ZERNIKE MOMENT OF INVARIANTS FOR EFFECTIVE IMAGE RETRIEVAL USING GAUSSIAN FILTERS

1Anirudha R.Deshpande, 2 Dr. Sudhir S. Kanade
1(Department of ECE, TPCT’s C.O.E.Osmanabad, India)
2(Head of Department of ECE, TPCT’s C.O.E.OsmanabadMaharashtra, India)

ABSTRACT

This paper proposes a steerable Gaussian filter and moment of invariant for effective image retrieval for color texture and shape features. Percentage of the small number of the dominant color can be obtained. Image can be defined by fast color quantization algorithm with cluster merging. It provides an efficient and flexible approximation of early processing in the human visual system. Pseudo-Zernike moment is applied in the sharp descriptor. It is more robust to noise and provides good feature representation than other representation. Finally the robust feature set for image retrieval can be obtained by the combination of the color, shape and texture feature. Experimental result shows that the proposed method provides better result than the other methods and it provides accurate user-interested image.

Keywords: Image retrieval, Moment of invariants, steerable Gaussian filters, Feature extraction.

1. INTRODUCTION

Efficient indexing and searching become essential for large image achieves due to increase of digital image on the internet. Diversity and ambiguity of the image content can be described by the keywords of manual labor to label images. Hence content base image retrieval (CBIR) [1] has drawn substantial. CBIR indexes images by low level visual feature such as texture, color and shape. Visual information cannot be completely characterized semantic content, but they are easy to integrate into mathematical formulation [2]. Extraction of good visual feature which compactly represent a query images is one of the important task in CBIR.

Color is most widely used in the low-level features and is invariant to image size and orientation [1]. Color Correlogram, color histogram and dominant color descriptor (DCD) are
the features used in CBIR. Color histogram is used for color representation, but it does not contain any spatial information. Li et al. [3] presents a novel algorithm based on running sub blocks with different similarity weights for object-based on running sub blocks the color region information. Using Matrix analysis images are retrieved under the query of special object. Color Correlogram describes about the probability of finding color pairs at a pixel at a fixed pixel distance and provides spatial information. Color Correlogram provides good retrieval accuracy as compared with the color histogram. It captures the spatial correlation between identical colors only and it provides significant computational benefit over color Correlogram, it is more suitable for retrieving the image. DCD is MPEG-7 color descriptor [4]. DCD describes about the salient color distribution in an image and provides a compact, effective and intuitive representation of color in an image. DCD matching does not fit human perception very well and it cause incorrect ranks for images with similar color distribution. [5, 6] yang et al. presented a color quantization in [7] and computation. Lu et al. [8] used color distribution, standard deviation and the mean value to represent the global characteristics of the image, to represent the global characteristics of the image for increasing the accuracy of the system.

Texture is an important feature in the visual feature and essential surface property of an object. Many objects in an image can be distinguished solely by their textures without any other information. Texture consists of some basic primitive which describes the structural arrangement of a region and the relationship of the surrounding regions [9]. Statistic texture feature using gray-level co-occurrence matrix (GLCM) Markov random field (MRF) model, simultaneous autoregressive (SAR) model, Edge histogram descriptor (EHD), Markov random field (MRF) model, and wavelet moments [2]. BVLC (block variation of local correlation coefficients) and BDIP (Block difference of inverse probabilities) is presented effectively measure local brightness variation and local texture smoothness [10]. In [11], texture is modeled by fusion of the marginal densities of the sub bands DCT coefficients. In this method one can extract samples from the texture distribution by utilizing small neighbor of scale-to-scale coefficients. In [12] Kokare et al. improves the image retrieval accuracy for new set of 2D rotate wavelet by using Daubechies’ eight tap coefficient.

Han et al. [13] proposed a rotation-invariant and scale-invariant Gabor representation, where each representation need only few summations on the conventional Gabor filter impulse response, and the texture feature are then from the new representation for conducting scale-invariant texture and rotation-invariant image retrieval. The shapes have some semantic information and shapes features are different from other elementary visual feature such as texture or color feature. Many shapes representation methods are their such as Fourier descriptor, B-splines, deformable templates, polygonal approximation and curvature scale space (CSS) [2]. CSS shape representation method is selected for moving picture expert group (MPEG)-7 standardization [14]. Fourier descriptor is efficient than the CSS in a review of shape representation and description techniques [15]. Xu et al. [16] described a innovation partial shape matching (PSM) technique using dynamic programming (DP) to obtain the spine X-ray images. In [17] Wei presented a novel content-based trademark retrieval system with a feasible set of the future descriptors. In [18], one dimensional or two dimensional histogram of the CIElab chromaticity coordinates is selected as the color feature, and variance extracted by discrete wavelet frames analysis are selected for texture features. In [19] Haar or Daubechies wavelet moment is used as texture feature and the color histogram is used as a color feature. In these method, their feature vector dimension is not important for combining multiple feature without increasing the vector dimension and it does not always provide better retrieval accuracy [20].
Chun et al. [9] proposed a CBIR method used to combine the color autocorrelation of hue and saturation components images and BDIP and BVLC moments of value components image in the wavelet transform domain. In [21, 22] presented novel retrieval framework for combining the color, texture and shape information. So as to improve the retrieval performance and to combine selected effectively without increase of feature vector dimension.

In this paper a detail description about the effective color image retrieval scheme is given in which the combination of the dynamic dominant color. Pseudo-Zernike moments and steerable filter descriptor. Rest of the paper as follows Section 2 gives the detail about the dynamic dominant color extraction. Section 3 describes the steerable filter decomposition and texture representation. Section 4 describes about the pseudo-Zernike moments based shape descriptor. Section 6 describes the experimental result. Section 7 provides the conclusion.

2. COLOR FEATURE REPRESENTATION

Color is one of the most distinguishable and dominating low-level feature to describe image. CBIR system provides the color to retrieve images such as QBIC system and Visual SEEK. In a given color image, the number of the actual color occupies only the small proportion of the total number of the colors only occupies a small proportion of the total number of colors in the whole color space. Dominant colors cover a majority of the pixel. MPEG-7 final committee draft, DCD contains two main components that represent the color and the percentage of each color. It provides a compact, effective and intuitive salient color representation. It provides the detail description about color distribution in an image or region of intersecting. Major part is located in the higher color distribution it is consistent with human perception because human eyes cannot differentiate the colors with close distance.

As per the experiment the selection of the color space is not a critical issue for DCD extraction. Without the loss of the generality, the RGB color space is used for the simplicity. As shown in Figure 1 the RGB color space is divided into the Colors are considered as same if there are several colors in the partitioned block.

After the above coarse partition, the centroid of each partition ("color Bin” in MPEG-7) is selected as its quantized color. Let \( X = (X^R, X^G, X^B) \) express the color components Red, Green, Blue, \( C_i \) be a quantized color partition i. Average value of the color distribution for each partition center can be determined by the

\[
\bar{x}_i = \frac{\sum_{x=0} X}{\sum_{x=C_i} 1}
\]

Fig 1: The coarse division of RGB color space
After the average value each quantized color can be estimated. We calculate the actual distance of two adjacent colors and then merge similar “color Bines” using weighted average agglomerative procedure in the following equation.

\[
X^R = X_1^R \times \left( \frac{P_{R1}}{P_{R1} + P_{R2}} \right) + X_2^R \times \left( \frac{P_{RF2}}{P_{R1} + P_{R2}} \right) \\
X^G = X_1^G \times \left( \frac{P_{G1}}{P_{G1} + P_{G2}} \right) + X_2^G \times \left( \frac{P_{G2}}{P_{G1} + P_{G2}} \right) \\
X^B = X_1^B \times \left( \frac{P_{B1}}{P_{B1} + P_{B2}} \right) + X_2^B \times \left( \frac{P_{B2}}{P_{B1} + P_{B2}} \right) \tag{2}
\]

In Equation (2), \(P_R, P_G, P_B\) represents the percentage of R, G, B component. Merging process is carried out until the minimum Euclidian distance between the adjacent color cluster center should be large than the threshold \(T_d\). Dominant colors is significant enough, therefore we will merge the insignificant color into its neighboring color. If the percentage is less than threshold \(T_m\), it will be merged into the nearest color. In the proposed method, we set the value of \(T_d\) as 25 and \(T_m\) as 6%. As the result, we obtain a set of dominant colors, and the final number of dominant colors is constrained to 4-5 on average. The dominant color descriptor is defined as

\[F_c = \{(C_i P_i), i = 1, \ldots, N\}\]

Where \(N\) is the total number of the dominant colors in an image, \(C_i\) is a 3D dominant color vector, \(P_i\) is the percentage for each dominant color, and the sum of the \(P_i\) is the percentage for each dominant color, and the sum of the \(P_i\) is equal to 1. The final number of the dominant color of the images after color quantization is five as shown in Figure 2. The dominant color of the image after color quantized is five; the dominant color and their percentage are shown in Table 1.

**TABLE 1**
Dominant color feature of Figure 2(a)

<table>
<thead>
<tr>
<th>N</th>
<th>C_i(R,G,B)</th>
<th>P_i</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>92,94,69</td>
<td>0.2642</td>
</tr>
<tr>
<td>2</td>
<td>115,134,119</td>
<td>0.1041</td>
</tr>
<tr>
<td>3</td>
<td>142,118,66</td>
<td>0.1035</td>
</tr>
<tr>
<td>4</td>
<td>173,146,94</td>
<td>0.3179</td>
</tr>
<tr>
<td>5</td>
<td>152,158,168</td>
<td>0.2103</td>
</tr>
</tbody>
</table>
3. STEERABLE FILTER DECOMPOSITION & TEXTURE REPRESENTATION

Surface shows texture, which is an important low level visual feature. Recognition of texture is the natural part of the many computer vision system. In this paper we presented a new rotation-invariant and scale-invariant texture representation for image retrieval based on the steerable filter decomposition.

3.1 Steerable filter

Oriented filter are used in the image processing task, such as texture analysis, edges detection, image data compression. Filter is applied in arbitrary orientation under adaptive control and to examine the filter output as a function of both orientation and phase. Resonance of filter is calculated in many orientation is applied in many version of the same filter, each of them are different in some rotation in angle. Steerable filter is a class of filter in which arbitrary orientation is synthesized as a linear orientation is synthesized as a linear combination of set of “basis filter” [23].

The edges of different orientation in an image can be detected by splitting the images into orientation sub-bands obtained by the basis filter having these orientation sub-bands obtained by the basis filter having these orientations. It allows one to adaptively “steer” a filter to any orientation. Calculate analytically the filter output as a function of orientation. The steering constant is

\[ F_\theta(m, n) = \sum_{k=1}^{N} b_k(\theta)A_k(m, n) \]  

Where \( b_k(\theta) \) is the interpolation function based on the arbitrary orientation \( \theta \) which controls the filter orientation the basis filter \( A_k(m, n) \) are rotated version of impulse response at \( \theta \). Convolution is the linear operation; we can synthesize an image filter at an arbitrary orientation by taking linear combination of the image filtered at an arbitrary orientation. By taking the linear combination of the image filtered with the basis filter. Where * represents convolution of image \( i(m, n) \).

\[ i(m, n) * F_\theta(m, n) = \sum_{k=1}^{N} b_k(\theta)i(m, n)) * A_k(m, n) \]  

(4)
Structure of the steerable filter is given in Figure 3. Generally 4-6 orientation sub bands are adopted to extract image texture information on applying steerable filter to analyze digital image. In our paper we extract the texture feature from four orientation sub bands, as shown in Figure 4. Figure 4 (a) shows the original images (Zoneplate), and Figure 4(b)-(e) are the filter image in different orientation.

Statistical measure is performed which provides the information which is used to capture the relevant image content into feature vectors. The mean \( \mu \) and standard deviation \( \sigma \) of the energy distribution of the filtered images represent horizontal orientation, rotation of \( 45^\circ \), vertical orientation, and rotation of \( -45^\circ \), by considering the presence of the homogeneous regions in texture images. An image \( I(x,y) \) is given, its steerable filter decomposition is given as:

\[
S_i(x, y) = \sum_{x_i} \sum_{y_i} I(x_i, y_i)B_i(x - x_1y - y_1)
\]  

(5)

Where \( B_i \) denotes the directional band pass filters at orientation = 1, 2, 3, 4. The energy distribution \( E_i(x, y) \) of the filtered images \( S_i(x, y) \) is defined as

\[
E_i = \sum_{x} \sum_{y} |S_i(x, y)|
\]  

(6)

Additionally, the mean \( (\mu_i) \) and standard deviation \( (\sigma_i) \) are found as follows:

\[
\mu_i = \frac{1}{MN} E_i(x, y) \]  

(7)

\[
\sigma_i = \sqrt{\frac{1}{MN} \sum_{x} \sum_{y} (S_i(x, y) - \mu_i)^2}
\]  

(8)

where M, and N is the width and height of the image \( I(x, y) \). Corresponding texture feature vector of the original image \( I(x,y) \) should be defined as

\[
F_T = (\mu_1, \sigma_1, \mu_2, \sigma_2, \mu_3, \sigma_3, \mu_4, \sigma_4)
\]  

(9)

4. THE PSEUDO-ZERNIKE MOMENTS BASED SHAPE DESCRIPTOR

Shapes are the important factor in human recognition and perception. To identify an object, shapes feature gives a powerful clue from which a human can identify. Shape descriptor, are used in the existing CBIR systems which is broadly classified into two groups, namely contour and region based descriptor [2]. Commonly used approaches for region-based shape descriptors moment and function of moments have been utilized as pattern feature in various application [1,2]. Theory of the moment, including Hu moments, wavelet moments, Zernike moments, Krawtchouk moments and Legendre moments, provides useful series expansion for the representation of object shapes. Pseudo-Zernike moments have set of complex number moments and orthogonal [24] which contains important properties. The
pseudo-Zernike moments are invariant under image rotation. Second moment will be less sensitive to the image noise. In this paper, the pseudo-Zernike moments of images are used for shape descriptor which provides a better feature representation capability and more likely to noise than other moment representation.

4.1 Pseudo-Zernike moments

It consist of set of polynomials [24] that form a complete orthogonal set over the interior of the unit circle, \(x^2 + y^2 \leq 1\). If the set of the polynomial is denoted by the \(\{V_{nm}(x, y)\}\), then the form of these polynomial is as follows

\[
V_{nm}(x, y) = V_{nm}(\rho, \theta) = R_{nm}(\rho) \exp(jm\theta)
\]  

(10)

Where \(\rho = \sqrt{x^2 + y^2}, \theta = \tan^{-1}(y/x)\) where \(n\) is a non-negative integer, \(m\) is restricted to be \(|m| \leq n\) and the radial pseudo-Zernike polynomial \(R_{nm}(\rho)\) is defined as the following

\[
R_{nm}(\rho) = \sum_{s=0}^{n-|m|} \frac{(-1)^s (2n + 1 - s)! \rho^{n-s}}{s! (n + |m| + 1 - s)! (n - |m| - s)!}
\]  

(11)

Like any other orthogonal and complete basis, the pseudo-Zernike polynomial can be used to decompose an analog image function \(f(x, y)\):

\[
f(x, y) = \sum_{n=0}^{\infty} \sum_{(m:|m|\leq n)} A_{nm} V_{nm}(x, y)
\]  

(12)

---

**Fig 3:** The structure of steerable filter
Fig 4: The filtered Images using steerable filter (a) The Original image (b) the sub bands image in horizontal orientation (c) Sub bands image in rotation of $45^0$ (d) Sub bands image in vertical orientation (e) the sub bands image for rotation of $-45^0$

Where $A_{nm}$ is the pseudo-Zernike moment of order $n$ with repetition $m$ which is defined as

$$A_{nm} = \frac{n+1}{n} \int \int x^2 + y^2 \leq 1 f(x, y) V_{nm}^*(x, y) dx dy$$  \hspace{1cm} (13)$$

It should be pointed out in case of digital image, Equation (13) cannot be applied directly but the approximate version is selected. Given a digital image of size $M \times N$, its pseudo-Zernike moments are estimated as

$$A_{nm} = \frac{n+1}{n} \sum_{i=1}^{M} \sum_{j=1}^{N} h_{nm}(x_i, y_j)f(x_i, y_i)$$ \hspace{1cm} (14)$$

Where the value of $i$ and $j$ are taken such that $x_i^2 + y_j^2 \leq 1$, and

$$h_{nm}(x_i, y_j) = \int_{x_i+\frac{\Delta x}{2}}^{x_i+\frac{\Delta x}{2}} \int_{y_j+\frac{\Delta y}{2}}^{y_j+\frac{\Delta y}{2}} V_{nm}^*(x, y) dx dy$$ \hspace{1cm} (15)$$
Where \( \Delta x = \frac{2}{M} \), \( \Delta y = \frac{2}{N} h_{mn}(x_i, y_i) \) can be estimated to address the non-trivial issue of accuracy. In this we use a formula the most commonly used in literature to calculate pseudo-Zernike moments of discrete images.

\[
\hat{A}_{nm} = \frac{n + 1}{n} \sum_{i=1}^{M} \sum_{j=1}^{N} V_{nm}^*(x_i, y_i) f(x_i, y_i) \Delta x \Delta y
\]  

(16)

4.2 The advantage of pseudo-Zernike moments

Pseudo-Zernike moments have the following advantages:

4.2.1 The invariance properties

We use pseudo-Zernike moment for shape descriptor because of some properties, i.e., their magnitudes are invariant under image rotation and image flipping. We now elaborate on those invariance properties.

If image \( f(r, \theta) \) is rotated \( \alpha \) degrees counter clockwise, the image under rotation is \( f' f^{\wedge^r}(r, \theta) = f(r, \theta - \alpha) \), and the pseudo-Zernike moments of \( f'(r, \theta) \) is given as

\[
A_{nm}^* = \frac{n + 1}{n} \int_{-\pi}^{\pi} \int_{0}^{\pi} f(r, \theta - \alpha) [R_{nm}(r)e^{-j \alpha}]^* r dr d\theta
\]  

(17)

assume \( \alpha' = \theta - \alpha \), we can get

\[
A_{nm}^* = \frac{n + 1}{\pi} \int_{-\pi}^{\pi} \int_{0}^{\pi} f(r, \theta) R_{nm}(r) \theta \theta e^{-j \alpha} dr d\theta
\]  

(18)

\[
= \left[ \frac{n + 1}{\pi} \int_{-\pi}^{\pi} \int_{0}^{\pi} f(r, \theta) R_{nm}(r) \theta \theta e^{-j \alpha} \right] e^{-j \alpha}
\]

\[
= A_{nm}^* e^{-j \alpha}
\]

It is given that the pseudo-Zernike moments of the result images are \( A_{nm}' = A_{nm} \exp(-j m \alpha) \) which leads to \( |A_{nm}'| = |A_{nm}| \). It shows that it is robust to rotation.

It can also be given as a image \( f(r, \theta) \) is flipped horizontally. The pseudo-Zernike moments of the resulting images are

\[
A_{nm}^{(hf)} = A_{nm}^*, \text{if } m \text{ even;}
\]

\[
A_{nm}^{(hf)} = -A_{nm}^*, \text{if } m \text{ odd.}
\]

Similarly, if an image \( f(r, \theta) \) is flipped vertically, the pseudo-Zernike moments of the result image \( A_{nm}^{(vf)} = A_{nm}^* \) for \( m \) even or odd, the magnitude of the pseudo-Zernike moments have perfect robustness to image attacks.
4.2.2 Multilayer expression

For an image, the low-order moments of the pseudo-Zernike moments can be given as the outline of the image: and the higher order moments of the pseudo-Zernike moments can be given in detail of the image. Figure 5 shows the binary image H and its reconstructed image. From left to right, the order is 5, 10, 15 and 25. It is not difficult to see that the low-order pseudo-Zernike moments of digital image contain contour, but the high-order provides the detail.

![Fig 5](image)

The Binary image H and its reconstructed image (a) Original image; (b) the reconstructed image (order is 5); (c) the reconstructed image (order is 10); (d) the reconstructed image (order is 15); (e) the reconstructed image (order is 20); (f) the reconstructed image (order is 25)

### 4.3 Shapes feature representation

Pseudo-Zernike moments are not scale or translation invariant. In our proposed method, the scaling and translation invariance are firstly obtained by normalizing the images, and then $|\hat{A}_{nm}|$ is selected as shape feature set for images retrieval. The pseudo-Zernike moments based shape feature set for image retrieval. The pseudo-Zernike moments based shape feature vector is given by:

$$F_s = (|\hat{A}_{00}|, |\hat{A}_{10}|, |\hat{A}_{11}|, |\hat{A}_{20}|, -, |\hat{A}_{54}|, |\hat{A}_{55}|)$$  \hspace{1cm} (19)

### 5. SIMILARITY MEASURE

After the color, texture and shape feature vectors are extracted, the retrieval system combines these feature vectors, determine system combines these feature vectors of the query image and that of that of each target images DB. Obtain a given number of the most similar target images.
5.1 Color feature similarity measure
MPEG-7 DCD matching does not fit human perception very well; it will cause incorrect ranks for images with similar color distribution [7]. We use a modification distance function to improve the robustness of color feature of query images \( Q \) and the color feature of each target image \( I \) in an image DB is

\[
S_{color}(Q, I) = \sum_{i=1}^{N_Q} \sum_{j=1}^{N_I} d_{ij} s_{ij}
\]  

![Fig 6](image-url)

**Fig 6:** Block diagram of the proposed method

Where \( N_Q \) and \( N_I \) denote the number of the dominant colors in query image \( Q \) and the target image \( I \): \( d_{ij} = \|C_i^Q - C_j^I\| \) denotes the Euclidean distance the dominant color \( C_i^Q \) of query image \( Q \) and the dominant color \( C_j^I \) of the target image \( I \). \( S_{ij} = [1 - \|P_i^Q - P_j^I\|] \times \min(P_i^Q \cdot P_j^I) \) denotes the similarity score between dominant colors. Here \( P_i^Q \) and \( P_j^I \) are the percentage of the \( i^{th} \) and \( j^{th} \) dominant color in the query image and target image, \( \min(P_i^Q \cdot P_j^I) \) is the intersection of the \( P_i^Q \) and \( P_j^I \) it represent the similarity between two colors in percentage. The term in bracket \( 1 - \|P_i^Q - P_j^I\| \) used to measure the difference of two colors in percentage. If \( P_i^Q \) equal to \( P_j^I \) then their percentage is same and their color similarity is given by \( \min(P_i^Q \cdot P_j^I) \) otherwise the large difference between \( P_i^Q \) and \( P_j^Q \) will decreases the similarity measure.
5.2 Texture Feature similarity measure

The texture similarity is given by

\[ S_{\text{Texture}}(Q, I) = \left( \sum_{i=1}^{4} \left( \frac{\mu_{Q}^{i} - \mu_{I}^{i}}{\sigma_{Q}^{i}} \right)^{2} + \left( \frac{\sigma_{Q}^{i} - \sigma_{I}^{i}}{\sigma_{I}^{i}} \right)^{2} \right) \]  

(21)

Where \( \mu_{Q}^{i} \) and \( \sigma_{Q}^{i} \) denotes the texture feature of query image \( Q \). \( \mu_{I}^{i} \) and \( \sigma_{I}^{i} \) denotes the texture feature of target image \( I \).

5.3 Shapes feature similarity measure

We provides the shape feature similarity as follows

\[ S_{\text{Shape}}(Q, I) = \sum_{i=0}^{5} \sum_{j} \sum_{k} \left( |A_{Q}^{i,j,k}| - |A_{I}^{i,j,k}| \right)^{2/2} \]  

(22)

Where \( |A_{Q}^{i,j,k}| \) and \( |A_{I}^{i,j,k}| \) denotes the shape feature of the query image \( Q \) and target image \( I \). Distance is used to compute the similarity between the query feature vector and the target feature vector which is given as

\[ S(I, Q) = w_{C}S_{\text{Color}}(Q, I) + w_{T}S_{\text{Texture}}(Q, I) + w_{S}S_{\text{Shape}}(Q, I) \]

Where \( W_{C} \), \( W_{T} \), \( W_{S} \) is the weight of the color, texture and shape features. It should be pointed out that \( S(Q, I) \) according to the formula, so we define the final similarity as:

\[ S'(Q, I) = \frac{S(I, Q) + S(Q, I)}{2} \]  

(23)

Where retrieving image, first we estimate the similarity between the query image and each target images in the image DB and the retrieval results according to the similarity value.

6. EXPERIMENTAL RESULTS

In this paper, we propose new and effective color image retrieval for combining color, texture and shape information, which provides higher retrieval method. The color image retrieval system has been implemented in Matlab 2010b environment on a Pentium dual core (3 GHz) PC. To verify the retrieval efficiency of the proposed method, performance with the general purpose image database consists of 1,000 images of 10 categories from the Corel image Gallery is tested. Corel images are used by the image processing and CBIR research communities. They cover a variety of topics, such as "flower", "bus", "eagle", "gun", "sunset", "horse", etc. to evaluate the overall performance of the proposed image feature in retrieval, a number of experiments were performed on image retrieval and the state-of-the-arts. The methods to be compared include traditional color histogram and the color histogram of subblocks [3]. The parameter settings are:

\[ T = 25, \quad T = 0.06, \quad w_{c} = w_{T} = w_{s} = 1/3 \]

Figure 7 the image retrieval result using the traditional color histogram, the color histogram, the color histogram of sub blocks [3], and the proposed method. Validity of the proposed algorithm is conformed. We randomly select 50 images as query image from the above image database (the tested 10 semantic class includes bus, flower, horse, dinosaur, building,
elephant, people, beach, scenery, and dish) Each kind is extracted 5 image, and each time returns the first 20 most similar image as retrieval results. The average normal precision and the average normal recall of 5times query result are calculated.

![Query Image](image1)

![Retrieved Images](image2)

**Fig 7**: (a) Query Image, (b), (c),(d) Retrieved Images

7. CONCLUSION

In image processing CBIR is a active research topic for pattern reorganization, and computer vision. In our method, CBIR method has been used as the combination of dynamic dominant color steerable filter texture feature, and pseudo- Zernike moments shape descriptor. Experimental result shows that our method is more efficient than the other conventional method with no greater feature vector dimension. Proposed method estimate for more various DB and to be applied to video retrieval and almost provides average retrieval time over the other methods.

REFERENCES


