggir palsu yang disebabkan oleh hingar. Prestasi kaedah cadangan diuji dengan data ujian bagi imej dengan pelbagai saiz. Hasil kajian dibandingkan dengan kaedah Canny dan kaedah pengesanan pinggir Sobel. Keputusan simulasi mempamerkan bahawa kaedah cadangan ini berupaya mengesan pinggir dengan sempurna dalam masa yang lebih singkat berbanding dengan kaedah pengesanan pinggir yang lain.

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LIST OF SYMBOLS

g_{mn}	The gray level of each pixel at the position (m,n)
μ_{mn}	The degree of brightness of each pixel
$\hat{\mu}_{mn}$	Heuristic Membership Function
α	The probability increase coefficient
β	The probability reduction coefficient

LIST OF ABBREVIATIONS

CLA	Cellular Learning Automata
CA	Cellular Automata
LA	Learning Automata
GA	Genetic Algorithm
NN	Neural Networks
FIS	Fuzzy Image Systems
OCLA	Open Cellular Learning Automata
ACLA	Asynchronous Cellular Learning Automata
SOFM	Self-Organization of Kohonen Feature Map
ACO	Ant Colony Optimization

CHAPTER 1

INTRODUCTION

1.1 Introduction

Vision is the most advanced of our senses, so that images play the single most important role in human perception. However, imaging machines cover almost the entire EM spectrum, unlike humans who are limited to the visual band of the electromagnetic (EM) spectrum, ranging from gamma to radio waves. They can operate on images generated by sources that humans are not accustomed to associating with images. These include ultrasound, electron microscopy, and computer-generated images. Thus, digital image processing encompasses a wide and varied field of applications.

Computer vision is the science and technology of machines that see. As a scientific discipline, computer vision is concerned with the theory for building artificial systems that obtain information from images. The image data can take many forms, such as a video sequence, views from multiple cameras, or multi-dimensional data from a medical scanner.

As a technological discipline, computer vision seeks to apply the theories and models of computer vision to the construction of computer vision systems. Examples of applications of computer vision systems include systems for:

- Controlling processes (e.g. an industrial robot or an autonomous vehicle).
- Detecting events (e.g. for visual surveillance or people counting).
- Organizing information (e.g. for indexing databases of images and image sequences).
- Modeling objects or environments (e.g. industrial inspection, medical image analysis or topographical modeling).
- Interaction (e.g. as the input to a device for computer-human interaction).

Computer vision can also be described as a complement (but not necessarily the opposite) of biological vision. In biological vision, the visual perception of humans and various animals are studied, resulting in models of how these systems operate in terms of physiological processes. Computer vision, on the other hand, studies and describes artificial vision systems that are implemented in software and/or hardware. Interdisciplinary exchange between biological and computer vision has proven increasingly fruitful for both fields.

Sub-domains of computer vision include scene reconstruction, event detection, tracking, object recognition, learning, indexing, motion estimation, and image restoration.

The term digital image processing generally refers to processing of a two-dimensional picture by a digital computer. In a broader context, it implies digital processing of any two-dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency, slide, photograph, or chart is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayed on high-resolution television monitor. For display, the image is

stored in a rapid-access buffer memory which refreshes the monitor at 30 frames to produce a visibly continuous display. Digital image processing has a broad spectrum of applications, such as remote sensing via satellites and other spacecrafts, image transmission and storage for business applications, medical processing, radar, sensor, and acoustic image processing, robotics, and automated inspection of industrial parts [1].

Edge detection technique has a key role in machine vision and image understanding systems. Particularly, in machine vision motion track and measurement system based on discrete feature, the exact feature edge orientation in the image is the precondition of the successful completion of the vision measurement task. The gray-level difference information between the object and background is often applied to orient the detected feature edge of images. However, because in the real scenes, images are often affected by noise, unstable or bad illumination, object motion, etc. the correct edge detection is too difficult to be completed successfully. Especially for the non-uniform, weak illumination and low contrast images, the gray-level difference between the object and background will possibly be low in some place of the image and variant in the whole image [2].

1.2 Problem Background

Edge detection is one of the most commonly used operations in image analysis, and there are probably more algorithms in the literature for enhancing and detecting edges than any other single subject. The reason for this is that edges form the outline of an object. An edge is the boundary between an object and the background, and indicates the boundary between overlapping objects. This means that if the edges in an image can be identified accurately, all of the objects can be located and basic properties such as area, perimeter, and shape can be measured.

Since computer vision involves the identification and classification of objects in an image, edge detection is an essential tool.

Edge detection is part of a process called segmentation - the identification of regions within an image. Technically, edge detection is the process of locating the edge pixels, and edge enhancement will increase the contrast between the edges and the background so that the edges become more visible. In practice the terms are used interchangeably, since most edge detection programs also set the edge pixel values to a specific grey level or color so that they can be easily seen. In addition, edge tracing is the process of following the edges, usually collecting the edge pixels into a list. This is done in a consistent direction, either clockwise or counter-clockwise around the objects [3].

It is difficult to design general edge detection algorithms which perform well in many contexts and captures of the requirements of subsequent processing stages. In this project, the goal is to have an edge detector which can perform well in many contexts with the highest performance level possible.

1.3 Problem Statement

Most previous edge detection techniques such as the Roberts edge operator [4], the Prewitt edge operator [5], and the Sobel edge operator [5] used first-order derivative operators. If a pixel falls on the boundary of an object in an image, then its neighborhood will be a zone of gray-level transition. The Laplacian operator [2] is a second-order derivative operator for functions of two- dimension operators and is used to detect edges at the locations of the zero crossing. However, it will produce an abrupt zero-crossing at an edge and these zero-crossings may not always correspond

to edges. Canny operator [6] is another gradient operator that is used to determine a class of optimal filters for different types of edges, for instance, step edges or ridge edges. A major point in Canny's work is that a trade-off between detection and localization emerged: as the scale parameter increases, the detection increases and localization decreases. The noise energy must be known in order to set the appropriate value for the scale parameter. However, it is not an easy task to locally measure the noise energy because both noise and signal affect any local measure.

The Kirsch masks [7], Robinson masks [8], Compass Gradient masks [9], and other masks [10] are popular edge-template matching operators. Although the edge orientation and magnitude can be estimated rapidly by determining the largest response for a set of masks, template mask methods give rise to large angular errors and do not give correct values for the gradient. Many edge detectors rely totally on gray-level differences for their approximation of the image gradient function either directly or by representing these differences in a more analytical form such as the Huekel edge detector [11].

In most edge detection methods which use fuzzy sets theory, the number of noise pixels that are detected as edges is usually very high. It is because the criterion for edginess in these methods is mostly only the high difference between the maximum and minimum gray levels. However, as mentioned earlier, in very noisy environments the same situation arises, and therefore, the number of errors increases. In order to solve this problem an additional rule is added to the edginess condition. We shall state that the center pixel in an edgy neighborhood must be between the minimum and maximum gray levels.

One of the most important points that must be taken into consideration while designing a feature extraction technique which naturally requires edge detection is that the more precise the earlier phase of edge detection is, the more easily the features can be extracted later. Therefore, in this project after the edges are detected, the edge pixels are strengthened and the non-edge pixels are weakened using Cellular

Learning Automata and the noises left from the earlier phase are removed. The complete process of both phases will be explained in details later on.

1.4 Project Aim

The aim of this project is to design and implement a robust and effective method for edge detection.

1.5 Objectives

Many existing edge detection methods such as Sobel, Perwitt, and Canny take advantage of the gradient of images and arithmetic operations. Most of these methods consider an edge as a set of pixels where the gray-level has an abrupt change in intensity. The mentioned-above edge detectors do not involve the neighborhood of an edge in the process of detecting an edge, while in Cellular Learning Automata, neighborhood plays a considerable role in edge detection. This increases the precision and accuracy of the edge.

This project is carried out with the following objectives:

1. To develop an accurate and relatively fast edge detector using fuzzy sets.
2. To enhance the previously-detected edges with the help of the repeatable and neighborhood-considering nature of Cellular Learning Automata.

In this study, a hybrid method, which not only reduces the noise pixels after edge detection, but also has the minimum number of errors in detecting the noise pixels, will be presented.

1.6 Project Scope

The scopes of this project are as follows:

1. Proper fuzzy membership functions will be chosen carefully to decrease the noise pixel detection as much as possible.
2. A Cellular Learning Automata will be used to weaken the non-edge pixels and strengthen the edge pixels.

In a typical edgy neighborhood, an edge is recognized when the difference between the maximum and minimum gray levels, dependant on the edge strength, is relatively high. However, this can also be the case in noisy environments. Therefore, in order to exclude the mentioned-above cases, we state that the gray-level intensity of the center pixel in an optimal edgy neighborhood is more or less between the minimum and maximum gray levels.

In the second phase of the method, with the help of Cellular Learning Automata, and a set of rules, detected edges of the previous phase are enhanced. In this stage, each cell of the image is considered to be a variable structure learning automaton, which is related to its neighboring automata by a neighborhood radius of 1. By rewarding and punishing the edge and non-edge states of each Learning Automata respectively, the edges are enhanced and the non-edge pixels are weakened.

1.7 Significance of the Project

This project is aimed to propose a robust approach to the edge detection that has been the center of the attention for the past decades in digital image processing. The method presented in this project takes advantage of a recently-proposed soft computing method, namely Fuzzy Sets Theory and Cellular Learning Automata. The project can contribute an evaluation of the mentioned soft computing method in the edge detection.

1.8 Organization of Report

The report for this project consists of four chapters. Chapter 1 presents introduction to project, problem background, objective, scope and significant of this project. Chapter 2 reviews Digital Image Processing, Fuzzy Sets Theory, and Cellular Learning Automata, which plays an important role in the method proposed in this project, classical and soft computing methods for edge detection. Chapter 3 discusses the methodology used in this project. It also explains details of the datasets being used. Chapter 4 presents the results of the proposed method and their comparison with other methods presented in this study. Finally, chapter 5 concludes the study.