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CBIR Using Region Emphasized Markov Stationary Features

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Abstract:
Homogeneous Markov chain-based Markov Stationary Features (MSF) in image analysis, is getting popularity day by day. Because, it not only takes care the distribution of colors, just as the histogram method does, but also considers the spatial co-occurrence of histogram patterns. However, treating a giant database of images with a degree of heterogeneity, simple MSF techniques are not sufficient to distinguish the images. In our article, a Region Emphasized MSF (REMSF) based on non-homogeneous Markov Chain is proposed to escape this shortcoming. By incorporating spatial weighted co-occurrence of image colors based on several potential image regions and exploiting time inhomogeneous Markov chain concept, it is possible to improve certain aspects of the existing methods. Without compromising effectiveness and robustness, the REMSF method keeps the feature level simplicity. Globally recognized databases namely WANG1000 and Corel10800, are exploited to investigate the performance of this algorithm with the existing methods. The empirical results justify the effectiveness our method clearly.
Key Word*:Image retrieval, Markov stationary feature, Non-homogeneous Markov chain, MSF, REMSF, CBIR.*

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I. Introduction

With the proliferation of world-wide-web (WWW), and the rapid increase of the multimedia data such as image and video, there is a strong demand for developing efficient techniques for storing, indexing, browsing and retrieving of the data to exploit the full benefit of explosive growth [1]-[4]. The traditional methods of image retrieval rely on manually annotated images which is expensive and time-consuming, especially given the large and constantly growing image databases. Instead, a fully automated content-based solution should be explored.

Images from database are indexed by summarizing their visual contents through automatically extracted quantities of features such as color, texture, shape and spatial relationship according to user's visual requirement. Color feature is one of the most flexible and reliable visual features used in image retrieval or other image pattern classification systems. It is almost independent of image size and orientation, and is robust to its background complication. Histogram is an effective way to represent the colors of an image. Color-histogram describes the global color distribution in an image. For this reason, it is robust to noise as well as to the local image transformations such as scaling, translation and rotation. It is also easy to compute, and insensitive to small change in viewing orientations. However, the histogram comparison cannot discriminate if the database contains a large number of images. To overcome this problem a joint histogram method is put forward by G. Pass and others [5]. The method works somewhat better for large scale image database, but for many applications it is not adequate. Because it does not take into account of spatial information similar to the simple histogram. With a large database, very similar images may have similar color histograms; on the other hand, very similar images with different lighting conditions may have different histograms.

To incorporate spatial information into image features several attempts have been made during the last couple of years. A number of techniques are proposed to integrate spatial information with color histograms. Hsu and others [6] did this by selecting a set of representative colors using maximum entropy quantization with event covering method. Another method, called the color coherence vector (CCV) was proposed by Pass and Zabih [7] to use the spatial information. In this case, the histogram bins are divided into two types. It is coherent if it belongs to a large color region or incoherent if it does not. The CCV method gives better performance than color histograms if the images, in the database, have mostly uniform colors and are texture dominated. Color correlogram introduced by Huang and others [8]-[9] is used to characterize both the color distribution of pixels and the spatial correlation of pairs of colors. Instead of the indirect use of spatial information, the correlogram method encodes local spatial structure information directly into the histograms. The Hidden Markov chain model [10]-[11] is employed to characterize spatial information between pixels in different colors.

A spatial co-occurrence matrix-based Markov stationary feature (MSF) method is introduced by Li and others [12] using homogeneous Markov chain model. They divided the database images into four categories depending on the discriminating capability of histogram analysis: histogram-level distinguishable, intra-bin distinguishable, extra-bin (that is, inter-bin) distinguishable and histogram undistinguishable images. The MSF was innovated to characterize the spatial co-occurrence of intra-bin and/or extra-bin histogram relationship pattern of an image which generally outperforms the corresponding earlier content-based methods. To form the so-called MSF, initial and stationary distributions of the homogeneous Markov chain are combined to encode the intra-bin and extra-bin relationship of histogram. Besides, some research such as Directed Markov Stationary Feature (DMSF) [14], Multi-direction Markov Stationary Feature (MDMSF) [15], Markov Stationary Features and Vector Quantization Histogram (MSFHQ) [16] and some other methods [17]-[19] based on the same model have been demonstrated to enhance the performance of the original MSF. In these enhanced MSF schemes, the color and intensity of an image are treated alone or sometimes separately to incorporate the spatial co-occurrence information; and the individual features are then concatenated. But all the methods suffer with same fate due to ignoring regional importance of image features.

Here, we propose REMSF scheme in which the contribution of position of color feature is recognized to capture the co-occurrence visual information in a significant level. The compactness of image feature is ensured in this method similar to the original MSF but using the concept of non-homogeneous model of Markov chains rather than the homogeneous one.

II. Preliminaries

The MSF is collected from the visual input (e.g., color) by analyzing the underlying image where a concept of Markov chain model [12] is used. Suppose, an image I is quantized into K levels, thus the set of histogram bins of the image is $S = \{s_1, s_2, ..., s_K\}$. The co-occurrence matrix containing spatial information is defined as $\mathbf{C} = \{c_{ij}\} \epsilon R^{K \times K}$ with each element

$$c_{ij} = \neq (x_1 = s_i, x_2 = s_j \,||x_1 - x_2| = d) \qquad (1)$$

where d indicates L_1 distance between two (adjacent if d = 1, that is in our case) pixels x_1 and x_2, and c_{ij} accumulates the number of co-occurrences between bins s_i and s_j. When the pattern s_i and s_j have large spatial co-occurrence, the possibility that s_i transit to s_j is high. It should be noted that the co-occurrence matrix C is a nonnegative symmetric matrix and can be interpreted from a statistical point of view [12]. Homogeneous Markov chain model is adopted to characterize the spatial relationship of histogram bins, which treats bins as states in that model.

Homogeneous Markov Chain Scheme

Markov chain is a sequence of random variables $X_1, X_2, ..$ with the Markov property, namely that, given the present state, the future and past states are independent. Formally,

$$\Pr[X_{t+1} = x_{t+1} | X_1 \ldots X_t = x_1 \ldots x_t] = \Pr[X_{t+1} = x_{t+1} | X_t = x_t] \qquad (2)$$

that is, X_{t+1}, the state of the system at time t+1 depends only on the state of the system at time t. Thus, Markov process must possess a property that is usually characterized as "memory less".

If the conditional probabilities are well defined, that is, if $\Pr[X_1 \ldots X_t = x_1 \ldots x_t] > 0$, then, the possible values taken by the random variable X_i form a countable set S called the state space of the chain, where the state space is analogous to the set of histogram bins and is assumed to be fixed for all the images of the database. The probability, $\Pr[X_{t+1} = x_{t+1} | X_t = x_t]$ is known as transition probability and the Markov chain can be modeled as a transition probability matrix or simply, transition matrix. This is statistically derived from the spatial co-occurrence matrix (discussed earlier) and is defined as $\mathbf{P} = [p_{ij}] \in \mathbb{R}^{K \times K}$, were

$$p_{ij} = \frac{c_{ij}}{\sum_{j=1}^{K} c_{ij}} \qquad (3)$$

p_{ij} is the $(ij)^{th}$ component of the transition matrix P. It should be noted that, every individual image can be represented by a Markov chain what should be modeled as an individual transition matrix. Thus, comparing two Markov chains (that is two images) means comparing the two corresponding transition matrices. However, the transition matrix is space expensive because it requires M (K2) spaces for K states that is bins. At the same time, time complexity of comparing two transition matrices is O (K2) which is impractical for a large image database. Therefore, to speed up the comparing process, it is desirable to obtain a space as well as speed efficient solution based on intrinsic properties of Markov chains. Considering the space and speed issues, one should try to build up a compact yet robust feature representation from the transition matrix.

Every transition matrix must satisfy [20]

$p_{ij} \geq 0 \, for all i, j \in \{1, \dots, K\}$, and

$$\sum_{j=1}^{K} p_{ij} = 1 \, for all i \in \{1, \dots, K\} \qquad (4)$$

Besides the transition matrix, the Markov chain has another characteristic, namely the initial distribution, which tells us how the Markov chain starts. The initial distribution is represented as a row vector $\boldsymbol{\mu}^{(0)}$ given by,

$$\boldsymbol{\mu}^{(0)} = \left(\mu_1^{(0)}, \mu_2^{(0)}, \dots, \mu_K^{(0)}\right) \qquad (5)$$

Since $\boldsymbol{\mu}^{(0)}$represents a probability distribution, we have,

$$\sum_{i=1}^{K} \boldsymbol{\mu}_i^{(0)} = 1 \qquad (6)$$

Once we know the initial distribution $\boldsymbol{\mu}^{(0)}$ and the transition matrix P, we can compute all the distributions $\boldsymbol{\mu}^{(1)}, \boldsymbol{\mu}^{(2)}$, ... at times 1, 2, ... respectively, of the Markov chain, by

$$\boldsymbol{\mu}^{(n)} = \boldsymbol{\mu}^{(0)} \mathbf{P}^n \qquad (7)$$

where $\mathbf{P}^n$ is for the n^{th} power of the matrix P, that means, the result is simply a matter of matrix multiplication. By the induction hypothesis, we have,

$$\boldsymbol{\mu}^{(m+1)} = \boldsymbol{\mu}^{(m)} \mathbf{P} = \boldsymbol{\mu}^{(0)} \mathbf{P}^m \mathbf{P} = \boldsymbol{\mu}^{(0)} \mathbf{P}^{m+1} \qquad (8)$$

which suggests that the state distribution of the Markov chain at time m+1 can be obtained by simply multiplication of initial distribution and the $(m+1)^{th}$ power of the transition matrix. Accordingly, we have,

$$\mathbf{P}^{m+n} = \mathbf{P}^m \mathbf{P}^n \qquad (9)$$

which is known as Chapman-Kolmogorov equation.

Perhaps, the most important feature of Markov chain is its stationary distribution. A Markov process $\{X_t : t \geq 0\}$ is stationary if the joint distribution of $(X_1, X_2, \dots X_t)$ is the same as the joint distribution of $(X_{1+m}, X_{2+m}, \dots X_{t+m})$, where $m \geq 0$.

For a Markov chain with state space $\{s_1, s_2, \dots, s_K\}$ and transition matrix P, a row vector $\boldsymbol{\pi} = (\pi_1, \pi_2, \dots, \pi_K)$ is said to be a stationary distribution, if it satisfies

(i) $\boldsymbol{\pi}_i \geq 0, for i = 1, \dots, K, and \sum_{i=1}^{K} \boldsymbol{\pi}_i = 1$

meaning that, $\boldsymbol{\pi}$ should describe a probability distribution on $\{s_1, s_2, \dots, s_K\}$, and

(ii) $\boldsymbol{\pi}\mathbf{P} = \boldsymbol{\pi}$, implies that

$$\sum_{i=1}^{K} \boldsymbol{\pi}_i \mathbf{P}_{i,j} = \boldsymbol{\pi}_j, for j = 1, \dots, K \qquad (10)$$

that is, if the initial distribution $\boldsymbol{\mu}^{(0)} = \boldsymbol{\pi}$, then the state distribution $\mu^{(1)}$ of the chain at time 1 satisfies,

$$\boldsymbol{\mu}^{(1)} = \boldsymbol{\mu}^{(0)} \mathbf{P} = \boldsymbol{\pi}\mathbf{P} = \boldsymbol{\pi} \qquad (11)$$

and iteratively we see that $\boldsymbol{\mu}^{(n)} = \boldsymbol{\pi}$ for every n. Thus, according to Chapman-Kolmogorov equation, we have, $\boldsymbol{\pi} = \boldsymbol{\pi}\mathbf{P} = \cdots = \boldsymbol{\pi}\mathbf{P}^n$. Hence, a stationary distribution is also known as an invariant distribution of a Markov chain.

An invariant distribution of a Markov chain should ensure of its existence, uniqueness and convergence. Otherwise, the chain will be trivial. For a Markov chain to be nontrivial, the transition matrix should satisfy two conditions: irreducibility and aperiodicity. In other words, any irreducible and aperiodic Markov chain has one and only one stationary distribution.

Markov Stationary Features

Based on the basic properties of the transition matrix and considering the Markov chain's two potential conditions, namely, irreducibility and aperiodicity, Li and others [12] formulates a space efficient (2K instead of K^2 in feature dimension) yet robust feature framework, exploiting the concept of Chapman-Kolmogorov equation. The so-called feature representation is known as Markov stationary features $[\boldsymbol{\pi}_0, \pi]$, which combines two K-dimensional vectors: initial distribution denoted by $\boldsymbol{\pi}_0$ (that is, $\boldsymbol{\mu}^{(0)}$) and stationary distribution denoted by π. The initial distribution, also known as auto-correlogram, encodes intra-bin transitions of histogram bins of the underlying image, can be obtained as,

$$\boldsymbol{\pi}_0 = \frac{c_{ii}}{\sum_{i=1}^{K} c_{ii}} \qquad (12)$$

With a regular Markov chain (i.e., the chain is irreducible as well as aperiodic), the stationary distribution of the transition matrix denoted by $\boldsymbol{\pi} = (\boldsymbol{\pi}_1, \boldsymbol{\pi}_1, \dots, \boldsymbol{\pi}_{\mathrm{K}})$, satisfies

$$\boldsymbol{\pi} = \boldsymbol{\pi}\mathbf{P} \qquad (13)$$

For a finite state space (because of quantized color image), the chain is obviously irreducible because there is no isolated pixel. However, when the chain is irregular (i.e., irreducible but aperiodic chain, also known as ergodic chain), there may not exist unique solution of (13) which indicates that the problem is non-converging. Thus, for a general case (i.e., for both regular and irregular chain), the fundamental limit theorem of Markov chain [21] with better solution can be expressed as

$$\mathbf{A}_{\mathrm{n}} = \frac{1}{n+1}(\mathbf{I} + \mathbf{P} + \mathbf{P}^2 + \cdots + \mathbf{P}^{\mathrm{n}}) \qquad (14)$$

where $\mathbf{I}$ is an identity matrix.

To mitigate the approximation error due to small n, it is a good ploy to average the rows of the matrix $\mathbf{A}_{\mathrm{n}}$ as shown below,

$$\boldsymbol{\pi} \approx \frac{1}{\mathrm{K}}\sum_{\mathrm{i}=1}^{\mathrm{K}} \vec{\mathrm{a}}_{\mathrm{i}}\,, \text{where } \mathbf{A}_{\mathrm{n}} = [\vec{\mathrm{a}}_1, \ldots, \vec{\mathrm{a}}_{\mathrm{K}}]^{\mathrm{T}} \qquad (15)$$

3.Non-homogeneous Markov Chain Scheme

With a finite state space, if a Markov chain has only one transition matrix (i.e., having stationary transition probabilities), then the chain is called time homogeneous or simply homogeneous Markov chain [20]. So far, we have discussed the homogeneous Markov chain where the transition matrix is P, which is stationary in time. With an initial distribution $\boldsymbol{\mu}^{(0)}$, already we have shown previous section, the distribution of the chain at time n is

$$\boldsymbol{\mu}^{(n)} = \boldsymbol{\mu}^{(0)}\mathbf{P}^n, \text{ and } \mathbf{P}^n = \mathbf{P}^{l+m} = \mathbf{P}^l\mathbf{P}^m \qquad (16)$$

where $n = l + m$

With a finite state space, if a Markov chain has m different transition matrices $\mathbf{P_1}, \mathbf{P_2}, \ldots, \mathbf{P}_m$, then it is called time inhomogeneous or simply non-homogeneous Markov chain. For any m, we have,

$$\boldsymbol{\mu}^{(m)} = \boldsymbol{\mu}^{(0)}\mathbf{P}_1.\mathbf{P}_2 \ldots.\mathbf{P}_m \qquad (17)$$

The existence of unique stationary distribution in non-homogeneous Markov chain depends on the two issues namely merging (total variation) and stability of the transition probabilities of the chain. By combining the m transition matrices by the following way, we can merge the total variation [22], as

$$\mathbf{P}^m = \mathbf{P_1}.\mathbf{P_2} \ldots.\mathbf{P}_m \qquad (18)$$

Thus, we have, $\boldsymbol{\mu}^{(m)} = \boldsymbol{\mu}^{(0)}\mathbf{P}^m$, where $\boldsymbol{\mu}^{(m)}$is a state distribution at time m. If all the transition matrices of the Markov chains are irreducible, and the sizes of the state spaces are same, then stability of the chain is not a question at all (in our case). If the sizes of state spaces are different, say q is for $\mathbf{P_1}$ and$r$ is for $\mathbf{P_2}$, then the one way to ensure the stability is,

$$\mathbf{P^2} = \mathbf{P_1}.\mathbf{P_2} \qquad (19)$$

where q < r and $\mathbf{P_1}.\mathbf{P_2} \neq \mathbf{P_2}.\mathbf{P_1}$

As an example, say two transition matrices are,

$$\mathbf{P_1} = \begin{pmatrix} .75 & .25 \\ .25 & .75 \end{pmatrix}, \text{and } \mathbf{P_2} = \begin{pmatrix} .4 & .3 & .3 \\ .25 & .25 & .5 \\ .4 & 0 & .6 \end{pmatrix},$$

then we have,

$$\mathbf{P^2} = \begin{pmatrix} .75 & .25 & 0 \\ .25 & .25 & 0 \\ .5 & .5 & 0 \end{pmatrix}\begin{pmatrix} .4 & .3 & .3 \\ .25 & .25 & .5 \\ .4 & 0 & .6 \end{pmatrix}$$

After combining all the transition matrices (i.e., merging the total variation with stability), the rest of the process of finding stationary distribution π of the non-homogeneous Markov chain is similar to the homogeneous one. Thus, the relation of homogeneous and non-homogeneous chain can be established via,

$$\boldsymbol{\mu}^{(n)} = \boldsymbol{\mu}^{(m)}\mathbf{P}^{n-m} \qquad (20)$$

where $n \gg m$.

Properties of the HSV color space

Among several color models, perhaps HSV is the most prominent color space for low level image processing. For instance, using HSV color space, the CBIR system results in better agreement with color perception than using RGB. This is because RGB is not perceptually uniform; thereby the small perceptual differences between some pairs of colors are equivalent to larger perceptual differences in other pairs. Therefore, it is fair to convert the RGB images in the database to corresponding HSV images before any computation.

In HSV model, the luminance (i.e., brightness) component of a color pixel is separated from its chrominance components (i.e., Hue and Saturation). Though, color images on computer monitors are made up of varying amounts of red, green, and blue phosphor dots, conceptually it is more appropriate to discuss colors as made up of Hue, Saturation and Brightness.

Hue represents the attribute that describes pure color. "Hue" slightly differs from "color" because a color can have saturation or brightness as well as hue. Hue is perceived with the incident of sufficient illumination of light containing single wavelength. Saturation is the colorfulness of a color (hue) relative to its own brightness. A pure color is fully saturated which is diluted by mixing of white light. Brightness is an attribute of visual perception in which a source appears to reflecting light. In other words, brightness is the perception elicited by the luminance of a visual target. Actually, the colorfulness is a function of brightness and saturation.

III. Region-Emphasized Markov Stationary Features

Unlike scene images, during capturing object interest images, it is common practice to ensure that the interest objects are concentrated in the middle region of the image. The pixel-based existing schemes are either based on color [12-14] or based on intensity [15] or based on both. However, all the pixels of an image are considered with same respect ignoring their regional positions. To be more specific, all the pixels in terms of color or intensity ignoring their regional location are treated with same weight, and the individual features (in terms of color and intensity) are then concatenated. Thereby the size of the resultant feature space is usually grown geometrically with very limited spatial co-occurrence information. While the feature spaces are giant, the positional weight of pixel components are compromised or still ignored. This paper proposes IRE-MSF technique which is essentially generalization of a number of color MSFs in which the contribution of several image regions is recognized with their respected positions. Since, the probability of searching objects can be located highly in the centered area of an image, the inner regions are emphasized according to their innerness. To be more clearly, the outer regions essentially contain the inner sections (i.e., regions) repeatedly. Thus, in computation of feature extraction, the innermost region is considered most. In other words, inner regions are automatically weighted than their outer counterparts. It is also remarkable that, to make some portion of features weighted, extra calculation is not necessary in this scheme.

This integrated approach extracts the features capturing the spatial co-occurrence of histogram patterns of pixel colors for different predefined regions of an image using the HSV color space. To do so, some of the useful properties of HSV color space (discussed earlier) are utilized. The main advantage of our proposed technique, in contrast to the other schemes, is that, the weighted color variations considering different image regions are contained in a single resultant feature. Thereby, the compactness of the feature space dimension can be assured without compromising robustness and efficiency.

In our algorithm, the RGB image is clipped rectangularly in several regions (say three regions R_1, $R_2 and R_{3.}$ Essentially, R_3 includes the whole image) from outer to inner sections in nested fashion shown in Fig. 1. The individual colors in terms of hue of the different image regions are then quantized into K levels. The individual co-occurrence matrices (that is, $\mathbf{C_1}, \mathbf{C_2}, and \mathbf{C}_3$,respectively) are computed using (1) among the neighborhood pixels (that is, d = 1) considering the opposite direction issue (discussed earlier). Equation (3) is then used to compute three corresponding transition matrices $\mathbf{P}_1$, $\mathbf{P_2}$ and $\mathbf{P_3}$. Using the matrices, the unique composite transition matrix $\mathbf{P^3}$is calculated exploiting the idea of non-homogeneous Markov chain model explained in subsection 3. This composite transition matrix $\mathbf{P^3}$ is the targeted transition matrix P of homogeneous Markov chain for finding the required unique stationary distribution. Finally, equation (15) is applied to compute the desired stationary distribution $\boldsymbol{\pi}$.

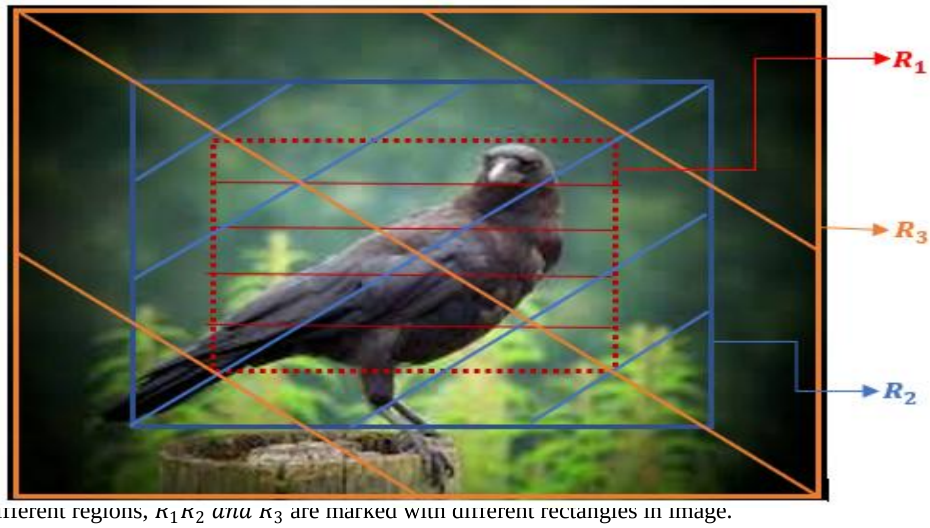

Fig. 1. Different regions, $R_1 R_2$ *and* R_3 are marked with different rectangles in image.

The resultant vector π is the required stationary distribution that encodes the extra-bin transitions of an image colors as well as intensities what is the part of our concerned MSF features. The other part of the MSF is initial distribution $\boldsymbol{\pi}(0)$. In order for the Markov chain to be well-defined, we must have an initial distribution $\boldsymbol{\pi}(0) = \boldsymbol{\mu}^{(0)}$. It is also noted from the extension theorem by Tulcea [23] that a Markov chain is uniquely determined by its transition matrix and its initial distribution. In practice, it is reasonable to incorporate the intra-bin transition of an image colors as well as intensities as an initial distribution of our MSF feature, which can be computed directly from the co-occurrence matrix, say C_1, defined as,

$$\boldsymbol{\pi}(0) = \frac{c_{ii}^{3}}{\sum_{i=1}^{K} c_{ii}^{3}} \tag{21}$$

After computing the initial distribution and stationary distributions, the required MSF is defined as the combination of the initial distribution $\boldsymbol{\pi}(0)$ (i.e., auto correlogram) and the stationary distribution $\boldsymbol{\pi}$ as,

$$\vec{h}_{\mathrm{ICI-MSF}} = [\boldsymbol{\pi}(0), \boldsymbol{\pi}]^{T} \tag{22}$$

The Block diagram of the proposed system is shown in Fig. 2.

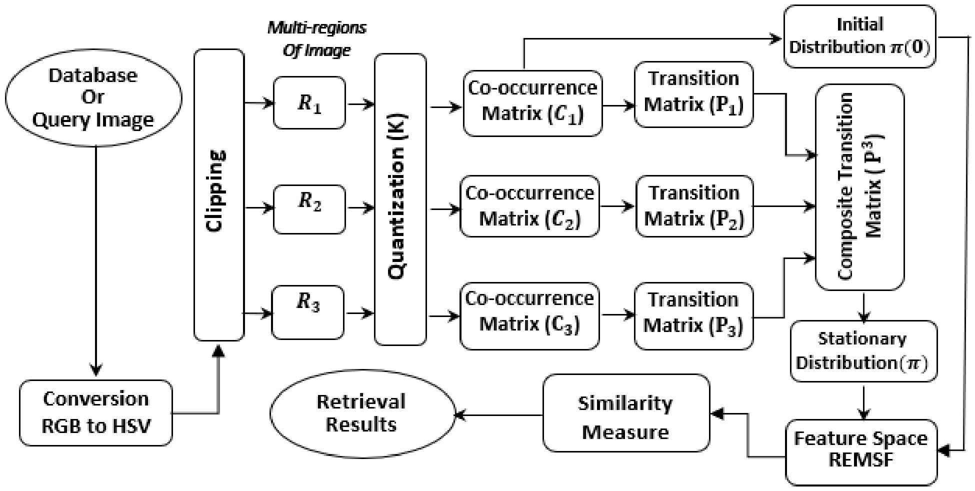

Fig. 2. Block diagram of the proposed system

IV. Similarity Measurement

We assume that no textual captions or other manual annotations of the images are given. Therefore, the proper representation of the visual features of an image will be the proper description of the image content, such as REMSF. In order for an image retrieval system to find images that are visually similar to the given query, it should have a measure that can determine how similar or dissimilar the different images are from the query. For matching between the REMSF features of the query and database images, any one of the well-known distance/similarity measures such as Euclidean distance, Mahalanobis distance, Chi square distance etc. can be selected. In the previous section we have seen that, each REMSF feature contains two K dimensional vectors where each vector is treated as a histogram due to the non-negative nature of its elements. Therefore, we can apply Chi square distance measure in our simulation results. For two histograms $\mathbf{h}_q$ and $\mathbf{h}_d$ of the images $I_q andI_d$, respectively, the chi square distance can be defined as,

$$\mathrm{D}(I_q, I_d) = \frac{1}{2}\sum_{k=1}^{K} \frac{[\mathbf{h}_q(k) - \mathbf{h}_D(k)]^2}{\mathbf{h}_q(k) + \mathbf{h}_D(k)} \tag{23}$$

The above distance formula will be used for initial and stationary distribution individually, which are then will be summed for totaling. The similarity result for each matching is then stored in an array in order to display the top matches from the database according to the ranking of similarity.

V. Experiment and Discussion

The Region Emphasized Markov Stationary Feature (REMSF) can be exploited in the various fields of image processing and pattern recognition problems. Here, Content-Based Image-Retrieval application is regarded as a field of study to evaluate the effectiveness of the REMSF features. The whole evaluation process followed the diagram illustrated in Fig.2.

To compare the general performance of histogram, Color Auto Correlogram (CAC), original MSF with our proposed REMSF method regarding image retrieval system, we have used two standard metrics, namely, recall and precision, which are defined as,

$$P(I_q,n) = \frac{1}{n}\sum_{i=1}^{n}\left[\gamma\left(f(I_i),f(I_q)\right) |\mathbf{Rank}(I_q,I_i) \le n\right] \quad (24)$$

$$R(I_q,n) = \frac{1}{N_G}\sum_{i=1}^{n}\left[\gamma\left(f(I_i),f(I_q)\right) |\mathbf{Rank}(I_q,I_i) \le n\right] \quad (25)$$

Where, f(I) stands for the category of image I, n indicates the number of retrieved images by a system, N_G indicates the number of relevant images of a G category in the database DB, Rank(I_q, I_i) returns the rank of image I_i according to the similarity metric for query image I_q,

$$\gamma\left(f(I_i),f(I_q)\right) = \begin{cases} 1 & \text{if } f(I_i) = f(I_q) \\ 0 & \text{Otherwise} \end{cases}$$ and,

$$\delta\left(f(I_i),f(I_q)\right) = \begin{cases} 1 & \text{if } f(I_i) \ne f(I_q) \\ 0 & \text{Otherwise} \end{cases}.$$

Average precision and recall at n are,

$$P_{av}^{n}(I_q) = \frac{1}{n}\sum_{i=1}^{n} P(I_q,i)|_{n<|DB|} \quad (26)$$

$$R_{av}^{n}(I_q) = \frac{1}{n}\sum_{i=1}^{n} R(I_q,i)|_{n<|DB|} \quad (27)$$

For the work reported in this paper, we conducted experiments on two different prominent databases namely: WANG1000 (also known as Corel1000) and Corel10800. The databases contain large number of images in various conditions and types ranging from animals and outdoor sports to natural images. Because of the heterogeneity of size, orientation, color and lighting, it is axiomatic that the Corel databases meet all the requirements to evaluate the performance of any CBIR system.

For the WANG1000 [24], the images of the database are pre-classified into 10 different categories named: African, Beach, Building, Bus, Dinosaur, Elephant, Flower, Horse, Mountain, and Food. Each category has 100 images.

The comparative retrieval results with the original histogram, color auto correlogram, original MSF and our REMSF method in terms of precision-recall curves for a single query image (e.g., African) are shown in Fig. 3. The average precision-recall curves of the concerned methods for 100 randomly selected query images against the WANG1000 database are summarized in Fig. 4.

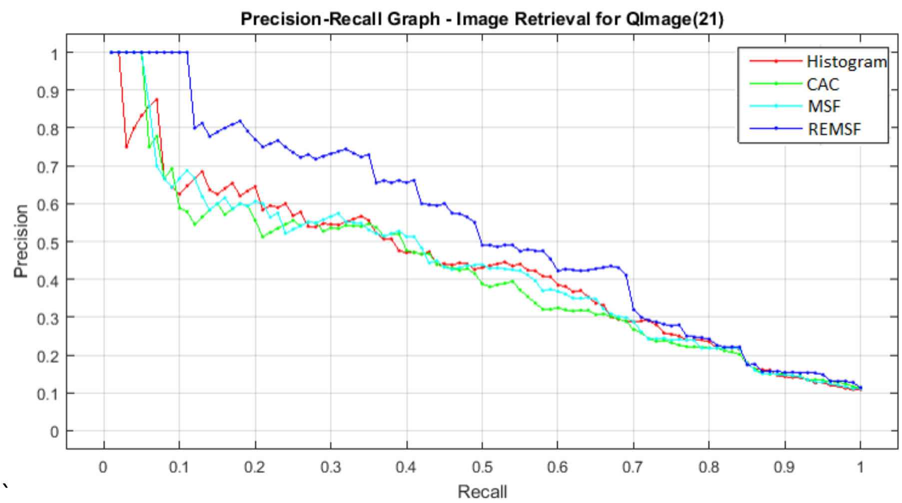

Fig. 3. Precision-recall curves for Histogram, CAC, original MSF, and proposed REMSF method for the query image-21 of WANG1000 db.

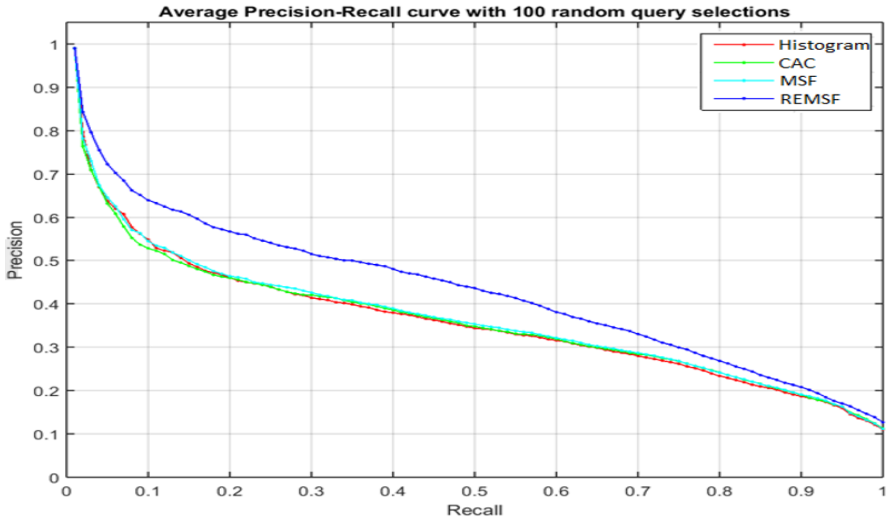

Fig.4. Average Precision-recall curves of Histogram, CAC, original MSF, and proposed REMSF for some 100 randomly selected images from the WANG1000 database.

For the Corel10800 [25], the images of the database are pre-classified into 80 different categories with different sizes ranging from 100 to 500 images in each, like, autumn, aviation, bonsai, bus, castle, cloud, dog, elephant, fitness, iceberg, primates, ship, stalactite, steam-engine, tiger, train, texture_1, texture_2, and so on. The comparative results in terms of precision-recall curves for a single query image (here the query image no. is 2311) are shown in Fig. 5. To evaluate the effectiveness of the proposed method over the other existing methods we select a category named "bus" containing 100 images. The average precision-recall curves with some 20 randomly selected query images from that (bus) category are shown in Fig. 6.

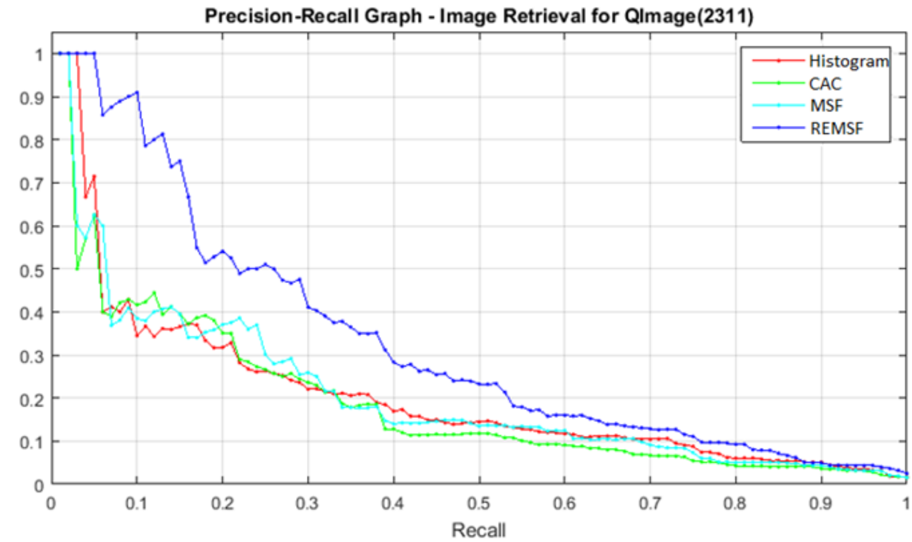

Fig. 5. Precision-recall curves for Histogram, CAC, original MSF, and proposed REMSF method for the query image-2311 against Corel10800 db.

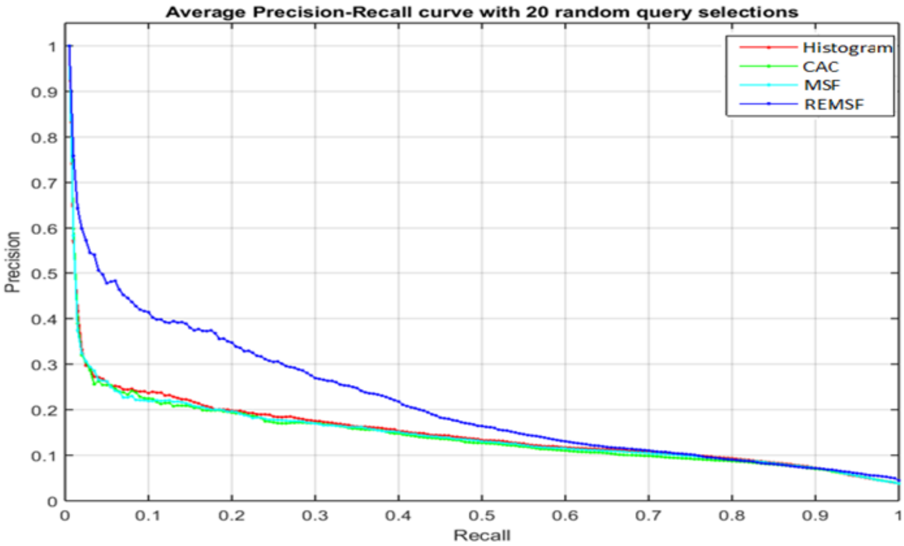

Fig.6. Average Precision-recall curves of Histogram, CAC, original MSF, and proposed REMSF for some 20 randomly selected images from the Corel10800 db.

From the comparison of results shown in Fig. 3, 4, 5 and 6, the following observations can be made: 1) the proposed REMSF method always shows better performance compared to the other existing algorithms against both of the databases. 2) When the database grows larger and the degree of heterogeneity increases, the performance (shown in Fig. 5 and 6) of the existing techniques is quite frustrating. On the other hand, the performance of the proposed technique is always satisfactory, which validates the effectiveness of our method. This is because, the spatial co-occurrence information of inner regionsis more emphasizedthan the ones of outer regions of images.

VI. Conclusion

Color histogram and color correlogram features are widely used in content-based image searching, matching, indexing, classification and other type of pattern recognition systems. Nowadays, Markov stationary features based on homogeneous Markov chain for content-based image and video analysis is being popularly used. However, handling with large scale database of images, the methods of the simple color histogram, color auto correlogram and MSF features are not sufficient to meet our expectation. By emphasizing some regions of an image during feature extraction, it is possible to overcome the difficulties of the earlier techniques to some extent. Our experimental results have justified the effectiveness of the proposed scheme.

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