

ENHANCED FEATURE SELECTIONS OF ADABOOST TRAINING
FOR FACE DETECTION USING GENETIC ALGORITHM

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To my beloved mother and father

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ABSTRACT

A wide variety of face detection techniques have been proposed over the past decades. Generally, a large number of features are required to be selected for training purposes. Often some of these features are irrelevant and do not contribute directly to the face detection techniques. This creates unnecessary computation and usage of large memory space. In this thesis, features search space has been enlarged by enriching it with seven additional new feature types. With these new feature types and larger search space, Genetic Algorithm (GA) is used within the Adaboost framework, to find sets of features which can provide a better cascade of boosted classifiers with a shorter training time. This technique is referred to as GABOOST for this training part of a face detection system. The GA carries out an evolutionary search to select features which results in a higher number of feature types and sets selected in less time. Experiments on a set of images from BioID face database proved that by using GA to search on a large number of feature types and sets, the proposed technique referred to as GABOOST was able to obtain the cascades of boosted classifiers for the face detection system that can give higher detection rates (94.25%), lower false positive rates (55.94%) and less training time (6.68 hours).

ABSTRAK

Pelbagai teknik pengesanan muka telah diperkenalkan sejak beberapa dekad lalu. Secara umumnya, sejumlah yang besar ciri-ciri diperlukan, bagi tujuan pemilihan untuk kegunaan latihan. Kebiasaannya, sebahagian dari ciri-ciri tersebut adalah tidak berkaitan dan tidak menyumbang secara langsung kepada teknik pengesanan muka. Keadaan ini mengakibatkan pengiraan mesin yang tidak sepatutnya dan penggunaan ruang ingatan mesin yang besar. Di dalam tesis ini, ruang carian bagi ciri-ciri telah diperluaskan dengan cara memperkayakannya dengan penambahan tujuh jenis ciri-ciri yang baru. Dengan adanya penambahan baru jenis ciri-ciri ini, dan ruang carian yang lebih luas, Algoritma Genetik (GA) telah digunakan di dalam lingkungan rangka kerja Adaboost, untuk mencari kumpulan ciri-ciri yang boleh memberi pengkelas teruja melata dengan waktu latihan yang lebih singkat. Teknik ini yang dikenali sebagai GABOOST untuk bahagian latihan bagi sistem pengesanan muka. GA menjalankan pencarian secara evolusi untuk memilih ciri-ciri yang membawa kepada keputusan yang merangkumi bilangan ciri-ciri yang lebih tinggi dan meletakkan pilihan dalam waktu yang lebih singkat. Ujikaji pada set gambar-gambar daripada pangkalan data muka BioID telah membuktikan bahawa dengan menggunakan GA untuk pencarian jenis-jenis dan kumpulan-kumpulan ciri-ciri dalam bilangan yang besar, teknik yang dikenali sebagai GABOOST ini mampu menghasilkan pengkelas teruja melata untuk sistem pengesanan muka yang boleh memberi kadar pengesanan muka yang lebih tinggi (94.25%), kadar ketidakbenaran positif yang lebih rendah (55.94%) dan jumlah penggunaan masa latihan yang kurang (6.68 jam).

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LIST OF ABBREVIATIONS

ACTS	-	Advanced Communications Technologies and Services
BioID	-	Biometric Identification
CCTV	-	Closed-Circuit Camera and Television
CSI	-	Crime Scene Investigation
D1	-	Mahanalobis distance
D2	-	Euclidean distance
EA	-	Evolutionary Algorithm
ES	-	Evolutionary Search
FLD	-	Fisher's Linear Discriminant
GA	-	Genetic Algorithm
HCI	-	Human Computer Interaction
HSV	-	Hue Saturation Value
M2VTS	-	Multi Modal Verification for Teleservices and Security Applications
MA	-	Memetic Algorithm
NN	-	Neural Networks
OpenCV	-	Open-sourced Computer Vision
PCA	-	Principal Component Analysis
PDM	-	Point Distribution Model
RBF	-	Radial Basis Function
SNoW	-	Sparse Network of Winnow
SVM	-	Support Vector Machines
F_k	-	Strong classifier stage k
Gen	-	Generation
H	-	Strong classifier
I	-	Integral Image
N	-	Size of population
T	-	Total Iteration

cr	-	Chromosome
dx	-	Width
dy	-	Height
e	-	Training sample
f	-	Feature
h	-	Weak classifier
i	-	Sequence of weak classifier i
l	-	Number of positives samples
m	-	Number of negatives samples
m	-	Horizontal displacement
n	-	Vertical displacement
p	-	Probability rate
p	-	Parity
x	-	Horizontal displacement
y	-	Vertical displacement
α	-	Weight
β	-	Weight update coefficient
ϑ	-	Threshold
ω	-	Weight
ε	-	Error

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Since the dawn of modern time, humans have been interested in how nature functions, including themselves. This understanding has allowed mankind to reproduce certain forms of nature functions and to extend human limitation. An impressive example is escaping gravitation; (in other words: flying), and now the human race is increasingly interested in reproducing one of the most impressive features of nature: *intelligence*. Researchers are trying to build intelligent machines that have different capabilities. Building machines or robot with the faculty of *vision* is probably one of the most challenging problems humans are trying to solve. The computer vision community started to pay attention to face processing about three decades ago, and it has been widely investigated recently [1 -16] and the list is very far from exhaustive.

For the past decades, many projects have started with the purpose of teaching the machine to recognize human faces and facial expressions. Computer vision has become one of the most challenging fields of study nowadays. The need to extract information from images is enormous. Face detection and extraction as computer-vision tasks have many applications and have direct relevance to the face-recognition and facial expression recognition problem. Face detection is the first stage towards automatic face recognition. Potential application of face detection and extraction are in human-computer interfaces, surveillance systems, census systems and many more. The importance of face detection can be rectified by the issues of public securities such as 9/11 World Trade Center Attack, London and Bali bombings. In major cities

like London or Paris for example, monitoring of people especially in the public places is done by closed-circuit cameras (CCTV) and televisions, which are linked via cables and some other devices (see Figure 1.1). Some specific software and applications are also integrated into these CCTV systems. These systems can also be found in highly monitored location such as casinos, banks and high access level laboratories or buildings.

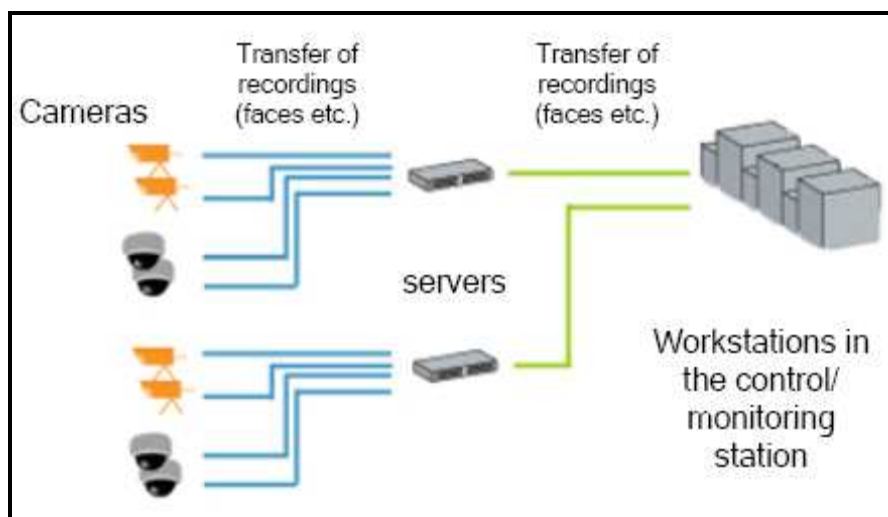


Figure 1.1: Structure of Closed-Circuit Television (CCTV) network

The set-up of CCTV is very simple. Some cameras exist to capture the images including faces of people as they pass through critical locations. Other cameras are able to detect a threat. Usually, the software and the applications in CCTV system will play their roles in detecting any kind of threat. In the case of the authorities who would like to monitor the presence of any suspected individual, CCTV, through its applications will act with a similar principle as a face detection and recognition system. First, a face is detected. Then, it can be tracked to enable important features to be extracted for analysis. The type of features extracted depends strongly on what the system wants to achieve. Features can be obtained for either the recognition of a face (identification) or the recognition of an emotion/expression. Face identification is relevant in retrieving a person's identity and emotion recognition has its contribution in the prevention of crime and calamities for instance. In the latter it concerns aggression detection, unusual or nervous behavioral detection. That is also

why extraction and recognition of facial expression have been a hot topic in the last decade. It is important to note that face detection and facial expression recognition are distinct subjects. In face detection the different expressions are considered as noise, whereas in facial expression recognition the identity is considered as noise. The latter implies that different persons have different neutral faces with different feature shapes (big/small eyes, big/small mouth, etc.).

This research is mainly interested in the face detection problem, which means how to find, based on visual information, all the occurrences of faces regardless of who the person is. Face detection is one of the most challenging problems in computer vision and no solution has been achieved with performance comparable to humans both in precision and speed. High precision is now technically achieved by building systems which learn from a lot of data in the training set in order to minimize errors on the test sets. In most cases, the increase in precision is achieved at the expense of degradation in run-time performance (computational time) and, in major applications, high precision is demanded, and hence dealing with computation to reduce processing time is now a problem with hard constraints.

Finally, the problem of detecting a face is well handled by the intelligence of human beings without us realizing it. This research which is dedicated to discover the magnificent human intelligence is really interesting and will be useful to be implemented for further research in this country. This is because our country is now building towards a more knowledgeable society.

1.2 Objectives of the Thesis

The main objective of this research is to enhance and improve the selection of features from a large feature solutions sets in training of cascade of boosted classifiers for face detection system by using an Evolutionary Algorithm (EA) with the characteristic of Genetic Algorithm (GA). The more specific objectives are described in the following:

1. To investigate various techniques that are able to detect and recognize human faces in images.
2. To investigate and review different techniques such as Haar-based Features, Adaboost algorithm, Neural Networks, Support Vector Machines (SVM), Eigenfaces and GA in face detection and face recognition applications.
3. To investigate and explore the existing Face Detection System using Haar-based Features and Adaboost algorithm specifically in Intel OpenCV software.
4. To implement GA inside the Adaboost framework to select features in building cascade of boosted classifiers.
5. To add seven new feature types in order to increase the quality of feature solutions thus enlarging feature search space.
6. To programme C/C++ source-codes of Intel OpenCV software to implement GA
7. To prepare the database for training and testing purposes of the cascades of boosted classifiers.
8. To analyze and compare the performances of the cascades of boosted classifiers built using GA with the cascade of classifiers built exhaustively.

1.3 Scope Of The Thesis

The scope of this research is described as follows:

1. The system is developed for human face detection and the tracking is based on the technique of Haar-features classifiers and Adaboost algorithm.
2. The system's primary concern is to train a cascade of boosted classifiers by using GA technique in the training part. For the detection part, the system will use this cascade of boosted classifiers that was created previously.
3. The research also concentrates on writing and modifying the program's source codes with the implementation of GA in the face detection system training part.
4. The research focuses on the improvement of the selections of features or weak classifiers which later form cascade of boosted classifiers using GA
5. The research also compares and analyzes the results of the performance of the trained cascades of boosted classifiers with these two different techniques: Evolutionary search with GA and exhaustive search.
6. The research will also analyze the performances of the seven new feature types proposed in the cascade of boosted classifiers training.

1.4 Thesis Contributions

This thesis is expected to make a lot of contributions which can be categorized as below:

1. The main contribution of this thesis is the implementation of GA inside Adaboost framework to select features from larger search space to build cascade of boosted classifiers. The module can be implemented in the

training part of face detection system. The feature selections will be done by GA from a large search space with low computational time as a replacement to the exhaustive features search from small search space with high computational time. Face detection experiments on a single image are conducted to assess the performance in terms of hit rates, missed rates, false positive rates and the training time of different cascade of boosted classifiers built using GA and exhaustive techniques. The results are compared and analyzed.

2. The second contribution is the seven newly proposed feature types to enrich features solutions set with more quality possible features or weak classifiers. The performance of these seven new feature types contributions toward the trained cascades of boosted classifiers are compared and analyzed.
3. Other contributions relate to providing a comprehensive review of existing face detection techniques for gray scale images applications. This is first done by describing the different challenges, then by presenting the most significant work after dividing the field into four categories.
4. The final contribution relates to the GA, by proposing and developing programs related to its structure, operators and parameters.

1.5 Thesis Outline

This thesis is divided into five chapters. Chapter 1 provides the Introduction. Chapter 2 presents some examples of real world applications of face detection and face recognition systems in four different applications categories. The four different categories of these applications describe the different functions of the systems used for face detection system and face recognition system in various requirements, situations and environments. Also present in this chapter is a full review of the

various issues in face detection with four existing categories of face detection techniques, as well as some review of the researches that involve usage of Evolutionary Algorithm in face detection. The four categories: 1) *Knowledge-based methods* are presented first, and they include rule-based methods which encode human knowledge on what should constitute a typical face. Usually, the rules capture the relationships between facial features. 2) *Feature-invariant approaches* are algorithms that aim to find structural features that exist even when the pose, viewpoint or lighting conditions vary, and then use these to locate faces. 3) Then, *template-matching methods* will be described. These usually consist of several standard facial patterns, which are stored to describe the face as a whole or as separate facial features. The correlation between an input image and the stored patterns are computed for detection. 4) The fourth and last category consists of *appearance-based methods*. In contrast to template matching, the models (or templates) used here are learned from a set of training images that are meant to capture the representative variability of facial appearance. Then, these learned models are used for image detection. The use of Evolutionary Algorithms in face detection especially the ones involve the appearance-based methods is also described.

Chapter 3 presents a thorough description of GA to select features in building cascade of boosted classifiers. The description includes the structure of population and chromosomes, initial parameters, selection schemes, crossover and mutations rates, termination criteria and the number of generations of GA. Two types of selection schemes, Ranking Scheme and Roulette Wheel Scheme are explained in detail as both of them are used in this research. A review of the selections of weak classifiers or features to form a set of strong classifiers in various training stages or layers by Adaboost is also presented. Furthermore, the proposed seven new feature types to enrich the quality of feature solutions are also presented in this chapter.

Chapter 4 is dedicated to the experiments done to assess the performance of the trained cascade of boosted classifiers. The main focus of this chapter is to compare and analyze the performance between cascades of boosted classifiers built by using two different selection schemes of GA, Ranking Scheme and Roulette

Wheel Scheme, with large feature solutions set and cascade of boosted classifiers built exhaustively from small feature solutions set. The results of these three different techniques used are shown and analyzed.

Finally, Chapter 5 concludes the thesis with a summary of the work that has been accomplished, a review of the objectives, their fulfillment, and a glimpse at future work to improve the proposed techniques.