FEATURE SELECTION FOR CONTENT-BASED IMAGE RETRIEVAL USING STATISTICAL DISCRIMINANT ANALYSIS

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"To my beloved family, thanks for your loves and support in every effort I did.
To all my friends, thanks for your encouragement and for willing to lend
your hands in this journey of dreams and hope..."

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ABSTRACT

As we known, the very large repository of digital media arise the challenge of various digital search applications. In order to make use of this huge amount of data, effective tools are required for retrieve multimedia information. An image retrieval system is one of the tools that can be used for searching and retrieving images from a large database of digital images. However, there are several challenges and problems need to be considered when applied image retrieval system such as the gap between high-level semantic concept and low-level visual features. This refers to problem of feature selection, which is critical to really solve the gap problem in CBIR. Recently, the most feasible feature selection method is discriminant analysis. Therefore, in this project, we proposed title feature selection in content-based image retrieval using statistical discriminant analysis. In the project, we intended to enhance performance by improve the feature selection process. Besides, we used fuzzy theory in content-based image retrieval to solve the problem of perspective subjectivity of human in image retrieval. The system would be more depends to the human-like and how to response with relevant images that match the concept of current query is always the research question in this project.

ABSTRAK

Seperti yang kita tahu, layan web membenarkan pengkumpulan maklumat yang berbilang besar. Maka, masalah wujud apabila seseorang pengguna ingin mencari gambar yang berkaitan sahaja dalam database yang begitu besar. Oleh sebab itu, teknik yang berkesan adalah diperlukan untuk pengguna dalam pencarian imej atau gambar. Sistem pencarian imej adalah salah satu teknik yang berkeupayaan melaksana pencarian imej dalam database yang berbilang besar. Walaubagaimanapun, terdapat juga beberapa cabaran perlu difikirkan semasa mengguna sistem pencarian imej seperti masalah sistem mengkenalpasti imej yang diperlukan oleh pengguna. Ini disebabkan sistem hanya boleh mencari imej berdasarkan ciri-ciri yang ada dalam suatu imej. Dengan menjalankan proses pengestrakan imej dan proses memkenalpasti kesamaan imej, sistem papar imej yang mempunyai kesamaan yang banyak. Oleh sebab itu, kami bercadang tajuk pengestrakan imej yang bermakna untuk membuat perbandingan dengan imej di database dalam sistem pencarian imej. Projek ini bercadang meningkatkan ketepatan pencarian imej dengan memilih ciri-ciri yang bermakna sahaja untuk membuat perbandingan imej. Kami juga bercadang menggunakan teori Fuzzy supaya memperbaiki masalah pencarian imej berdasarkan keinginan pengguna. Sistem ini adalah lebih mengikut keperluan pengguna dan bagaimana papar imej yang berkaitan dengan keperluan pengguna merupakan soalan pengkajian dalam projeck ini.

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CBIR	-	Content-based Image Retrieval
HSV	-	Hue Saturation Intensity
HSL	-	Hue Saturation Value
CRT	-	Catorade Ray Tube
FS	-	Feature Selection
RF	-	Relevance Feedback
BDA	-	Bias Discriminant Analysis
NDA	-	Nonparametric Discriminant Analysis
SDA	-	Statistical Discriminant Analysis
PBDA	-	Proposed Bias Discriminant Analysis
PNDA	-	Proposed Nonparametric Discriminant Analysis
CBDA	-	Conventional Bias Disciminant Analysis
CNDA	-	Conventional Nonparametric Discriminant Analysis

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CHAPTER 1

INTRODUCTION

1.1 Introduction

With the advances in computer technologies and the advent of the World-Wide Web, there has been an explosion in the amount and complexity of digital data being generated, stored, transmitted, analyzed, and accessed. Much of this information is multimedia in nature, including digital images, video, audio, graphics, and text data. In order to make use of this vast amount of data, efficient and effective techniques to retrieve multimedia information based on its content need to be developed. Among the various media types, images are of prime importance. Thus, this study deals with the feature selection investigation in the relevance feedback learning process to improve the retrieval performance of the region-based image retrieval system.

An image retrieval (Wikipedia, access on 2008) system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. The reason behind research on multimedia systems and content-based image retrieval (CBIR) is the fact that multimedia databases deal with text, audio, video and image data which could provide enormous amount of information and which has affected life style of human for the better.

CBIR is the application of computer vision to the image retrieval problem, that is, the problem of searching for digital images in large databases. Content-based image retrieval (Wikipedia, access on 2008) also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR). "Content-based" means that the search will analyze the actual contents of the image. The term 'content' in this context might refer colors, shapes, textures, or any other information that can be derived from the image itself. There are some types of feature used for image retrieval such as colour retrieval, textual retrieval, shape retrieval and so on. Figure 1.1 show diagram fundamental of content-based image retrieval system.

Relevance feedback (RF) learning is a common approach that gathering semantic information from user interaction and attempts to reduce the semantic gap between high-level concepts and low-level features. Based on feedback, the user labels each image returned in the previous query round as relevant or irrelevant. The retrieval scheme is adjusted and the next set of images is presented to the user for labeling. There are two main RF learning approaches have been used which are distance re-weighting and query modification. Query modification changes the representation of the user's query in a form that is closer to the semantic intent of the user. Distance re-weighting changes the calculation of image to image similarity to strengthen the contribution of relevant image components in regard to the current query.

Feature selection (FS) is the technique used to select and find an optimal subset of relevant features in machine learning. FS technique select only the relevant features and remove most irrelevant or redundant features from the data to improve the performance of learning models. FS technique can be used to improve performance by alleviating the effect of the curse of dimensionality, enhancing generalization capability, speeding up learning process, and also improving model interpretability. In CBIR system, feature selection is a keys step in relevance feedback. Since it ideally to select the optimal feature subset (most important features) and their combinations for describing and querying items in the database to reduce retrieval (time and computational) complexity while maintaining high retrieval performance. In other words, how to select the optimal feature subset to describe a learning system is always regarded as a key technology in domain of machine learning.

Research works had been undertaken in the past decade to design efficient image retrieval techniques from the image or multimedia databases. Although large numbers of indexing and retrieval techniques have been developed, there are still no universally accepted feature extraction, indexing and retrieval techniques available. Despite the shortcomings of current CBIR technology, several image retrieval systems are now available as commercial packages, with demonstration versions of many others available on the Web. Some of the most prominent such as commercial systems and experimental systems. Beside that, a wide range of possible applications for CBIR technology has been identified (Gudivada V N and Raghavan V V, 1995). Some potentially fruitful areas include crime prevention, intellectual property, architectural and engineering design, medical diagnosis, geographical information and remote sensing systems, education and training, web searching.

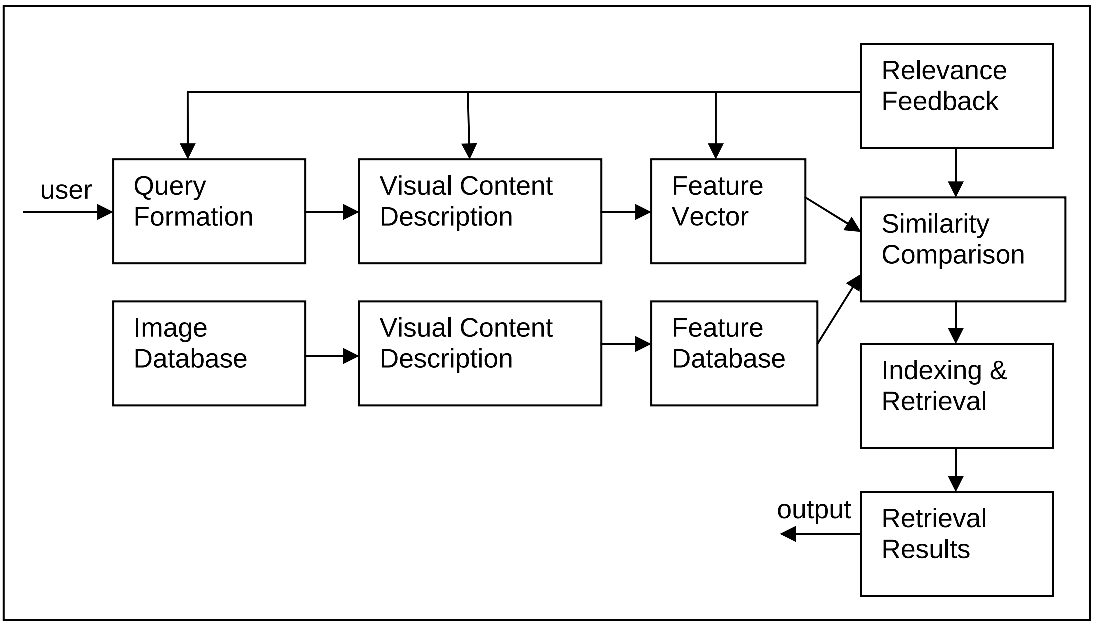


Figure 1.1: Diagram fundamental of content-based image retrieval system (F. Long and H. Zhang)

1.2 Problem Background

Content-based image retrieval (CBIR) has become one of the most active research areas in the past few years. Thus, many visual feature representations have been explored and many CBIR systems have been built. However, there are several problems and challenges need to be consider in attempt to apply CBIR systems.

Firstly, the gap between high-level semantic concept and low-level visual features is great. In the CBIR context, an image is represented by a set of low-level visual features which are the features have no direct correlation with high-level semantic concept. Human prefer to retrieve images according to the “semantic” or “concept” of an image. But, CBIR depends on the absolute distance of image features to retrieve similar images (X. Wang, K. Xie, 2005). Thereby, appear the gap between high-level concepts and low-level features which is the major difficulty that hinders further development of CBIR systems (W. Jiang, G. Er and Q. Dai and J. Gu, 2006). In other sentence, the semantic gap problem is the lack of coincidence between the image representation and the human interpretation for an image (C. Chiu, H. Lin, 2003).

Furthermore, each person has his or her own subjective when thinking about something. So, we know that different user normally may have different subjective perception for same image (C. Chiu, H. Lin, S. Yang, 2003). In such case, the semantic concept and semantic view of same image which user desire to retrieve image may different in perception of user. The question should be considered in this problem is (X. Wang, K. Xie, 2005):

How to reflect subjective perception of user in image retrieval is rather few?

Beside that, the feature extraction of images costs much time due to the large amount of images is the other frequently in current CBIR systems. This results in the slowness of image retrieval (H. Xuelong and Y. Li, 2007). Moreover, CBIR learning has several challenges (W. Jiang, G. Er and Q. Dai and J. Gu, 2006)(F. Li,

Q. Dai, W. Xu, 2006)(W. Jiang. M. Li, H. Zhang, J. Gu, 2004)(J. Yu, Y. Lu, N. Sebe, Q. Tian, 2007) shown as below:

i. Small size of the training set.

   The training samples are the labeled images from the user during each query session, which are very few compared with the feature dimensionality and the size of the database. The CBIR learning algorithm usually encounters severe problems due to the curse of dimensionality.

ii. Intrinsic asymmetry.

   The images labeled to be “relevant” during a query session share some common semantic cues, while the “irrelevant” images are different from the “relevant” ones in different ways. Thus, the “relevant” images are more important for the system to grasp the query concept. This asymmetry requirement makes it necessary to treat the “relevant” and “irrelevant” sets unequally with an emphasis on the “relevant” one.

iii. High Dimensionality.

   In many data analysis application, the observed data have very high dimensionality. Specifically the images in CBIR are represented by image feature vector whose dimensionality ranges from tens to hundreds in most cases.

To really face the fundamental problem of CBIR, two effective learning mechanisms have been proposed which are relevance feedback and region-based image retrieval (RBIR). In general, the RBIR approaches (W. Jiang, G. Er and Q. Dai and J. Gu, 2006) segment images into several regions and retrieve images with low-level features extracted based on these regions. Since region-based features represent images in the object level and better fit the human perception than the global low-level features extracted from the entire image. But, in the RBIR context (F. Li, Q. Dai, W. Xu, 2006), it is difficult to represent the images of the database in a uniform feature space, because the number of regions in different images may not be the same. Thus, not much work has been done to deal with the problem of online feature selection in RBIR systems. Beside, the relevance feedback mechanism is considered as an iterative supervised learning process (W. Jiang, G. Er and Q. Dai and J. Gu, 2006)(F. Li, Q. Dai, W. Xu, 2006) and widely used to improve the performance of CBIR. A CBIR system with relevance feedback can refine the query by users' feedback to improve the retrieval accuracy and performance (C. Chiu, H. Lin, S. Yang, 2003). Query-point moving and weight updating approach are the most two research approaches used in relevance feedback.

Feature selection is a key step in relevance feedback. In other word, how to select a subset of features from a large-scale feature pool and to construct a suitable dissimilarity measure are the key steps in RF (D. Tao, X. Tang, 2004). Thus, problem of feature selection is critical to really solve the fundamental problem in CBIR. There are many existing feature selection techniques such as distribution-based approaches, Kullback-Leibler divergence (K-LD), boosting manner, discriminant analysis (DA) method and others. However, these feature selection techniques remains a challenging problem for image retrieval.

In recent year, there are a lot of discriminant analysis method had been proposed and used as a feature selection method to improve relevance feedback. These methods included multiple discriminant analysis (MDA), biased discriminant analysis (BDA), kernel-biased discriminant analysis (KBDA) and nonparametric Discriminant analysis (NDA). The goal of discriminant analysis is to find a weight matrix such that the distances between the two scatter class matrixes are maximized. However, these methods have their own drawback that must be solved to improve the performance of CBIR. Basic single Gaussian assumption which proposed by MDA and BDA usually doesn't hold, since the few training samples are always scattered in the high dimensional feature space, and their effectiveness will be suffer (W. Jiang. M. Li, H. Zhang, J. Gu, 2004). Moreover, single Gaussian distribution means all positive samples should be similar with similar view angle and similar illumination, which are not the case for CBIR. To overcome the problem of single Gaussian distribution assumption, KBDA had been introduced. But, this kernel-based method has two major drawbacks which is regularization approach is often unstable and it is rely on parameter tuning. Then, NDA had been proposed to solve the problem in MDA, BDA and also KBDA. This approach can only barely match the accuracy performance of KBDA. As a conclusion, many feature selection methods can not satisfy the requirements in CBIR even though there are many method has been apply in content-based image retrieval.

1.3 Problem Statement

In all CBIR systems, the learning process must tackle a fundamental problem which is the gap between high-level semantics and low-level visual features in content-based image retrieval. To really overcome the problem, a problem that must be solved is:

Which features are more representative and suitable for explaining the current query concept?

This question can be refers to the problem of feature selection. By now, the most feasible feature selection method is discriminant analysis. The latest problems faced by statistical discriminant analysis are single Gaussian distribution problem and parameter tuning problem.

In a generic CBIR system, images are represented by image feature vector whose dimensionality ranges are high, which from tens to hundreds in most cases. Also, it is impossible to know what features can be used to capture the unique identity of certain groups of images. Hence, one idea is to employ as many image features as possible in hope that at least one has captured the unique feature of the query image. But, this idea introduces problems because its arrangement may increase the chances of "polluting" the feature element that uniquely identifies the selected image group. This also known as curse of dimensionality and reflect on high dimensionality. To minimize the high dimensionality, a problem must be solved is:

How to select only relevant features to minimize the dimensionality of feature vector?

Beside that, human perception subjectivity is a problem in CBIR which mentioned that different user may has different perception of same images. Thus, the real problem in this point is:

How to reflect the different perception of different user of same image in image retrieval?

This question can be refers to the problem of human thinking. By using relevance feedback in CBIR, we can grasp the current query concept of user.

Therefore, in this study, the improved feature selection method in CBIR system has been proposed to covers the issues with below question:

i. How to reflect human-like and enhance the performance of CBIR system.
ii. Which is the suitable feature selection method can be used to select optimal features in relevance feedback of image retrieval?

Due to current feature selection methods through relevance feedback could not fully representative the query concept from user which make the performance of CBIR is not satisfied. Hence, a better feature selection method is required and the issue of features selection through relevance feedback in CBIR would be highlight or focus in this study.

1.4 Project Aim

The project aims to improve relevance feedback learning process of image retrieval through the feature selection method.

1.5 Objectives

In order to accomplish the purpose of the study, objectives of study have been identified as states below.

1. To investigate the feature selection methods in content-based image retrieval.
2. To enhance the performance of content-based image retrieval by modifying the statistical discriminant analysis feature selection method.
3. To evaluate the performance of improved feature selection method by using standard information retrieval formula such as precision, recall and F1.

1.6 Project Scope

The main focus of this study is on the improved retrieval performance of similarity-based feature selection in content-based image retrieval system. The scopes of this project as follows:

i. The samples consist of 10 images categories which are bus, horse, flower, human, building, food, beach, mountain, dinosaur and elephant.
ii. Both the color feature extraction and shape feature extraction are using in content-based image retrieval.
iii. For color feature extraction, colorspace HSV have been used to extract the color contents of an image.
iv. For shape feature extraction, canny operator has been used to extract the shape contents of an image.
v. Statistic discriminant analysis feature selection methods are used to select optimal features subset.

1.7 Significance of Project

i. The project can significantly improve the performance of feature selection process and the effect of feature selection towards the performance of CBIR system can be shown.

ii. Besides that, this project is important to identify the effectiveness of feature selection in content-based image retrieval. This is because features are more representative for explaining the current query concept than the others.

iii. Furthermore, the effectiveness and efficiency of project is important for future study and can be implemented in real world application.

1.8 Organization of Project

This report consists of five chapters. Chapter 1 presents the introduction of the study, problem background, the hypothesis, project aims, objectives, project scope and significance of project. Next, chapter 2 gives literature reviews on the content-based image retrieval, feature extraction methods, feature selection methods, similarity measurement, relevance feedback, theory of fuzzy logic. Methodology of the study is discusses in chapter 3. Besides, chapter 4 discuss about the experimental result. Lastly, the conclusion and suggestion for future work are explained in chapter 5.

1.9 Summary

In this chapter, the main subjects of the work have been introduced including the problem background, problem statement, objectives, project aims, and scopes, significance of project and organization of project.

CHAPTER 2

LITERATURE REVIEWS

2.1 Introduction

In this chapter, literature review provides some basic concepts for better understanding of the project. The literature review of research is important to identify and understand the study. For this project, some related studies are including as the following:

i. Content-based image retrieval
ii. Image descriptors
iii. Feature selection
iv. Similarity measurement
v. Fuzzy logic theory
vi. Relevance feedback

2.2 Overview of Content-based Image Retrieval

In the last few years, the potential of digital images has increased widely and rapid growth of imaging on the World-Wide Web. The difficulties faced by text-based retrieval became more and more severe. Thus, the searches for solutions in image retrieval problem are becoming widely recognized and increased active area for research and development. Textual information about images can be easily searched using existing technology, but requires humans to personally describe every image in the database (Wikipedia, accessed on 2008). There are many problems and weaknesses (Y. Huang, T. Chang, C. Huang, 2003) exist in conventional image database search based on keywords or text descriptions, which are manually assigned to the images. These problems include the following:

i. Consume much time and labor to annotate keywords or text descriptions to an image.
ii. The semantic views are normally different for each user.
iii. Previous methods did not take the image contents into account.
iv. It lacks the capacity to utilize the human intuition and emotion in retrieving images and leads to an inconsistency of keywords agreements.

In attempt to solve the problems mentioned as above, a new mechanism which is Content-Based Image Retrieval (CBIR) was proposed in the early 1990. CBIR operates on a totally different principle from keyword indexing and aimed at efficient retrieval of relevant image databases based on automatically derived imagery features. In CBIR systems, primitive features characterizing image content such as color, texture and shape, are computed for both stored images and query images. Then, the results of computation are used for matching stored images and query images to retrieve relevant images from an image database. There are several potential uses for CBIR have been showed as the following (Wikipedia, accessed on 2008):

i. Art collections
ii. Photograph archives

iii. Retail catalogs
iv. Medical diagnosis
v. Crime prevention
vi. The military
vii. Intellectual property
viii. Architectural and engineering design
ix. Geographical information and remote sensing systems

According to Wikipedia, CBIR (Wikipedia, accessed on 2008), also known as QBIC and CNVIR which are stand for query by image content and content-based visual information retrieval. In the short form CBIR, the term 'content' in this context might refer to colors, shapes, textures, spatial layout or any other information that can be derived from the image itself. For the "Content-based" means that the search will analyze the actual contents either the colors, shapes or texture of the images. Besides, “image retrieval” means that searching and browsing aims at retrieving images from a large database of digital images. In other sentence to describe CBIR, we can say that content-based image retrieval is a application of computer vision which used visual contents to search images from large scale image databases according to users’ requirement and intuitive.

In the CBIR system, an image is represented by a set of low-level visual features (the content of images refers as color, shape, texture and spatial layout) and the query image which users prefer to retrieve is called high-level semantic concepts. For the diagram fundamental of CBIR system, we show the diagram in (F. Long and H. Zhang) (figure 1.1). The visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with query image. The system then changes the query image into its internal representation of feature vectors. The similarities or distances between the feature vectors of the query image and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search for the image database. Retrieval systems have incorporated users' relevance feedback to modify the retrieval process in order to generate perceptually and semantically more meaningful retrieval results. In overall, the CBIR images retrieval system consists of three main aspects which are feature extraction, retrieving method and system design.

The recently CBIR online learning has three challenges which are small size of the training set, intrinsic asymmetry and fast response requirement. For the first challenge, CBIR learning algorithm usually encounters severe problems due to the curse of dimensionality. This is because training samples are the labeled images from the user during each query session, which are very few compared with the feature dimensionality and the size of the database. For the second challenge, images labeled to be “relevant” during a query session share some common semantic cues, while the “irrelevant” images are different from the “relevant” ones in different ways. Thus, the “relevant” images are more important for the system to grasp the query concept. This asymmetry requirement makes it necessary to treat the “relevant” and “irrelevant” sets unequally with an emphasis on the “relevant” one. For the third challenge, the system should give out the retrieval results within a tolerable amount of time.

The existing problems and challenges in CBIR system due to the features from image data are low level character, which are not enough to describe the high-level semantics. In past decades, many research works had been done to solve and reduce such problem. Relevance Feedback and region-based image retrieval (RBIR) are both methods have been proposed to solve these problems.

2.3 The Existing Content-based Image Retrieval System

There is several various type of existing content-based image retrieval systems had been done in past few years. According to (Remco C, T. Mirela, 2002), a survey to content-based image retrieval system had been done by Remco C. Veltkamp and Mirela Tanase. The survey provides an overview of the functionality of temporary image retrieval systems in terms of technical aspects which are querying, relevance feedback, features, matching measures, indexing data structures, and result presentation. The example of CBIR system that involves in that survey such as ADL (Alexandria Digital Library), CBVQ (Content-Based Visual Query), FIR (Formula Image Retrieval), MARS (Multimedia Analysis and Retrieval System), QBIC (Query By Image Content), WISE (Wavelet Image Search Engine) and others.

2.3.1 FIR (Formula Image Retrieval)

FIR (Remco C, T. Mirela, 2002) is an image retrieval system that used multi resolution wavelet decomposition to represent low-level features shape and color information of images. A query image is submitted to retrieve relevant images from system. There are several steps in the preprocessing system. Firstly, rescale the image to a square thumbnail of 128 x 128 pixels and also transform the thumbnail colors from the RGB space to Luv space. Next, a non-standard two-dimensional Haar wavelet transform is performed on each color channel individually, followed by a truncation of the resulting coefficients. Only the coefficients larger than a threshold are retained and after rounding to integer values they are stored in a feature vector. Distance measurement between two feature vectors is a weighted Euclidean distance, with different weights for each of the resolution levels in the wavelet decomposition.

2.3.2 MARS (Multimedia Analysis and Retrieval System)

MARS (Remco C, T. Mirela, 2002) is the system supports queries on combinations of several visual content low-level features (color, texture, shape) and textual descriptions. Complex queries can be formulated by using Boolean operators. In the system, color is represented by using a 2D histogram over the HS coordinates of the HSV space. Beside, texture is represented by two histograms to measuring the coarseness, directionality of the image and scalar defining the contrast. In order to extract the color or texture layout, the image is divided into 5 x 5 subimages. Color histogram is computed each subimage and vector based on wavelet coefficients is used for subimage texture. The object in an image is segmented out in two phases. First, a k-means clustering method in the color-texture space is applied, and then the regions detected are grouped by an attraction based method.

When users submit a query image, the similarity distance between two color histograms is computed by histogram intersection. The similarity between two textures of the whole image is determined by a weighted sum of the Euclidean distance between contrasts and the histogram intersection distances of the other two components, after a normalization of the three similarities. For computing the texture similarity between two corresponding subimages, the Euclidean distance between the vector representations is used. After similarities have been computed, system will listed and feedback the relevant in order of decreasing similarity. Here, user also can do relevance feedback by re-weighting relevant images.

2.3.3 WISE (Wavelet Image Search Engine)

WISE (Remco C, T. Mirela, 2002) is a system that known as WBIIS which is called Wavelet-Based Image Indexing and Searching. In WISE system, it performs queries on color layout information encoded using Daubechies wavelet transforms. In preprocessing of system, the image is rescaled to 128 x 128 pixels and converted from RGB color space representation to another color space. Querying is done by example, where the query image is either a database image or a hand drawn sketch. The low resolution images or partial images which are images that contain non-specified areas represented by black rectangles also can be query images to the system.

When a user submits a query image, system wills do the matching process that performed in two steps. In the first step, the standard deviations computed for the query image are compared with the corresponding values, stored for each database image. If the acceptance criterion is not achieved, the distance between the two images is set to 1. In the second step, the images that passed the first matching phase are compared to the query using a weighted Euclidean distance between wavelet transform coefficients. After the computation, the first few matches are presented in decreasing similarity order.

2.4 Image Descriptors

Generally, image descriptors also can known as visual content descriptor, are the common methods for extracting content from images. A visual content descriptor (F. Long and H. Zhang) can be either global or local. A global descriptor uses the visual features of the whole image, whereas a local descriptor uses the visual features of regions or objects to describe the image content. A good visual content descriptor should be invariant to the accidental variance introduced by the imaging process (e.g., the variation of the illuminant of the scene).

An image descriptor in (Ricardo, Alex, 2006) represented as a pair, feature vector extraction function and distance function, used for image indexation by similarity. The extracted feature vector subsumes the image properties and the distance function measures the dissimilarity between two images with respect to their properties. There are four kinds of image descriptors which are color descriptor, shape descriptor, texture descriptor and spatial layout descriptor. In the following section, we will discuss these kinds of descriptor and some widely used techniques for extracting color, texture, shape and spatial relationship from images.

2.4.1 Color Descriptors

Color (X. Wang, K. Xie, 2005) is one of the most salient and commonly used visual features in content-based image retrieval. Each pixel of the image (color information) can be represented as points in three-dimensional color spaces. In image retrieval system, commonly used color space include RGB, Munsell, CIE

L*a*b*, CIE L*u*v*, HSV (also known as HSL, HSB), and opponent color space, where a, b, u and v are chromatic components. They allow discrimination between color stimuli and permit similarity judgment and identification (Ricardo, Alex, 2006). The desirable characteristic of choosing an appropriate color space for image retrieval is its uniformity. Uniformity means that two color pairs that are equal in similarity distance in a color space are perceived as equal by viewers.

2.4.1.1 Color Space

There is various type of color space such as RGB, CMY, CIE L*a*b* or CIE L*u*v*, and HSV. We will discuss them as following.

RGB (Red, Green, Blue) color space composed of three color components which are red, green and blue. These components are called "additive primaries" since color in RGB space is produced by adding them together. This kind of color space is widely used in processing digital images. It is device-dependent and perceptually non-uniform.

CMY (Cyan, magenta, Yellow) color space composed of three color components are cyan, magenta, and yellow. These components are called "subtractive primaries" since a color in CMY space is produced through light absorption. CMY is a device-dependent and perceptually non-uniform.

CIE L*a*b* or CIE L*u*v* consist of a luminance or lightness component (L) and two chromatic components a and b or u and v. CIE L*a*b* is designed to deal with subtractive colorant mixtures, while CIE L*u*v* is designed to deal with additive colorant mixtures. Both of them are device independent and considered to be perceptually uniform.

HSV (Hue, Saturation, Value) is a color space which also known as HSL or HSB. HSV consist of three color components which are hue, Saturation (lightness) and value (brightness). The hue is invariant to the changes in illumination and camera direction and hence more suited to object retrieval. This kind of color space is widely used in computer graphics.

2.4.1.2 Color Description Techniques

There are some commonly used color description techniques which are the color histogram, color coherence vector, color correlogram, and color moments. The following shows the discussion of color description techniques.

Color histogram is the most commonly color descriptor techniques used in processing digital image. In image processing, similarity between two color histograms can be measured by computing weighted Euclidean distances. This type of technique is invariant and robust to translation and rotation. In additional, it is easy to compute and effective in characterizing both the global and local distribution of colors in an image. The extraction algorithm can be divided into three steps. Firstly, partition of the color space into cells. Then, associate of each cell to a histogram bin and counting of the number of image pixels of each cell. Lastly, store this count in the corresponding histogram bin. The more bins a color histogram contains, the more discrimination power it has.

However, large numbers of bins will increase the computational and also inappropriate for building efficient indexes for image databases. There are two ways to reduce number of bins. The first is using opponent color space which enables the brightness of the histogram to be down sampled. Second way is using cluster methods to determine the K best colors (histogram bin) in a given space for a given set of images. There are two mainly problem of color histogram technique. The first problem is color histogram does not take the spatial information of pixels into consideration, thus very different images can have similar color distributions. The second problem appears when an image database contains a large number of images, histogram comparison will saturate the discrimination. Joint histogram technique is introduced to solve this problem.

Color Moments descriptor technique was successfully used in many retrieval systems such as QBIC, especially when the image contains just the object. The first order (mean), the second (variance) and the third order (skewness) color moments are used to form the feature vector and have been proved to be efficient and effective in representing color distributions of images. The third-order moment improves the overall retrieval performance compared to using only the first and second order moments but it sometimes makes the feature representation more sensitive to scene changes and thus may decrease the performance. In additional, it is very compact representation and may lower discrimination power since only 9 (three moments for each of the three color components) numbers are used to represent the color content of each image. However, this technique is performs better if it is defined by both the L*u*v* and L*a*b* color spaces.

CCV, Color Coherence Vector is a technique that provides better retrieval results, especially for those images which have either mostly uniform color or mostly texture regions. In CCV, each histogram bin is partitioned into two types which are coherent and incoherent. Coherent if it belongs to a large uniformly-colored region and incoherent if it does not. For both the color histogram and color coherence vector representation, the HSV color space provides better results than CIE L*u*v* and CIE L*a*b* space.

Color correlogram technique characterizes the color distributions of pixels and also the spatial correlation of pairs of colors. The color auto correlogram provides the best retrieval results if compared to the color histogram and CCV but also the most computational expensive due to its high dimensionality.

2.4.2 Shape Descriptors

Shape of objects or regions is an important characteristic and features to identify and distinguish objects in pattern recognition and many used in CBIR. The main objective of shape description in object recognition is to measure geometric attributes of an object, which can be used for classifying, matching, and recognizing objects (Maytham, Cyrus, X. Sun, 2000).

A good shape representation feature for an object should be invariant to translation, rotation and scaling. However, shape features (F. Long and H. Zhang) are usually described after images have been segmented into regions or objects. Since robust and accurate image segmentation is difficult to achieve, the use of shape features for image retrieval has been limited to special applications where objects or regions are readily available.

Shape representation techniques (Maytham, Cyrus, X. Sun, 2000) are divided into two categories which are boundary-based and region-based. Boundary based methods use only the contour or border of the object shape and completely ignore its interior. On the other hand, the region based techniques take into account internal details (the whole shape region) besides the boundary details. These two classes (Ricardo, XF. Alex, 2006), in turn, can be divided into structural (local) and global descriptors which are based on whether the shape is represented as a whole or represented by segments/sections. Another classification categorizes shape description methods into spatial and transform domain techniques which are depending on whether direct measurements of the shape are used or a transformation is applied.

In the shape feature extraction process, the phase starts with an edge detection process. An edge detector like canny, sobel, prewitt and roberts are used to extract all contours in an image. The section 2.4.2.1 shows the edge detection operators and its description. After the first phase, the resulting edges pixels are used as input to a shape descriptor. There is some brief overview of shape descriptors represent in the following section which is table 2.4.2.2. The table shows shape description techniques and its description.

2.4.2.1 Edge Detection Operators

An edge is a property attached to an individual pixel and is calculated from the image function behavior in a neighborhood of the pixel. As mentioned before, there are various type of edge detection such as canny operator, sobel operator and robert operator. These types of operator have different function used in edge detection process. We had discussed them as following.

Canny operator is design to be a standard an optimal edge detector. It takes a gray scale image as an input and produces an image showing the positions of tracked intensity discontinuities as output. However, different scale for the Canny detector is represented by different standard deviations of the Gaussians.

Sobel operator is an operator consists of a pair of 3×3 convolution kernels. This kind of operator is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. Sobel operator is quite popular used to perform 2-D spatial gradient measurement on an image.

Roberts operator consists of a pair of 2×2 convolution kernels. It performs a simple 2-D spatial gradient measurement on an image.

2.4.2.2 Shape Description Techniques

As mentioned in the section above, shape description technique used edge pixels that detect by edge operator as input to describe the shape of an image. There are several types of shape description techniques such as moment invariants, curvature scale space, beam angle statistics, tensor scale descriptor, contour salience and others. We will discuss these types of techniques as following.

In moment invariants technique, each object is represented by a 14-dimensional feature vector. Normally, Euclidean distance is usually used to measure the similarity between different shapes as represented by their moment invariants.

CSS, Curvature Scale Space is used in the MPEG-7 standard and represents a multi scale organization of the curvature zero-crossing points of a planar curve. A special matching algorithm is necessary to compare two CSS descriptors due to the dimension of its feature vectors varies for different contours.

BAS, Beam Angle Statistics is a technique based on the beams (set of lines connecting a contour pixel to the rest of the pixels along the contour) originated from a contour pixel. Angle between a pair of lines is calculated at each contour pixel and shape descriptor is defined by using the third-order statistics. Optimal correspondent subsequence (OCS) algorithm is used to measure the similarity between two BAS moment functions.

TSD, Tensor Scale Descriptor is a technique based on the tensor scale concept. It is obtained by extracting the tensor scale parameters for the original image and then computing the ellipse orientation histogram.

CS, Contour Salience consists of the salience values of salient pixels and their location along the contour, and on a heuristic matching algorithm as distance function. In the process of contour salience, image foresting transform is used to compute the salience values of contour pixels and to locate salience points along the contour by exploiting the relation between a contour and its internal and external skeletons.

2.4.3 Texture Descriptors

Texture descriptor (F. Long and H. Zhang) can be classified into two categories which are structural and statistical. These two categories brief discuss as following:

i. Structural methods
   Including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules.

ii. Statistical methods
   Including Fourier power spectra, co-occurrence matrices, shift-invariant Principal component analysis (SPCA), Tamura feature, Wold decomposition, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and wavelet transform, characterize texture by the statistical distribution of the image intensity.

2.5 Feature Selection

In general, feature selection also known as feature reduction, is the technique used to select a subset of relevant features in machine learning for building robust learning models. The goal of feature selection is to find the optimal feature subspace where the “relevant” and “irrelevant” image sets can be best separated. Feature selection is required cause by set of attributes which are relevant, irrelevant or redundant from the viewpoint of managing a dataset can be huge. Thus, there is necessary reducing the number of attributes by selecting only the relevant and desirable. By removing most irrelevant and redundant features from the data, feature selection helps improve the performance of learning models by alleviating the effect of the curse of dimensionality, enhancing generalization capability, speeding up learning process, and also improving model interpretability.

To achieve significantly higher semantic retrieval performance, many CBIR systems tend to combine low-level features with high-level features that contain perceptual information for human (Esin Guldogan, Moncef Gabbouj, 2006). However, such combinations increase time and memory requirements together with retrieval complexity of feature extraction process. Thus, feature selection (Esin Guldogan, Moncef Gabbouj, 2006) is one of the key challenges for optimization of systems. It ideally to select the optimal feature subset (most important features) and their combinations for describing and querying items in the database to reduce retrieval (time and computational) complexity while maintaining high retrieval performance. Moreover, it helps end-users by automatically associating proper features and weights for a given database. Therefore, feature selection is very important for machine learning due to its potential of speeding up and reducing the costs of the followed stage of concept learning or instance classification, and improving the performance of the learned results. In other words, how to select the optimal feature subset to describe a learning system is always regarded as a key technology in domain of machine learning.

2.5.1 Feature selection methods

There are various type of feature selection method in CBIR have been proposed to obtain optimum feature subspace which can separated well the “relevant” and “irrelevant” image sets. For example, Wei Jiang and Guihua Er (W. Jiang, G. Er and Q. Dai and J. Gu, 2006) have been proposed a boosting manner which incorporates with Real Adaboost framework. Also, Mingjing Li et al. (W. Jiang. M. Li, H. Zhang, J. Gu, 2004) have been proposed a feature selection criterion which is Generalized Feature Contrast Model that based on based on Feature Contrast Model. Others classical feature selection criterion such as the distribution-based approach (e.g., mutual information maximization, MMI and Kullback-Leibler, K-LD) and the discriminant analysis (DA) approach (e.g., multiple discriminant analysis approach, MDA, biased discriminant analysis approach, BDA, symmetric maximized minimal distance in subspace method, SMMS). The table 2.1 shows an overview of feature selection techniques.

Table 2.1: Overview of Feature Selection Techniques

	Techniques	Description
1.	Distribution-based approaches	- It is hardly to well estimate the samples' distribution since few training samples are usually not representative of the whole dataset. Thus, it is not suitable for CBIR online learning. - One of the challenges of CBIR which is asymmetry requirement is not considered in this method.
2.	Conventional Boosting method	- It is not perform well because of the poor generalization ability due to the training-error-based feature selection criterion. - One of the challenges of CBIR which is asymmetry requirement is not considered in this method.
3.	Discriminant Analysis approaches (DA)	- DA approaches generalize linear discriminant analysis and assume that "relevant" images group together as one cluster. - For "irrelevant" images, DA approaches do not assume it in one-cluster distribution. This aimed to meet the asymmetry requirement. - MDA assumes that each "irrelevant" image is from a different class. - BDA assumes that the "irrelevant" images come from an uncertain number of classes. - SMMS selects the feature subspace which is perpendicular to the subspace spanned by the "relevant" samples.
4.	BiasMap (kernel BDA) approach	- Map training samples to a higher dimensional space with the kernel method to solve the one-cluster assumption problem. - It suffers the matrix singularity problem, and the regularization method which adds small quantities to the diagonal of the singular matrices may lead to ill-posed problem.
5.	Boosting manner	- Incrementally learned features into an ensemble classifier with a decreased training error.

		- Can select only feature axes parallel to the original one. - Since there are operations of “max” and “min” in the calculation of the similarity between the “relevant” and “irrelevant” sets, no analytical optimal expression can be found.

2.5.2 Feature Selection method: Discriminant Analysis

There are various type of feature selection discriminant analysis such as biased discriminant analysis (BDA), kernel bias discriminant analysis (KBDA) and nonparametric discriminant analysis (NDA). These kinds of feature selection methods will be discussed in the following section.

Comparison of diverse feature selection methods in content-based image retrieval

Category	Paper	Technique	Advantages	Disadvantages
1. Boosting	Similarity-Based Online Feature Selection In Content-Based Image Retrieval (W. Jiang, G. Er, Q. Dai and J. Gu. 2006)	Boosting feature selection	1. The feature selection that implemented in a boosting manner select the most representative feature axes for the current query concept. 2. The approach has been improve the retrieval performance and save the processing time if compare with other approaches like MDA and BDA.	1. Can select only feature axes parallel to the original one. 2. Since there are operations of “max” and “min” in the calculation of the similarity between the “relevant” and “irrelevant” sets, no analytical optimal expression can be found.
	Kullback-Leibler Boosting (C. Liu and H.Y. Shum. 2003)	Kullback-Leibler Analysis (KLA) or KL Boosting	1. The coefficients to combine the histogram divergences are learnt by minimizing the recognition error once a new feature is added to the classifier.	1. The codebook size is usually quite large. 2. In each iteration step of the boosting process, a new optimal feature axis would be selected, so the computational complexity of sequential 1D optimization is too high to satisfy the requirement of fast response in CBIR.

2. Mutual Information	Improved Similarity-Based Online Feature Selection In Region-Based Image Retrieval (F. Li, Q. dai, W. Xu. 2006)	Mutual Information	1. Can select not only feature axes parallel to the original one, but can also select combined feature axes effectively. 2. Determine codebook size effectively.	1. The computational load will become heavier due to the number of axes increase. 2. The computational load can not reduce effectively.
3. Discriminant Analysis	Small Sample Learning during Multimedia Retrieval using BiasMap (S. Xiang, Thomas S. Huang. 2001)	Kernel Bias Discriminant Analysis (KBDA)	1. The KBDA has been overcome the single Gaussian distribution assumption (which means all positive samples should be similar with similar view angle, similar illumination, etc.) in bias discriminant analysis. 2. The approach is designed to address the asymmetry between the positive and negative data sample. 3. It strikes a critical balance between informative and discriminative learning based on a limited number of training samples.	1. The regularization approach as used for avoiding matrix singularity problem is often unstable. 2. The parameters used in the kernel function require to be manually tuned for maximum retrieval accuracy. 3. Kernel-based learning has to rely on parameter tuning, which the kernel parameter tuning makes the online learning unfeasible.

	Nonparametric Discriminant Analysis is Relevance Feedback for Content-based Image Retrieval (D. Tao, X. Tang. 2004)	Nonparametric Discriminant Analysis (NDA)	1. The kernel transformation is not required in this approach. 2. The NDA approach has been proposed to overcome the problem of single Gaussian distribution assumption in BDA and the parameter tuning problem in KBDA. 3. It was used the three method which are regularization method, null-space method, and full-space method to solve sss (small, sample, size) problem.	1. This approach can only barely match the accuracy performance of KBDA.
	A Feature Selection Framework for Small Sampling Data in Content-based Image Retrieval System (K. Chung, C. Fung, K. Wong. 2005)	Statistical Discriminant Analysis (SDA)	1. This approach attempt to maximize the distances between different labeled data so that can select only the important features for performing the similarity measurement in the next iteration of image retrieval.	1. The Discriminant analysis approach may not be able to meet the asymmetry requirement due to one-cluster assumption for the negative labeled data.

			2. It provides a framework with a clear indication of the overlapping of the data.	

2.5.2.1 Statistical Discriminant Analysis

Statistical discriminant analysis (SDA) (K. Chung , C. Chun, W. Kok, 2005) is a pattern recognition approach that attempts to maximize the distances between different labeled data samples. A weight matrix can be finding by using the discriminant analysis such that the distance between the two scatter class matrixes are maximized. In paper (K. Chung , C. Chun, W. Kok, 2005), K. Chung, C. Fung and K. Wong had been analyzed the discriminant ability of each feature separately by using ratio formula as follow.

$$ratio = \frac{\sum_{n=1}^{N_y} d'_n \Big/ N_y}{\max(d_p)}$$

$$d'_n = \begin{cases} \max(d_p), d_n > \max(d_p) \\ d_n, d_n \le \max(d_p) \end{cases}$$

Where N_y = Total number of negative samples.

d_p = Distance of the positive label image from the positive centroid.

d_n = Distance of the negative label image from the positive centroid.

The formula provides a framework with a clear indication of the overlapping of the data. The KBDA and NDA methods had been implemented with and without feature selection framework. The result show the feature selection approach is more superior without feature selection framework when the training samples are small.

2.5.2.1.1 Biased Discriminant Analysis

The biased discriminant analysis (BDA) is an approach tries to find the subspace to discriminate the positive (relevant images that concerned by user) and negatives (irrelevant images) samples. To do this, BDA minimize the variance of the positive samples. Then, it maximizes the distance between the center of the positive feedbacks and all negatives feedback. There are occurs a problem in biased discriminant analysis approach, which is it assumes all positive samples from a single Gaussian distribution, which means all positive samples should be similar view angle, similar illumination.

2.5.2.1.2 Kernel Bias Discriminant Analysis

Kernel bias discriminant analysis (KBDA) (X. zhou, Thomas, 2001), is the kernel version of the biased discriminant analysis. This kernel-based approach had been introduced to eliminate the problem on BDA, which is assumes Gaussian distribution on positive examples. Besides, it was used to perform non-linear discrimination for non-linear data distributions.

However, the approach has been created a few disadvantages. The kernel-based learning has to rely on parameter tuning, which makes the online learning unfeasible. In (K. Chung , C. Chun, W. Kok, 2005), the authors mentioned that there are two drawbacks on this approach. Firstly, the regularization method as used by (X. zhou, Thomas, 2001) for avoiding matrix singularity problem is often unstable. To solve this problem, Tao and Tang (D. Tao, X. Tang, 2004) have been proposed nonparametric discriminant analysis method. The second problem is parameters used in the kernel function require to be manually tuned for maximum retrieval accuracy. This problem was suggested solved by maximizing the discriminant ratio of inter and intra covariant matrix in (L. Wang, K. Chan, P. Xue, 2005).

2.5.2.1.3 Nonparametric Discriminant Analysis

The nonparametric discriminant analysis (NDA) is an approach to finds the optimal feature set to maximize the margin between all positive feedbacks and all negative feedbacks in the input feature space (L. Wang, K. Chan, P. Xue, 2005).

NDA has an advantage which is the approach does not require all positive samples to be based on a single Gaussian distribution. In additional, it was used to solve the problem in kernel-bias discriminant analysis, Tao and Tang (L. Wang, K. Chan, P. Xue, 2005) have been reported a full rank null-space method for calculating the eigenvalues and vectors of inter and intra covariant scatter matrix. The sss (small-sample-size) problems also can be solving by three method which are regularization method, null-space method and full-space method.

2.5.3 Technologies for Feature Selection

The evaluation of performance feature subset may be in different ways. Therefore, the results were different in differ models of feature selection. There are two main categories or two different models for feature selection which are Filter Model and Wrapper Model. These two models will be discussed as following.

i. Filter Model of Feature Selection

The Filter Model regards the process of feature selection as a pretreatment on a learning system in practice which usually prefers to mini-feature biased subset, in other words, which usually tries to describe the target concepts of a learning system by features as few as possible. The figure 2.1 shows Filter Model

ii. Wrapper Model of Feature Selection

The Wrapper Model is centered on a specific machine-learning algorithm. It evaluates a feature subset according to its learning accuracy, which is estimated with the help of the central learning algorithm (C. Chiu, H. Lin, S. Yang, 2003). The figure 2.2 shows Wrapper Model.

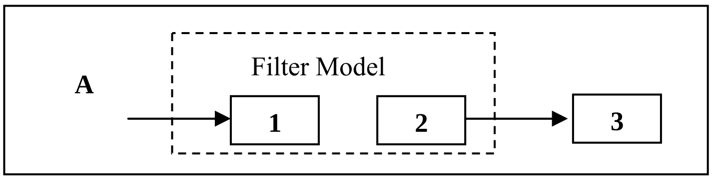


Figure 2.1: Filter Model

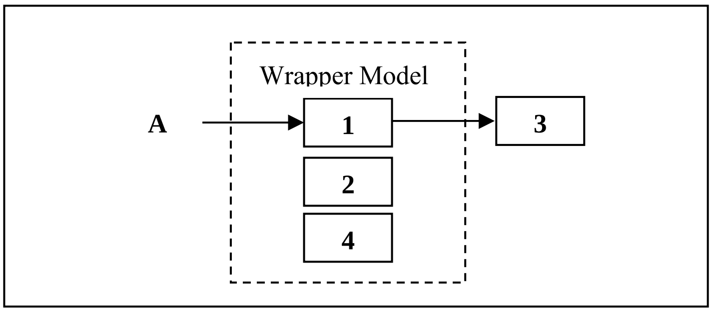


Figure 2.2: Wrapper Model

In the figure,

‘A’ represented as inputted candidate feature set,

‘B’ represented as outputted feature subset,

‘1’ represented as feature subset generator,

‘2’ represented as feature subset evaluator,

‘3’ represented as followed machine learning algorithm,

‘4’ represented as central machine learning algorithm.

Table 2.2: Advantages and Disadvantages of Filter Model

Advantages	Disadvantages
i. There is no machine-learning process while selecting feature. ii. It easier to realize. iii. Its time consumption is also absolutely much lower than Wrapper Model.	i. Filter model based algorithm is not assured of, because it usually evaluates a feature subset only based on the mini-feature biased principle, but without considering the accuracy of learning results. ii. The evaluation function usually biased in value to some extent, so they cannot objectively evaluate the importance of features.

The table 2.2 shows advantages and disadvantages of filter model. The Wrapper Model may be superior to Filter Model in performance of the learning results. But most of the reported algorithms adopt Filter Model rather than Wrapper Model. There have three reasons as follows:

i. The learning process is so time expensive than the time taken by a Wrapper Model based algorithm is even intolerant.
ii. To some extremely large sized systems, the Wrapper Model is impractical, whose scale should be diminished before a machine-learning algorithm can be applied.
iii. The evaluation results of Wrapper Model heavily depend on the central machine-learning algorithm.

2.6 Similarity Measurement

Similarity is quantity that reflects the strength of relationship between two objects or two features. In CBIR system, one of the important parts of system is the similarities measurement between a query image and the images in a database. The result of image retrieval is a list of images ranked by images similarities with the query image. How to calculate the similarities measure effectively always the issue to be considered while in choosing the technique to implement it. Since similarity measures will affect retrieval performances of a content-based image retrieval system significantly. Many similarity measures have been developed for image retrieval based on empirical estimates of the distribution of features in recent years (F. Long and H. Zhang). There are some commonly used similarity measures shows as following section.

2.6.1 Fuzzy Feature Contrast Model

In the 1977, the famous feature contrast model (FCM) has been proposed by Tversky as a psychological similarity measurement between two objects (W. Jiang, G. Er and Q. Dai and J. Gu, 2006). Instead of considering stimuli as points in a metric space, Tversky characterized them as sets of binary features. In other words, a stimulus *a* is characterized by the set A of features that the stimulus possesses. Let *a*, *b* be two stimuli, *A* and *B* the respective sets of features, and s(a, b) a measure of the similarity between *a* and *b*. Tversky's theory is based on the following assumptions (S. Santini and R. Jain, 1999):

$$
\begin{aligned}
&Matching : s(a,b) - F(A \cap B, A - B, B - A) \\
&Monotonicity : s(a,b) > s(a,c) whenever \\
&A \cap C \subseteq A \cap B, A - B \subseteq A - C, B - A \subseteq C - A
\end{aligned}
$$

A function that satisfies matching and monotonicity is called a matching function. Let the expression F(X, Y, Z) be defined whenever there are A, B such that X = A ∩ B,
Y = A - B, Z = B - A. Define V ≈ W if there is exist X, Y, Z such that one or more of the following holds (W. Jiang, G. Er and Q. Dai and J. Gu, 2006):

$$
\begin{aligned}
&F(V,Y,Z) - F(W,Y,Z) \\
&F(X,V,Z) - F(X,W,Z) \\
&F(X,Y,V) - F(X,Y,W)
\end{aligned}
$$

The pairs of stimuli *(a, b)* and *(c, d)* are said to agree on one (two, three) components whenever one of the following hold (W. Jiang, G. Er and Q. Dai and J. Gu, 2006):

$$
\begin{aligned}
&(A \cap B) \approx (C \cap D) \\
&(A - B) \approx (C - D) \\
&(B - A) \approx (D - C)
\end{aligned}
$$

Based on these definitions, Tversky postulates a third property of the similarity measure (S. Santini and R. Jain, 1999):

Independence:

Suppose the pairs *(a, b)* and *(c, d)*, as well as the pairs *(a', b')* and *(c', d')*, agree on the same two components, while the pairs *(a, b)* and *(a', b')*, as well as *(c, d)* and *(c', d')*, agree on the remaining (third) component.

Then:

$s(a,b) \geq s(a',b') \Leftrightarrow s(c,d) \geq s(c',d')$

The main result of Tversky's paper is the following representation theorem:

Theorem 1: Let s be a similarity for which matching, monotonicity and independence hold. Then, there are a similarity function S and a nonnegative function f and two constants $\alpha, \beta \geq 0$ such that, for all stimuli a, b, c, d:

- $S(a,b) \geq S(c,d) \Leftrightarrow s(a,b) \geq s(c,d)$,
- $S(a,b) - f(A \cap B) - \alpha f(A - B) - \beta f(B - A)$.

This result implies that any similarity ordering that satisfies matching, monotonicity, and independence can be obtained using a linear combination (contrast) of a function of the common features (A ∩ B) and of the distinctive features (A - B and B - A.) This representation is called the contrast model (W. Jiang, G. Er and Q. Dai and J. Gu, 2006).

There are exist one serious problem for the adoption of the feature contrast model of Tversky's theory in visual information systems. The problem is its characterization of features. This is because each stimulus in theory Tversky is characterized by the presence or absence of features. This convention forces to adopt complex mechanisms for the representation of numerical quantities. In computer vision, the assumption of binary features would appear the problem of evaluating logic predicates based on some continuous and noisy measurements. The use of fuzzy logic will allow extending Tversky's results to situations in which modeling by enumeration of features is impossible or problematic. Thus, fuzzy feature contrast model (FFCM) was generated.

In paper (W. Jiang, G. Er and Q. Dai and J. Gu, 2006), the FFCM is specifically used to calculate the asymmetric similarity between images. In assumption, *a* and *b* are represented by two fuzzy feature vectors A = [$A_{1,\ldots,}A_d$] and B = [$B_{1,\ldots,}B_d$]. FFCM defines operators ∩ and - in a traditional way as

$$A \cap B = [\min\{A1, B1\}, ..., \min\{Ad, Bd\}$$
$$A - B = [\max\{A1 - B1, 0\}, ..., \max\{Ad - Bd, 0\}$$

Then, the similarity between a and b can be calculates by generalizing the definition shown as followed:

$$\widetilde{S}(a,b) = f(A \cap B) - \alpha f(A - B) - \beta f(B - A)$$

and as definition shown as followed:

$$\widetilde{S}(a,b) = \sum_{i=1}^{d} (\min\{A_i, B_i\} - \alpha \max\{A_i - B_i, 0\} - \beta \max\{B_i - A_i, 0\})$$

2.6.2 Unified Feature Matching

Unified feature matching (UFM) is a fuzzy logic approach can be used for region-based image retrieval. For example, Y. Chen and James Z. Wang (Y. Chen and James, 2002) has been used UFM measurement to calculate the image-to-image similarity based on region-based features. In additional, W. Jiang et. al. (W. Jiang, G. Er and Q. Dai and J. Gu, 2006) has been proposed UFM measurement to calculate the similarity between the “relevant” and “irrelevant” image sets.

In the paper (Y. Chen and James, 2002), describe the unified feature matching scheme which characterizes the resemblance between images by integrating properties of all regions in the images. Based upon fuzzy feature representation of images, characterizing the similarity between images becomes an issue of finding similarities fuzzy feature. In other words, an image is represented by a set of segmented regions in this retrieval system. Each of which is characterized by a fuzzy feature (fuzzy set) reflecting color, texture, and shape properties. So, an image is associated with a family of fuzzy features corresponding to regions and UFM measure integrates properties of all the regions in the images. In this paper, there are several step of concept by using UFM show as following:

i. Firstly, an introduction of fuzzy similarity measure for two regions has been proposed in the paper.
ii. Next, the result is extended to construct a similarity vector which ncludes the region-level similarities for all regions in two images.
iii. Then, a similarity vector pair is defined to illustrate the resemblance between two images.
iv. Finally, the UFM measure maps a similarity vector pair to a scalar quantity, within the real interval [0,1], which quantifies the overall image-to-image similarity.

2.7 Fuzzy Classification

2.7.1 Fuzzy Logic

In recent years, the number and variety of applications of fuzzy logic have increased significantly. Fuzzy logic has two different meanings. In a narrow sense, fuzzy logic is a logical system, which is an extension of multivalued logic. However, in a wider sense fuzzy logic (FL) is almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects with unsharp boundaries in which membership is a matter of degree.

The major steps involved in developing fuzzy logic system are fuzzification, rule evaluation, aggregation of the rule output and defuzzification. Following show the example of fuzzy logic system step by step.

Step 1 : Fuzzification

Firstly, take the crisp inputs and determine the degree to which these inputs belong to each of the appropriate fuzzy sets.

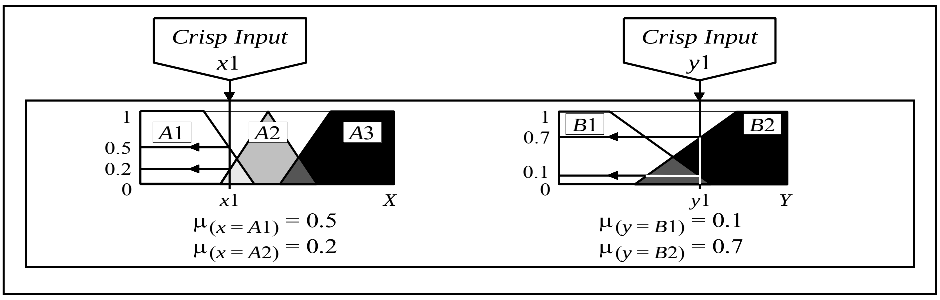


Figure 2.3: Fuzzification

Step 2 : Rule Evaluation

The second step is to take the fuzzified inputs in degree form, and apply them to the antecedents of the fuzzy rules. If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value) is then applied to the consequent membership function. To evaluate the disjunction of the rule antecedents, we use the OR fuzzy operation

$$\mu A \cup B(x) = max\ [\mu A(x),\ \mu B(x)]$$

while to evaluate the conjunction of the antecedents, apply AND fuzzy operation intersection

$$\mu A \cap B(x) = min\ [\mu A(x),\ \mu B(x)]$$

Step 3 : Aggregation of the rule outputs

Aggregation is the process of unification of the outputs of all rules. We take the membership functions of all rule consequents previously clipped or scaled and combine them into a single fuzzy set. The input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable.

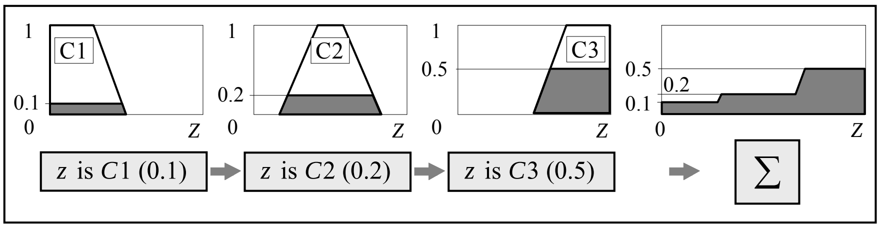


Figure 2.4: Aggregation of rules output

Step 4 : Deffuzification

The process of the deffuzification is to change the aggregate output fuzzy set in crisp number. The most popular deffuzification method is centroid technique. This method is finds a point representing the centre of gravity (COG) of the fuzzy set. A reasonable estimate can be obtained by calculating it over a sample of points.

$$COG = \frac{(0+10+20)\times 0.1+(30+40+50+60)\times 0.2+(70+80+90+100)\times 0.5}{0.1+0.1+0.1+0.2+0.2+0.2+0.2+0.5+0.5+0.5+0.5} = 67.4$$

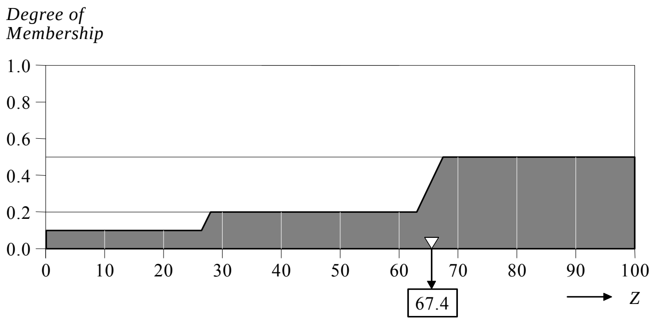


Figure 2.5: Deffuzification

2.7.2 Fuzzy Inference System

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy theory of fuzzy sets. Fuzzy inference system (FIS) has three main processes which are define membership functions, fuzzy logic operator and fuzzy if-then rules. There are two known types of FIS, which are Mamdani-style inference and Sugeno-style inference.

i. Mamdani FIS
   - The most commonly seen fuzzy methodology.
   - It is widely accepted for capturing expert knowledge.
   - It allow to describe the expertise in more intuitive, more human-like manner.

ii. Sugeno FIS
   - It is computationally effective.
   - It works well with optimization and adaptive techniques.

2.8 Relevance Feedback

Relevance Feedback (H. Zhang, 2003) in CBIR is a supervised active learning technique aims to improve the effectiveness of information systems by bridging the gap between high level semantic and low level visual features. The key issue in relevance feedback is how to incorporate relevant and irrelevant images to refine the query and to adjust the similarity measure. Different human has different perception to same images. Thus, relevance feedback was introduced to solve the semantic problem. Relevance feedback (W. Jiang, G. Er and Q. Dai and J. Gu, 2006) is used in CBIR systems for two reasons as following:

i. There can be a big gap between high level concepts perceived by the user and low level features that are used in the system.

ii. Human perception of similarity is subjective.

The approaches of relevance feedback can be classified into two main approaches, which are query-point moving approach and weight updating approach.

i. Query-point moving approach
   This approach tries to improve the estimate (in terms of low level features) of the ideal query point by moving the current query point by a certain amount based on user feedback. Some researchers

generate pseudo document vectors from image feature vectors. Other researchers estimate the distribution of the relevant samples based on a parametric or nonparametric estimator.

ii. Weight updating approach

This approach is a refinement method based on modifying the weights or parameters used in the computation of similarity based on the user's feedback. Choi et al. (Y. Choi, D. Kim, and R. Krishnapuram, 2000) have described a method to learn the similarity measure based on the Choquet integral and show that it generally outperforms the weighted average method.

The process of relevance feedback is given as following:

1. User give a query image, CBIR system first retrieves a list of ranked images according to a predefined similarity metrics.
2. Next, user marks the retrieved images as relevant (positive) or irrelevant (negative) to the query image.
3. The system will refine the retrieval results based on the feedback and present a new list of images to the user.

2.9 Summary

There are many existing CBIR system has been built in past decade. System image retrieval build for satisfy the requirement of user when they desire to find some relevant images. For content-based image retrieval, user request to system with an image query. By using the visual content in image query, system searches the most relevant images to user. In attempt design an ideal CBIR system, many researchers have been built several systems that can solve some problems and challenges in the field.

From previous research work, we can know that the gap between high level semantic and low level visual features is the main problem that faces by CBIR system. Many solutions have been proposed to improve performance of system such as using the better feature selection method and a good classifier. In this project, feature selection is supposed to be the best way to enhance the performance of CBIR system. The research methodology will be discussed detail in next chapter about how the proposed project can be solving the limitations.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, we propose and discuss a method for this project. In the section 3.2, we will be showed and discussed the overview of research methodology. Next, we will discuss the detail of main steps involve in the research methodology. The main steps are data collection, feature extraction, image segmentation, feature selection, similarity measurement, fuzzy classification and relevance feedback.

3.2 Overview Proposed Methodology

The main problem that hinders further improvement for current CBIR system is the gap between low-level visual features and high-level semantic concepts. In (W. Jiang, G. Er and Q. Dai and J. Gu, 2006), W. Jiang et. al. have been emphasized that problem of online feature selection is the critical to really bridge the gap problem. Also, in (K. Chung , C. Chun, W. Kok, 2005), K. Chung et. al. have been proposed a relevance feedback framework in feature selection method to select only the relevant images in iteration image retrieval cycle. Thus, to line the visual features and semantic concept, we proposed the related research methodology that suppose can improve the feature selection process. Proposed research methodology in system view shown in Figure 3.1.

In preprocessing stage for the proposed CBIR system, features of images data that store in the image database have been extracted and form in the features vector. Then, segment the features vector through segmentation process. Finally, the features vector will be store in feature database.

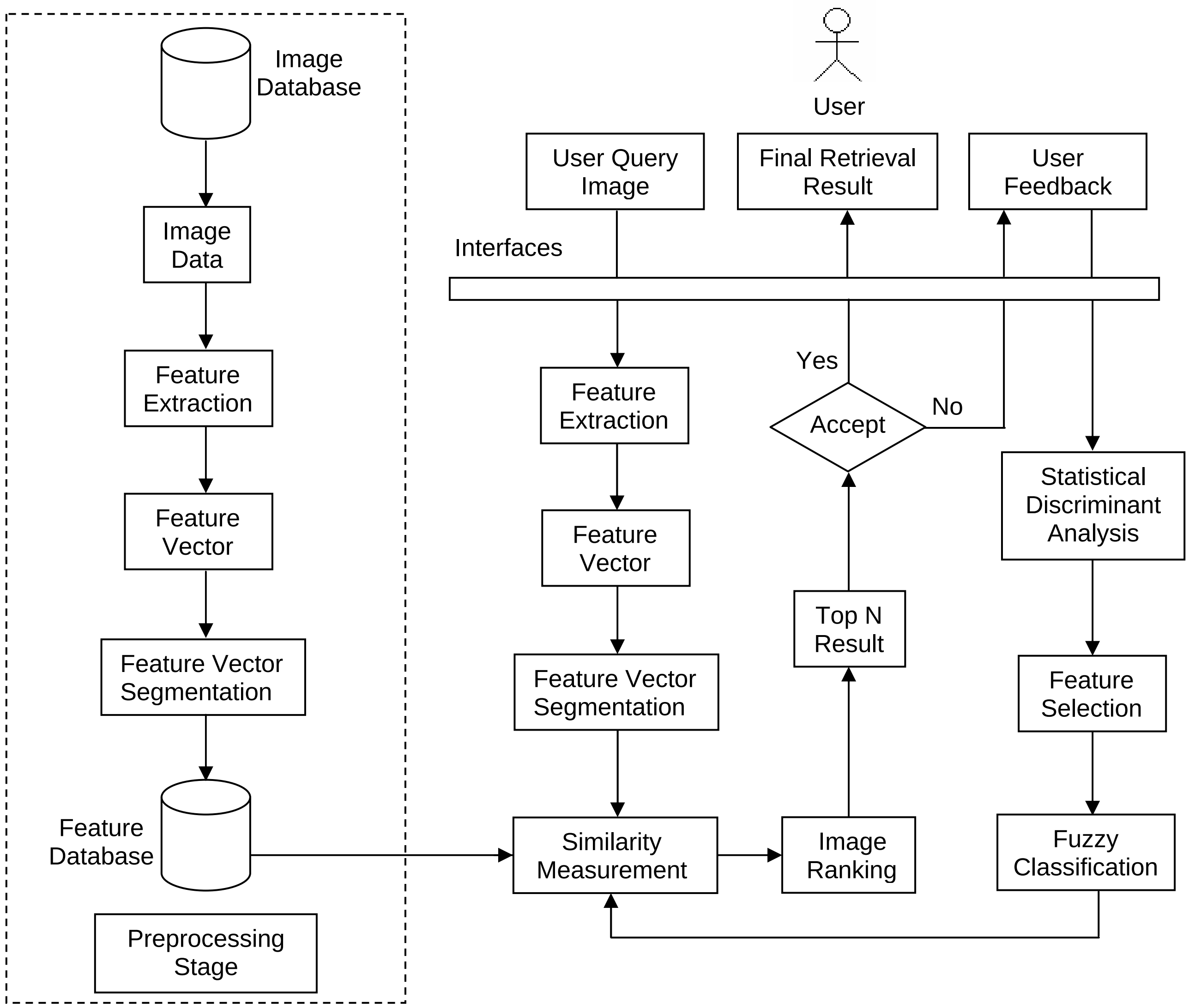


Figure 3.1: The Research Methodology in System View

When a user upload the image query and submit to the CBIR system, the visual features of image query will be extracted and form in feature vectors. Then, matching function has been applied, which measures the similarity between image query and images in database. In this module, the similarity of images can be measured by calculated distance of weight features image query and images database. After that, those relevant images will be sorted by process of image ranking which the most similar image should be the highest ranking. But, only the top N (N is a constant number that refer to the number of images retrieval, e.g. N=20) result will be display to the user through interfaces. If the user did not satisfied the result of image retrieval, she or he can doing the iteration of relevance feedback by labeling images retrieval as "relevant" (positive), "irrelevant" (negative) images or not sure images. User submits the labeling image to system, and then system will be do response to user. System performed feature extraction and the proposed features selection method using the labeled images done by user. The iteration of relevance feedback will be stop while the images retrieval result was satisfied and accepted by user.

From the Figure 3.1, we have showed the whole idea of how the implementations of research methodology in system view. Next, we will show the proposed research methodology in research view in Figure 3.2 for more clearly understanding. According to the proposed research methodology, the main steps will be taken in this methodology as following:

i. Data collection
ii. Feature extraction
iii. Feature selection
iv. Similarity measurement
v. Relevance Feedback

Table 3.1 shows the description of main process involved in the research methodology.

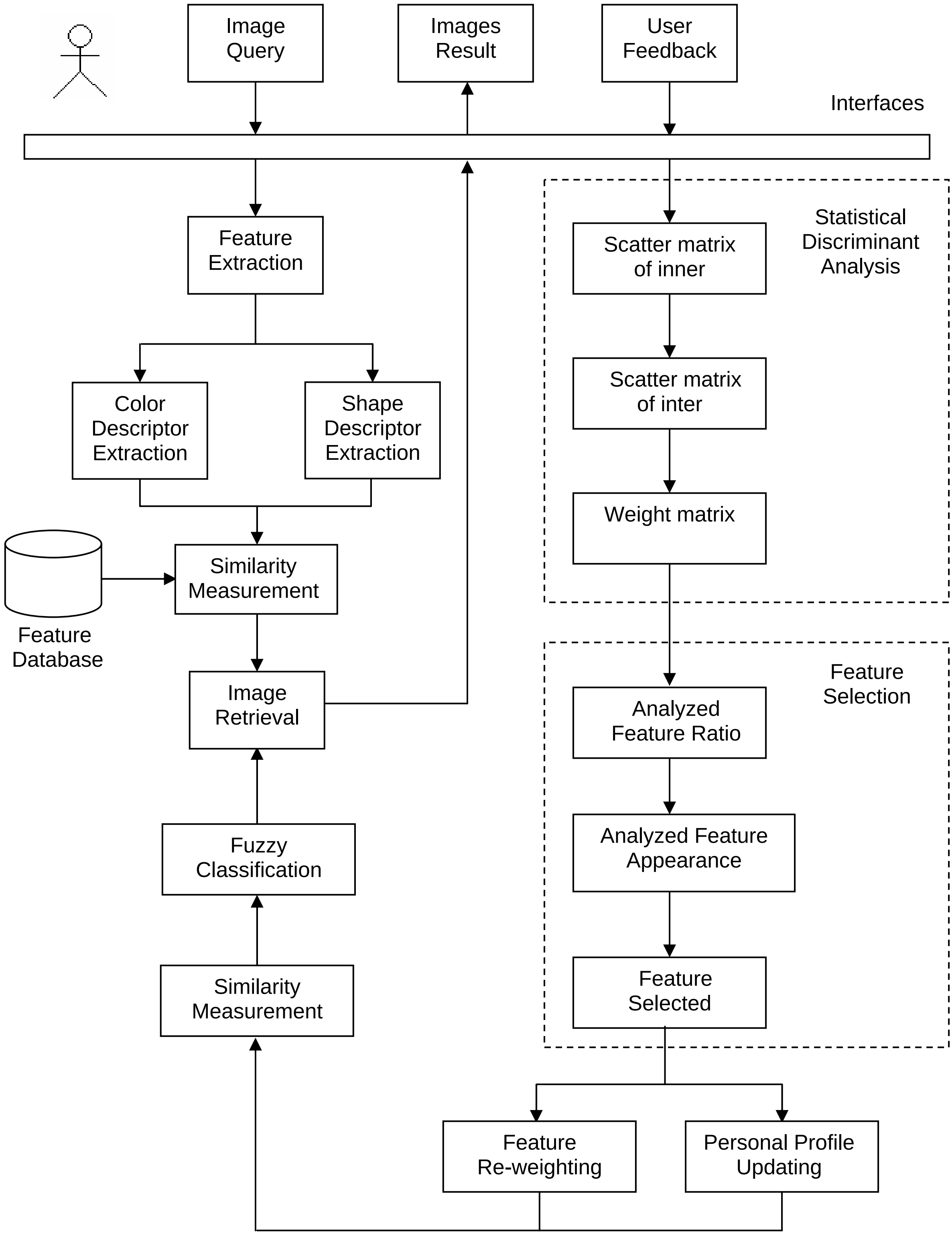


Figure 3.2: The Research Methodology in Research View

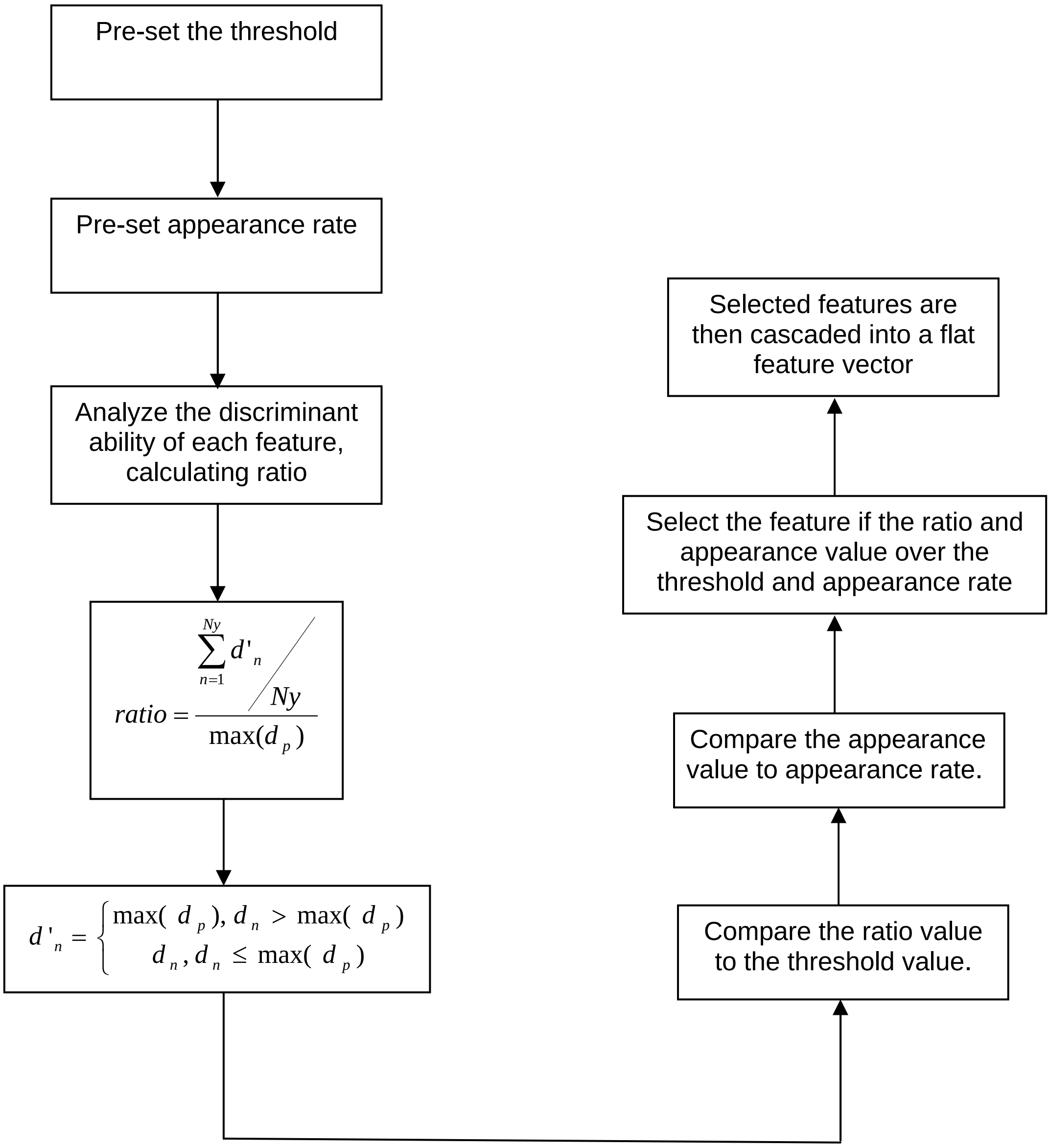


Figure 3.3: The Modeling of Feature Selection

Table 3.1: The Main process Description in Research Methodology

	Modules	Objective	Research Question	Process
1	Data Collection	To collect data which include positive and negative images data.	What types of images data are best to represent the image retrieval and how to collect it?	Collect positive and negative images data.
2	Feature Extraction	To extract the color features and shape features.	What are the most suitable feature descriptors that can represent colors and shapes feature?	- Select suitable color space to represent color of an image. - Using edge operator to represent shape of an image.
3	Feature Selection	To improved feature selection method.	How to improve feature selection process?	Feature selection and producing improved feature selection process.
4	Similarity Measurement	To find the most similar images by calculate the similarity between image query and images database.	What type of similarity measure method that more suitable to used?	Determine matching function and calculate the distance weight of feature vector.
5	Classification	To classify the result of similarity	What type of classifier adapt to used in CBIR	Determine the classes for each result similarity.
6	Relevance Feedback	To grasp the user's perception subjectivity.	How the learning relevance feedback can be implementing more human-like?	Performed iteration relevance feedback by user label images as positive or negative.

3.3 Data Collection

As we know, CBIR system aims at allow users to search images related to the image query that users uploaded. The system will be started search the relevant images in the database while the users upload the image query and request to the system. For the module data collection, data means the images data which need to collect in preprocessing stage. The collected images data are stored in the images database.

In this project, the various types of images data have been collected. The images data will then label as “relevant” images and “irrelevant” images in different experiment used. For example, if the image query of CBIR system only focuses on the kind of vehicles, then all vehicles images are the images data which called “relevant” or positive. Besides, the rest of images data are know as “irrelevant” or negative images.

3.4 Feature Extraction

Feature extraction is a fundamental component in a CBIR system. For this module, actually, occur in both preprocessing stage and the time when users do request to system with an image query. The objective of feature extraction is to automatically determine a set of features to describe each image. In this step, the features of images data are extracted from images. For this project, we intend to extract two kinds of features images which are color information and also shape information. These features are used to classify features database into segment. After the shape and color features extraction module, the features have been form in feature vectors which represent each color pixel and edge pixel. The following section will discuss about the step in color images extraction and shape images extraction.

3.4.1 Color Images Descriptor

As mentioned in previous section, we need to find out the suitable color space and color images description technique. There are many existing colors space are used in current CBIR system to represent color such as RGB, CMY, CIE L*a*b*, HSV (also known as HSL, HSB) and others. Among them, HSV color space is selected to use in the project. HSV composed of three color components which are hue, saturation (lightness), and value (brightness). It is a popular color space which widely used in processing digital images and hue attribute is sensitive for human vision. The extraction algorithm can be divided into three steps:

i. Read RGB image file.
ii. Get RGB value of each pixel of images file.
iii. Convert RGB value of each pixel to HSV color space.

3.4.2 Shape Images Descriptor

In general, shape representation can be categorized into either boundary-based or region-based. For this project, canny edge detector will be used to detect each edge pixel of image. In order to be stored shape images in database, a new image is subjected to a processing phase aimed to identify objects appearing to it. The processes of phase are show in as following:

i. The phase is starting with an edge detection process.
ii. The edge detector canny extracts all contours in the new image and resulting edge pixel.

3.5 Image Segmentation

In general, visual content descriptor can be either global or local. For local descriptor, it uses the visual features of regions or objects to describe the image content. The simplest way of dividing an image to regions is to use a partition which is also known as segmentation. Segmentation (Wikipedia, accessed on 2008) refers to the process of partitioning a digital image into multiple regions (sets of pixel). The objective of segmentation is to simplify and change the representation of an image into more meaningful and easier to analyze.

In image segmentation, an image is partition into a set of homogeneous regions or a set of discontinuous object. For this project, k-mean clustering algorithm is a technique used to apply image segmentation. K-mean is allowed to group sets of feature vector. In other means, feature vector clustering or segmentation can be done by applying k-mean clustering algorithm. The algorithm of k-mean is run as following:

i. Define number of clusters, k.
ii. Assign each of the remaining (N-k) training samples to the cluster with the nearest centroid. After each assignment, recomputed the centroid of the gaining cluster.
iii. Take each data in sequence and compute its distance from the centroid of each of the clusters. If a data is not currently in the cluster with the closest centroid, switch this sample to that cluster and update the centroid of the cluster gaining the new data and the cluster losing the data.
iv. Repeat step (iii) until convergence is achieved, that is until a pass through the training data causes no new assignments.

Finally, the result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image.

3.6 Similarity Measurement

Similarity measurement occurs after the visual features of image query have been extracted. In this module, image query will be compare with each images in database based on the low-level visual features that have been extracted. For this project, we have been proposed the concept of Euclidean distance to measure the similarity between two images. The following show the formula of Euclidean distance that used in similarity measurement.

$$ED = \sqrt[2]{(R_2 - R_1)_1{}^2 + ... \ + (R_2 - R_1)_i{}^2} \qquad \text{…… (3.1)}$$

Where ED = Euclidean Distances

R_1 = Visual features of image query

R_2 = Visual features of images in database

i = Feature in which i start with i=1

The steps taken in this module showed as follow:

i. Get the value of each feature content that describe the image query. This step can achieve by using feature extraction method that we discuss in section 3.4.
ii. Defined the formula Euclidean distance.
iii. Replace the symbols in formula *ED* with the real value we obtained in step one.
iv. Do the similarity measurement between image query and each image in database.

3.7 Statistical Discriminant Analysis

We performed statistical discriminant analysis after the first iteration of user feedback. In this module, we achieved the goal of discriminant analysis by calculating a weight matrix such that the distances between the two scatter class matrixes are maximized. There are two kind of statistical discriminant analysis have been proposed in the project which are bias discriminant analysis (BDA) and nonparametric discriminant analysis (NDA). There are tree main steps are implemented in statistical discriminant analysis.

i. Find the scatter matrix of inner-classes. The inner matrix of BDA and NDA have been showed as follow:

$$S_x = \sum_{i=1}^{Nx} (x_i - m_x)(x_i - m_x)^T \qquad \text{…… (3.2)}$$

$$S_x = \sum_{i=1}^{Nx} (x_i - m_{xi}^{kx})(x_i - m_{xi}^{kx})^T \qquad \text{…… (3.3)}$$

Where $\{\{x_i = 1,..., Nx\}\}$,

m_x = mean vector of positive samples.

m_{xi}^{kx} = mean vector of the k positive nearest neighbors of the i^th^ positive feedback samples x_i.

ii. Find the scatter matrix of inter-classes. The inter matrix of BDA and NDA has been showed as follow:

$$S_y = \sum_{i=1}^{Ny} (y_i - m_x)(y_i - m_x)^T \qquad \text{…… (3.4)}$$

$$S_y = \sum_{i=1}^{Ny} (y_i - m_{yi}^{kx})(y_i - m_{yi}^{kx})^T + \sum_{i=1}^{Nx} (x_i - m_{xi}^{ky})(x_i - m_{xi}^{ky})^T \qquad \text{... (3.5)}$$

Where $\{\{y_i = 1,..., Ny\}\}$,

m_x = mean vector of positive samples.

m_{yi}^{kx} = mean vector of the k negative nearest neighbors of the i^{th} positive feedback samples x_i.

m_{xi}^{ky} = mean vector of the k positive nearest neighbors of the i^{th} negative feedback samples y_i.

iii. Find the weight matrix of statistical discriminant analysis.

$$W_{opt} = \arg_w \max \frac{\| W^T S_y W \|}{\| W^T S_x W \|} \qquad \text{…… (3.6)}$$

3.8 Feature Selection

When a user request to CBIR system by an image query, the system will be process the image and compare with the images database to find out the relevant images and feedback to user. The top N (e.g. 20) relevant images with highest rank then display to user. The user cans response to system by doing relevance feedback if he or she did not satisfy the result. In the process of relevance feedback, user requires to label the images result as "relevant" or "irrelevant" images then feedback to the system. The feature selection module occurs since the first iteration of relevance feedback.

For this project, feature selection module responsible to determine the discriminant ability of feature before using the fuzzy logic approach classification. In the feature selection process, system treat the labeled images as positive if it is labeled as "relevant" images and negative if it is labeled as "irrelevant" images. By using the labeled images, perform the feature selection module and select the features accordingly. After the feature selection process, only the selected features will be used to analyze the rest of the image database and performed similarity measurement. A feature is selected if it is satisfy the condition in process of feature selection, which are calculated ratio value over the threshold value and calculated appearance rate over the appearance value. The algorithm has been showed in figure 3.4. The steps of feature selection are showed as following:

i. Firstly, we required to analyze the discriminant ability of each feature by calculating the ratio as below:

$$ratio = \frac{\left. \sum_{n=1}^{N_y} d'_n \middle/ N_y \right.}{\max(d_p)} \qquad \ldots\ldots (3.7)$$

$$d'_n = \begin{cases} \max(d_p), d_n > \max(d_p) \\ d_n, d_n \le \max(d_p) \end{cases} \qquad \ldots\ldots (3.8)$$

Where N_y = Total number of negative samples.

d_p = Distance of the positive label image from the positive centroid.

d_n = Distance of the negative label image from the positive centroid.

ii. Ratio value of color and shape are used as input of fuzzy classification. In the end of this module, we will get one ratio output.

iii. The system pre-set threshold value and appearance rate because selection process is based on the both value.

iv. If a calculated ratio value is over the threshold value and appearance rate, then a feature is selected.

$$Appearance = \frac{\sum_{n=1}^{Nf} Kn}{Nf} \quad \text{…… (3.9)}$$

Where *Kn* = Total number of the ratio feature over threshold.

Nf = Total number of iteration relevant feedback.

v. The selected features are then cascaded into a flat feature vector.

```
Start

   1. Start with read the relevant (positive) images and irrelevant
      (negative) images that user feedback.

   2. Preset the feature threshold and feature appearance rate.

   3. Analyzed the discriminant ability of each feature separately
      by calculating ratio value as equation (3.7). The process of
      feature ratio can refer to figure 3.5.
      3.1   Used the positive images, find the positive centroid of
            images.
      3.2   Based on value of positive centroid, find the distances
            Of positive images from positive centroid.
      3.3   Find the max distances value among the distances of
            positive images from positive centroid.
      3.4   Based on value of positive centroid, find the distances
            of negative images from positive centroid.
      3.5   By using the equation as (3.8), sum the distances of
            negative images from positive centroid.
      3.6   Replace all calculated value to equation (3.7).
      3.7   Calculate and get ratio value.

   4. Ratio of color and ratio of shape as input of fuzzy
      Classification (showed in section 3.9) and output an optimal
      ratio.
```

```
    5. Based on calculated feature ratio, calculate and get feature
       appearance value. The process of feature appearance rate can
       refer to figure 3.6.
       5.1    If calculated ratio over preset threshold, calculated
              The appearance value by using equation (3.9)
       5.2    If both the calculated ratio over threshold and
              Appearance value over appearance rate, then the feature
              would be selected.

end
```

Figure 3.4: Algorithm for Feature Selection

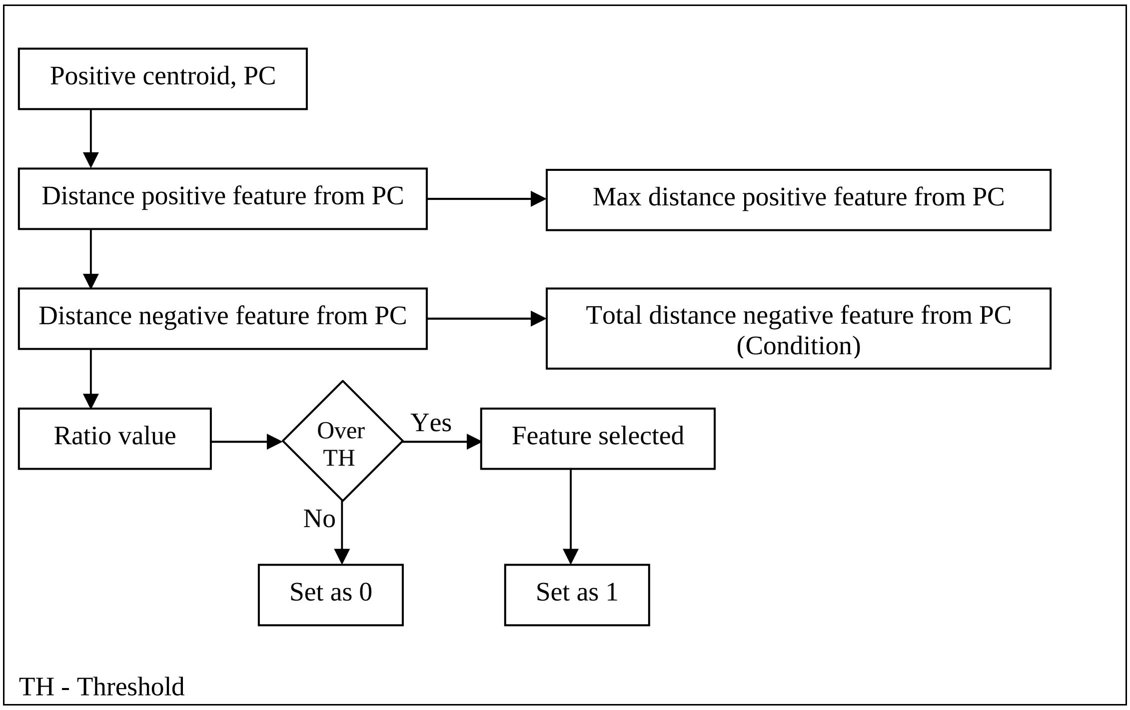


Figure 3.5: The Process of Feature Ratio

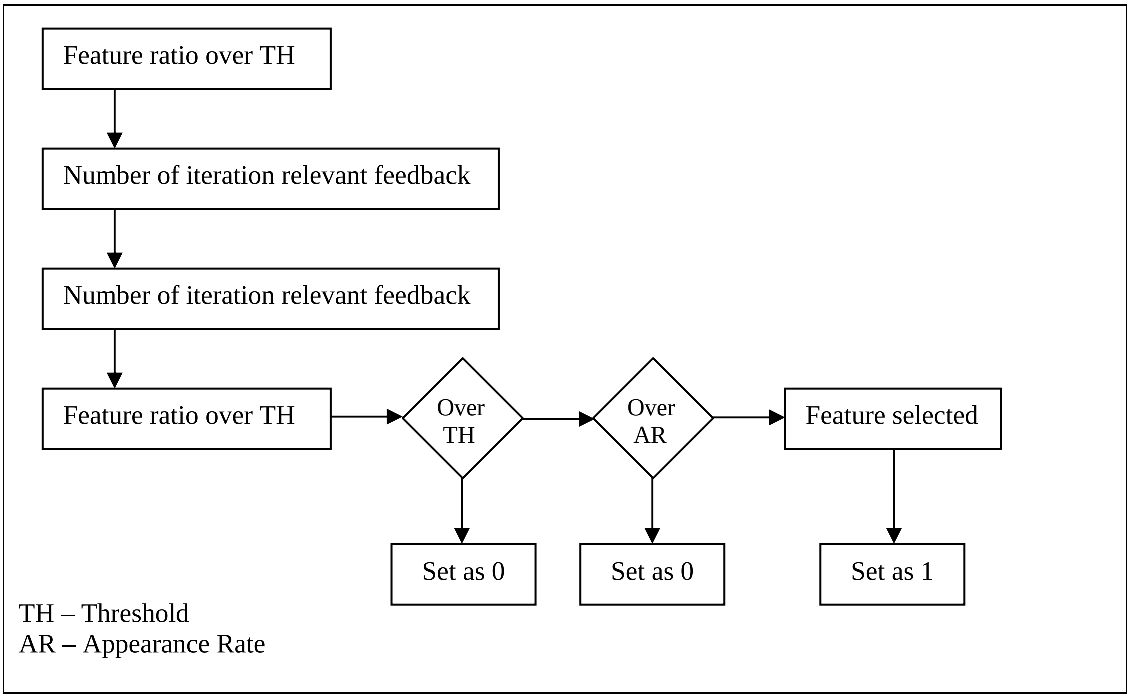


Figure 3.6: The Process of Feature Appearance Rate

3.9 Fuzzy Classification

For this project, we used the fuzzy logic theory in classification. There are two types of fuzzy inference systems which are mamdani and sugeno. The mamdani fuzzy inference system (FIS) has been choosing as fuzzy classification tool. Before running the FIS, we are required to define the crisp inputs, the degree of membership of inputs and also interpret fuzzy rules. There are consists of five steps in processing ratio in FIS. The Table 3.2 shows the steps of operation FIS.

Table 3.2: Steps of Operation FIS

Step	Module	Explanation
1	Define fuzzification of the input variables	- Take the calculated ratio value as crisp inputs. - For this case, the crisp inputs are the ratio values of color and shape. - Determine the degree to which these inputs belong to each of the appropriate fuzzy sets.

2	Fuzzy logical operation	- Fuzzy operator can either AND or OR, is applied to obtain a single number that represents the result of the antecedent evaluation. - Then, the number will be applied to the output function.
3	Implication method	- To determine the output of each fuzzy'rule consequent.
4	Aggregation	- To done the process of unification of the outputs of all rules. - Take the membership function of all rule consequents and combine them into a single fuzzy set.
5	Defuzzification	- To change the aggregate output fuzzy set into a single crisp number.

3.10 Relevance Feedback

Relevance feedback is a technique that can improve the retrieval system effectively. The approaches of relevance feedback can be classified into two main approaches, which are query-point moving approach and weight updating approach. The query-point moving approach is the query refinement and essentially tries to improve the estimate of the ideal query point. The weight updating approach is the similarity measure refinement and used to enhance the importance of the dimensions of a feature that help in retrieving the relevant images.

In the CBIR system, the relevance feedback processes are performed as following steps:

i. A user request to CBIR system by submitting a query image.
ii. Firstly, the system will be extracted the color contents and shape contents in query image. For this project, the color histogram technique has been used to extract the color space RGB (Red, Green,

and Blue) of an image. The edge detector canny used to detect contours image and moment invariant technique has been use to extract the shape of an image.

iii. After the feature extraction, all extracted feature will be form in feature vector.

iv. The query image then compare with images database by calculating the distance of dissimilarity between them.

v. Ranking all relevant images and sorting them in ascending order based on the distance of dissimilarity.

vi. Display the top 20 images with highest rank.

vii. If user did not satisfy the retrieval result that display by system, then user can feedback the relevant images to system.

viii. User label the images as positive if it is relevant to image query and negative if it is irrelevant to image query, the rest of images will be automatically labeled as not sure for relevant or irrelevant group.

ix. As before, system processes the feature extraction module.

x. After that, system analyzes the labeled images by using statistical discriminant analysis and fuzzy logic theory to select the important and characteristic feature that can represent the image query.

xi. The system then ranking the images and display the top 20 images to user.

xii. Go back to step vii for the next iteration of relevance feedback.

The iteration of relevance feedback will be continuing until the user is satisfied with the retrieval result. Then, the images will be the as final retrieval result that display by system.

3.11 Summary

In this chapter, we have been proposed and discussed the research methodology that will be implemented in the proposed project. The research methodology consists of seven modules which are data collection, feature extraction, image segmentation, similarity measurement, feature selection, classification and relevance feedback. The idea how to run the proposed CBIR system has been discussed in each subsection. By processing these modules step by step, the project's objectives are expected can be achieved.

CHAPTER 4

EXPERIMENTAL RESULT

4.1 Introduction

The Chapter 4 discusses the result from research methodology described in Chapter 3. In this chapter, we show how the content-based image retrieval working through graphical user interfaces. One of the objectives of the experiment implementation is to find relevant images by measuring similarity between the image query and the images data in database. Besides, we utilize concept of statistical discriminant analysis (SDA) feature selection in the experiment to verify the performance of content-based image retrieval. We have been proof that the proposed SDA feature selection is better than the conventional SDA feature selection.

The following section gives a brief description of how the experiment working step by step and then finally gets the result. Section 4.2 explore about experimental setup for content-based image retrieval design. Next, the experimental result of experiment will be showed in section 4.3. The brief discussion of that experimental result will be shows in section 4.4. The section 4.5 define summary of experiment and discussion of experiments have been showed in section 4.6. Lastly, the conclusion of this chapter has been provided in section 4.7.

4.2 Concept of Content-based Image Retrieval System Design

The concept of content-based image retrieval system comprises of five main parts which are feature extraction, similarity measurement, SDA feature selection, fuzzy classification and relevance feedback. In the preprocessing stage, color and shape visual content of images in database have been extracted and store in the features database.

While a user request to system with an image query, system will then response to user by processing the image query. Firstly, visual content of color information and shape information of an image query will be extracted. Those extracted color and shape features will be used to identify the dissimilarity of image query and images database. Similarity measurement will then decide which images in database are more closed to the image query that user request. Then, the top 20 less distances of images database will be displayed and feedback to users.

If users did not satisfy with the result, she or he cans response to system by doing relevant feedback. System then calculated the weight matrix by using concept of SDA and also the ratio value to decide which visual features are more suitable to represent the image query. Only the selected features will be used for performing the similarity measurement.

After that, the distances results of color features and shape features are used as the input of fuzzy classifier to identify the degree of similarity between image database and image query. The success classification is highly effect by the result of the accuracy weights of similarity measure. In additional, it also depending on how the fuzzy rules are defined. After the classification phase, we then can decide the images is belonged to which similarity group. Finally, the images will automate ranking and sorting by system. The top ten similar images will display to user. The iteration of relevant feedback will be stopped since users satisfy with the retrieval result.

4.3 Experimental Setup

There are several approaches and parameters had been used to test the framework of experimental modules. Section 4.3.1 show the data collection. Section 4.3.2 has been discussed about the techniques of feature extraction that used to extract the visual content of images. The feature extraction section discusses two types of feature descriptors which are color HSV and canny edge operator. Both of them will describe in section 4.3.2.1 and 4.3.2.2 respectively. Next, section 4.3.3 has been shows the SDA feature selection aspect of threshold. We need a few of training experiment to define the threshold of feature selection. After that, we will show how the similarity measure can be performed by using Euclidean distances in section 4.3.4. The next section, which is section 4.3.5 showed the implementation of fuzzy logic theory in classification. Lastly, section 4.3.6 showed graphical user interfaces of relevance feedback.

The following shows the experiment environment:

i. Intel Pentium M processor 760
ii. Intel Graphics Media Accelerator 900
iii. 60 GB HDD
iv. 2GB DDR2 (support dual channel)

4.3.1 Data Collection

Before implement the experiment, several images data have been collected by exploring internet. The experiments were conducted by using ten categories of images data such as bus, building, horse, flowers, dinosaurs and others. Each of the categories consists of one hundred data images. Since, we have one thousand images have been used as data for this project. For different cases in experiment, we treated the category of image query as relevant or positive images. The rest of images set will be treated as irrelevant or negative images. The figure 4.1 shows some sample of both positive and negative images. We can refer to appendix for all images that have been used in the experiment.

Assume that image query is relevant to bus. Thus, some relevant images are:

Some irrelevant images show as following:

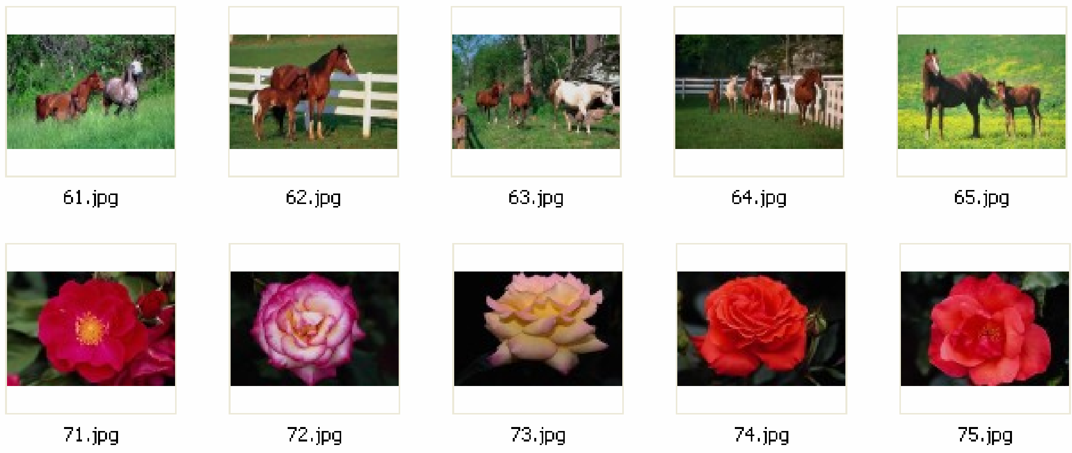


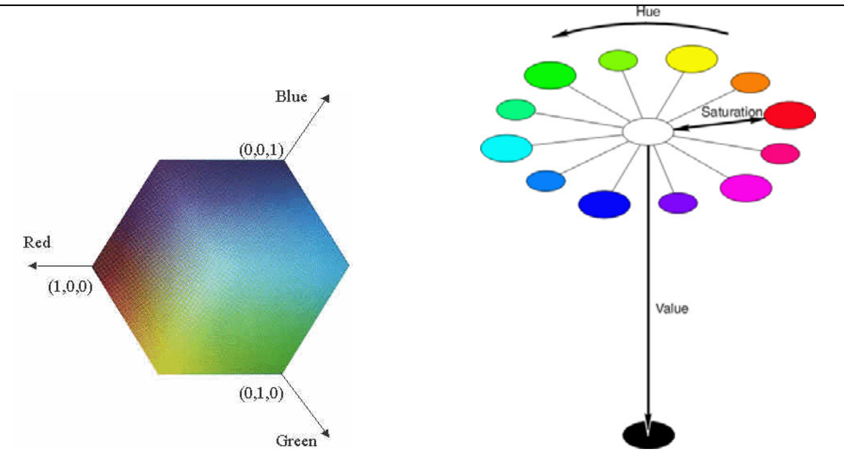
Figure 4.1: Example of Relevant Images and Irrelevant Images

4.3.2 Feature Extraction

In this module, we have been used color space HSV and canny edge operator to represent the color and shape information of images. For color space HSV, each pixel of image represents information in form of hue, saturation and value. For canny edge operator, information shape of an image is represented by edge pixels. The following section discusses both of them in detail.

4.3.2.1 Color Space HSV

As mentioned before, HSV consists of three color information which is hue, saturation and value. Figure 4.2 (a) shows RGB model by using the Cartesian coordinate system and 4.2 (b) shows the hue, saturation, value (HSV) color model. Figure 4.3 show value of pixel in certain pixel.



(a) (b)

Figure 4.2: (a) RGB Model Uses the Cartesian coordinate system (b) The Hue, Saturation, Value (HSV) color model.

To get the color information, the steps to get color HSV of images have been showed as following:

Step 1: Select an image as query and submit to system / Select images database.

Step 2: Transform each of the images to dimension 24 x 16.

Step 3: Extract each pixel color value of an image query or images database in form of RGB color space.

Step 4: Convert the RGB color space to HSV color space.

Step 5: Index the color value with its position in an image. Table 4.1 shows an example HSV pixels and its value.

Step 6: Information of the color space HSV used in the next module.

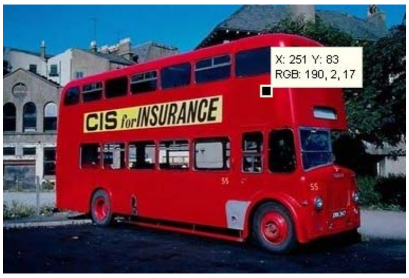


Figure 4.3: Value of Pixel in Certain Coordinate

Table 4.1: Example Pixel and Its HSV Value

Pixel X	Pixel Y	Hue	Saturation	Value
24	16	0.5256	0.1780	73.0
24	15	0.5000	0.0508	118.0
24	14	0.0714	0.0445	157.0
24	13	0.0634	0.2658	79.0
24	12	0.4444	0.0540	111.0
24	11	0.1666	0.0143	139.0
24	10	0.0769	0.0764	170.0
24	9	0.0652	0.2674	86.0
24	8	0.0595	0.0813	172.0
24	7	0.0588	0.0949	179.0
24	6	0.0652	0.1055	218.0
24	5	0.0666	0.2205	136.0
24	4	0.0530	0.1864	118.0
24	3	0.0533	0.1760	142.0
24	2	0.0595	0.1255	223.0
24	1	0.0591	0.1781	174.0
23	16	0.0289	0.3432	67.0
23	15	0.0303	0.1732	127.0
23	14	0.0303	0.1139	193.0
23	13	0.0416	0.1388	144.0
23	12	0.9444	0.1318	91.0
23	11	0.9444	0.0833	144.0

4.3.2.2 Canny edge operator

In the project, canny edge operator has been used as a tool to detect edge of an object. Figure 4.4 shows the original image and the image after processing by using canny edge operator. The steps of edge detection have been showed as following:

Step 1: Read the image file.

Step 2: Filter the image.

Step 3: Smoothed the image.

Step 4: Detected the edge strength of an object in image. The detection is in aspect of gradient amplitude and also the orientation image (in degrees
0-180, positive-clockwise)

(a) Original image bus (b) Image after canny edge operator

Figure 4.4: (a) Original image bus (b) Image after canny edge operator

4.3.3 Statistical Discriminant Analysis Feature Selection

The concept of statistical discriminant analysis feature selection has been used in this project to select the most representative features for each image query. As mentioned in section 3.8, chapter 3, the features only will be selected if the ratio value of a feature is over the preset threshold value and appearance value of that feature is over the preset appearance rate. The problem is how we preset the threshold value to make sure a better performance? Based on this research question, we had done several training of different threshold value. Table 4.2 shows training of different threshold value based on proposed BDA feature selection. Table 4.3 shows training of different threshold value based on proposed NDA feature selection. Both of the tables show threshold training range from 0.2 to 0.6. The results showed that the best performance of retrieval images when we preset both threshold value as 0.4. Since, we will be used the selected threshold value in process feature selection.

4.3.4 Similarity Measurement

In this module, similarity measure had been used to identify which images in database are more similar and close to the image query that user request. The objective of this module is analyzed the distances between images database and image query. To achieve this objective, we have been used the concept of Euclidean distance to find the distances between image query and images database. The low distances of image database mean the high similar it relevant to image query.

The following have been showed the steps of similarity measure after the module of color space HSV extraction and module of canny edge operator.

Step 1: After color extraction, we get the color pixel of image query as H_1, S_1 and V_1. Besides, we also obtain the color pixel of images database as H_2, S_2 and V_2. After shape extraction, we get the edge pixel of image query defined as E and also edge pixel of images database defined as P.

Step 2: To get the distance of each color pixel and edge pixel, we defined the formula of Euclidean distance as follow:

$$\text{Color } ED = \sqrt[2]{(H_2 - H_1)^2 + (S_2 - S_1)^2 + (V_2 - V_1)^2}$$

$$\text{Shape } ED = \sqrt[2]{(E_1 - P_1)^2 + ... + (E_i - P_i)^2}$$

Where ED = Euclidean Distances

Table 4.2: Training of Different Threshold Value based on Proposed BDA Feature Selection

Proposed BDA Feature Selection											
Threshold 1	Threshold 2	Iteration									Total Images
		1	2	3	4	5	6	7	8	9	
0.3	0.4	13	3	4	3	4	2	6	5	1	41
0.3	0.5	13	2	5	4	2	6	5	4	3	44
0.3	0.6	13	3	2	1	3	4	4	3	3	36
0.4	0.4	13	8	6	5	3	2	7	6	5	55
0.4	0.5	13	7	5	1	4	8	5	5	2	50
0.4	0.6	13	7	9	8	3	5	1	5	3	54
0.5	0.3	13	4	4	9	2	6	5	2	5	50
0.5	0.4	13	4	5	8	3	3	6	3	6	51
0.5	0.5	13	4	5	8	3	3	6	3	6	51
0.5	0.6	13	4	5	8	9	3	5	3	3	53
0.3	0.4	13	3	4	3	4	2	6	5	1	41
0.3	0.5	13	2	5	4	2	6	5	4	3	44

Table 4.3: Training of Different Threshold Value based on Proposed NDA Feature Selection

proposed NDA											
Threshold 1	Threshold 2	Iteration									Total Images
		1	2	3	4	5	6	7	8	9	
0.2	0.3	13	4	0	1	3	5	6	2	2	36
0.2	0.5	13	4	0	1	4	2	4	2	2	32
0.3	0.4	13	4	4	2	3	4	2	3	3	38
0.3	0.5	13	4	5	2	4	3	6	3	1	41
0.3	0.6	13	3	2	1	3	4	4	3	3	36
0.4	0.4	13	7	1	9	1	7	6	4	5	53
0.4	0.5	13	7	1	9	1	7	4	0	10	52
0.4	0.6	13	3	2	9	0	0	4	17	1	49
0.5	0.3	13	4	4	9	2	6	5	2	5	50
0.5	0.4	13	0	0	10	18	0	5	0	0	46
0.5	0.5	13	0	0	10	18	0	5	0	0	46
0.5	0.6	13	4	5	8	9	3	5	3	3	53

Step 3: We used *ED* to calculate the distances of each pixel value between images query and images database.

Step 4: The distance value of color and distance value of shape will then use as input in fuzzy classification to identify and measure degree the similarity.

4.3.5 Fuzzy Classification

In this project, we have been used fuzzy classification to classify the images based on the degree of images similarity. We applied fuzzy logic in classification deal with the ambiguity and vagueness of human judgment of image similarity. In this case, we defined two inputs for fuzzy classifier which are the distances of image query between images database in aspect of color and shape. The output of the classification will be the result that identifies the degree of similarity images whether the certain images similarity measure belong to very similar, similar or not similar.

Mamdani fuzzy inference method had been conducted and used for this classification module. The process of Mamdani fuzzy inference method ha shown in Figure 4.5 and inputs variable, output variable, rules viewer of Mamdani Fuzzy Inference have been showed in Figure 4.6. The following show the steps to perform the fuzzy classification.

Step 1: We need to define the number of input and input type. In this case, two inputs are defined which are color distances and shape distance between image query and images database. Figure 4.6 shows the defined inputs and output used in this classification.

Step 2: We defined the degree of membership function for both input. There are three different fuzzy sets identified for each input which are low, moderate and high.

Step 3: Besides, we also identify three output fuzzy sets, which are not similar, similar and very similar.

Step 4: A fuzzy rule can be defined as a conditional statement in the form of if-then. To set up fuzzy rules, we had using logical operator. The set up fuzzy rules have showed as below.

A = Color distances between image query and images database.
B = Shape distances between image query and images database.
C = The result of images similarity.

i. If A is low and B is low, then C is very similar.
ii. If A is low and B is moderate, then C is very similar.
iii. If A is low and B is high, then C is similar.
iv. If A is moderate and B is low, then C similar.
v. If A is moderate and B is moderate, then C similar
vi. If A is moderate and B is high, then C is not similar
vii. If A is high and B is low, then C is similar.
viii. If A is high and B is moderate, then C is not similar.
ix. If A is high and B is high, then C is not similar.

Step 5: To process the mamdani fuzzy inference method, we take the crisp inputs and fuzzifies them to determine the degree to which these inputs belong to each of the appropriate fuzzy sets.

Step 6: We have been applied the fuzzy operator to get one number that represents the result of antecedent of rules. The output is a single truth value.

Step 7: Then, we go to the process of unification of the outputs of all rules that we obtain in step 6. The output of this step is one fuzzy set for each output variable. This process also called as aggregation.

Step 8: Lastly, the aggregate output fuzzy set should transform to a single crisp number. We used process of defuzzification to done it.

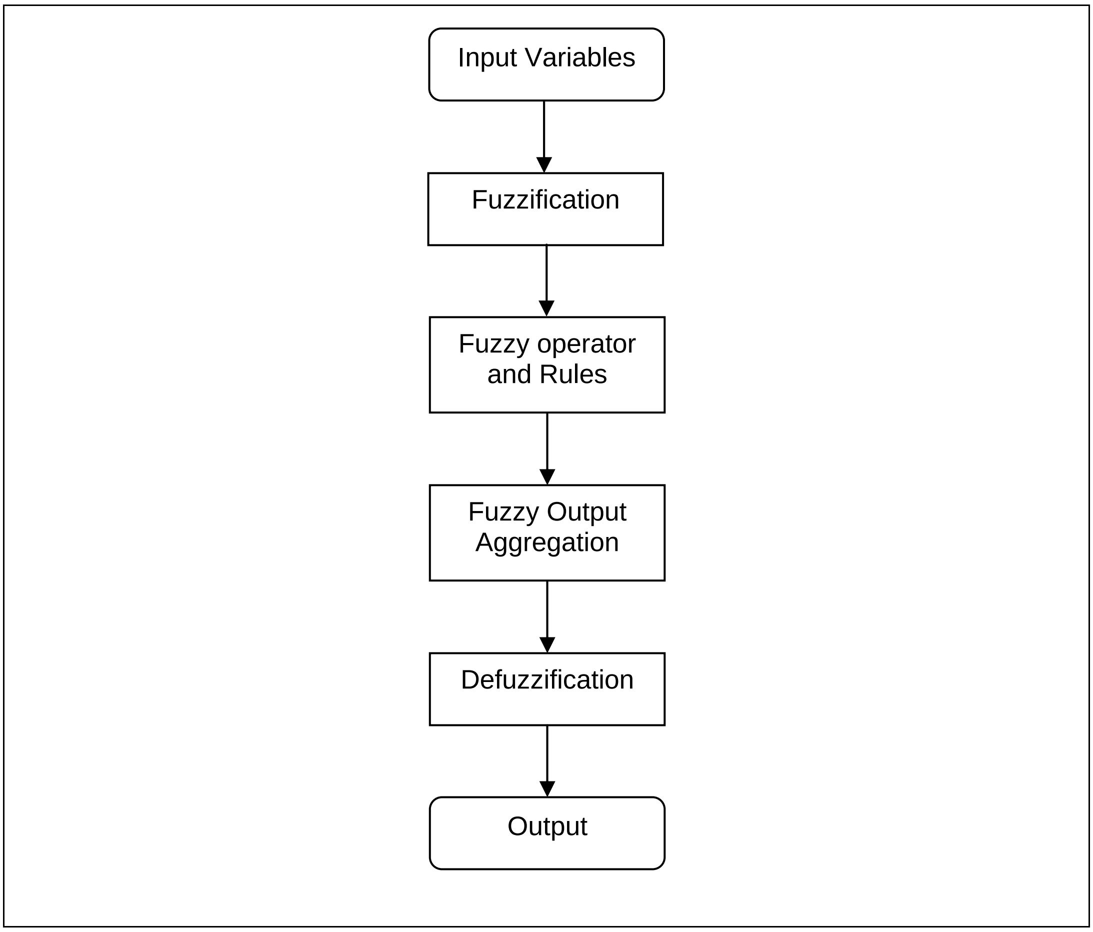
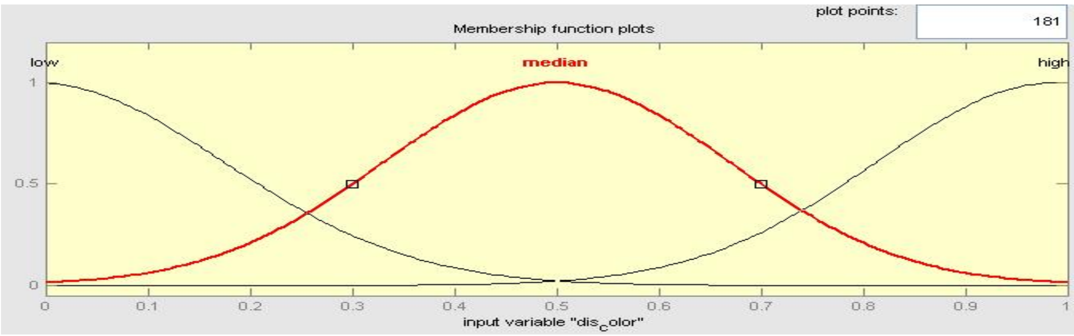
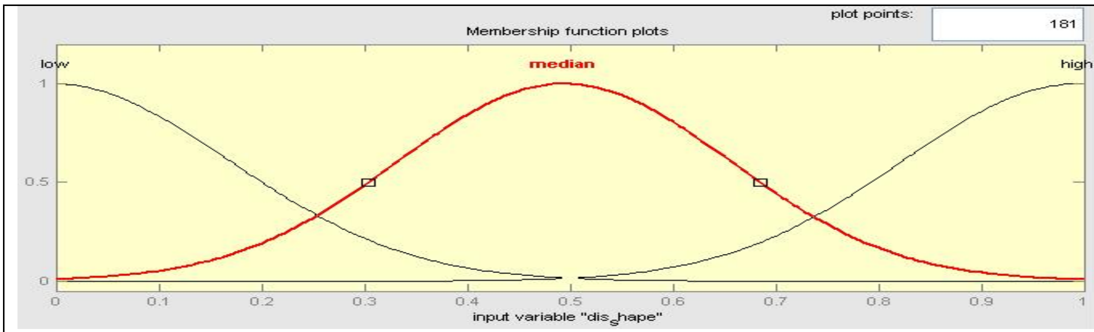


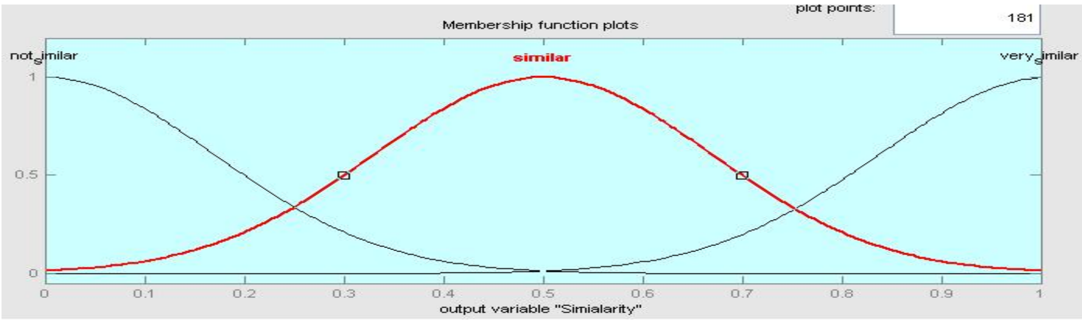
Figure 4.5: Process of Mamdani Fuzzy Inference Method



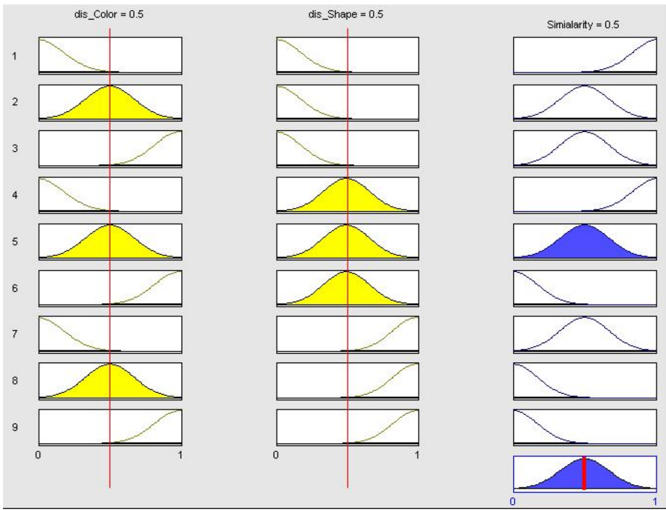
(a) Input 1



(b) Input 2



(c) Output



(d) Rules Viewer

Figure 4.6: Inputs Variable, Output Variable and Rules Viewer in Mamdani Fuzzy Inference

4.3.6 Graphical User Interfaces

The graphical user interfaces (GUI) of content-based image retrieval (CBIR) system have been showed in figure 4.7. By using the GUI, user can browse any interest image and submit to system aims at searching several related images from image database. After processing certain modules as mentioned in chapter 3, result of relevant images will be displayed to user like the right hand side of the GUI. Besides, GUI of CBIR system also provides relevance feedback to capture user perception. All selected relevant images will be stored in personal profile of user. Finally, user can get all the selected images by clicking button result.

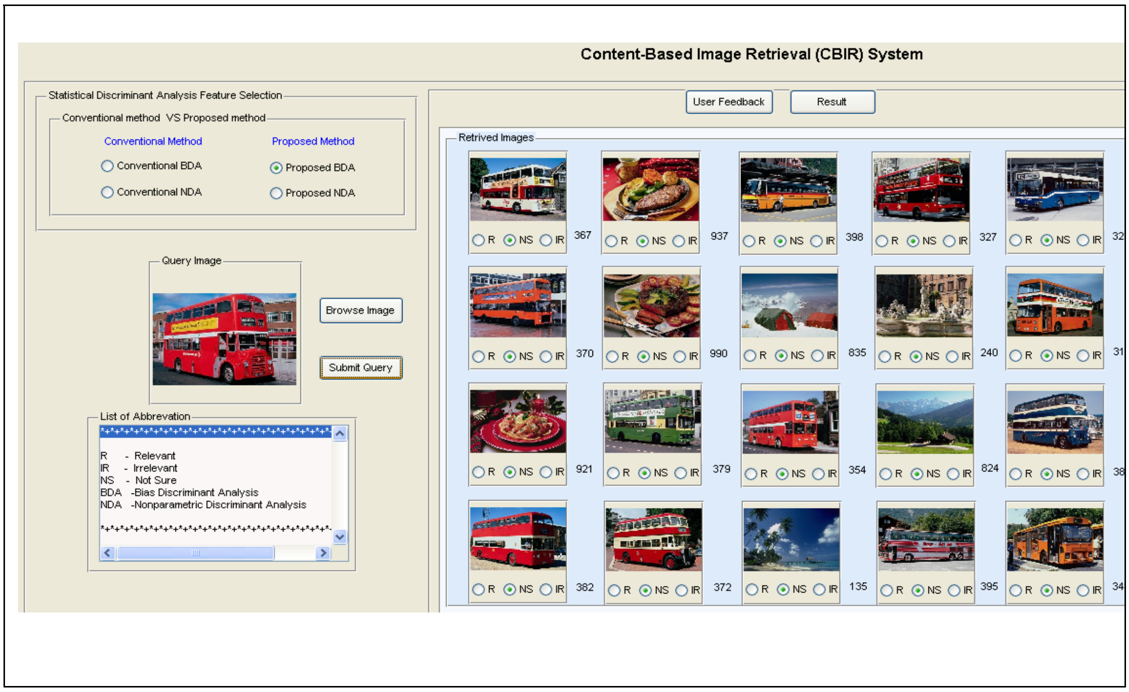


Figure 4.7: GUI of CBIR System

4.4 Experiment Result

In order to evaluate the performance of proposed statistical dicriminant analysis (SDA) feature selection and conventional SDA feature selection, several experiments with different category images had been used for testing. We had test 5 images for 3 images category and then calculated the precision, recall, F1. From the result, we take the result average of 5 experiments. There are seven iteration had been done to retrieve relevant images. The relevant images will be stored to personal profile of user in iteration feedback. Number of relevant images we get in every iteration feedback will be used to calculate the precision, recall and F1 of that iteration. We have been analyzed the performance of modified feature selection method by using standard information retrieval formula which are calculating the accuracy of precision, recall and F1. The standard information retrieval formula which used to show the performance rate of experiment show as following:

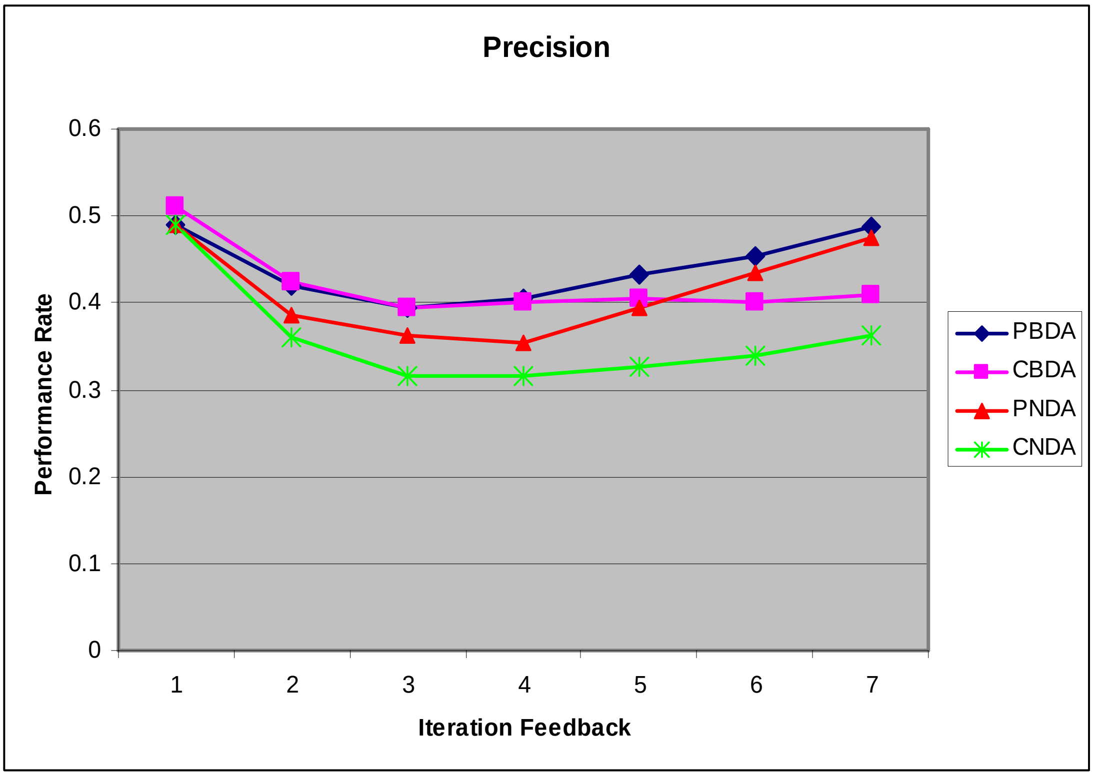
	Expert		
System		Yes	No
	Yes	a	b
	No	c	d

$\Pr ecision = \frac{a}{a+b}$	$\operatorname{Re} call = \frac{a}{a+c}$	$F1 = \frac{2PR}{P+R}$ Where P = Precision R = Recall

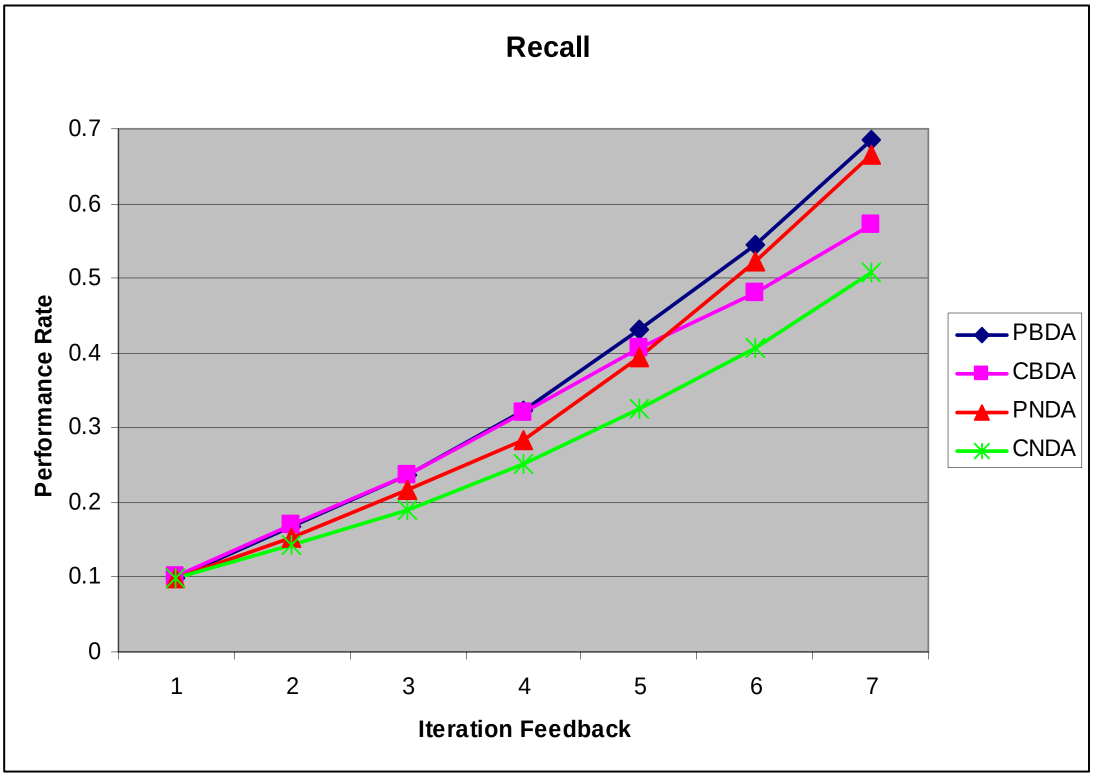
The next section show the result in aspect of precision, recall and F1 of different images category experiment. We have been tested the experiment by using one thousand images data set. In those images data, 100 images are treating as relevant images and 900 images are treating as irrelevant images in every experiment. The experiments shown are the retrieval accuracy rate of first seven feedback cycles.

4.4.1 Analysis of Experiment in Category of Bus Images

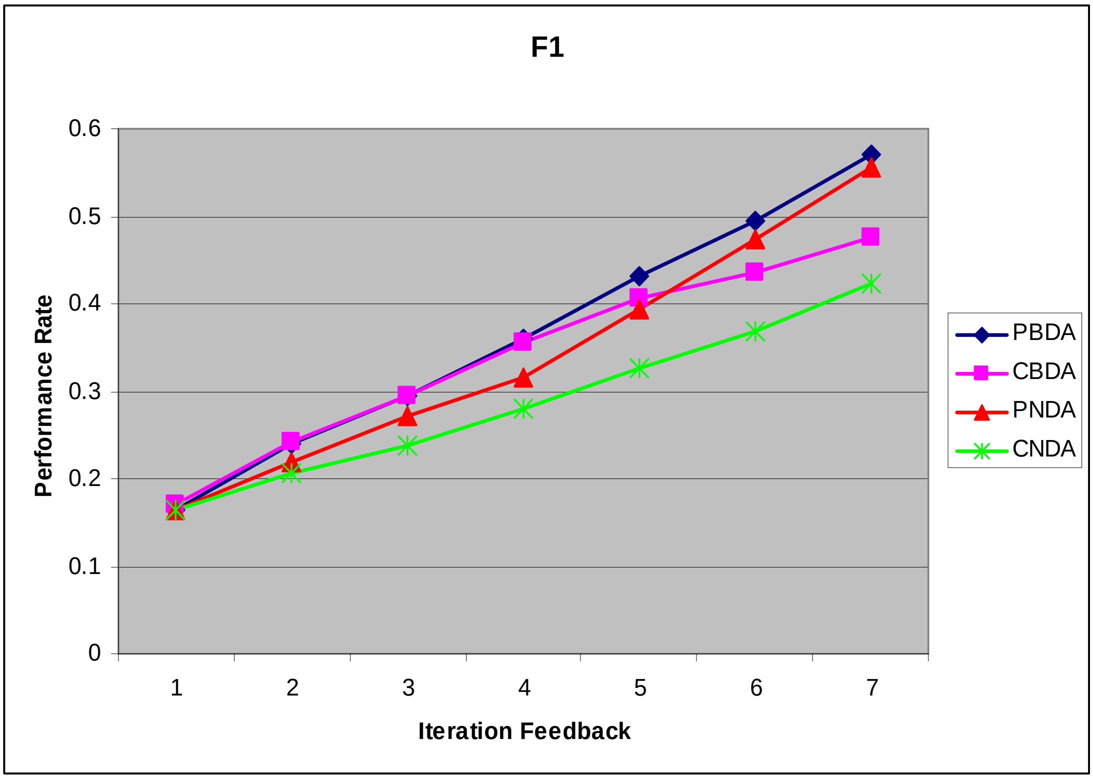
Analysis of bus image category and its accuracy rate in aspect of precision, recall and F1had was showed in figure 4.8. There are comparisons between proposed BDA and conventional BDA has been showed in figure 4.8. And also, there are comparisons between proposed NDA and conventional NDA has been showed in figure 4.8. Based on the graph shown in figure 4.8, there are obviously showed that the performance rate of proposed SDA feature selection method are superior to the conventional SDA feature selection method.



(a) Precision of Image Bus



(b) Recall of Image Bus



(c) F1 of Image Bus

Figure 4.8: Precision, Recall and F1 of Category Image Bus

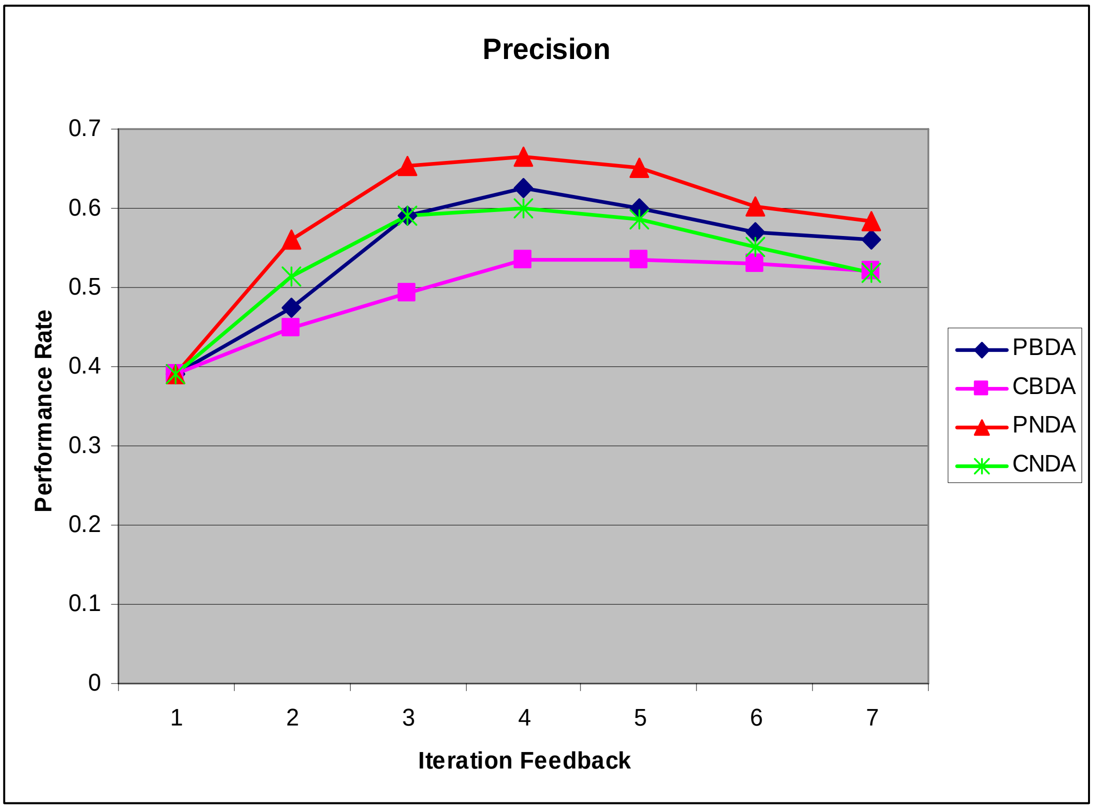
For both Proposed method and conventional method, there are difficult to differential the result between proposed methods and conventional methods from the first to fourth iteration feedbacks. This is cause by the retrieval image for these iterations are almost same. But, the differential of performance rate of them is obviously after the fourth iteration. For this image category, the highest performance rate in F1 of proposed NDA is 0.56 but the most rate of conventional NDA is 0.42. Besides, the highest performance rate in F1 of proposed BDA is 0.57 but the most rate of conventional BDA is 0.48. Therefore, proposed NDA and BDA feature selection method are superior to conventional NDA and BDA feature selection method after the fourth iteration. Besides, among the two SDA methods, the proposed NDA feature selection method is better than the proposed BDA feature selection method.

4.4.2 Analysis of Experiment in Category of Flower Images

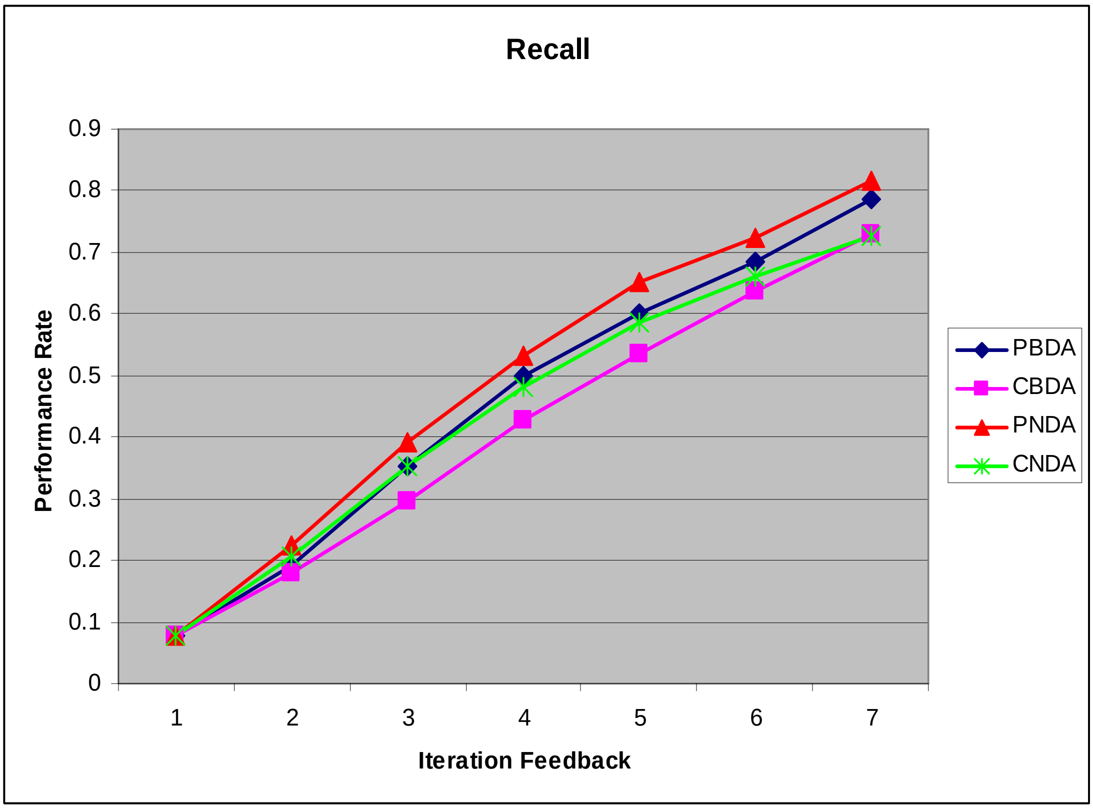
Analysis of flower image category and its performance rate in aspect of precision, recall and F1had was showed in figure 4.9. Like figure 4.8, four methods which are proposed BDA, proposed NDA, conventional BDA and conventional NDA has been represented by four different color line.

Based on the graph shown in figure 4.9, we can known that the performance rate of proposed SDA feature selection method are superior than the conventional feature selection method. In the first three iteration feedback, the performance of proposed BDA is less than the conventional NDA. But, performance of proposed BDA is over than conventional NDA. Although there are little big superior performance rate of proposed methods over conventional methods. It is shown that performance rate of proposed methods better than the conventional methods in the whole of process iteration feedbacks.

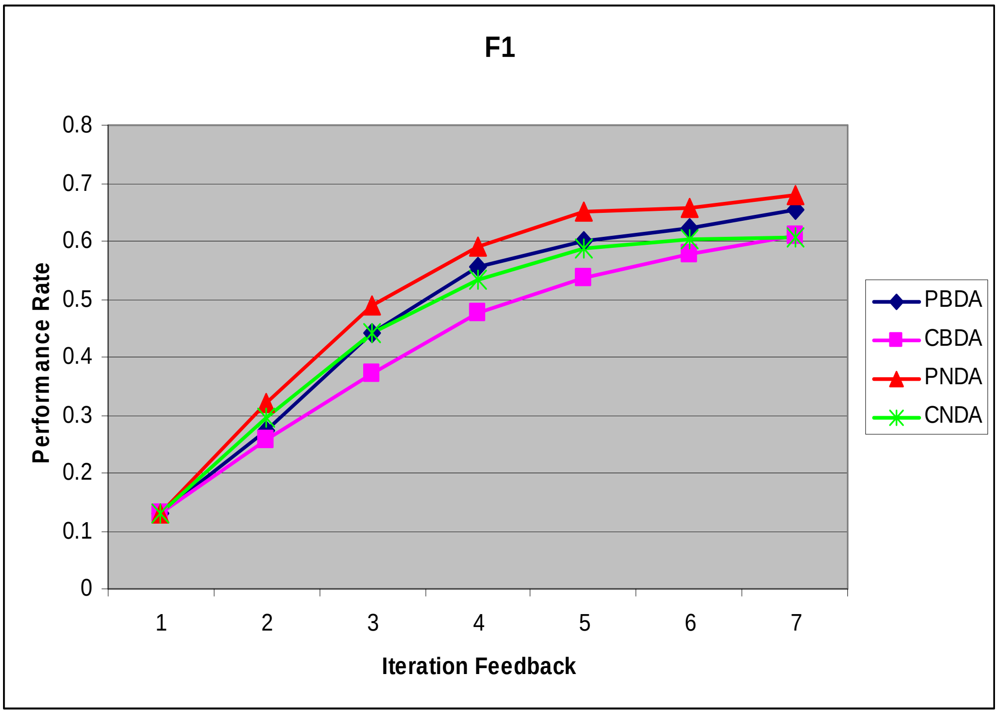
For this image category, the highest performance rate in aspect F1 of proposed NDA is 0.68 but the most performance rate of proposed BDA is 0.66. Besides, the highest rate of conventional NDA is 0.61 but the most rate of conventional BDA is 0.60. Therefore, proposed NDA and BDA feature selection method are superior to conventional NDA and BDA feature selection method after the fourth iteration. Besides, among the two SDA methods, the proposed BDA feature selection method is better than the proposed NDA feature selection method.



(a) Precision of Image Flower



(b) Recall of Image Flower



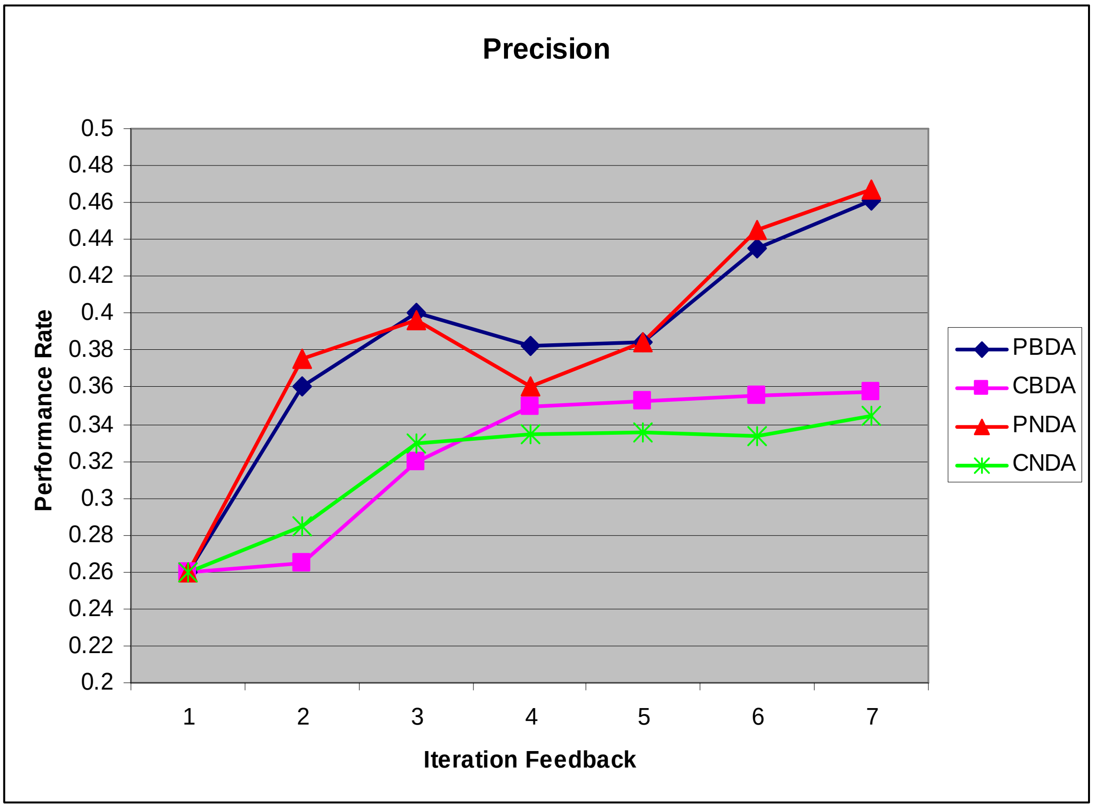
(c) F1 of Image Flower

Figure 4.9: Precision, Recall and F1 of Images Flower

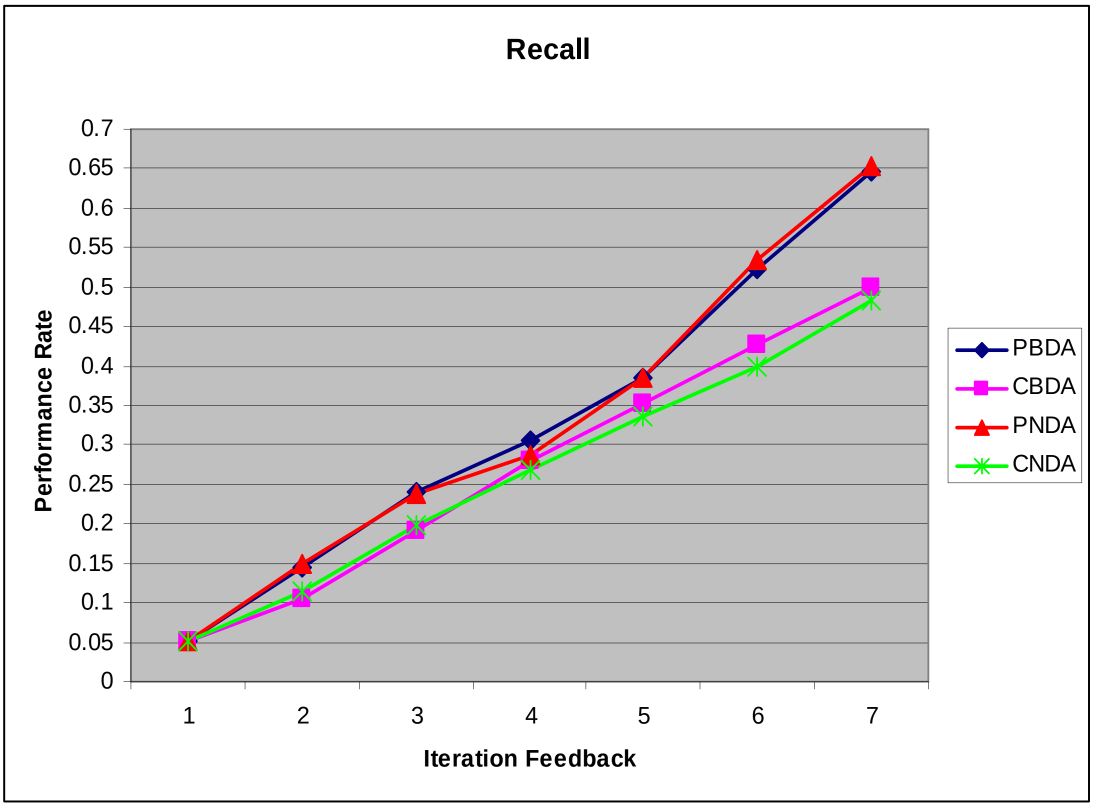
4.4.3 Analysis of Experiment in Category of Horse Images

Analysis of horse image category and its performance rate in aspect of precision, recall and F1had was showed in figure 4.10. There are four methods which are proposed BDA, proposed NDA, conventional BDA and conventional NDA has been represented by four different color lines.

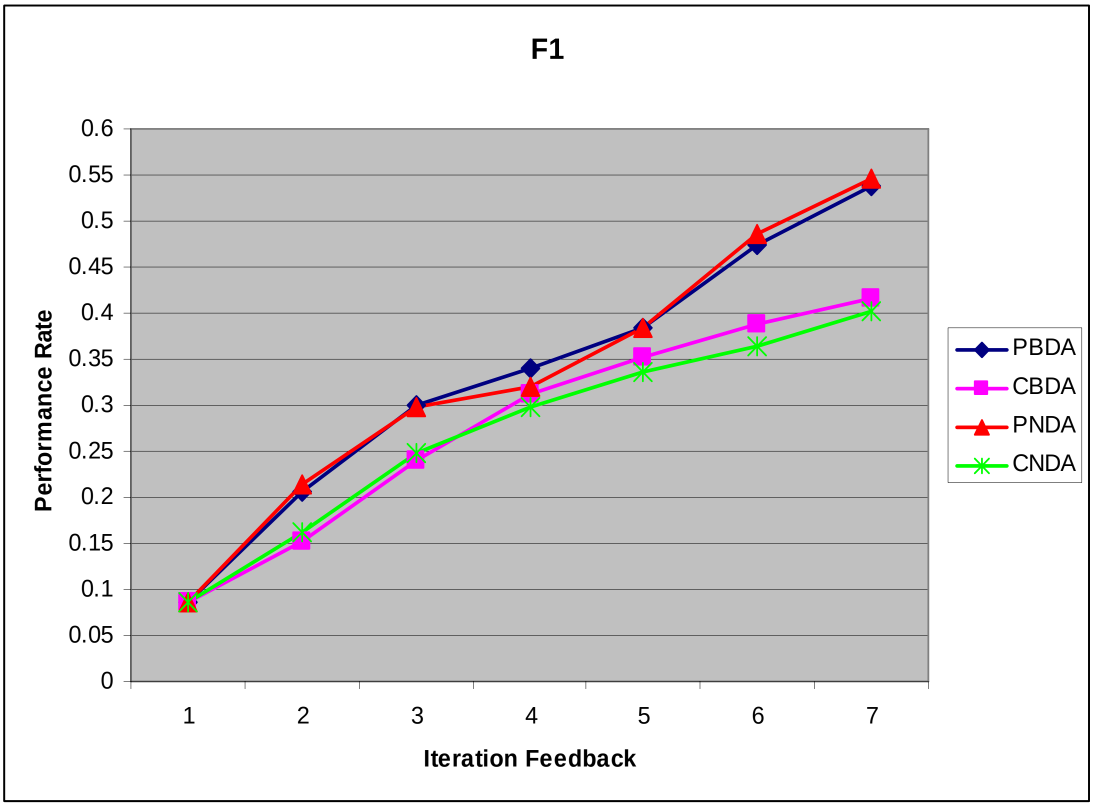
Based on the graph shown in figure 4.10, we can known that the performance rate of proposed SDA feature selection method are superior than the conventional feature selection method. In the whole iteration feedback, the performance rate of proposed BDA and proposed NDA are almost same. This situation also occurs in conventional BDA and conventional NDA. Based on the graph, it is obviously shown that performance rate of proposed methods better than the conventional methods in the whole of process iteration feedbacks. For this image category, the highest performance rate in aspect F1 of proposed NDA is 0.55 but the most



(a) Precision of Image Horse



(b) Recall of Image Horse



(c) F1 of Image Flower

Figure 4.10: Precision, Recall and F1 of Images Horse

performance rate of proposed BDA is 0.53. Besides, the highest rate of conventional NDA is 0.40 but the most rate of conventional BDA is 0.42. Therefore, proposed NDA and BDA feature selection method are superior to conventional NDA and BDA feature selection method after the fourth iteration. Besides, among the two SDA methods, the proposed BDA feature selection method is better than the proposed NDA feature selection method.

4.5 Summary of Experiments

As mentioned before, we have showed three analyses of experiments about two different categories of images. Based on the experiments shown as above, there are obviously showed that the performance rate of proposed SDA feature selection methods is superior to the conventional SDA feature selection methods. Next, we have compared the proposed NDA feature selection method and proposed BDA feature selection method. For the first analysis of experiment, the proposed BDA feature selection method is superior to proposed NDA feature selection method. For the second analysis of experiment, the proposed NDA feature selection method is superior to proposed BDA feature selection method. For the third analysis of experiment, the proposed BDA and NDA are almost same with the conventional BDA and NDA.

4.6 Discussion

The experiments were carried out to analyze the performance rate of two methods of SDA feature selection in different images categories. For the experiments analysis, proposed NDA and BDA feature selection methods are superior to conventional NDA and BDA feature selection methods. This may caused by the existence appearance rate module. In this module, we have calculated the appearance value of the features in which its ratio value over the threshold. If the ratio value over threshold, also the appearance value over appearance rate then the feature will be selected. For example, if a feature has been selected only one time in four iteration feedbacks, then the appearance value of the feature in fourth iteration was 0.25 (1/4). This will cause the feature cannot be selected because it is less than appearance rate which is 0.4. Thereby, this existence module are reduce the change of features can be selected. The feature will be selected if it was satisfy the both condition in both modules. This situation reduce the change of features can be selected but at the same time it also increase the important rate of selected features. In other mean, the more time a feature can be selected the more important of the feature to represent the image query.

Besides that, we have integrating concept of fuzzy theory in SDA feature selection method to grasp the user perception. This may also one of the factors of why the proposed SDA feature selection methods are better than conventional methods. Normally, in image retrieval system, computer analyzed and compared the image query and images in database based on the rigid distance metric to decide image similarity. But, this is not the property of image retrieval system. Therefore, fuzzy theory has been used to reflect as what human thinking. In the both analysis, we adopting the fuzzy language variable to describe the similarity degree of image feature and also expressing the subjectivity of human perceptions by the fuzzy rules.

For the first analysis, there are showed that performance rate of proposed BDA feature selection method was better than the proposed NDA feature selection method. But, for the second analysis, there are showed that performance rate of proposed NDA feature selection method was superior to the proposed BDA feature selection method. In the third analysis of experiment, performance rate of both the proposed methods are almost same. These different situations might be because the different categories of images testing experiment have different characteristic that suitable to proposed feature selection methods. In other word, different proposed SDA feature selection methods have different sense to images type. However, based on the experiments have been done; the proposed NDA feature selection method is more stable than the proposed BDA feature selection method.

Next, it was showed that performance rate of the flower images experiment are superior to bus image experiment. This situation might be cause by the images in database. Even though there are different color of flower images, but almost the flower images having same background and same shape which are circle. Therefore, it is easier for system to find out the relevant images (flower images). For the bus images in image database, there are many different color and different shape of bus. Such that the size and also the look view of bus are different. Figure 4.10 showed the two flower images and two bus images to proof situation just mentioned above. It is also called as not consistent problem of image database. There are more images can refer to section appendix.

(a) Bus Images (b) Flower Images

Figure 4.11: Not consistent Problem of Image Database

4.7 Conclusion

This chapter describes the experiment to determine and analysis the performance rate of SDA feature selection methods. To achieve this objective, we have been discussed the step by step how to get the result in each module. Finally, the result of experiments was showed in graph. In additional, we also done the comparison and analyzed the result between the proposed experiments and conventional experiments.

Based on the experiments carried out for the analyses, we can conclude that the proposed SDA feature selection method is superior to conventional SDA feature selection method. However, some of the experiments only showed the little big superior performance of proposed method than conventional method.

CHAPTER 5

CONCLUSION

5.1 Introduction

In this century, the technology explosion in computer technologies means that there has been an explosion in the complexity and amount of digital data being generated, transmitted, and accessed. The very large repository of digital media arise the challenge of various digital search applications. In order to make use of this huge amount of data, effective tools are required for retrieve multimedia information. An image retrieval system is one of the tools that can be used for searching and retrieving images from a large database of digital images.

In past decade, image retrieval has been an active research field. In that time, many system have been proposed to retrieve image by using keyword or textual. However, this kind of search system has several problems such as consumes much time and labor to annotate keyword to image. Thus, the content-based image retrieval has been introduce to solve this kind of problem and aims to uses image visual content features to retrieve relevant images.

However, there are several challenges and problems need to be considered when applied CBIR system. The gap between high-level semantic concept and low-level visual features is the fundamental problem in CBIR. Beside that, problem of user's subjective perception also a problem background in CBIR. This is because different person have different own perception subjectivity.

Therefore, in this project, we intend to improve the retrieval performance by using feature selection method. Feature selection aims at select representative and suitable features for explaining current query concept. Thus, in the feature selection process, we select only the meaningful features may improve the performance of retrieval. Besides, we used fuzzy theory to identify and classify the degree of similarity between image query and images in database. The propose methodology for this project had been showed in chapter 3 and the experiment result in testing the performance of system had been showed in chapter 4.

5.2 The Analysis of Contribution

As discussed in Chapter 4, the analysis of performance rate of SDA feature selection method was done. The result of experiments showed that the performance rates of proposed SDA feature selection methods are superior to the conventional SDA feature selection methods. By adding the appearance rate module and integrating fuzzy theory in feature selection method, the performance rate of content-based image retrieval system have been improved. The improvement of performance can reduce the problem faced by statistical dicriminant analysis which is Gaussian distribution problem and parameter tuning problem.

5.3 Suggestion for Future Work

For this project, only 1000 images data had been used to testing the experiments. In future work, more images data can be used to evaluate the performance of content-based image retrieval. The more images data, the difficult for system to find out the relevant images form a big database.

Besides that, there are possible to consider about auto set the threshold value in feature selection module. Based on different situation in feature selection process, system might be auto set the threshold that suitable for different environment.

Also, we know that the decision of selection feature is very depending on discriminant factor and appearance factor. This can be misleading. Thus, alternative ways of performing feature selection can be to explore in the future.

5.4 Conclusion

The proposed method intends to improve the feature selection method to solve the fundamental problem in CBIR which are the gap between high level concept and low level visual feature. Beside that, we have reduced the high dimensionality of feature vector. Also, fuzzy classification has used to implement vagueness judgment of human when search for image.

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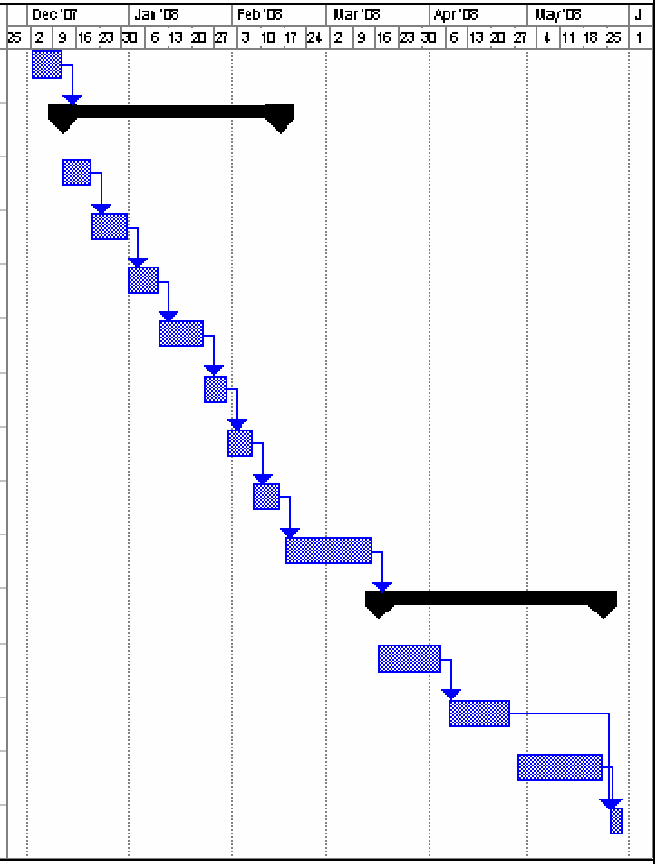
Appendix A: Gantt Cart

Carta Gantt Master Project I

ID	Task Name	Duration	Start	Finish
1	Research title	7 days	Mon 12/3/07	Tue 12/11/07
2	**Literature review**	**48 days**	**Wed 12/12/07**	**Fri 2/15/08**
3	Content-based image retrieval(CBIR)	7 days	Wed 12/12/07	Thu 12/20/07
4	Current Issue of CBIR	7 days	Fri 12/21/07	Mon 12/31/07
5	Feature extraction techniques	7 days	Tue 1/1/08	Wed 1/9/08
6	Feature selection techniques	10 days	Thu 1/10/08	Wed 1/23/08
7	Similarity measurement methods	5 days	Thu 1/24/08	Wed 1/30/08
8	classification techniques	6 days	Thu 1/31/08	Thu 2/7/08
9	Relevance feedback methods	6 days	Fri 2/8/08	Fri 2/15/08
10	Research methodology	20 days	Mon 2/18/08	Fri 3/14/08
11	**Preliminary result**	**50 days**	**Mon 3/17/08**	**Fri 5/23/08**
12	Color-based feature extraction	15 days	Mon 3/17/08	Fri 4/4/08
13	Fuzzy classification	15 days	Mon 4/7/08	Fri 4/25/08
14	Experiment testing	20 days	Mon 4/28/08	Fri 5/23/08
15	conclusion and future work	4 days	Mon 5/26/08	Thu 5/29/08

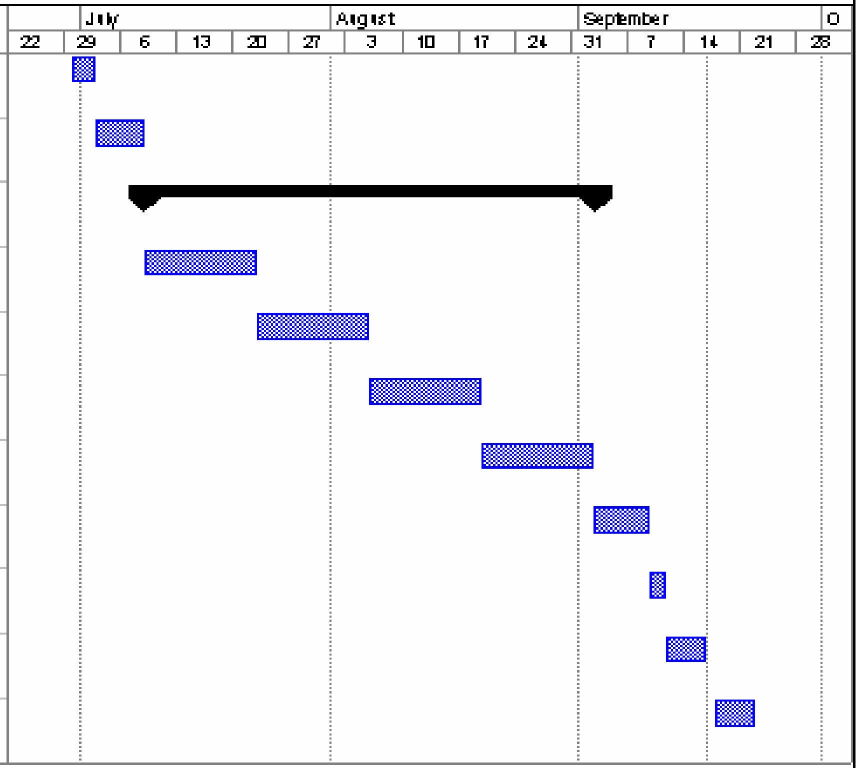


Project: Project I
Date: Wed 9/17/08

Task | Split | Progress | Milestone | Summary | Project Summary | External Tasks | External Milestone | Deadline

GanttCart Master Project II

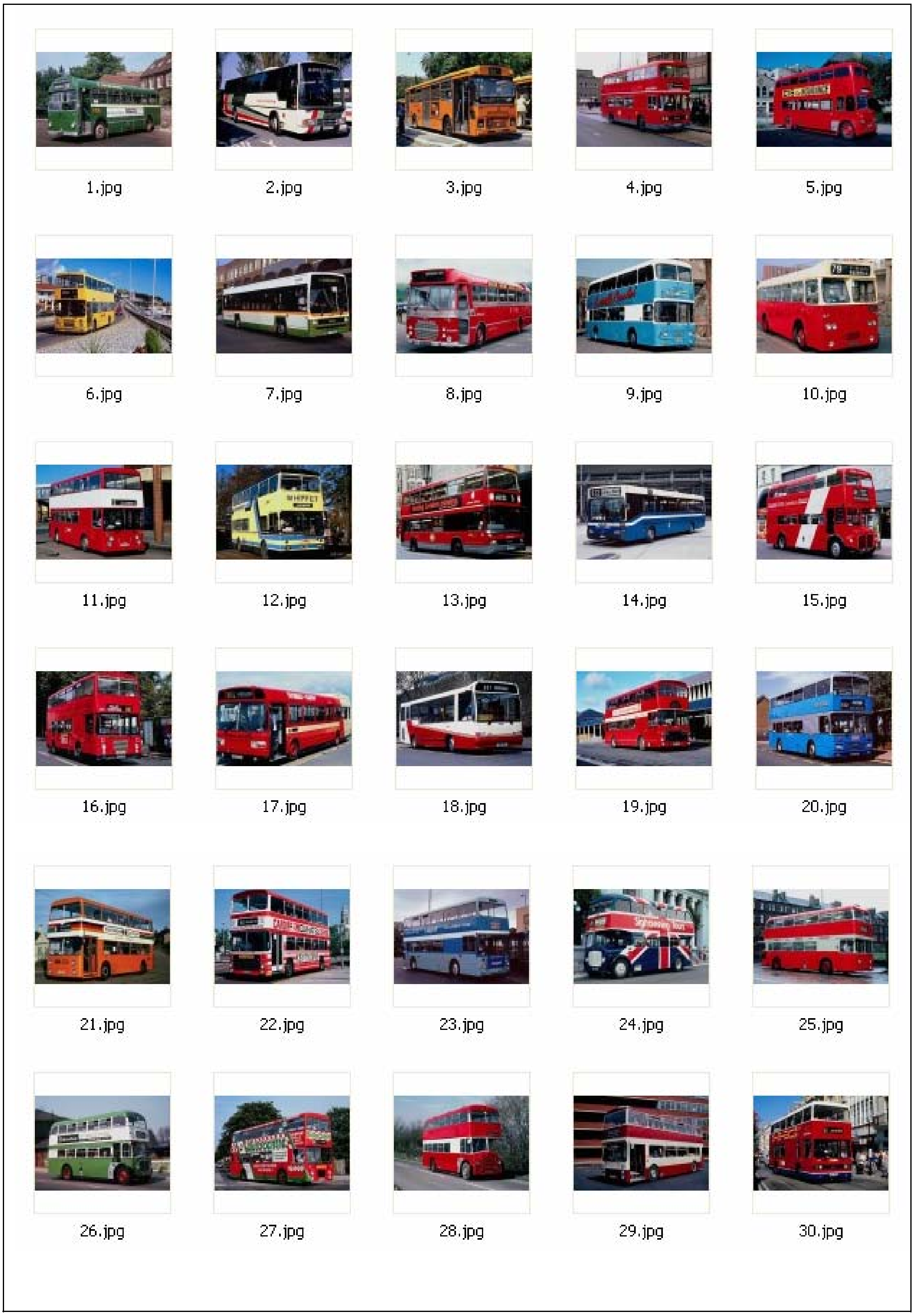
ID		Task Name	Duration	Start	Finish
1		Study problem of feature selecti	3 days	Mon 6/30/08	Wed 7/2/08
2		Analyze research methodology	4 days	Thu 7/3/08	Tue 7/8/08
3		Start Coding	40 days	Wed 7/9/08	Tue 9/2/08
4		Conventional BDA feature s	10 days	Wed 7/9/08	Tue 7/22/08
5		Conventional NDA feature s	10 days	Wed 7/23/08	Tue 8/5/08
6		Proposed BDA feature selec	10 days	Wed 8/6/08	Tue 8/19/08
7		Proposed NDA feature selec	10 days	Wed 8/20/08	Tue 9/2/08
8		Testing results	5 days	Wed 9/3/08	Tue 9/9/08
9		Discuss the analysis of result	2 days	Wed 9/10/08	Thu 9/11/08
10		Start writing report	3 days	Fri 9/12/08	Tue 9/16/08
11		Make correction on report	3 days	Thu 9/18/08	Mon 9/22/08

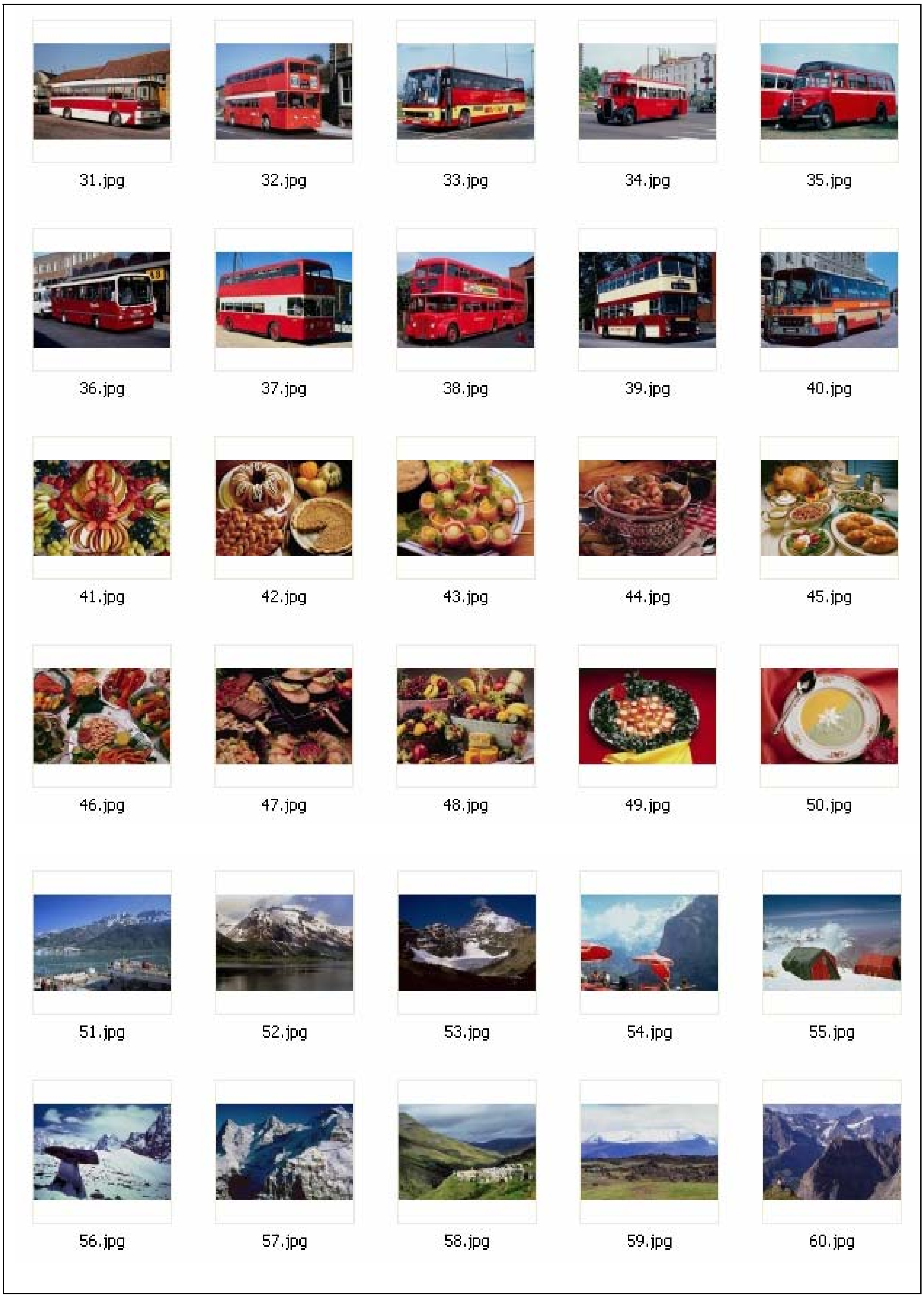


Project: Project II
Date: Wed 9/17/08

Task	Milestone	External Tasks	
Split	Summary	External Milestone	
Progress	Project Summary	Deadline	

Appendix B: 100 Samples Image Data

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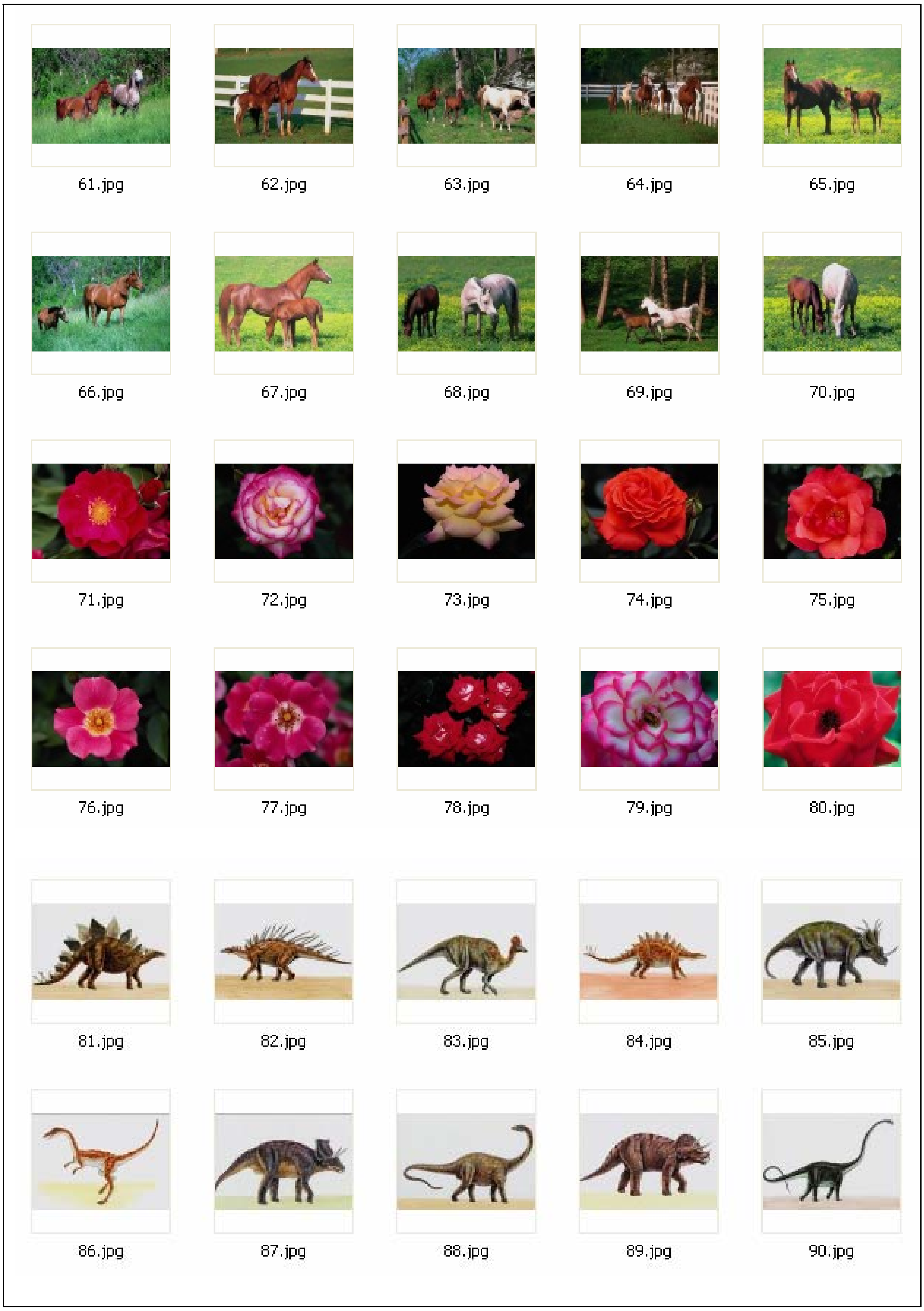
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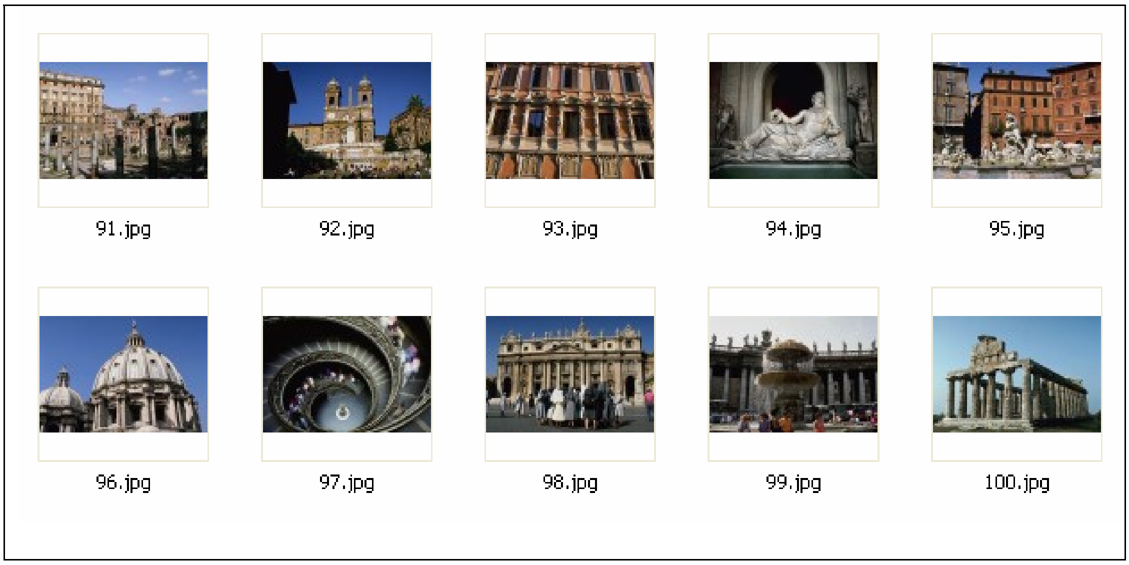
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