Information retrieval method with shape features extracted by layered structure representation and its application to shape independent clustering

June 2013

Department of Science and Advanced Technology Graduate School of Science and Engineering Saga University

CAHYA RAHMAD

Information retrieval method with shape features extracted by layered structure representation and its application to shape independent clustering

A dissertation submitted to the Department of Science and Advanced Technology, Graduate School of Science and Engineering, Saga University in partial fulfillment for the requirements of a Doctorate degree in Information Science

By

CAHYA RAHMAD

Nationality : Indonesianese

Previous degrees : B.S. in Electrical engineering
Faculty of engineering
Brawijaya University, Indonesia
M.S. in Informatics engineering
Graduate School
Tenth of Nopember Institute of Technology, Indonesia

Department of Science and Advanced Technology Graduate School of Science and Engineering Saga University

JAPAN

March 2013

APPROVAL

Graduate School of Science and Engineering

Saga University

1 - Honjomachi, Saga 840-8502,
Japan

CERTIFICATE OF APPROVAL

Dr.Eng. Dissertation

This is to certify that the Dr.Eng. Dissertation of

CAHYA RAHMAD

has been approved by the Examining Committee for the dissertation requirements for the Doctor of Engineering degree in Information Science in June 2013.

Dissertation Committee :

Supervisor, Prof. Kohei Arai

Department of Science and Advanced Technology

Member, Prof. Shinichi Tadaki

Department of Science and Advanced Technology

Member, Associate Prof. Hiroshi Okumura

Department of Science and Advanced Technology

Member, Associate Prof. Koichi Nakayama

Department of Science and Advanced Technology

DEDICATION

To my family; my beloved wife: **Siti asnipah**, All my children(Anggun Audita Alifia Fatimah, Muhammad Ega Fadhilla Rahmat and Muhammad Aga Febrian Rahmat), my parents, my brother and my sister.

ABSTRACT

The new method for retrieving image based on shape extraction is proposed for improving the accuracy. Image retrieval has been used to seek an image over thousand database images. In the image search engine, the image retrieval has been used for searching an image based on text input or image. Once an input taking into account, the method will search most related image to the input. The correlation between input and output has been defined by specific role. we develop the image retrieval method based on shape features extracted. In conventional method, centroid contour distance (CCD) is formed by measuring distance between centroid (center) and boundary of object, however these method cannot capture if an object have multiple boundary in the same angle.

In this research we proposed new method that able to capture represent of image (feature vector) although the image have multiple boundary in same angle. Firstly the input image have to be converted from RGB image to Grayscale image and then follow by edge detection process. After edge detection process the boundary object will be obtained and then calculate distance between center of object and the boundary of object and put it in the feature vector and if there is other boundary on same angle then put it in the different feature vector with different layer or multi layer centroid contour distance(MLCCD). We applied that method to the simulation dataset and plankton dataset and the result show that the proposed method better than the conventional method (CCD, Hsv and Fourier descriptor). We also implement the proposed method with some modification to cluster a group of data and compare with K-MEAN clustering method and other clustering method Hierarchical clustering algorithms (Single Linkage, Centroid Linkage, Complete Linkage and Average Linkage). The experiment result by using the proposed clustering method show better than K-MEAN and other clustering method.

ACKNOWLEDGEMENTS

This study would not have been possible without the assistances, suggestions and supports of many individuals and organizations, which I would like to express my deepest gratitude to them all.

First of all, I would like to thank my supervisor, Prof. Kohei Arai for giving excellent guidance, useful ideas and patience during my research at Saga University, Japan. As my teacher and supervisor, Prof. Kohei Arai has given to me a lot of knowledge and research directions therefore I am able to accomplish my study. This dissertation work could not complete without his advice, support, guidance and inspiration to conduct my research.

The author is also very grateful to Prof. Shinichi Tadaki, Associate Prof. Hiroshi Okumura, and Associate Prof. Koichi Nakayama for their help, suggestion and serving as members of his doctoral program committees. The author is also very grateful to all the lecturers and staffs of the Chair of Information Science of Saga University for their kind support and help.

Sincere thanks are due to my colleagues Mr Achmad Basuki, Mr. Tri Harsono, Mr. Lipur Sugiyanta, Mr. Ronny Mardiyanto, Mr. Tran Sang, Mr. Herman Tolle, Mr Steven Sentinuwo,Mr. Indra Nugraha Abdullah, Mr. Rosa Andrie Asmara , Mrs Anik Handayani and all Indonesian student at saga university (Union of Indonesian student), for their help and encouragement.

I would like to thank the Indonesian Government for awarding me the Dikti scholarship. This scholarship helps me not only to pursue my study, but it also gives me the opportunity to know about the Japanese culture, society and new technologies.

Most importantly, I would like to thank my family: the author wishes to express his love and gratitude to his parents, brother and sister and especially to author's wife Siti Asnipah, author's daughter Anggun Audita Alifia Fatimah also author's son Muhammad Ega Fadhilla Rahmat and Muhammad Aga Febrian Rahmat for their patience, sacrifice, support, understanding, and endless love in authors life among his studies.

Cahya Rahmad

Contents

List of Figures

List of Tables

List of Abbreviations

IR	:	Image Retrieval
CBIR	:	Content Base Image Retrieval
CCD	:	Centroid Contour Distance
MLCCD	:	Multi Layer Centroid Contour Distance

1. Introduction

This chapter presents the information retrieval, Image retrieval, motivation and objective, principle of CBIR also outline of the thesis.

1.1 Information Retrieval

In the past decade, With expansion in the multimedia technologies and the Internet, more and more information has been published in computer readable formats. Big archives of films, music, images, satellite pictures, books, newspapers and magazines have been made accessible for computer users. Internet makes it possible for the human to access this huge amount of information. Information retrieval (IR) is the area of study concerned with searching for documents, for information within documents, and for metadata about documents, as well as that of searching relational databases and the World Wide Web. IR is interdisciplinary, based on computer science, mathematics, library science, information science, information architecture, cognitive psychology, linguistics, and statistics.

1.2 Image Retrieval

Image retrieval (IR) is system of computer for searching, browsing and retrieving image from database of digital images. Content based image retrieval(CBIR) also known as query by image content is technique which uses visual content that well known as features for extracting similar images from an image in database.

The Content Based Image Retrieval (CBIR) technique uses image content to search and retrieve digital images. Content-based image retrieval systems were introduced to address the problems associated with text-based image retrieval. Content based image retrieval is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features.

With expansion in the multimedia technologies and the Internet, CBIR has been an active research topic since the first 1990's. The concept of content based retrieval (CBR) in image start from the first 1980s and Serious applications started in the first 1990s.

Retrieval from databases with a large number of images has attracted considerable attention from the computer vision and pattern recognition society.

Recently every time amount of image in the world are increasing very fast and there is a big concern to recognize an object in large collections of image databases. Image database every time become bigger and it make a problem dealing with database organization so the necessity of efficient algorithm is obvious needed [7][8]. Content Based Image Retrieval (CBIR) is any technology that in principle helps to organize digital image archives by their visual content [9].

Content base image retrieval or CBIR is a technique for retrieving images that automatically-derived features such as color, texture and shape. In these case to search an image a user have to provide query terms such as image file/link or click on some image, and the system will extract the feature vector and compare it with feature vector in the dataset then return images that similar to the query. The similarity used for search criteria could be color and texture distribution in images, region/shape attributes, etc.

Brahmi et al. mentioned the two drawbacks in the keyword annotation image retrieval. First, images are not always annotated and The manual annotation expensive also time consuming. Second, human annotation is not objective the same image may be annotated differently by different observer[10]. Unlike the traditional approach that using the keyword annotation as a method to search images, CBIR system performs retrieval based on the similarity feature vector of color, texture, shape and other image content. Comparing to the traditional systems, the CBIR systems perform retrieval more objectiveness[11].

Global features related to color or texture are commonly used to describe the image content In image retrieval. The problem using global features is this method cannot capture all parts of the image having different characteristics[12]. In order to capture specific parts of the image the local feature is used. On The Content based Image Retrieval (CBIR) local feature of an image is computed at some point of interest location in order to recognizing an object. In order to recognize the object firstly the image have to be represented by a feature vector. These feature vector be converted to different domain to make simple and efficient image characteristic, classification and indexing[13]. Many techniques to extract the image feature is proposed [8][9][14]. Shape is one of important visual feature of an image and used to describe image content[15]. One of the shape descriptor is The Centroid contour distance (CCD), it is formed by measuring distance between centroid (center) and boundary of object[16].

1.3 Motivation and objective

Content-Based Image Retrieval (CBIR) is a technology that helps to search digital image according to their visual content. This system distinguishes the different regions present in an image based on their similarity in color, pattern, texture, shape, etc. and decides the similarity between two images by reckoning the closeness of these different regions.

Research on retrieval systems have been carried out in the media text, image, voice, and video. With expansion in the multimedia technologies and the Internet, Image retrieval systems is one technology that is needed in the search for accurate information. The main objective of this thesis propose a new CBIR system regarding precision and recall. We tried to do some image retrieval research on low-level features based on color, texture and shape.

1.4 Principle of CBIR

Content-based retrieval uses the contents of images to represent and access the images. A typical content-based image retrieval system is illustrated in Figure 1.1, in this system there are tree part. The first part is interface consist Data insertion, Query image and Result display. The Second part is Query processing consist feature extraction and similarity process. The third part is feature vector data set and image dataset.

Firstly by using the data insertion some images one by one insert into the system from the data insertion block go to Feature extraction block. In the feature extraction block, the system automatically extract visual attributes (color, shape, texture, and spatial information) of each image based on its pixel values and the result of these process is feature vector.

The feature vector also known as image signature for each of the visual attributes of each image is very much smaller in size compared to the image data, thus the feature vector contains an abstraction (compact form) of the images in the image database. One advantage of a signature over the original pixel values is the significant compression of image representation.

However, a more important reason for using the signature is to gain an improved correlation between image Representation and visual semantics. These feature vector then stores in a feature vector dataset also the image of these feature vector stores in to image dataset with same index.

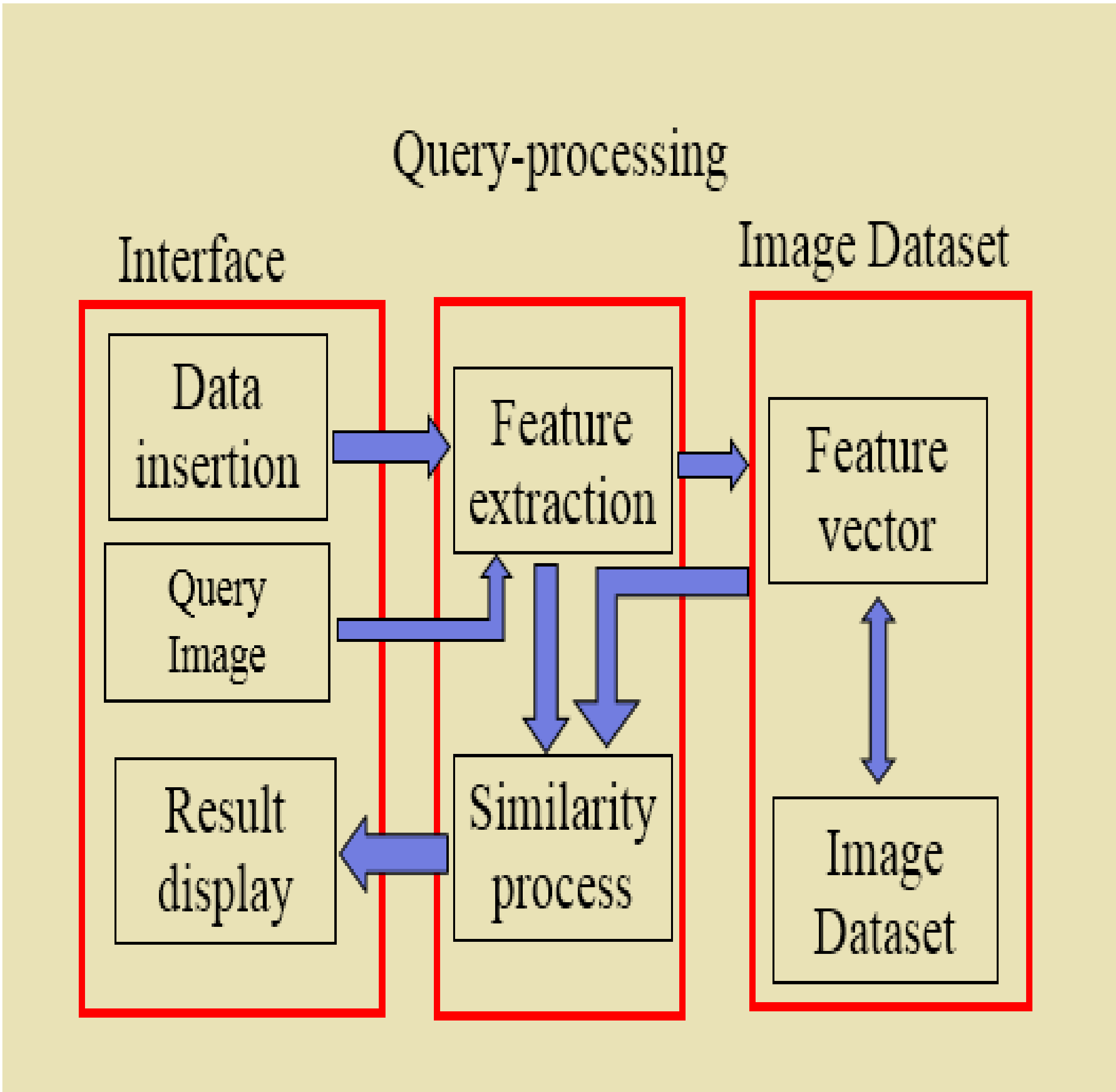


Figure 1-1. A typical content-based retrieval system

Secondly by using the query image block, the image as a query pass to the feature vector block to be extracted then the feature vector of these query image is compared with feature vector in the feature vector dataset by using similirities process.

In these process, retrieval is conducted by applying an indexing scheme to provide an efficient way of searching the image database. Finally, the system CBIR ranks the search results and then returns the results that are most similar to the query image throught the result display.

1.5 Outline of The Thesis

This dissertation is organized as five chapters. The structure and relation among chapters are shown in Figure 1-2.

Chapter 1 This chapter presents the information retrieval, Image retrieval, motivation and objective, principle of CBIR also outline of the thesis.

Chapter 2 introduces some backgrounds necessary to understand the remainder of the thesis. In particular, This chapter presents, content base image retrieval, clustering, hierarchical clustering methods and non-hierarchical clustering methods, cluster structure etc., will be discussed.

Chapter 3 presents the proposed method, multi layer centroid contour distance, shift invariance process, Scale invariance process and shape independence clustering

Chapter 4 In this section presents the experiment and result, performance measuring, precision, recall, The simulation dataset and experiment with real dataset.

Chapter 5 presents conclusion

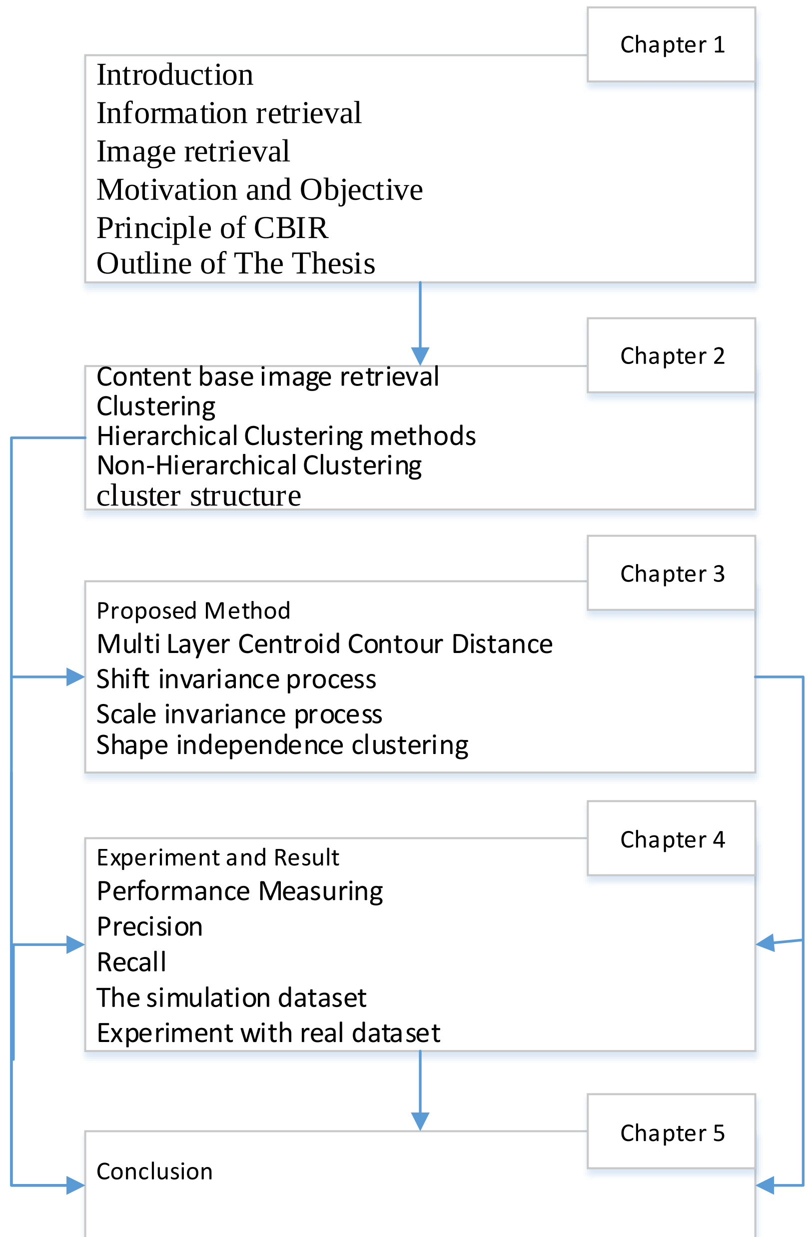


Figure 1-2. Flow Chart of the Thesis Continuity

2. Literature Review

This chapter presents the Information retrieval, Content base image retrieval, Clustering, Hierarchical Clustering methods and Non-Hierarchical Clustering methods.

2.1 Information retrieval

In the past decade, With expansion in the multimedia technologies and the Internet, more and more information has been published in computer readable formats. Big archives of films, music, images, satellite pictures, books, newspapers and magazines have been made accessible for computer users. Information Retrieval is the field of knowledge that deals with the representation, storage, and access to information items. More specifically, when the retrieved information is a collection of images, this field of knowledge is called Image Retrieval [17] [18].

2.2 Content base image retrieval

Image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. The problems of image retrieval are becoming widely recognized, and the search for solutions an increasingly active area for research and development. There are three fundamental bases for content based image retrieval i.e. visual feature extraction, multi-dimensional indexing, and retrieval system design.

Content-based image retrieval (CBIR) is a technique for retrieving images on the basis of automatically-derived features. The architecture of a CBIR system can be understood as a basic set of modules that interact within each other to retrieve the database images according to a given query. Content-based image retrieval, uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. In typical content-based image retrieval systems, 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 example images or sketched figures. The system then changes these examples into its internal representation of feature vectors. The similarities /distances between the feature vectors of the query example or sketch 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[5].

2.2.1 Image

An image may be defined as a two-dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the amplitude values of fare all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. Note that a digital image is com-posed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements and pixels. Pixel is the term most widely used to denote the elements of a digital image[19].

2.2.2 Color

Color is visual perceptual property corresponding in human to the category called red, green, blue, black, yellow, etc. Color is produced by spectrum of light that absorbed or reflected then received by the human eye and processed by the human brain. Color is one of the most widely used features for image similarity retrieval, Color retrieval yields the best results, in that the computer results of color similarity are similar to those derived by a human visual system that is capable of differentiating between infinitely large numbers of colors.

One of the main aspects of color feature extraction is the choice of a color space. A color space is a multidimensional space in which the different dimensions represent the different components of color. Mostly color spaces are three dimensional. Example of color space is RGB, which assigns to each pixel a three element vector giving the color intensities of the three primary colors, red, green and blue. The space spanned by the R, G and G values completely describes visible colors, which are represented as vectors in the 3D RGB color spaces.

2.2.3 RGB Color

The RGB model uses three primary colors, red, green and blue, in an additive fashion to be able to reproduce other colors (see figure 2-1). As this is the basis of most computer displays today, this model has the advantage of being easy to extract. In a true-color image each pixel will have has a red, green and blue value ranging from 0 to 255 giving a total of 16777216different colors. Varying levels of the three colors are added to produce more or less any color in the visible spectrum. This space is device dependent and perceptually non-uniform. This means that a color relative close together in the RGB space may not necessarily be perceived as being close by the human eye. RGB space is normally used in Cathode Ray Tube (CRT) monitors, television, scanners, and digital cameras. For a monitor the phosphor luminescence consists of additive primaries and we can simply parameterize all colors via the coefficients (α, β, γ), such that $C = \alpha R+\beta G+\gamma B$. The coefficients range from zero (no luminescence) to one (full phosphor output). In this parameterization the color coordinates fill a cubical volume with vertices black, the three primaries (red, green, blue), the three secondary mixes (cyan, magenta, yellow), and white as in figure2-2 [18].

If only the brightness information is needed, color images can be transformed to gray scale images[20]. The transformation can be made by using equation (see equation 2.1).

$$I_{gray}=0.3Fr+0.3Fg+0.3Fb \tag{2.1}$$

But human vision gives more weight to the G channel. The standard conversion to grayscale mimics the proportion of RGB sensors in the human eye [21] (see equation 2.2):

$$Igray =0.3Fr+0.59Fg+0.11Fb \tag{2.2}$$

Where Fr, Fg and Fb are the intensity of R, G and B component respectively and I_{gray} is the intensity of equivalent gray level image of RGB image.

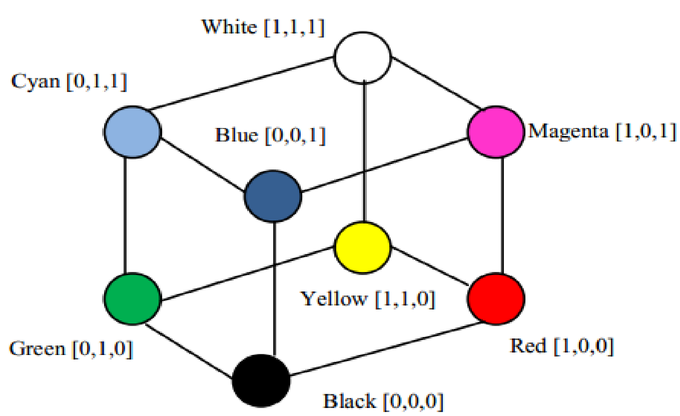


Figure 2-1 RGB Color Space

Another color space model is the Hue-Saturation-Value Model (HSV) that is based on color descriptions rather than individual color components. HSV model, defines a color space in terms of three constituent components.

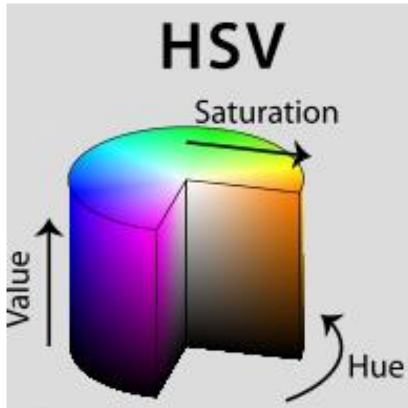


Figure 2-2 HSV Color Space Model

In the figure 2-2, Hue is defined as an angle in the range from 0 to 360 degree, the corresponding colors vary from red through yellow, green, cyan,blue, magenta, and black to red. S, is the depth or purity of color and is measured as a radial distance from the central axis with value between 0 at the center to 1 at the outer surface. value, or brightness, varies from 0 to 1.0, the corresponding colors become increasingly brighter.

2.2.4 Shape

The shape of an object is a binary image representing the extent of the object. Since the human perception and understanding of objects and visual forms relies heavily on their shape properties, shape features play a very important role in CBIR. Shape is one of the most important image features of recognizing objects by human perception. Humans generally describe objects either by giving examples or by sketching the shape. In computer vision, shape is the most commonly used feature for characterising objects and in image retrieval. Queries for shapes are generally achieved by selecting an example image provided by the system or by having the user sketch a shape.

The primary mechanisms used for shape retrieval include identification of features such as lines, boundaries, aspect ratio, and circularity, and by identifying areas of change or stability via region growing and edge detection. Of particular concern has been the problem of dealing with images having overlapping or touching shapes[22].

Boundary based shape descriptors have been widely used in image retrieval problems. A plethora of contour-based descriptors regarding the shape as a 1-D signal sequences, can be found in literature. Centroid Contour Distance (CCD) as well as Angle Code Histogram (ACH) are well known and extensively used descriptors.

The (CCD) descriptor is formed by the consecutive boundary-to-centroid distances. Let i be a shape contour point having (x_i, y_i) coordinates. Assuming that the shape centroid has coordinates (x_c, y_c), the CCD curve is computed for all n boundary points:

CCD(d) = [d1 d2 ... di... dn], $d_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}$

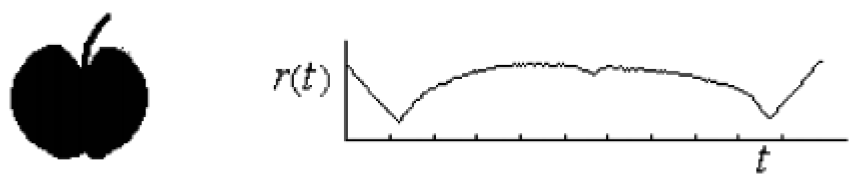


Figure 2-3 An apple shape and its centroid distance signature [23]

The distance between two shapes represented by CCD sequences is acquired by calculating the Euclidean distance of all the rotated versions[7][23][16] (see figure 2-3).

Other shape descriptor is fourier descriptor. The concept of fourier descriptor (FD) has been widely used in the field of computational shape analysis[24] [25]. The idea of the FD (Fourier Descriptor) is to use the Fourier transformed boundary as a shape Feature. Suppose A shape signature z(u) is a 1-D function that represents 2-D areas or boundaries. The discrete Fourier transform of an signature z(u) is defined as follows:

$$a_n = \frac{1}{N} \sum_{u=0}^{N-1} z(u)\, e^{-j2\pi nu / N} \tag{2.3}$$

Where :

n = 0,1,2, … n-1

The coefficients a_n (n=0,1,..N-1) are called the Fourier descriptors (FDs) of the shape.

2.2.5 Feature Extraction

Feature extraction is the process of creating a representation for, or a transformation from the original data. within the visual feature system, feature can be further classified as general feature and domain specific features. Feature extraction is the basis of any content-based image retrieval technique. In a broad sense, features may include both text-based features (key words, annotations) and visual features (color, texture, shape, etc.). Within the visual feature scope, the features can be further classified as low-level features and high-level features. The selection of the features to represent an image is one of the keys of a CBIR system. Because of perception subjectivity and the complex composition of visual data, there does not exist a single best representation for any given visual feature [18].

Image feature can be either global or local. A global feature uses the visual features of the whole image, whereas a local descriptor uses feature of the regions or objects to describe the image content. To obtain the local feature, an image is often divided into parts first. The simplest way of dividing an image is to use a partition, which cuts the image into tiles of equal size and shape. A simple partition does not generate perceptually meaningful regions but is a way of representing the global features of the image at a finer resolution. A better method is to divide the image into homogenous regions according to some criterion using region segmentation algorithms that have been extensively investigated in computer vision.

2.2.6 Similarity / Distance Measures

Instead of exact matching, content-based image retrieval calculates visual similarities between a query image and images in a database. Accordingly, the retrieval result is not a single image but a list of images ranked by their similarities with the query image. Many similarity measures have been developed for image retrieval based on empirical estimates of the distribution of features in recent years. Different similarity/distance measures will affect retrieval performances of an image retrieval system significantly[5].

Similarity metric is very important on the retrieval result. One of The similarity measure is Euclidean distance (See Equation 2.4) between feature representation of image in database image and feature representation of image query. These feature representation of image feature that refer to the characteristics which describe the contents of an image. The retrieval result is a list of image ranked by their similarity. Suppose S_1 and S_2 are shape of object represented multi layer of feature vectors each ($db_1, db_2,\ldots,db_k$) and ($qr_1, qr_2,.....,qr_k$) then the Distance between S_1 and S_2 is:

$$\mathrm{dis}(F_{db}, F_{qr}) = \sqrt{\sum_{j=1}^{k} (db_j - qr_j)^2} \tag{2.4}$$

where :

Fdb = Feature vector of image in database image
Fqr = Feature vector of query image.
k = Number element of feature vector

in these case if the distance between feature representation of image in database image and feature representation of image query small enough then it to be considered as similar.

2.3 Clustering

Cluster analysis is the process of partitioning data objects (records, documents, etc.) into meaningful groups or clusters so that objects within a cluster have similar characteristics but are dissimilar to objects in other clusters. Cluster analysis aims at identifying groups of similar objects and, therefore helps to discover distribution of patterns and interesting correlations in large data sets. It has been subject of wide research since it arises in many application domains in engineering, business and social sciences. Especially, in the last years the availability of huge transactional and experimental data sets and the arising requirements for data mining created needs for clustering algorithms that scale and can be applied in diverse domains[26].

Clustering, in data mining, is useful for discovering groups and identifying interesting distribution in the underlying data. Clustering problem is about partitioning a given data set into groups (clusters) such that the data points in a cluster are more similar to each other than points in different clusters [27].

For many years, many clustering algorithms have been proposed and widely used. It can be divided into two categories, hierarchical and non-hierarchical methods. It is commonly used in many fields, such as data mining, pattern recognition, image classification, biological sciences, marketing, city-planning, document retrieval, etc. The clustering means process to define a mapping, $f: D \rightarrow C$ from some data $D=\{t_1, t_2, \ldots, t_n\}$ to some clusters $C=\{c_1, c_2, \ldots, c_n\}$ based on similarity between t_i [28].

2.3.1 Hierarchical Clustering methods

Hierarchical methods is One of the most famous methods in clustering is that classified method as hierarchical clustering. In hierarchical clustering the data are not partitioned into a particular cluster in a single step. It runs with making a single cluster that has similarity, and then continues iteratively. Hierarchical clustering algorithms can be either agglomerative or divisive [26][29]. Agglomerative method proceeds by series of fusions of the "n" similar objects into groups, and divisive method, which separate "n" objects successively into finer groupings. Agglomerative techniques are more commonly used. One of similarity factors between objects in hierarchical methods is a single link that similarity closely related to the smallest distance between objects.[30]

Hierarchical clustering involves creating clusters that have a predetermined ordering from top to bottom. For example, all files and folders on the hard disk are organized in a hierarchy. There are two types of hierarchical clustering, *Divisive* and *Agglomerative* [30].

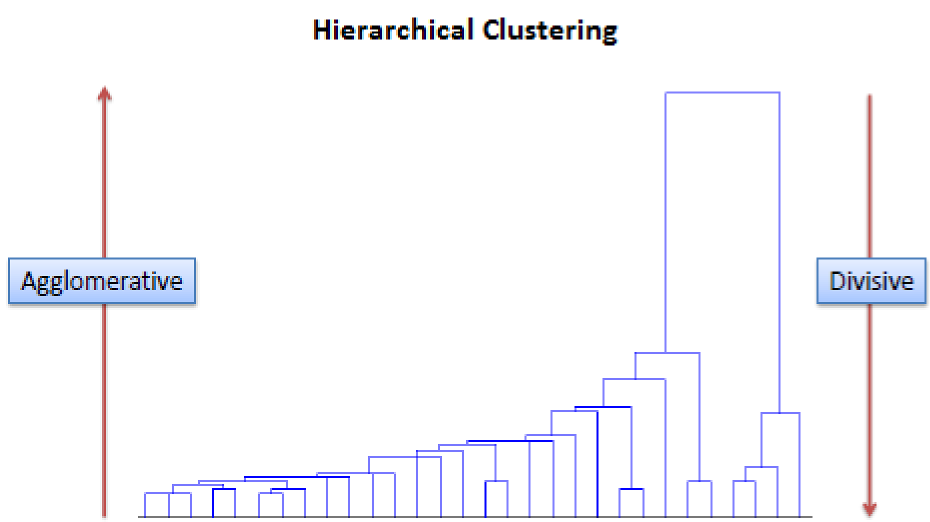


Figure 2-4 Dendrogram of hierarchical clustering[30]

A. Divisive method

In this method we assign all of the observations to a single cluster and then partition the cluster to two least similar clusters. Finally, we proceed recursively on each cluster until there is one cluster for each observation.

B. Agglomerative method

In this method we assign each observation to its own cluster. Then, compute the similarity (e.g., distance) between each of the clusters and join the two most similar clusters. Finally, repeat steps 2 and 3 until there is only a single cluster left.

2.3.2 Non-Hierarchical Clustering methods

An example of non-hierarchical methods is K-Means Clustering .K-Means Clustering is an algorithm to classify or to group some objects based on attributes/features into K number of group. K is positive integer number. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid. Thus, the purpose of K-mean clustering is to classify the data.

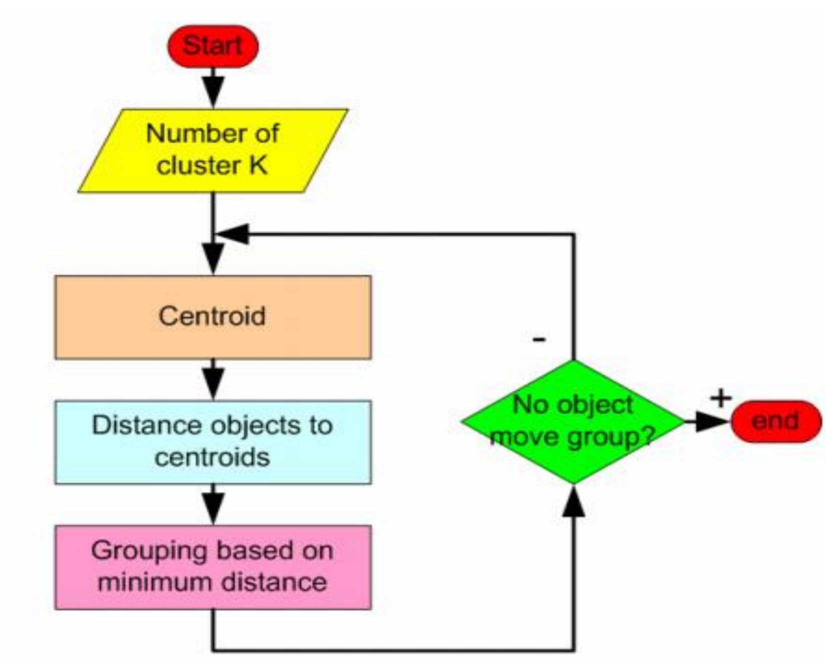


Figure 2-5 The numerical example below is given to understand this simple iteration [31]

The basic step of k-means clustering is simple. In the beginning, we determine number of cluster K and we assume the centroid or center of these clusters. We can take any random objects as the initial centroids or the first K objects can also serve as the initial centroids. Then the K means algorithm will do the three steps below until convergence[31].

Iterate until stable (= no object move group):

1. Determine the centroid coordinate
2. Determine the distance of each object to the centroids
3. Group the object based on minimum distance (find the closest centroid)

2.3.3 Cluster structure

The condensed cluster is defined as the cluster members gathered in closely surrounding locations as is shown in figure 2-5. In the case of condensed cluster, the center of gravity resides in circle weight of the cluster members. The condensed cluster is very different from the shape independence cluster that its similar can be seen as such shape patterns. It, in this case, is very difficult to determine the centroid as illustrated in figure 2-6[32].

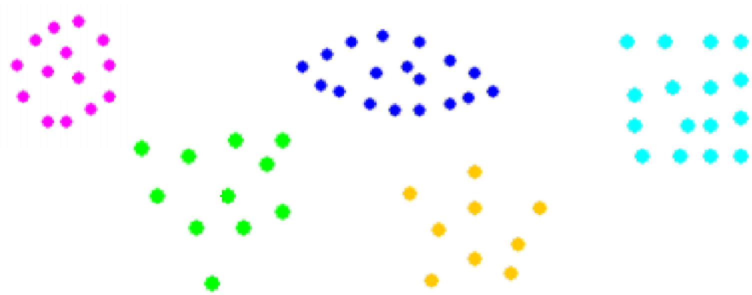


Figure 2-6 Examples of condensed clusters (centroids are shown with red dots)[32]**.**

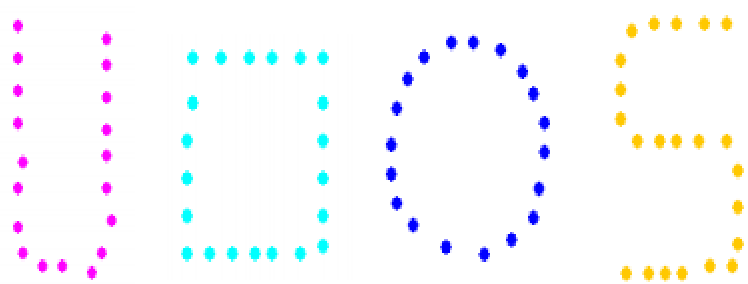


Figure 2-7 Examples of shape independent clusters [32]

3. Desain Proposed Method

In this chapter we will describe our proposed method dealing with shape feature extraction by using multi layer centroid contour distance.

3.1 Multi Layer Centroid Contour Distance

Figure 3.1 is Diagram block of the proposed CBIR.

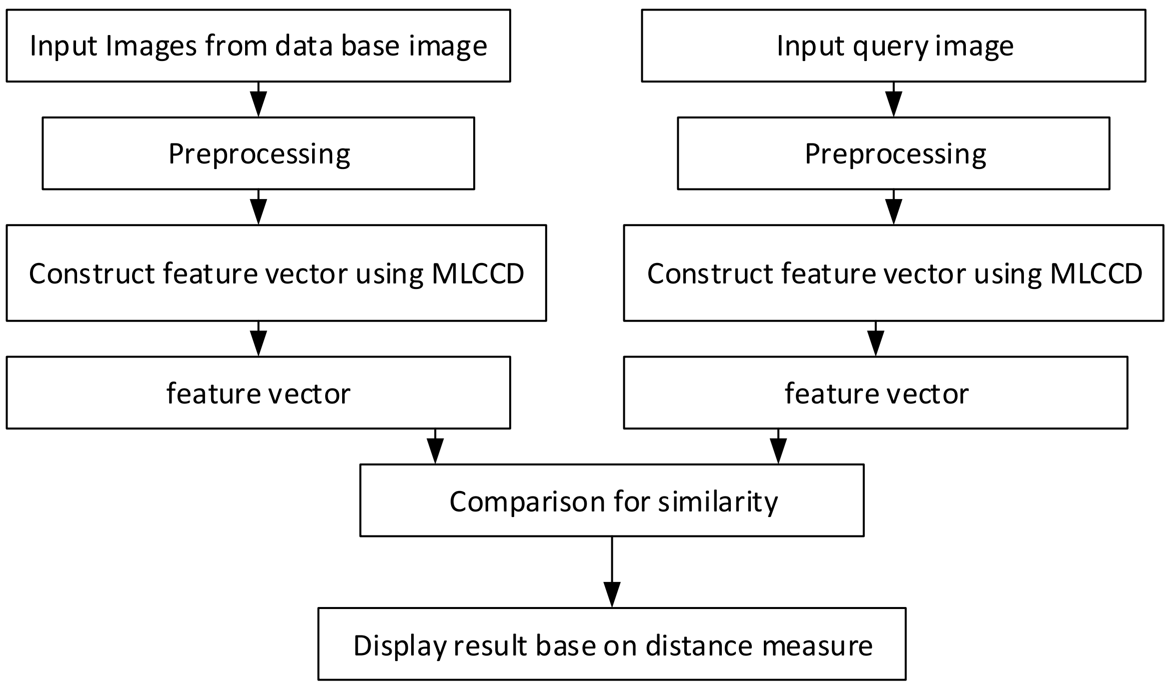


Figure 3-1 Diagram block of Proposed Cbir

Firstly images in the database image one by one is extracted. The local feature of an image at some point at interest location is computed. Interest location of the local feature can be obtained by converting RGB image to grayscale image and implement the canny filter to detect edge position then use morphology filter to ensure the shape of object clear. Feature vector is computed by measuring distance between center of object and point in the boundary object then the result is placed to the feature vector layer 1 and if the object have other point in the same angle (see Figure 3-2) the result is placed into next layer. All image in the database image is processed by using same method.

Secondly, when a query image is provided then applied same method to obtain feature vector. These feature vector is compared with other feature vector by using the Euclidean distance.

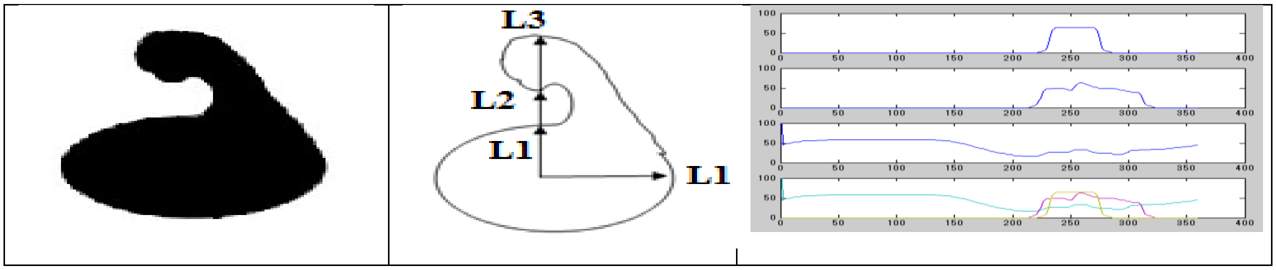


Figure 3-2a An object and its Proposed method pattern

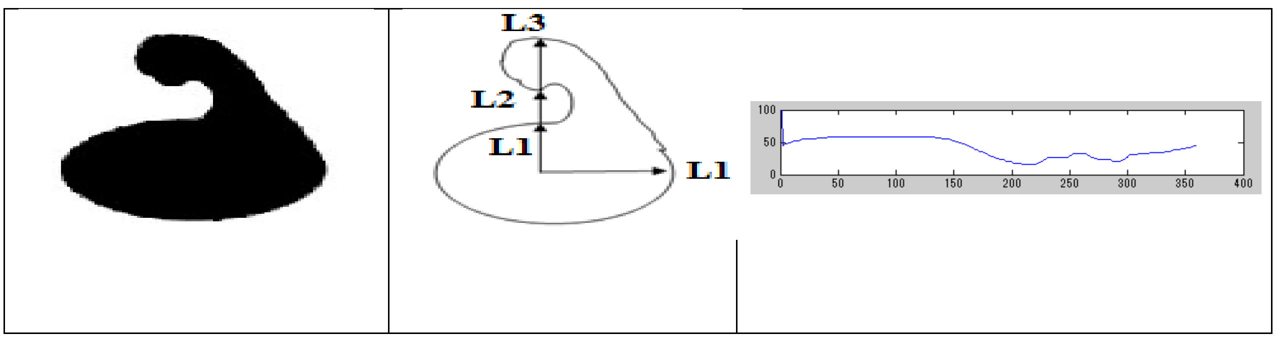


Figure 3-3b An object and its conventional pattern

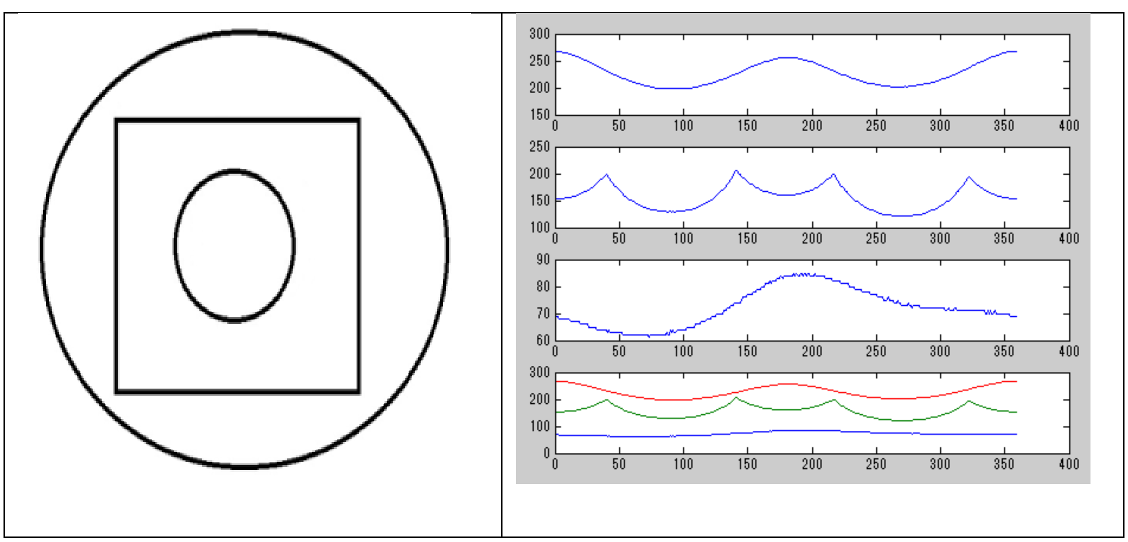


Figure 3-4 An simulation data and its Proposed method pattern

In figure 3-2a when the angle 0 there is one point have to be captured. However, when the angle is 270 degree there are three point have to be captured by using MLCCD in these case other method just capture one point see figure 3-2 b. In Figure 3-3, The object have three point that have to be captured for all different angle and the result is placed into three layer.

In order to obtain the MLCCD firstly position of the centroid have to be computed (see equation 3.1) then calculate the distance between centroid and the boundary of object repeat this method for other boundary in same angle and different angle.

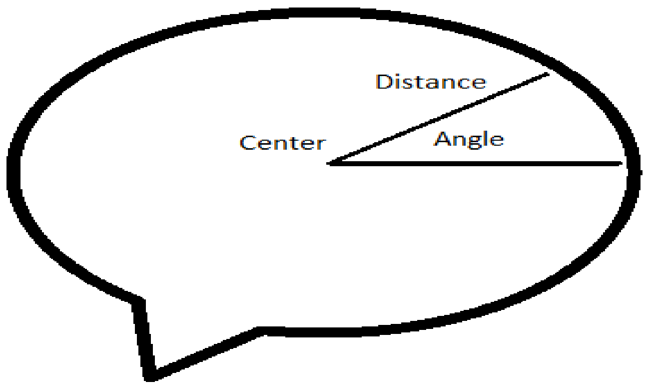


Figure 3-5 an object with center and distance

position of the centroid is:

$$X_c = \frac{X_1+X_2+X_3+.... + X_n}{n} \quad , \quad Y_c = \frac{Y_1+Y_2+Y_3+....+ Y_n}{n} \tag{3.1}$$

Where:

X_c = position of the centroid in the x axis

Y_c = position of the centroid in the y axis

n = Total point in the object (every point have x position and y position)

After the location centroid is founded then calculate the distance between centroid and the boundary of object by using equation 3.2 repeat this method for other boundary in different angle.

Suppose there are t point in the boundary the distance every point in the boundary with center is :

$$Dis(n) = \sqrt{(x(n) - x_c)^2 + (y(n) - y_c)^2} \quad (3.2)$$

Where :

n = number point in the boundary(1,2,..t)

t = total point in the boundary

x_c = position center in the x axis

y_c = position center in the y axis

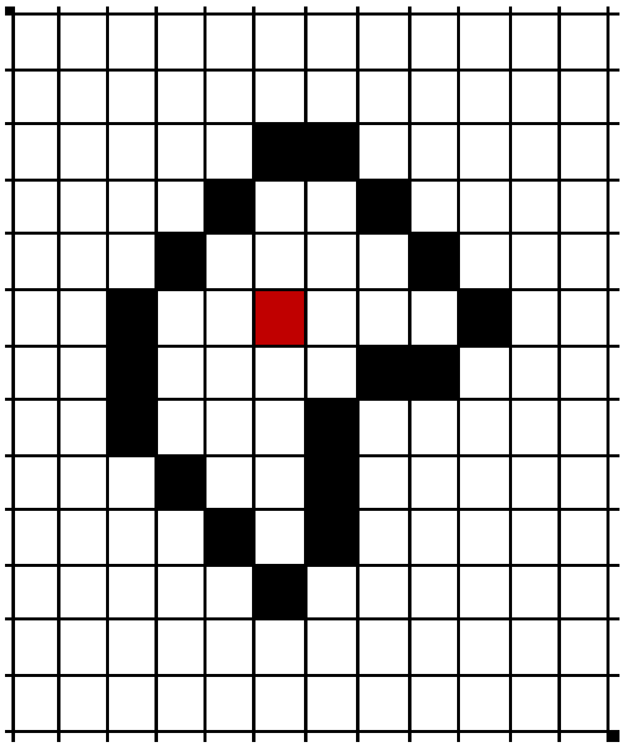
x(n) = position point number n in the x axis

y(n) = position point number n in the y axis

The computed distances are saved in a vector. In order to achieve rotation invariance and scale invariance the implementation shifting and normalization to these features vector is needed. Comparison between two object is conducted by measure distance between two features vector by using Euclidean distance.

3.1.1 Shift invariance process

In order to achieve rotation invariance the implementation shifting to the features vector is needed.

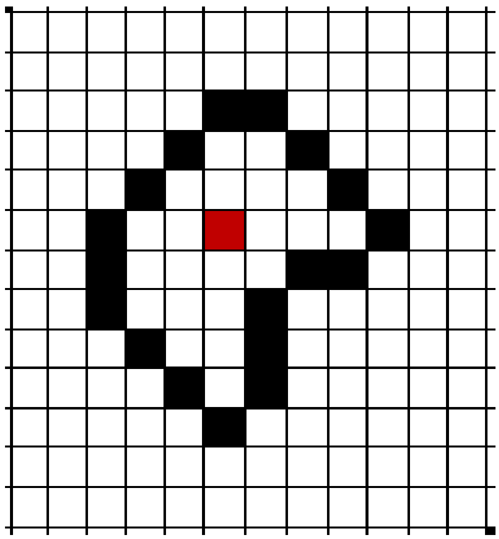


Distance	4	3	3	5
Angle	0	90	180	270

Figure 3-6 Example object with its distance and angle

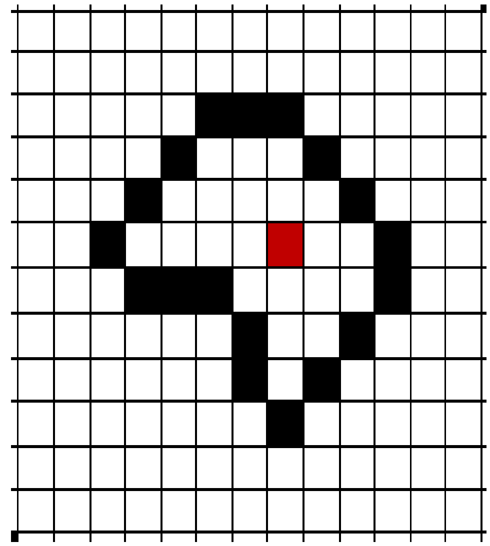
In the figure 3-5 distance between center and the boundary of object are 4 at angle 0 degree, 3 at angle 90 degree, 3 at angle 180 degree and 5 at angle 270 degree, however this will change if the object be rotated. In the figure 3-6 there are 4 object that actually same but different in rotation around 90 degree and the order of the distance also different.

In the figure 3-6 there are four similar object with different rotation and the distance between centroid and the boundary also different in same angle. When angle is zero (0) the distance of object a 4, object b 3, object c 3 and object d 5. When angle 90 the distance object a 3, object b 3, object c 5 and object d 4. When angle 180 the distance object a 3, object b 5, object c 4 and object d 3. When angle 270 the distance object a 5, object b 4, object c 3 and object d 3. Base on the figure 3-5 the feature vector of object a, object b, object c and object d are 4 3 3 5, 3 3 5 4, 3 5 4 3 and 5 4 3 3 as be shown at table 3-1.



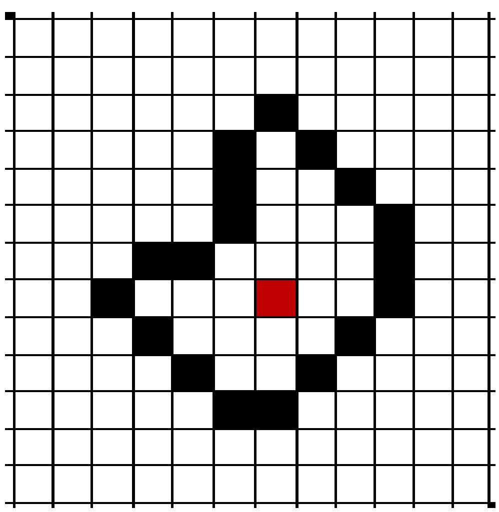
Distance	4	3	3	5
Angle	0	90	180	270

A



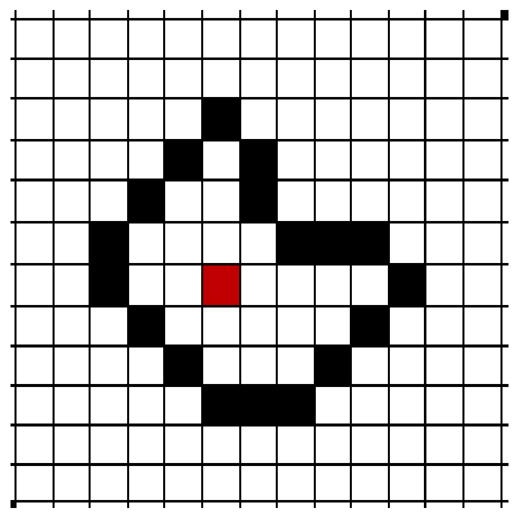
Distance	3	3	5	4
Angle	0	90	180	270

B



Distance	3	5	4	3
Angle	0	90	180	270

C



Distance	5	4	3	3
Angle	0	90	180	270

D

Figure 3-7 Four Same object with different rotation

Table 3-1 is features vector of object A, Object B, object C and object D, Table 3-2 is a distance between two object in the Table 3-1obtained by using euclidean distance between two features vector. These distance still high although the objects actually same object that is happened due to that object is different in rotation.

Table 3-1 Feature Vector of object with different rotation

Object	Feature Vector			
A	4	3	3	5
B	3	3	5	4
C	3	5	4	3
D	5	4	3	3

Table 3-2 Distance between two object with different rotation before shifting process

Object	Distance between two object
A-B	2.4495
A-C	3.1623
A-D	2.4495
B-C	2.4495
B-D	3.1623
C-D	2.4495

Table 3-3 is features vector of object A, Object B, object C and object D after shifting process, In order obtained these value shifting the features vector one by one. In these case there are four possibility 5433 or 4335 or 3354 or 3543. The highest value is 5433 then choose these value.

Table 3-3 Feature vector of object after shifting process

Object	Feature Vector			
A	5	4	3	3
B	5	4	3	3
C	5	4	3	3
D	5	4	3	3

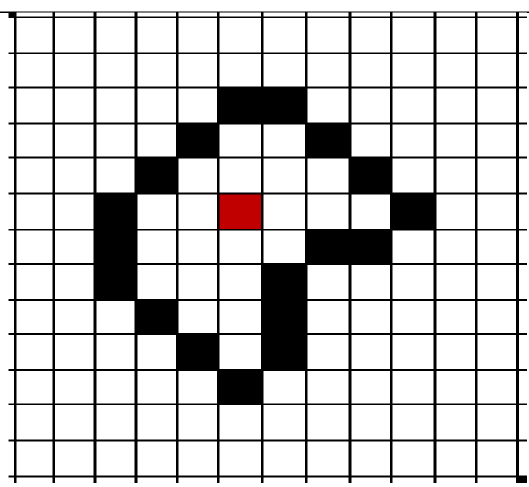
Table 3-4 a distance between two object at table 3-3 is obtained by using euclidean distance between two features vector. After shifting process The distance is now become 0.

Table 3-4 Distance between two object after shifting process

Object	Distance between two object
A-B	0
A-C	0
A-D	0
B-C	0
B-D	0
C-D	0

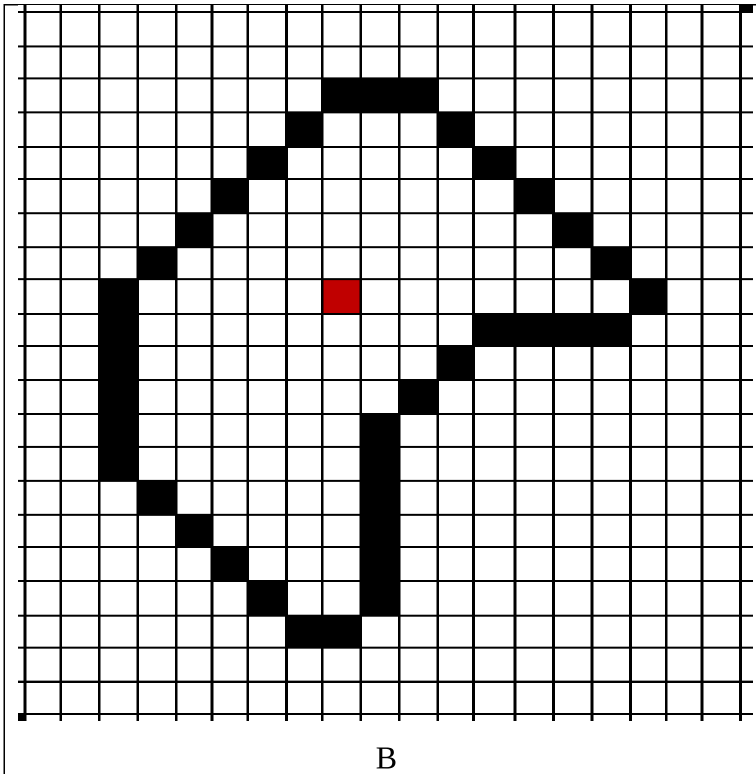
3.1.2 Scale invariance process

In order to achieve scale invariance the implementation normalization to the feature vector is needed.



A

Distance	4	3	3	5
Angle	0	90	180	270



Distance	8	6	6	10
Angle	0	90	180	270

Figure 3-8 Two same object with different scaling

Figure 3-7 is two same object, object A and object B actually same object with different scaling and both object have also different features vector as shown in the table 3-5. The distance between object A and object B is shown in the table 3-6. Although the object A and object B same object but the distance between them still high.

Table 3-5 Features Vector of object with different scaling before normalization process

Object	Feature Vector				highest
A	4	3	3	5	5
B	8	6	6	10	10

Table 3-6 Distance between two object with different rotation before normalization process

Object	Distance between two object
A-B	7.6811

Table 3-7 Features Vector of object with different scaling after normalization process

Object	Feature Vector			
A	0.8	0.6	0.6	1
B	0.8	0.6	0.6	1

Table 3-8 Distance between two object with different rotation after normalization process

Object	Distance between two object
A-B	0

Features vector in the Table 3-7 is obtained from features vector in the table 3-5 devided by the highest value of its features vector and the feature vector object A and feature vector object B become same. The table 3-8 shown distance between both object A and object B become 0.

3.2 Shape independence Clustering by using layered structure representation

In this subsection we implemented the layered structure representation with some modification to the shape independence clustering.

The algorithm is described as follow:

1. Begin with an assumption that every point "n" is it's own cluster c_i, where i =1,2,…n

2. Calculate the centroid location

3. Calculate the angle and distance for every point

4. Make multi layer centroid contour distance based on step 2 and 3

5. Set i = 1 as initial counter

6. Increment i = i + 1

7. Measure distance between cluster in the location i with cluster in the location i-1 and cluster

in the location i+1.

8. Merge two cluster become one cluster base on the closet distance as shown in the step 7

9. Repeat from step 6 to step 8 while i< 360

10. Repeat step 5 to step until the required criteria is met

Firstly in the step 1, let every point “n” is it’s own cluster, if there are n data it mean there are n cluster. Step 2 obtain the centroid by using equation 3.1 in this case every point have contribution to find the centroid location. Step 3 Calculate the angle and distance for every point, the angle is obtained by using arctangent of dy/dx, dy is differences y position between position y of point in the boundary and y of centroid and dx is differences x position between position x of point in the boundary and x of centroid. The distance can be obtained by using pythagoras formula. By using the angle of every point and its distance then make the multi layer centroid contour distance and set i as counter start from 1 to 360 then calculate distance between every point that pointed by i on every layer and every point on every layer that pointed i-1 and i+1. After the distance was calculated then merge two cluster become one cluster base on the closet distance.

4. Experiment and Result

In this section, we describe the experiments, using both simulation and real data and then we verify performance of retrieval by using precision and recall.

4.1 Performance Measuring

In image retrieval contexts, precision and recall are defined in terms of a set of retrieved image and a set of relevant image. There is two step approach to retrieve the relevant image from dataset. Firstly, cbir system have to extract a feature vector for every image and put it into feature dataset. Secondly, The user provide a query image, The cbir system extract its feature vector then matched with feature vector in the dataset by computing the distances between two feature vector.

The performance of cbir system is calculated by showing image with x top ranking from the dataset. There is a common way to evaluate the performance of the cbir system such as precision and recall.

4.2 Precision

Precision measures the retrieval accuracy, it is ratio between the number of relevant images retrieved and the total number of images retrieved (See equation 4.1).

$$\text{Precision} = \frac{\text{NRRI}}{\text{XR}} \tag{4.1}$$

Where :

NRRI = Number of relevant retrieved images

XR = X Top ranking of retrieved images

4.3 Recall

Recall measures the ability of retrieving all relevant images in the dataset. It is ratio between the number of relevant images retrieved and the whole relevant images in the dataset (See equation 4.2).

$$\text{Recall} = \frac{\text{NRRI}}{\text{TR}} \tag{4.2}$$

Where:

NRRI = Number of relevant retrieved images

TR = Total number of relevant images in dataset

4.4 The simulation dataset

The simulation dataset consist combination of curve shape, oval shape, rectangle shape, Triangle shape, Diamond shape, star shape as shown in Figure 4-1. Also we make these shapes with different scaling, translation and rotation. Graphic average precision results on simulation dataset are then shown in Table 4-1.

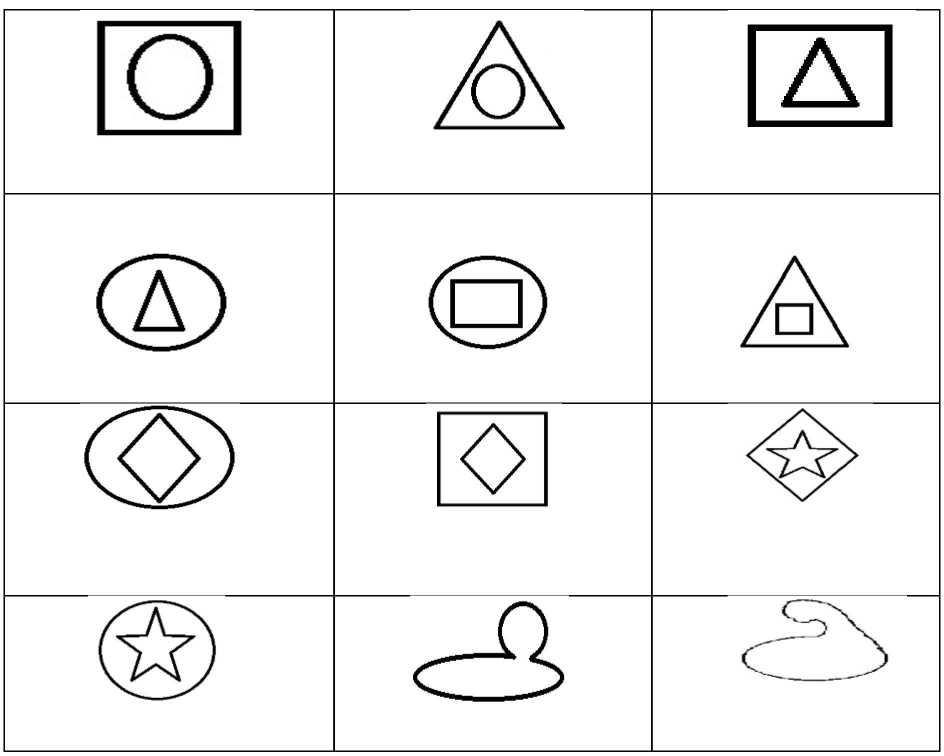


Figure 4-1 Example of simulation dataset

The experiment on the simulation dataset in the Table 4-1 is obtained base on equation 4.1 shows average precision result is superior to the conventional method for all cases by approximately 8.67 %.

Table 4-1 Average precision on simulation dataset.

Number Group	Shape	CCD	MLCCD
1	oval rectangle	86	93
2	oval triangle	80	85
3	Triangle rectangle	81	86
4	Rectangle oval	80	85
5	Triangle oval	70	75
6	rectangle triangle	88	96
7	Diamond oval	85	89
8	Diamond rectangle	68	92
9	Star diamond	74	85
10	Star oval	67	81
11	shape with concave 1	85	91
12	shape with concave 2	83	93
Average		78.91	87.58

4.5 Experiment with real image

In order to show the feasibility of the shape recognition scheme, We used Image database of phytoplankton[33] for experiment to real data. On the phytoplankton, Alga blooms (red tides) are a phenomenon of clear ecological importance in many regions of the world. Caused by a nutrient influx (e.g. agricultural pollution) into the ocean, by either natural or anthropogenic causes, they can be toxic to marine life and humans under certain conditions.

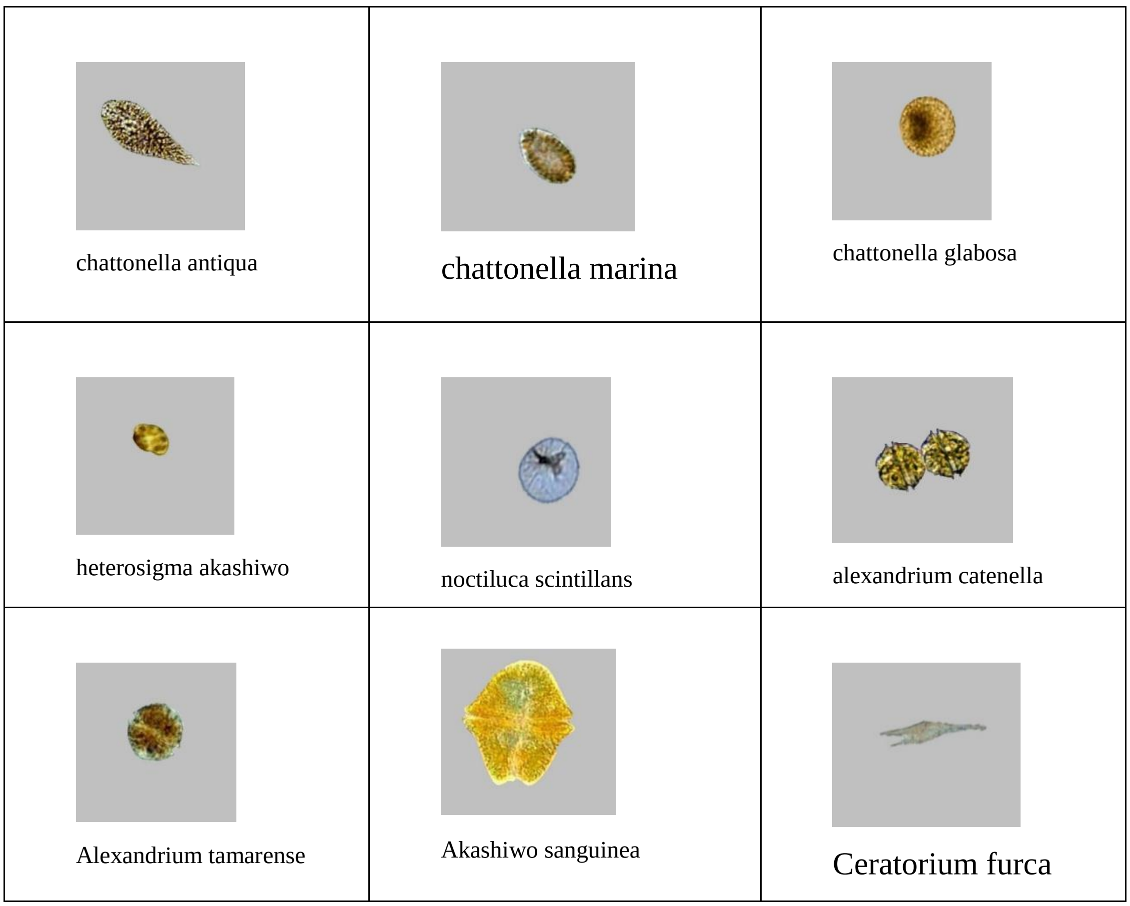


Figure 4-2 A small portion of phytoplankton image database

Red tide is a significant problem not only for fisherman but also ocean biologist. Red tide is one of measure for representation of ocean healthy. Red tide occur in a nutrition rich ocean. Nutrition rich water makes chlorophyll-a then phytoplankton is increase thus red tide occurs. Figure 4-2 shows a portion of phytoplankton image database[33].

In order to detect red tide, many researcher check phytoplankton in water sampled from the ocean with microscope. Immediately after they check phytoplankton, they have to identify the species of phytoplankton. Image retrieval is needed for identification. The proposed method is to be used for image retrieval and identification.

Table 4-2 Average precision on real dataset

Number Group	Total Image	Phytoplankton name	precision		Recall	
			CCD	MLCCD	CCD	ML CCD
1	18	chattonella antiqua	85	91	47	50
2	17	chattonella marina	84	90	49	52
3	17	chattonella glabosa	82	87	48	51
4	17	heterosigma akashiwo	85	88	50	51
5	17	noctiluca scintillans	83	87	48	51
6	20	alexandrium catenella	84	93	42	46
7	22	Alexandrium tamarense	84	94	38	42
8	23	Akashiwo sanguinea	83	93	36	40
9	24	Ceratorium furca	82	94	34	39
	Average		83.5	90.7	43.5	46.8

The experiment on the real dataset in the Table 4-2 is precision measure base on equation 4.1 and recall measure base on equation 4.2. Average precision result by using new approach is higher 3 percent up to 12 percent rather than the coventional method also for average recall result by using new approach is higher 1 percent up to 5 percent rather than conventional method.

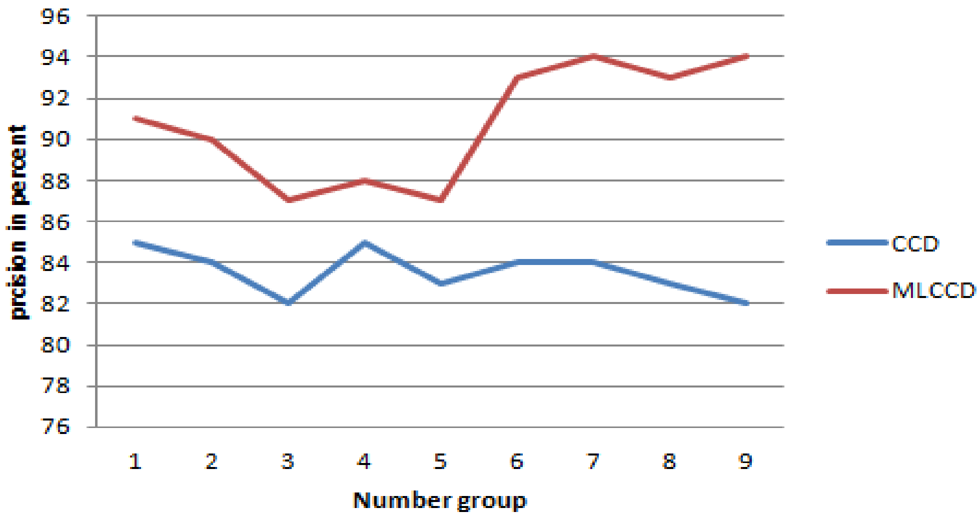


Figure 4-3 Graphic Average precision and recall on real dataset

From the experiment show if the image have more concave then differences of result between new approach and the conventional method will increase see graphic in Figure 4-3 and Figure 4-4. From these table and figure, it may said that the proposed method is superior to the conventional method for all cases by approximately 7.22 %.

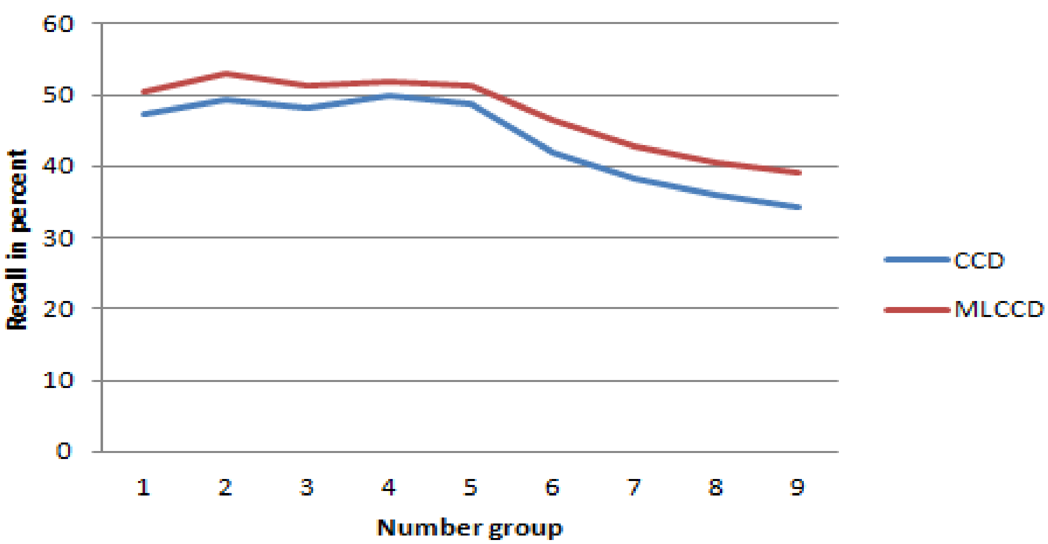


Figure 4-4 Graphic Average recall on real dataset

Table 4-3 Average precision result by using Color (Hsv) and Shape fourier descriptor

Number Group	Total Image	Phytoplankton name	Precision	
			Color (HSV)	Fourier descriptor
1	18	chattonella antiqua	70	85
2	17	chattonella marina	83	86
3	17	chattonella glabosa	81	83
4	17	heterosigma akashiwo	82	84
5	17	noctiluca scintillans	84	84
6	20	alexandrium catenella	73	85
7	22	Alexandrium tamarense	71	84
8	23	Akashiwo sanguinea	70	85
9	24	Ceratorium furca	72	83
	Average		76.222	84.33

The experiment on the real dataset in the Table 4-3 is precision measure base on equation 4.1. Average precision result by using color (Hsv) is 76.222 and by using Fourier descriptor is 84.33 the proposed method still have higher result compare these both method.

4.6 Clustering Experiment Result

In order to analyze the accuracy of our proposed method we represent error percentage as performance measure in the experiment. It is calculated from number of misclassified patterns and the total number of patterns in the data sets[34]. We compare our method with k-means clustering method to the same dataset.

$$Error = \frac{Number\ of\ misclassified}{Number\ of\ pattern}\ x\ 100\ \% \tag{5.1}$$

The dataset consist Circular nested dataset contain 96 data 3 cluster with cluster1 contain 8 data, cluster 2 contain 32 data and cluster 3 contain 56 data, inter related dataset contain 42 data 2 cluster with cluster 1 contain 21 data and cluster 2 contain 21 data, S shape dataset contain 54 data 3 cluster with cluster1 contain 6 data, cluster 2 contain 6 data and cluster 3 contain 42 data. u shape dataset contain 38 data 2 cluster with cluster 1 contain 12 data and cluster 2 contain 26 data. The 2 cluster Random dataset contain 34 data 2 cluster with cluster1 contain 15 data and cluster 2 contain 19. The 3 cluster condense dataset contain 47 data 3 cluster with cluster1 contain 16 data, cluster 2 contain 14 data and cluster 3 contain 17. The last data is 4 cluster condense dataset contain 64 data 4 cluster with cluster1 contain 14 data, cluster 2 contain 18 data cluster 3 contain 15 data and cluster 4 contain 17 data.

4.7 Result by using layered structure representation

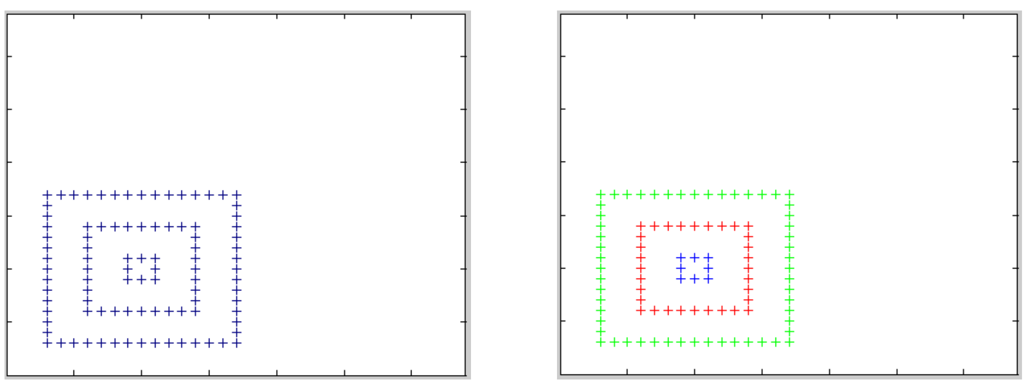


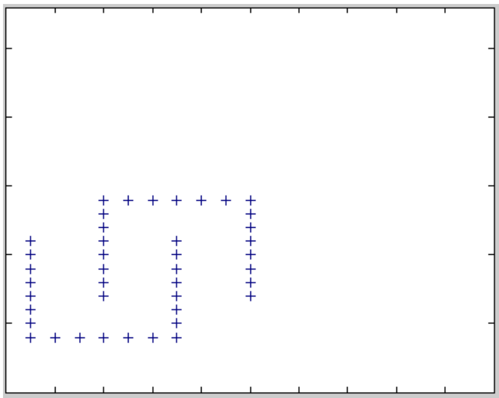
Figure 4-5 Result by using layered structure representation on the Circular nested dataset

In figure 4-5 is Result by using layered structure representation on the Circular nested dataset and the percentage of error as shown in table 4-3 are 0% for cluster1, 0 % for cluster2 and 0% for cluster3 average is 0 %.

Table 4-4 clustering by using layered structure representation on circular nested dataset

Cluster	Number pattern	Misclassified	Error in %

Cluster1	8	0	0
Cluster2	32	0	0
Cluster3	56	0	0
Average			0



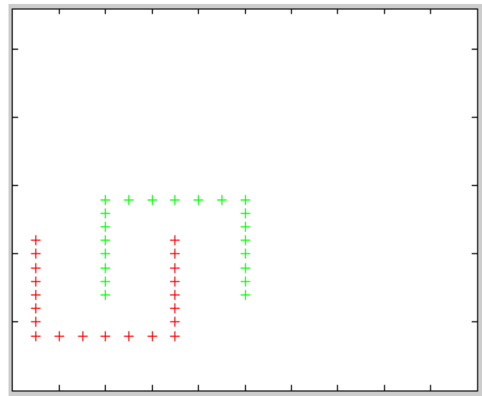


Figure 4-6 Result by using layered structure representation on the inter related dataset

In figure 4-6 is Result by using layered structure representation on the inter related dataset and the percentage of error as shown in table 4-4 are 0 % for cluster1 and 0 % for cluster2 average is 0 %.

Table 4-5 clustering by using layered structure representation on inter related dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	21	0	0
Cluster2	21	0	0
Average			0

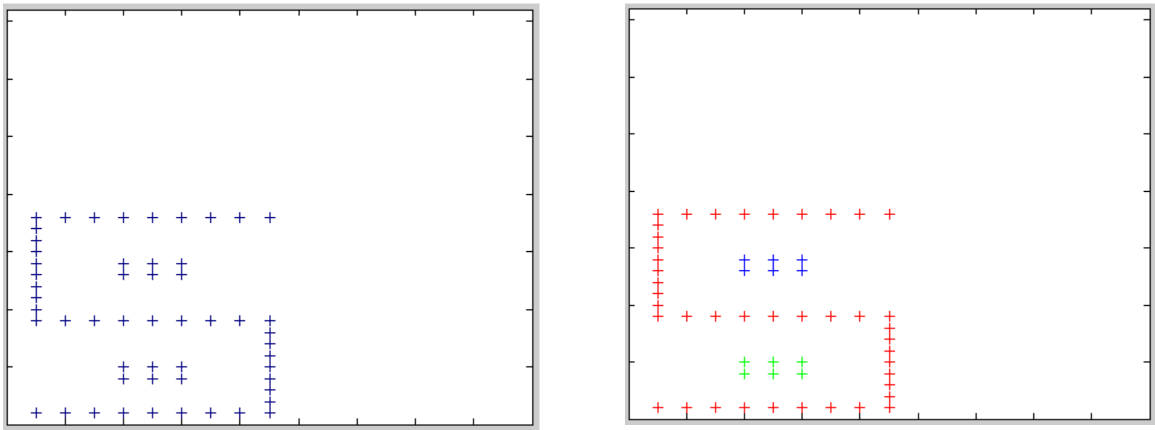


Figure 4-7 Result by using layered structure representation on the S shape dataset

In figure 4-7 is Result by using layered structure representation on the S shape dataset and the percentage of error as shown in table 4-5 are 0 % for cluster1, 0 % for cluster2 and 0% for cluster3 average is 0 %.

Table 4-6 clustering by using layered structure representation on S shape dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	6	0	0
Cluster2	6	0	0
Cluster3	42	0	0
Average			

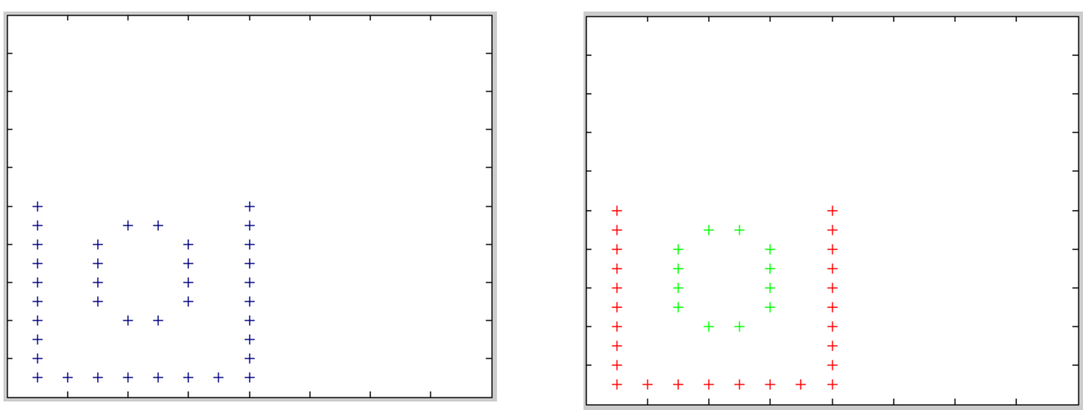


Figure 4-8 Result by using layered structure representation on the u shape dataset

In figure 4-8 is Result by using layered structure representation on the u shape dataset and the percentage of error as shown in table 4-6 are 0 % for cluster1 and 0% for cluster2 average is 0 %.

Table 4-7 clustering by using layered structure representation on u shape dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	12	0	0
Cluster2	26	0	0
Average			0

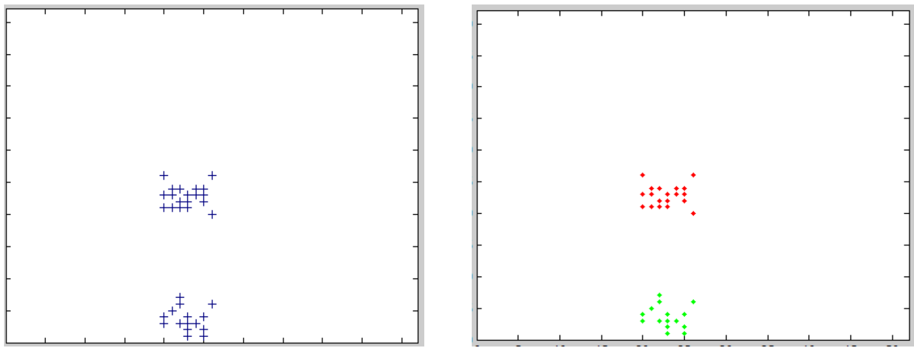


Figure 4-9 Result by using layered structure representation on the 2 cluster condense dataset

In figure 4-9 is Result by using layered structure representation on the 2 cluster condense dataset and the percentage of error as shown in table 4-7 are 0 % for cluster1 and 0% for cluster2 average is 0 %.

Table 4-8 clustering by using layered structure representation on 2 cluster condense dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	15	0	0
Cluster2	19	0	0
Average			0

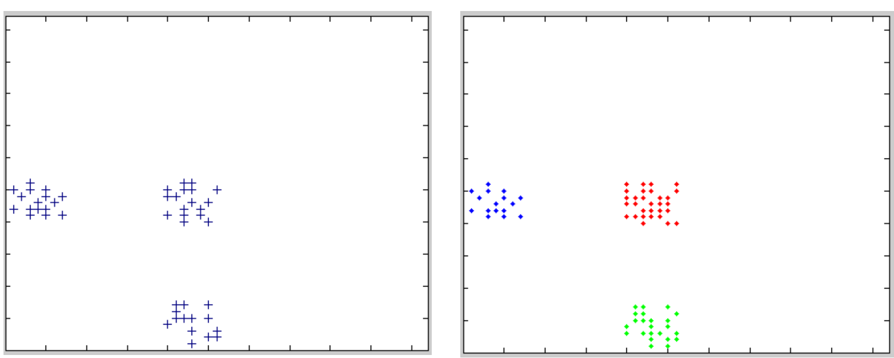


Figure 4-10 Result by using layered structure representation on the 3 cluster condense dataset

In figure 4-10 is Result by using layered structure representation on the 3 cluster condense dataset and the percentage of error as shown in table 4-8 are 0 % for cluster1, 0% for cluster2 and 0% for cluster3 average is 0 %.

Table 4-9 clustering by using layered structure representation on 3 cluster condense dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	16	0	0
Cluster2	14	0	0
Cluster3	17	0	0
Average			0

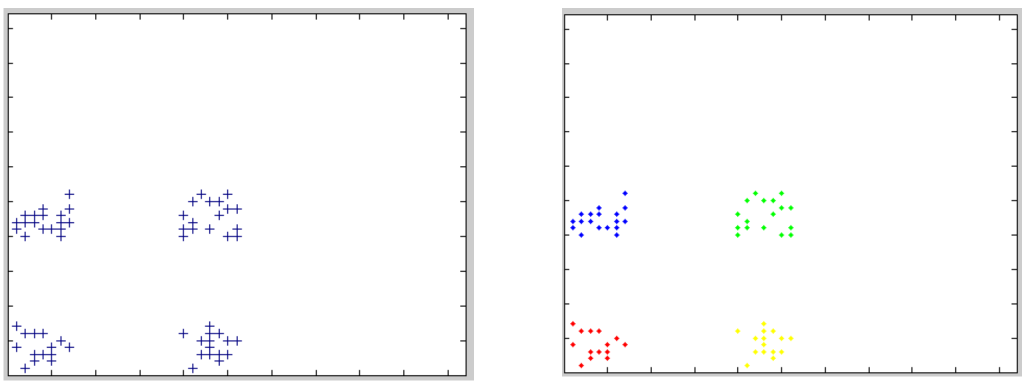


Figure 4-11 Result by using layered structure representation on the 4 cluster condense dataset

In figure 4-11 is Result by using layered structure representation on the 4 cluster condense dataset and the percentage of error as shown in table 4-9 are 0 % for cluster1, 0% for cluster2, 0 % for cluster3 and 0% for cluster4 average is 0 %.

Table 4-10 clustering by using layered structure representation on 4 cluster condense dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	14	0	0
Cluster2	18	0	0
Cluster3	15	0	0
Cluster4	17	0	0
Average			0

4.8 Result by using k-mean

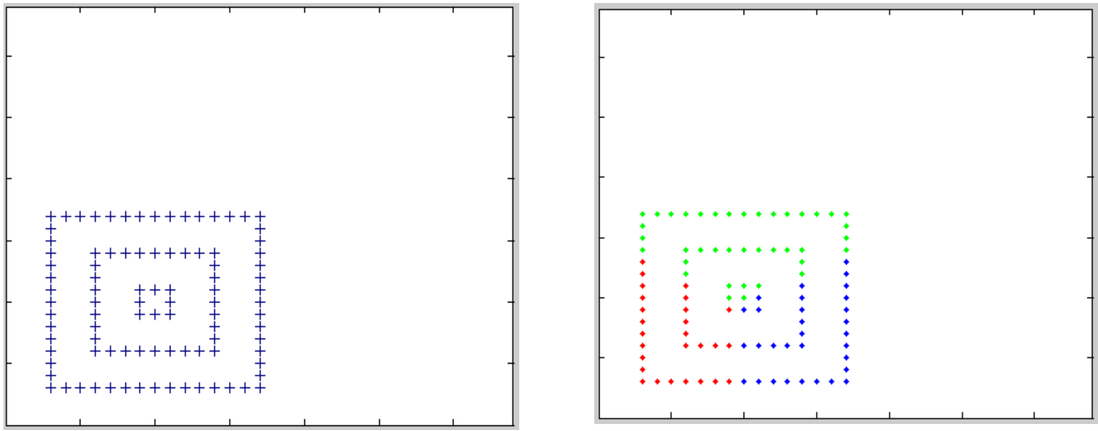


Figure 4-12 Result by using k-mean on the Circular nested dataset

In figure 4-12 is Result by using k-mean on the Circular nested dataset and the percentage of error as shown in table 4-10 are 50% for cluster1, 90.625% for cluster2 and 62.5% for cluster3 average is 67.7 %.

Table 4-11 clustering by using k-mean clustering on circular nested dataset

cluster	Number pattern	Misclassified	Error in %
Cluster1	8	4	50
Cluster2	32	29	90.625
Cluster3	56	35	62.5
Average			67.7

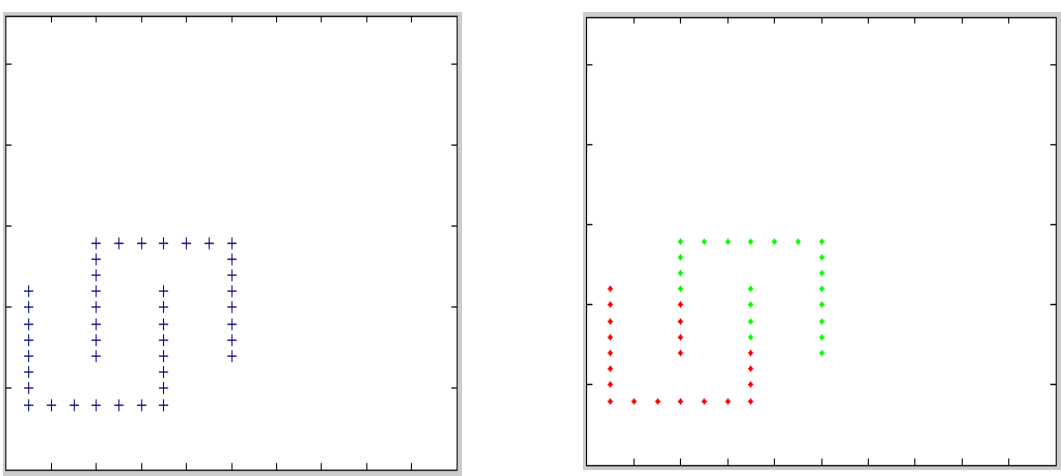


Figure 4-13 Result by using k-mean on the inter related dataset

In figure 4-13 is Result by using k-mean on the inter related dataset and the percentage of error as shown in table 4-11 are 19.04% for cluster1 and 19.04% for cluster2 average is 19.04 %.

Table 4-12 clustering by using k-mean on inter related dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	21	4	19.04
Cluster2	21	4	19.04
Average			19.04

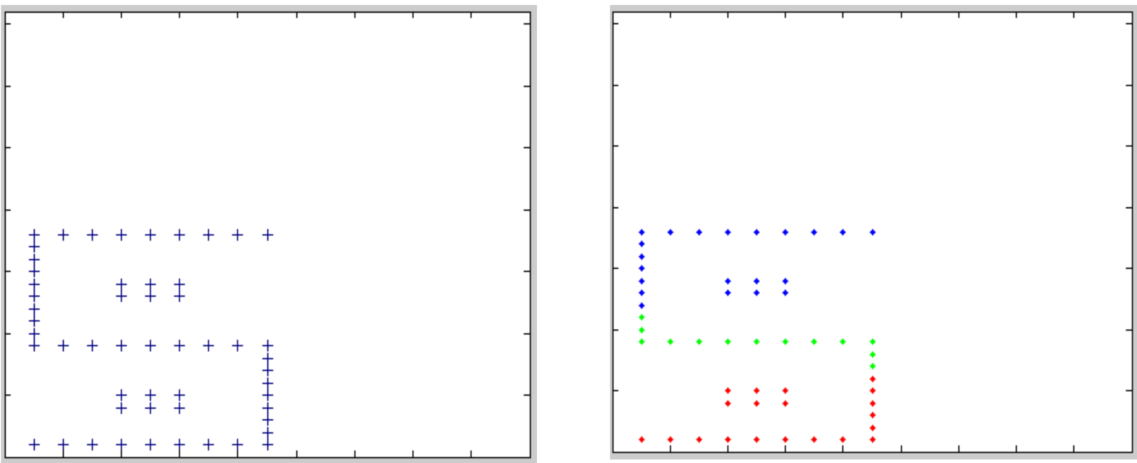


Figure 4-14 Result by using k-mean on the S shape dataset

In figure 4-14 is Result by using k-mean on the S shape dataset and the percentage of error as shown in table 4-12 are 0% for cluster1, 0% for cluster2 and 69.04% for cluster3 average is 23.01 %.

Table 4-13 clustering by using k-mean on S shape dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	6	0	0
Cluster2	6	0	0
Cluster3	42	29	69.04
Average			23.01

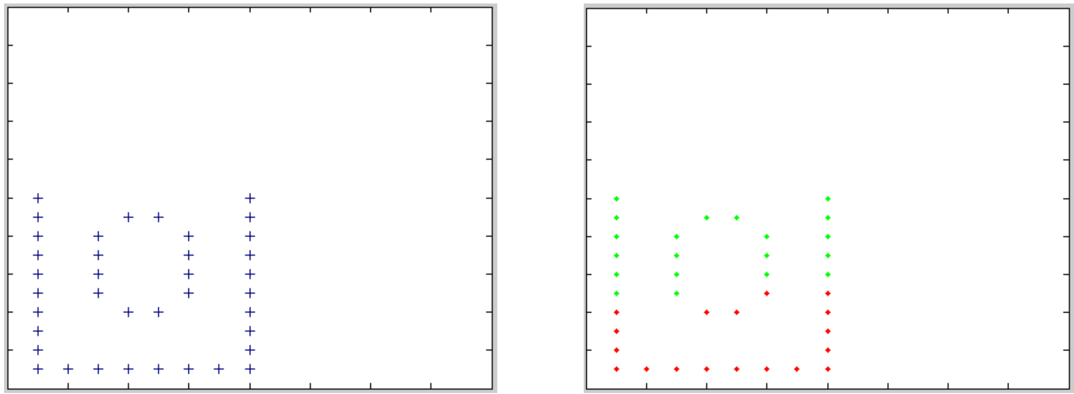


Figure 4-15 Result by using k-mean on the u shape dataset

In figure 4-15 is Result by using k-mean on the u shape dataset and the percentage of error as shown in table 4-13 are 25% for cluster1 and 42.30% for cluster2 average is 33.65 %.

Table 4-14 clustering by using k-mean on u shape dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	12	3	25
Cluster2	26	11	42.30
Average			33.65

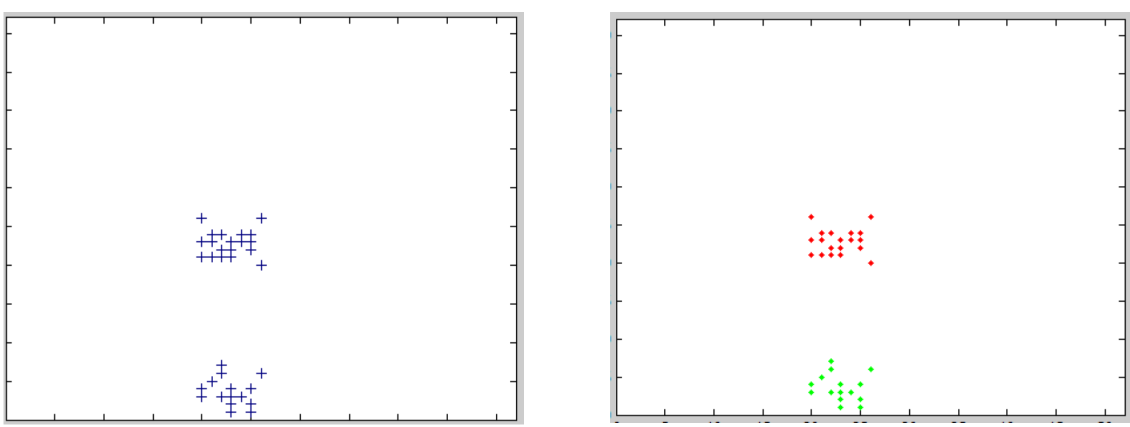


Figure 4-16 Result by using k-mean on the 2 cluster condense dataset

In figure 4-16 is Result by using k-mean on the 2 cluster condense dataset and the percentage of error as shown in table 4-14 are 0% for cluster1 and 0% for cluster2 average is 0 %.

Table 4-15 clustering by using k-mean on 2 cluster condense dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	15	0	0
Cluster2	19	0	0
Average			0

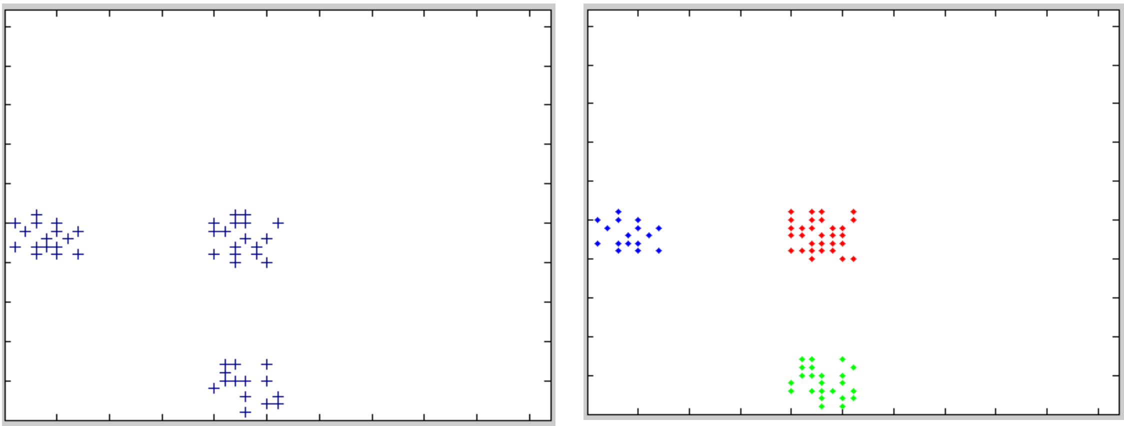


Figure 4-17 Result by using k-mean on the 3 cluster condense dataset

In figure 4-17 is Result by using k-mean on the 3 cluster condense dataset and the percentage of error as shown in table 4-15 are 0% for cluster1, 0% for cluster2 and 0% for cluster3 average is 0 %.

Table 4-16 clustering by using k-mean on 3 cluster condense dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	16	0	0
Cluster2	14	0	0
Cluster3	17	0	0
Average			0

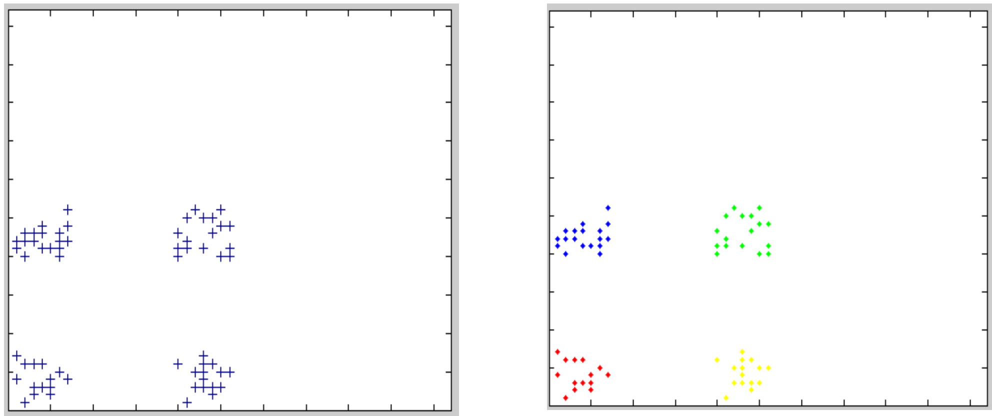


Figure 4-18 Result by using k-mean on the 4 cluster condense dataset

In figure 4-18 is Result by using k-mean on the 4 cluster condense dataset and the percentage of error as shown in table 4-16 are 0% for cluster1, 0% for cluster2, 0% for cluster3 and 0% for cluster4 average is 0 %.

Table 4-17 clustering by using k-mean on 4 cluster condense dataset

Cluster	Number pattern	Misclassified	Error in %
Cluster1	14	0	0
Cluster2	18	0	0
Cluster3	15	0	0
Cluster4	17	0	0
Average			0

Table 4-17 is Average error in percent clustering using layered structure representation and clustering using k-mean show average error clustering using layered structure representation 0 % and average misclassified clustering using k-mean 20.48%.

Table 4-18 Average error in percent clustering using layered structure representation and clustering Using k-mean

Dataset	Using layered structure representation Error in %	Using k-mean Error in %
Circular nested	0	67.7
inter related	0	19.04
S shape	0	23.01
u shape	0	33.65

2 cluster condense	0	0
3 cluster condense	0	0
4 cluster condense	0	0
Average	0	20.48

We also implement some other clustering method that are Hierarchical clustering algorithms (Single Linkage, Centroid Linkage, Complete Linkage and Average Linkage) to the same dataset the average result shown in the table2.

Table 2 Average error in percent of clustering by using hierarchical clustering

Clustering Method	Single linkage	Centroid linkage	Complete linkage	average linkage
Average	19.32	57.82	57.94	58.21

In the Table 1 and table2 are shown that the proposed method compare with other method allows to identifying any shape of cluster as well as condensed dataset.

5. Conclusion

A shape feature based multi layer centroid contour distance has been implemented. In this research, we propose a new approach to extract features of an object shape that has some points with the same angle. In the conventional method if there is multiple point in same angle just capture one point that nearest to the centroid and placed it into one layer. While using the proposed method if there is multiple point in the same angle all point will be captured and the result be placed into multiple vector layers.

The experiment results on simulated data demonstrate a new approach has the advantage of 8.67 percent higher than using conventional method. Precision results on real data (real data on phytoplankton dataset) with a new approach has also the advantage of 7.22 percent higher than using conventional method. We applied that method to the simulation dataset and plankton dataset and the result show that the proposed method better than the conventional method (CCD, Hsv and Fourier descriptor).

We also implement the proposed method with some modification to cluster a group of data and compare with K-MEAN clustering method and other clustering method. The experiment result by using the proposed clustering method show better than K-MEAN and hierarchical clustering (Single linkage, Centroid Linkage, Complete linkage and average linkage)

[1] K. Jung, K. In Kim, and A. K. Jain, “Text information extraction in images and video: a survey,” *Pattern Recognition*, vol. 37, no. 5, pp. 977–997, May 2004.

[2] P. B. Thawari and N. J. Janwe, “CBIR BASED ON COLOR AND TEXTURE,” vol. 4, no. 1, pp. 129–132, 2011.

[3] C. Carson and S. Belongie, “Blobworld: Image segmentation using expectation-maximization and its application to image querying,” *Pattern Analysis and …*, 2002.

[4] R. Datta, D. Joshi, J. Li, and J. Z. Wang, “Image retrieval: Ideas, influences, and trends of the new age,” *ACM Computing Surveys*, vol. 40, no. 2, pp. 1–60, Apr. 2008.

[5] F. Long, H. Zhang, and D. Feng, “Fundamentals of content based image retrieval,” *“Multimedia Information Retrieval and Management. Technological Fundamentals and Applications,”Multimedia Signal Processing Book, Chapter 1, Springer-Verlag, Berlin Heidelberg New York*, pp. 1–26, 2003.

[6] H. Müller and A. Geissbuhler, “Benchmarking image retrieval applications,” *Proc. of the 10th Intern. …*, 2004.

[7] FotopoulouF and EconomouG, “Multivariate angle scale descriptor of shape retrieval,” *Proc. Signal. Process Appl. Math. Electron …*, pp. 105–108, 2011.

[8] Y. Liu, D. Zhang, G. Lu, and W.-Y. Ma, “A survey of content-based image retrieval with high-level semantics,” *Pattern Recognition*, vol. 40, no. 1, pp. 262–282, Jan. 2007.

[9] N. Singhai and S. K. Shandilya, “A Survey On: Content Based Image Retrieval Systems,” *International Journal of Computer Applications*, vol. 4, no. 2.

[10] M. Kherfi, Brahmi, and Ziou, “Combining Visual Features with Semantics for a More Effective Image Retrieval,” in *in ICPR ’04, vol. 2,*, 12012BC, pp. 961–964.

[11] H. Yu, M. Li., Zhang, and Feng, “Color texture moments for content-based image retrieval,” in *In International Conference on Image Processing*, 2002, pp. 24–28.

[12] N. Sebe, Q. Tian, E. Loupias, Lew, and Huang, “Evaluation of salient point techniques,” *Image and Vision Computing*, vol. 21, no. 13–14, pp. 1087–1095, Dec. 2003.

[13] J.-R. Ohm, F. Bunjamin, W. Liebsch, B. Makai, K. Müller, a. Smolic, and D. Zier, “A set of visual feature descriptors and their combination in a low-level description scheme,” *Signal Processing: Image Communication*, vol. 16, no. 1–2, pp. 157–179, Sep. 2000.

[14] D. Zhang and G. Lu, "A Comparative Study of Three Region Shape Descriptors," no. January, pp. 1–6, 2002.

[15] K. Arai and C. Rahmad, "Content Based Image Retrieval by using Multi Layer Centroid Contour Distance," vol. 2, no. 3, pp. 16–20, 2013.

[16] S. C.Chang, S. Hwang, and D.Buehrer, "A Shape recognition scheme based on relative distance of feature points from the centroid," *Pattern Recognition*, vol. 11, pp. 1053–1063, 1991.

[17] "Blaser, A. 1979. Database Techniques for Pictorial Applications, Lecture Notes in Computer Science, Springer Verlag GmbH. 81."

[18] A. Khokher and R. Talwar, "Content-based Image Retrieval: Feature Extraction Techniques and Applications," *International Conference on Recent Advances and Future Trends in Information Technology (iRAFIT2012) proceedings published in International Journal of Computer Applications® (IJCA) 9*, 2012.

[19] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, Second Edi. Tom Robbins, 2001.

[20] G. D. Finlayson, G. Qiu, and M. Qiu, "Contrast Maximizing and Brightness Preserving Color to Grayscale Image Conversion," 1999.

[21] "http://www.math.ucla.edu/~wittman/10c.1.11s/Lectures/Lec24.pdf." .

[22] A. A. Goodrum, "Image Information Retrieval : An Overview of Current Research," vol. 3, no. Special issue on information science research, 2000.

[23] D. Zhang and G. Lu, "Review of shape representation and description techniques," *Pattern Recognition*, vol. 37, no. 1, pp. 1–19, Jan. 2004.

[24] FUNTOURA Costa and C. R. M., "Shape Analysis and Classifica tion: Theory and Practice," *Boca Raton, FL.: CRC Press, 2001.*

[25] G. E. Q. Jeffrey, "Fourier Descriptors with Different Shape Signatures : a Comparative Study for å," vol. 47, no. 50728503, 2011.

[26] M. Halkidi, "On Clustering Validation Techniques," *Journal of Intelligent Information Systems*, pp. 107–145, 2001.

[27] S. Guha, R. Rastogi, and K. Shim, "CURE: An Efficient Clustering algorithm for Large Databases," in *SIGMOD '98 Proceedings of the 1998 ACM SIGMOD international conference on Management of data*, 1998, pp. 73–84.

[28] K. Arai and A. R. Barakbah, “Cluster construction method based on global optimum cluster determination with the newly defined moving variance,” vol. 36, no. 1, pp. 9–15, 2007.

[29] D. Frossyniotis, a. Likas, and a. Stafylopatis, “A clustering method based on boosting,” *Pattern Recognition Letters*, vol. 25, no. 6, pp. 641–654, Apr. 2004.

[30] “http://www.saedsayad.com/clustering_hierarchical.htm.” .

[31] K. Teknomo, “K-Means Clustering Tutorial,” *Medicine*, pp. 1–12, 2006.

[32] K. Arai and A. R. Barakbah, “Automatic shape independent clustering with global optimum cluster determinations By,” vol. 36, no. 1, pp. 1–6, 2007.

[33] “Kohei Arai and Yasunori Terayama, Polarized radiance from red tide, Proceedings of the SPIE Asia Pacific Remote Sensing, AE10-AE101-14, Invited Paper, 2010.”

[34] K. Arai and A. Ridho, “Hierarchical K-means: an algorithm for centroids initialization for K-means,” vol. 36, no. 1, pp. 25–31, 2007.

Appendix

Shape is one of the primary features in Content Based Image Retrieval (CBIR). Shape is also one of important visual feature of an image and used to describe image content. The shape of an object is a binary image representing the extent of the object.

Since the human perception and understanding of objects and visual forms relies heavily on their shape properties, shape features play a very important role in CBIR. Shape is one of the most important image features of recognizing objects by human perception.

The algorithm of A shape features extracted by layered structure representation is described as follow:

1. Input image from database image / Query Image
2. Convert RGB image To Gray Image
3. Edge detection
4. Morphology Filter
5. Construct feature vector using multi layer centroid contour distance (MLCCD)
6. Comparison for similarity retrieval
7. Display Result based on distance measure

Image from database image or from query image convert from RGB image into Gray scale image then implement the canny filter to detect edge position then use morphology filter to ensure the shape of object clear. Then local feature of an image at some point at interest location is computed.

Feature vector is computed by measuring distance between center of object and point in the boundary object Then the result is placed to the feature vector layer by layer and then the feature vector that obtained from database image and Query Image be compared each other (similarity process) then display the result.

The retrieval result is not a single image but a list of image ranked by their similarity. in these case if the distance between feature representation of image in database image and feature representation of image query small enough then it to be considered as similar.

Centroid position :

$$X_c = \frac{X_1+X_2+X_3+....+X_n}{n} \quad , \quad Y_c = \frac{Y_1+Y_2+Y_3+....+Y_n}{n}$$

X_c is position of the centroid in the x axis and Y_c is position of the centroid in the y axis and n is Total point in the object .

Distance between centroid and boundary of shape :

$$Dis(n) \quad = \sqrt{(x(n)-x_c)^2 + (y(n)-y_c)^2}$$

n is number point in the boundary of object (1,2,..t), t is total point in the boundary, x_c is position center in the x axis, y_c is position center in the y axis, x(n) is position point number n in the x axis and y(n) is position point number n in the y axis.

The computed distances are saved in a vector layer by layer. The next layer will happen if there are more than one point in the boundary with same angle.

In order to achieve rotation invariance, scale invariance and translation invariance implementation shifting and normalization to these vector is needed. The rotation invariance can be obtained by shifting the feature vector, the biggest value shift to the left side. The scale invariance can be obtained with all feature vector divided by the highest value. The translation invariance can be obtained after the centroid location found.

Cluster analysis is the process of partitioning data objects (records, documents, etc.) into meaningful groups or clusters so that objects within a cluster have similar characteristics but are dissimilar to objects in other clusters. Cluster analysis aims at identifying groups of similar objects and, therefore helps to discover distribution of patterns and interesting correlations in large data sets. Cluster: a collection of data objects. Similar to one another within the same cluster; Dissimilar to the objects in other clusters. Some example of clustering are K-Mean Clustering, Single linkage clustering, Centroid linkage clustering, Complete linkage clustering and Average linkage clustering.

K-Mean Clustering

K-Means Clustering is an algorithm to classify or to group some objects based on attributes/features into K number of group. K is positive integer number. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid. Thus, the purpose of K-mean clustering is to classify the data.

The basic step of k-means clustering is simple. In the beginning, we determine number of cluster K and we assume the centroid or center of these clusters. We can take any random objects as the initial centroids or the first K objects can also serve as the initial centroids. Then the K means algorithm will do the three steps below until convergence.

The algorithm k-means clustering

1. Determine number of cluster K then choose randomly the object to the cluster
2. Determine the centroid coordinate
3. Determine the distance of each object to the centroids
4. Group the object based on minimum distance (find the closest centroid)
5. Iterate step 2 ,3 and 4 until stable (no object move to other group)

Single linkage clustering, Centroid linkage clustering, Complete linkage clustering and Average linkage clustering are Hierarchical methods. The Hierarchical methods is One of the most famous methods in clustering is that classified method as hierarchical clustering.

In hierarchical clustering the data are not partitioned into a particular cluster in a single step. It runs with making a single cluster that has similarity, and then continues iteratively. Hierarchical clustering algorithms can be either agglomerative or divisive.

The agglomerative method proceeds by series of fusions of the “n” similar objects into groups, and divisive method, which separate “n” objects successively into finer groupings. The Agglomerative method they produce a sequence of clustering schemes of decreasing number of clusters at each step. The clustering scheme produced at each step results from the previous one by merging the two closest clusters into one cluster.

The divisive algorithms. These algorithms produce a sequence of clustering schemes increasing the number of clusters at each step. Contrary to the agglomerative algorithms the clustering produce at each step results from the previous one by splitting a cluster into two cluster. Agglomerative techniques are more commonly used.

Hierarchical clustering proceeds successively by either merging smaller cluster into larger ones, or by splitting larger clusters. The result of the algorithm is a tree of clusters, called dendogram, which shows how the clusters are related. By cutting the dendogram at a desire level, a clustering of the data items into disjoint groups is obtained.

Basic algorithm Most popular hierarchical clustering technique is

1. Compute the distance matrix between the input data points
2. Let each data point be a cluster
3. Repeat
4. Merge the two closest clusters
5. Update the distance matrix
6. Until only a single cluster remains

Distance between two clusters

Single-link distance between clusters C_i and C_j is the minimum distance between any object in C_i and any object in C_j The similarity is based on closely related to the smallest distance between objects at two cluster.

The distance is defined by the two most similar objects

$$D_{sl}(C_i, C_j) = \min_{x,y}\{d(x,y) \mid x \in C_i, y \in C_j\}$$

Centroid link distance between clusters C_i and C_j is the distance between the centroid r_i of C_i and the centroid r_j of C_j.

$$D_{centroids}(C_i, C_j) = d(r_i, r_j)$$

Complete-link distance between clusters C_i and C_j is the maximum distance between any object in C_i and any object in C_j

The distance is defined by the two most dissimilar objects

$$D_{cl}(C_i, C_j) = \max_{x,y}\{d(x,y) \mid x \in C_i, y \in C_j\}$$

Average link distance between clusters C_i and C_j is the average distance between any object in C_i and any object in C_j

$$D_{avg}(C_i, C_j) = \frac{1}{|C_i| \times |C_j|} \sum_{x \in C_i, y \in C_j} d(x, y)$$

Shape recognition can be useful for any time we want to detect a distinct shape. Seek one description that can characterize all shapes to a desired accuracy. The Fourier coefficients have this property. We can approximate with the first M coefficients. Shape is one of the primary features in Content Based Image Retrieval (CBIR). Shape is also one of important visual feature of an image and used to describe image content. Among them is methods based Fourier descriptors (FDs).

Fourier descriptors are obtained by applying Fourier transform on shape boundary, The concept of fourier descriptor (FD) has been widely used in the field of computational shape analysis fourier descriptor. The idea of the FD (Fourier Descriptor) is to use the Fourier transformed boundary as a shape Feature. Suppose a shape signature Z(u) is a 1-D function that represents 2-D areas or boundaries. The discrete Fourier transform of an signature z(u) is defined as follows:

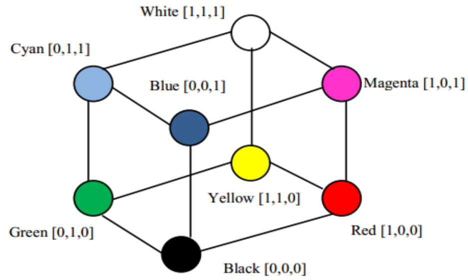
$$a_n = \frac{1}{N} \sum_{u=0}^{N-1} Z(u)\ e^{-j2\pi nu/N}$$

Where :

n = 0,1,2, … n-1

The first M coefficients of a_n (n = 0 ,1 ,..N-1) are called the Fourier descriptors (FDs) of the shape. They represent the discrete contour of a shape in the Fourier domain.

RGB Color as a colour space, RGB is represented by a cube. The black (0,0,0) while the white is the (1,1,1).

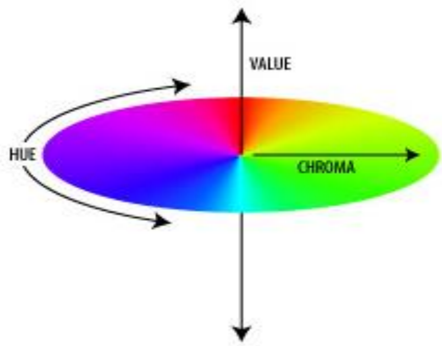


Normalize individual components of RGB

- r = R / (R+G+B)
- g = G / (R+G+B)
- b = B / (R+G+B)

HSV The components of the HSV colour space are Hue, Saturation and Value.

Colour is the result of the perception of light at different wavelengths. Usually, we do not experience light at a single wavelength but a blend of waves at different wavelengths.



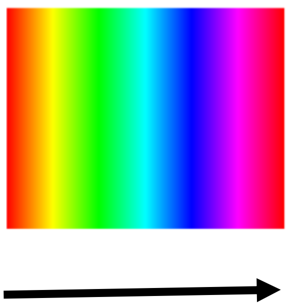
The hue corresponds to the dominant wavelength and determines the type of the colour, for example red, yellow, or blue. The hue is given by the angle about the vertical axis

- red at 0°
- yellow at 60°
- green at 120°
- cyan at 180°
- blue at 240°
- magenta at 300°

The saturation determines the purity of the colour. High saturation gives pure colours (narrow wavelength band), while low saturation means colours mixed with a lot of white (white light combines all the visible wavelengths).

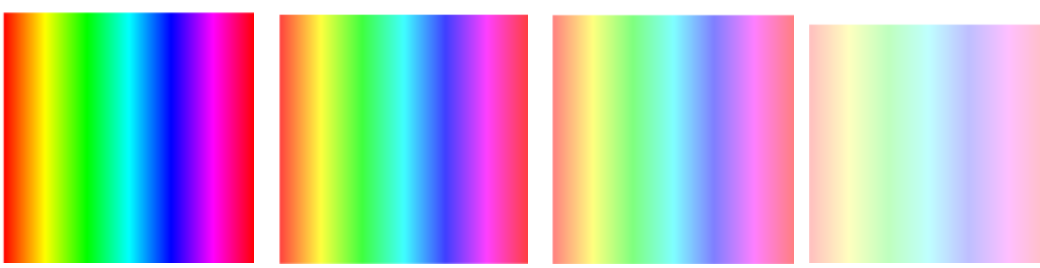
The value determines the brightness. A value equal to zero represents absence of light, while a high value gives bright colours.

The HSV spectrum of bright pure colours (s = 1, v = 1). Notice the cyclicality of the hue. The red corresponds both to h=0 and h=1.



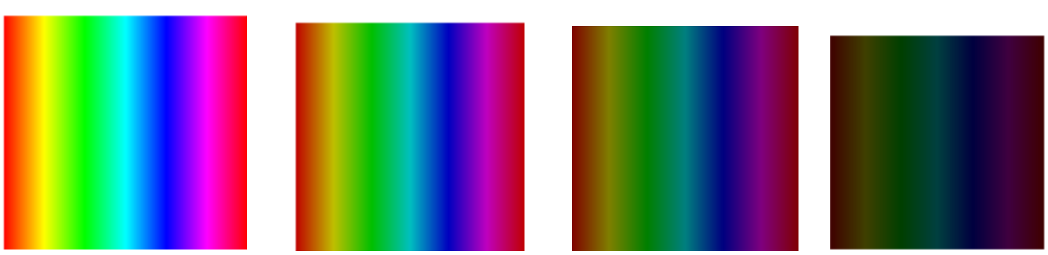
h = 0 h = 1

Saturation, bright colours (v=1) with decreasing values of saturation.



S=1 S= 0.75 S= 0.5 S= 0.25

Value, Pure colours (s=1) with decreasing values of "value" (brightness).



V = 1 V = 0.75 V = 0.5 V = 0.25