

Colored Image Retrieval Based on Content by Using Integration of Features for Many Color Space Models

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ABSTRACT

Indexed retrieval is required because the size of image database increases very rapidly, and retrieval times have not been reduced sufficiently to keep up. Therefore, we aim to develop new techniques for indexing images that approach the quality of classic retrieval algorithms both in terms of speed and retrieval accuracy. The first aim of this work is to present a technique for image retrieval based on features of gray image such as grayscale histogram, gray level distribution moment, and gray level Co-occurrence matrices. Instead of using each feature alone, we combine all these features by a weighted sum of the similarities provided by each of the features; this is called integration of features. Secondly, although the integration of features is more effective than using each feature alone, but this method does not give us 100% retrieval. Therefore, we use color features of three color space models (RGB, CIE L*a*b*, CIE L*u*v*), color histogram, color moment, and color Correlogram; and also combine all these features to produce “Combined Method”. The third aim of this work is to present and develop a novel image retrieval scheme, Cluster Based Retrieval of image, by using K-means clustering algorithm. At search time, the query image is not compared with all the images in the database, but only with a small subset. It aims at also improving the k-means by using a better similarity distance to obtain m1k-means clustering algorithm and we used m2k-means that developed of m1k-means algorithm by generating the initial clusters; this algorithm is an efficient algorithm and produce efficient retrieval.

Keyword: feature extraction, color space models, gray level histogram, distribution moments, co-occurrence matrix, color histogram, color moments, color Correlogram, clustering algorithm ,wavelet transform.

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1-INTRODUCTION

Recent years have witnessed a rapid increase in the size of digital image collections together with the fast growth of the Internet. Digital images have found their way into many application areas, including Geographical Information System and Medical Imaging. There are currently billions of web pages available on the Internet using hundreds of millions (both still and moving) images. However, we cannot access or make use of the information in these huge image collections unless they are organized so as to allow efficient browsing, searching, and retrieval overall textual and image data[1]. In this research a comparison of content based image retrieval is presented. The methods of extracting the properties of the graylevel images and the methods of extracting the properties of the colored images in several color models were used, and the retrieval of the images depends on these properties individually, in addition to the merging of the properties after making a normalization by using linear scaling as well as using normal and developed clustering methods. In addition to extracting the properties of the frequency domain. Finally the results were compared of all these methods.

2-FEATURE EXTRACTION

Texture is widely used and intuitively obvious but has no precise definition due to its wide variability. One existing definition states that “Texture is generally a visual property of a surface, representing the spatial information contained in object surfaces”[1]. There exist three main approaches to the task of texture feature extraction: spectral approach, structural (or syntactic) approach and statistical approach.

2.1-Spectral Approach

The spectral approach to texture analysis deals with images in the frequency domain. The two-dimensional power spectrum of an image reveals much about the periodicity and directionality of its texture. For instance, an image of coarse texture would have a tendency towards low frequency components in its power spectrum, whereas another image with finer texture would have higher frequency components. Stripes in one direction would cause the power spectrum to concentrate near the line through the origin and perpendicular to the direction [2].

The word transform refers to a mathematical representation of an image. There are several texture classifications using transform domain features, such as Discrete Fourier Transform (DFT), and discrete wavelet transforms (DWT) [3]. The three vectors are mean vector, variance vector, and energy vector representing the mean, variance, and energy of coefficients in each sub and, respectively. First, for each feature vector, a Euclidean distance L_2 between the corresponding components at each decomposition level is computed. This generates three distance values for each feature vector, totally nine distance value. Given a query image q and the i^{th} image in the search range, the distance between the component c_j

in two vectors of texture feature k (mean, variance, and energy) at level l is : $D(q, i)^{(k,l)} = \sqrt{\sum_j (c_j^{(k,l)}(q) - c_j^{(k,l)}(i))^2}$ Where j

refers to the sub and j at level l . Secondly, all nine distance values are normalized by dividing them by their maximum distance values. The normalization is necessary because the coefficients at higher decomposition level are usually much larger than those at the lower level. A total distance is computed for each feature (mean, variance, and energy) using the mean of the three normalized distance values at three levels. Given a query image q and the i^{th} image in the search range, the distance between the two vectors of their texture feature k (mean, variance, and energy) is:

$D(q, i)^{(k)} = \frac{1}{3} \sum_{l=1}^3 \left(\frac{D(q, i)^{(k,l)}}{\max_i D(q, i)^{(k,l)}} \right)$ Where l refers to the decomposition level l . Thirdly, a total texture distance between

a query image q and the i^{th} image in the search range is computed using the mean of the three texture feature distances as shown below. $D_{texture}(q, i) = \frac{1}{3} \sum_{k=1}^3 D(q, i)^{(k)}$ Where k represents the k^{th} texture feature[4]. Daubechies wavelets are chosen in this research. The maximum decomposition level is three.

2.2-Structural Approach

The structural approach is based on the theory of formal languages. A textured image is considered as a sentence in a language, of which the alphabet is a set of texture primitives called textons, constructed in accordance with a certain grammar determining the layout of such texture primitives within a pattern. Although the structural approach is very fruit full as long as it deals with deterministic patterns, the vast majority of textures found in the universe are not of such strict geometry but exhibit a level of uncertain random behavior [2].

The structural models of texture assume that textures are composed of texture primitives. They consider that the texture is produced by the placement of the primitives according to certain placement rules. Structural methods are related to primitive methods because both model textures are being composed of primitives. However, structural methods tend to have one arbitrarily complex primitive, whereas primitive methods model texture are composed of many, simple primitives. Moreover, the relative placement of primitives is important in structural methods but plays no role in primitive methods.

Structural-based algorithms are in general limited in power unless one is dealing with very regular textures. The texture primitives can be as simple as a single pixel that can take a gray value, but is usually a collection of pixels. The placement rule is defined by a tree grammar. A texture is then viewed as a string in the language defined by the grammar whose terminal symbols are the texture primitives. An advantage of these methods is that they can be used for texture generation as well as texture analysis [5].

2.3-Statistical Approach

From the statistical point of view, an image is a complicated pattern on which statistics can be obtained to characterize these patterns. The techniques used within the family of statistical approaches make use of the intensity values of each pixel in an image, and apply various statistical formula to the pixels in order to calculate feature descriptors. Texture feature descriptors, extracted through the use of statistical methods, can be classified into two categories according to the order of the statistical function that is utilized: First-Order Texture Features and Second Order Texture Features. First Order Texture Features are extracted exclusively from the information provided by the intensity histograms, thus yield no information about the locations of the pixels. Another term used for First-Order Texture Features is Gray Level Distribution Moments. In contrast, Second-Order Texture Features take the specific position of a pixel relative to another into account. The most popularly used of Second-Order methods is the Spatial Gray Level Dependency Matrix (SGLDM) method. Another term used is Gray Level Co-occurrence Matrices (GLCM). The method roughly consists of constructing matrices by counting the number of occurrences of pixel pairs of given intensities at a given displacement [2]. The standard representation for color information in content based image retrieval CBIR has been the color histogram. The color histogram describes the distribution of different colors in an image in a simple and computationally efficient manner. Other commonly used color features include color moments and the color correlogram [6].

3-COLOR SPACE MODELS

There exist various color models, dictated by the means through which an image is intended to be used. Most color space models define colors in three dimensions, such that each color is represented by three Co-ordinates. Furthermore, the color models are classified as uniform/non-uniform depending upon the difference in color space, as perceived by an observer. The difference between any two colors is approximated to be the Euclidean distance in a color space. The selection of a color space is crucial for deriving potentially more useful object-related color information; and it has been the focus of various studies. Several researchers have evaluated various color models for the purpose of image retrieval under varying sets of imaging conditions [7]. Although the human perception is more accurately reflected using the CIE $L^*a^*b^*$ and CIE $L^*u^*v^*$ color space, nevertheless, the RGB color space is used in this research and it is very efficient in image retrieval.

4-CLUSTERING

Clustering can be used to produce an effective image index as follows: After clustering, each cluster is represented by its centroid or sometimes a single representative data item (i.e. the image label for that cluster) and, instead of the original data items, the query point is compared to the centroids or the cluster representatives. The best cluster or clusters, according to the used similarity measure, are then selected and the data items belonging to those clusters are retrieved also according to the used similarity measure [8]. The k-mean algorithm is the most frequently used clustering algorithm due to its simplicity and efficiency. K-means is a partitional clustering algorithm. It performs iterative relocation to partition a dataset into k cluster [9]; and it is based on the minimization of a performance index which is defined as the sum of the squared distances from all points in a cluster domain to the cluster center [9,10]. The performance of k-means algorithm is not only dependent on the type of data being analyzed, but is also strongly influenced by the chosen measure of pattern similarity i.e. the measure used for identifying clusters in the data. In the preceding algorithm (i.e. k-means clustering algorithm) we considered the Euclidean distance for comparing two feature vectors. Here we use the k-means by using L_1 norm distance metrics instead of Euclidean distance; in practice, L_1 norm performs better than Euclidean distance since it is more robust and computationally efficient, and this algorithm is called M_1 -k-means. In the k-means, the initial cluster assignment is random; different runs of the k-means clustering algorithm may not give the same final clustering solution; or when selected as the first k samples of the sample set the same as modified, k-means, these two states may not give the good solution. To deal with this, we need to get good starting points for the initial cluster assignment. This leads to develop a modified, k-means clustering algorithm where an additional step is used to provide the initial cluster centers and L_1 norm distance metric when computing the distance between two feature vectors [11]. In this research, we based on M_2 -K-means algorithm to cluster all the images in the database into classes.

5-EXPERIMENTAL AND RESULTS

Here, we present a technique for image retrieval based on color from large databases. The goal is to group similar images into clusters and to compute the cluster centers, so that during retrieval, the query image need not be compared exhaustively with all the images in the database. To retrieve similar images for a given query, the query image is initially compared with all the cluster centers. Then a subset of clusters that have the largest similarity to the query image is chosen and all the images in these clusters are compared with the query image. The CBIR system has a three-step approach to retrieve images from the databases. The first step is *indexing*: for each image in a database, feature vector is computed and stored in feature

space. The second step is *clustering*: the images in the database are grouped into clusters of images with similar color content using clustering algorithm. The third step is *searching*: given a query by a user, its feature vector is computed and the system retrieves images having feature vectors with a small subset of clusters that best match the query feature vector. Figure (1) shows the steps of image retrieval based on clustering.

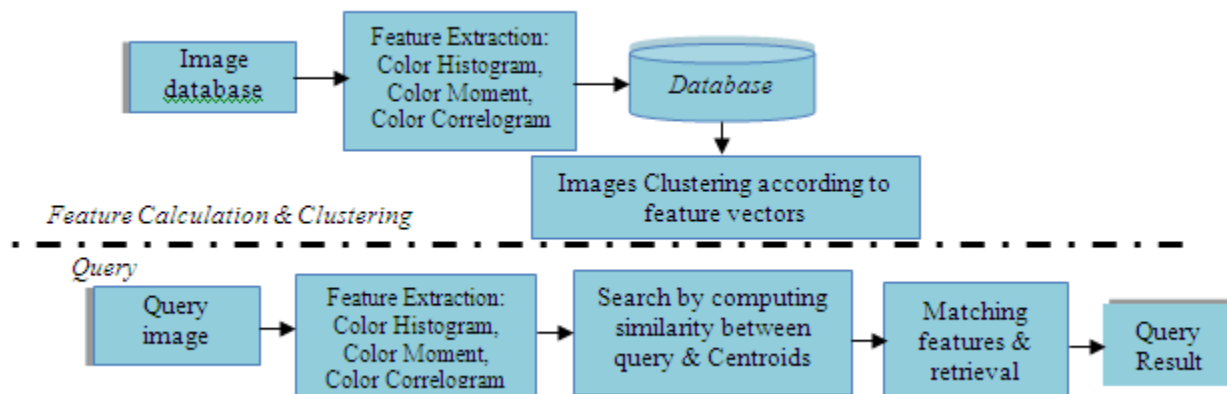


Figure 1: The steps of image retrieval based on clustering

Feature Extraction

The feature extraction process aims to describe each image in the database in terms of low level features. These low level features, known as descriptors, are used to provide similarity measures between different images. Descriptors are typically smaller in size compared to the original image. In this research, we use gray-scale histogram, gray-level distribution moments, and gray-level co-occurrence matrices for gray images. While in color images we use color histogram, color moment, and color correlogram, in three model of color RGB CIE L*a*b* and CIE L*u*v*, and also use integration of all features in gray level in method called gray IGM and in color we used combined method that mearge all color features in one method after normalized them by using linear scaling. All the above was statistical approach. Finally used spectral approach by using wavelet transform.. Figures (2,3) shows the feature extraction process.

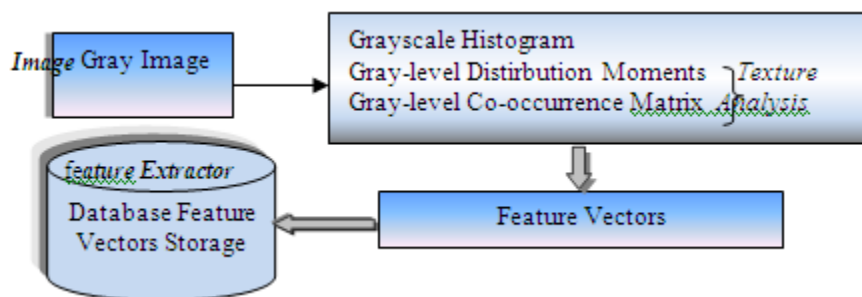


Figure 2: Gray-level Image

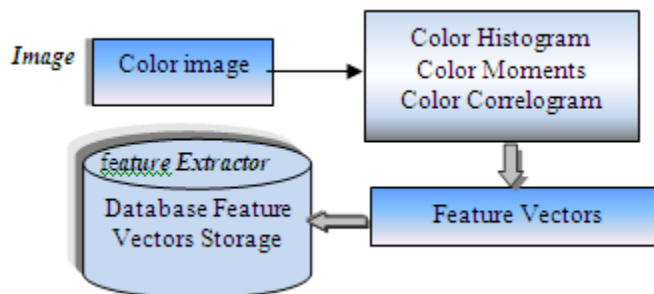


Figure 3: Color Image

Image Clustering

The image clustering process aims to decrease the number of image (or feature) vectors compared with the query image. The query is compared to the centroids only; the best clusters are then selected and the image belonging to this cluster are retrieved. Figure (4) shows the clustering algorithms used in this research.

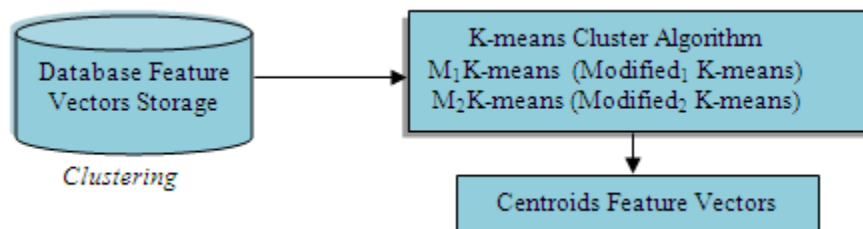


Figure 4: Clustering Algorithms

5.1-Comparison between Gray level Methods And Color Methods

All color methods (Color Histogram, Color Moment, and Color Correlogram) are better than the gray level methods (Grayscale Histogram, Gray level Distribution moments, GLCM). In addition to that, the combined method of color methods is efficient and also M₂K-means are very effective. Therefore, the focus of this research is on the linear combiner of color features (Combined Method) and on the M₂K-means. as shown in the following tables.

Table 1: Comparison between Grayscale Histogram and Color Histogram with M₂K-means

Images	Relevant retrieved	Relavent no.	Retrieved no.	Recall	Precision	Method
Balloon	10	25	36	0.400000	0.277778	Grayhist
	21	25	21	0.840000	1.000000	ColorHist
Lion	10	21	34	0.476190	0.294118	Grayhist
	12	21	12	0.571429	1.000000	ColorHist
Monkey	9	15	13	0.600000	0.692308	Grayhist
	15	15	22	1.000000	0.681818	ColorHist
Rabit	4	11	12	0.363636	0.333333	Grayhist
	8	11	8	0.727273	1.000000	ColorHist
Livestock	9	14	17	0.642857	0.529412	Grayhist
	10	14	10	0.714286	1.000000	ColorHist
Tiger	19	25	37	0.760000	0.513514	Grayhist
	25	25	30	1.000000	0.833333	ColorHist

Table 2: Comparison between Graylevel Distribution Moment and Color Moment with M₂K-means

Images	Relevant retrieved	Relavent no.	Retrieved no.	Recall	Precision	Method
Balloon	16	25	44	0.640000	0.363636	GLDM
	20	25	27	0.800000	0.740741	Mom
Lion	7	21	28	0.333333	0.250000	GLDM
	18	21	20	0.857143	0.900000	Mom
Rabit	4	11	20	0.363636	0.200000	GLDM
	10	11	22	0.909091	0.454545	Mom
Livestock	8	14	18	0.571429	0.444444	GLDM
	10	14	17	0.714286	0.588235	Mom
Tiger	10	25	43	0.400000	0.232558	GLDM
	11	25	13	0.440000	0.846154	Mom

Table 3: Comparison between Co-occurrence and Color Correlogram with M₂K-means

Images	Relevant retrieved	Relavent no.	Retrieved no.	Recall	Precision	Method
Balloon	1	25	1	0.040000	1.000000	GLCM
	8	25	14	0.320000	0.571429	Corr
Lion	11	21	20	0.523810	0.550000	GLCM
	17	21	23	0.809524	0.739130	Corr
Monkey	1	15	8	0.066667	0.125000	GLCM
	3	15	8	0.200000	0.375000	Corr
Rabit	3	11	18	0.272727	0.166667	GLCM
	3	11	13	0.272727	0.230769	Corr
Livestock	4	14	4	0.285714	1.000000	GLCM
	13	14	16	0.928571	0.812500	Corr
Tiger	2	25	2	0.080000	1.000000	GLCM
	9	25	14	0.360000	0.642857	Corr

Table 4: Comparison between Integration of Features and Combined Method with M₂K-means

Images	Relevant retrieved	Relavent no.	Retrieved no.	Recall	Precision	Method
Balloon	11	25	25	0.440000	0.440000	grayIGM
	25	25	25	1.000000	1.000000	colorCom
Lion	8	21	8	0.380952	1.000000	grayIGM
	21	21	21	1.000000	1.000000	colorCom
Monkey	6	15	6	0.400000	1.000000	grayIGM
	14	15	14	0.933333	1.000000	colorCom
Rabit	4	11	7	0.363636	0.571429	grayIGM
	11	11	11	1.000000	1.000000	colorCom
Livestock	12	14	12	0.87143	1.000000	grayIGM
	14	14	14	1.000000	1.000000	colorCom
Tiger	15	25	15	0.600000	1.000000	grayIGM
	24	25	25	0.960000	0.960000	colorCom

5.2-Comparison between Color Histogram and Histogram of Intensity for Color Image

In color image, one possible way of storing the color information is to use three different color histograms for color image, and this is called histogram of intensity. Another possible method is to have a single color histogram for all of the color channels. The latter approach which is efficient is used in this research. Table (5) shows that the color histogram in combined method with M₂K-means is better than the histogram of intensity.

Table 5: Comparison between Color Histogram and Intensity Histogram in Combined Method with M₂K-means

Images	Relevant retrieved	Relavent no.	Retrieved no.	Recall	Precision	Method
Lion	20	21	33	0.952381	0.606061	Intensity
	21	21	21	1.000000	1.000000	RGB
Monkey	12	15	12	0.800000	1.000000	Intensity
	14	15	14	0.933333	1.000000	RGB
Tiger	12	25	12	0.480000	1.000000	Intensity
	25	25	27	1.000000	0.958333	RGB

5.3-Comparison between RGB and CIE Color Space of Combined Method with M₂k-Means

In this research, first we used a gray level feature extraction when use found that these methods did not produce an efficient retrieval; then we used color feature extraction, we used RGB color space and CIE L*a*b* and CIE L*u*v*. Here we discovered that the RGB color space is the best when using (Color Histogram, Color Moment and Color Correlogram) as feature extraction method and combined method with M₂K-means clustering algorithm as retrieval method. See tables (6, 7, 8).

Table 6: Comparison between Lab₁ and Lab₂ for Combined Method with M₂K-means

Images	Relevant retrieved	Relavent no.	Retrieved no.	Recall	Precision	Method
Balloon	10	25	10	0.400000	1.000000	Lab ₁
	11	25	11	0.440000	1.000000	Lab ₂
Lion	21	21	23	1.000000	0.913043	Lab ₁
	21	21	21	1.000000	1.000000	Lab ₂
Monkey	11	15	22	0.733333	0.500000	Lab ₁
	14	15	14	0.933333	1.000000	Lab ₂
Tiger	20	25	23	0.800000	0.869565	Lab ₁
	24	25	24	0.960000	1.000000	Lab ₂

Table 7: Comparison between Luv₁ and Luv₂ for Combined Method with M₂K-means

Images	Relevant retrieved	Relavent no.	Retrieved no.	Recall	Precision	Method
Balloon	12	25	12	0.480000	1.000000	Luv ₁
	14	25	14	0.560000	1.000000	Luv ₂
Tiger	19	25	19	0.760000	1.000000	Luv ₁
	20	25	21	0.800000	0.952381	Luv ₂

Table 8: Comparison between Lab₂, Luv₂ and RGB for Combined Method with M₂K-means

Images	Relevant retrieved	Relavent no.	Retrieved no.	Recall	Precision	Method
Monkey	9	15	21	0.600000	0.428571	Luv ₂
	14	15	14	0.933333	1.000000	Lab ₂
	14	15	14	0.933333	1.000000	RGB
Tiger	14	25	14	0.560000	1.000000	Luv ₂
	20	25	20	0.800000	1.000000	Lab ₂
	24	25	25	0.960000	0.960000	RGB

5.4-Comparison between Wavelet and Statistical Methods for Combined with M₂k-Means

Wavelet method is used here in image retrieval, but this method is very good performance on the standard Brodatz data. Therefore, this method does not give us efficient retrieval in natural image. Table (9) shows the difference between wavelet and combined method with M₂K-means in various color space. We noted that the RGB color space is the best.

Table 9: The Difference between Wavelet and Statistical Method

Images	Relevant retrieved	Relavent no.	Retrieved no.	Recall	Precision	Method
Balloon	16	25	59	0.640000	0.271186	Wave
	11	25	25	0.440000	0.440000	Gray IGM
	11	25	11	0.440000	1.000000	Luv ₂
	11	25	11	0.440000	1.000000	Lab ₂
	22	25	22	0.880000	1.000000	Intensity
	25	25	25	1.000000	1.000000	RGB
Monkey	9	15	59	0.600000	0.152542	Wave
	6	15	6	0.400000	1.000000	grayIGM
	9	15	21	0.600000	0.428571	Luv ₂
	14	15	14	0.933333	1.000000	Lab ₂
	12	15	12	0.800000	1.000000	Intensity
	14	15	14	0.933333	1.000000	RGB



Balloon query, 24 matches from the Top 50 Using Combined Method



Balloon query, 23 matches from the Top 23 Using Combined Method with K-means Clustering Algorithm



Balloon query, 25 matches from the Top 25 Using Combined Method with M_1K -means Clustering Algorithm



Balloon query, 25 matches from the Top 25 Using Combined Method with M_2K -means Clustering Algorithm



Balloon query, 20 matches from the Top 27 Using Color Moment with M_2K -means Clustering Algorithm



Balloon query, 16 matches from the Top 33 Using Color Correlogram with M₂K-means Clustering Algorithm



Balloon query, 25 matches from the Top 25 Using Combined Method with M₂K-means Clustering Algorithm

CONCLUSIONS

Here, we extract a Grayscale Histogram, Gray level Distribution Moments, and Gray level Co-occurrence Matrices of the images. We integrated all these features after normalizing similarity; the total similarity between the query and the image in the data collection is calculated via a weighted sum of the similarities provided by each of the features; this method is called gray IGM. For the color content extraction, a well-known and powerful techniques, Color Histogram, Color Moment and Color Correlogram are used in one method by combining all these features to produce efficient method called 'Combined Method'. Though gray IGM is more effective than using each feature alone but this method does not yield 100% retrieval. Therefore, we used the Combined Method. This research introduces a cluster based retrieval of image, a novel image retrieval scheme, based on a rather simple assumption: semantically similar images tend to be clustered in some feature space. Cluster based retrieval of an image attempts to retrieve semantically coherent image clusters from unsupervised learning of how images of the same semantics are alike. At search time, the query image is not compared with all the images in the database, but only with a small subset. Here we used k-means clustering algorithm and also the improved of the k-means that used a better similarity distance called M₁k-means and M₂k-means this algorithm advanced of M₁k-means by generating the initial clusters. This algorithm is an efficient algorithm and produce efficient retrieval. We conclude that color methods are useful in content based image retrieval. Combining color information usually improves the performance of the method; and it further improves the performance if the M₂k-means clustering algorithm are used. These methods proved an efficient performance when used in content based image retrieval.

REFERENCES

- [1] Tran L.V.,(2003), Efficient Image Retrieval With Statistical Color Descriptors, PhD Thesis, Department of Science and Technology, Linköping University, Sweden.
- [2] Konak E., (2002), a content-Based Image Retrieval System for Texture And Color Queries, MSc thesis, Department of Computer Engineering, University of Bilkent.
- [3] Aulia E., (2005), Hierarchical Indexing For Region Based Image Retrieval, MSc Thesis, Department of Industrial and Manufacturing Systems Engineering, University of Louisiana State.
- [4] Wang, James Z., Wiederhold G., (1997), Content-Based Image Indexing and Searching Using Daubechies Wavelet, International Journal of Digital Libraries, pp. 311-328.
- [5] Lew M. S., (2001), Principles of Visual Information Retrieval, Springer-Verlag London Berlin Heidelberg, London.
- [6] KosKela M., (2003), Interactive Image Retrieval Using Self-Organizing Maps, PhD Thesis, Department of Computer Science and Engineering, University of Technology.
- [7] Chikara V., (2001), Color-Based Image Retrieval Using Compact Binary Signatures, Technical Report TR 01-08, Department of Computing Science, University of Alberta, Canada.
- [8] Dachapak C., Kanae S., Yang Z., Wada K., (2004), Orthogonal Least Squares For Radial Basis Function Network In Reproducing Kernel Hilbert Space, IFAC Workshop on Adaptation and Learning in Control and Signal Processing, Japan, pp. 847-852.
- [9] Long F., Zhang H., Feng D., (2002) Fundamentals of Content-Based Image Retrieval, Ch 1.
- [10] Tou J., Gonzalez R., (1974), Pattern Recognition Principles, Addison-Wesley Publishing Company, USA.
- [11] Shailendra S., PremNarayan A., (2012), Comparison of K-means and Modified K-mean algorithms for Large Data-set, International Journal of Computing, Communications and Networking, Volume 1, No.3, pp. 106-110 .