An Efficient Perceptual of CBIR System using MIL-SVM Classification and SURF Feature Extraction

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Abstract: *Hasty increase in use of color image in recent years has motivated to the need of retrieval system for color image. Content Based Image Retrieval (CBIR) system is used to retrieve similar images from large image repositories based on color, texture and shape. In CBIR, the invariance to geometrical transformation is one of the most desired properties. Speeded Up Robust Feature (SURF) and Multiple Instance Learning Support Vector Machine (MIL-SVM) are proposed for extracting invariant features and improving the accuracy of image retrieval respectively. The proposed system consists of the following phases: image segmentation using quad tree segmentation, extraction of features using SURF, classification of images using MIL-SVM, codebook design using Lindae-Buzo-Gray (LBG) algorithm, and measurement of similarity between query image and the database image using Histogram Intersection (HI). In comparison with the existing approach, the proposed approach significantly improves the retrieval accuracy from 74.5% to 86.3%.*

1. Introduction

Images are being generated at an ever increasing rate by sources such as defence, civilian satellites, surveillance flights, bio-medical imaging and scientific experiment systems. With the cheaper storage, faster internet, and the off-the-shelf price for personal digital cameras, today image collections are expanding at a very fast rate. Under this background, there are booming needs for image retrieval systems.

The limitations in the metadata based system enkindle the interest of a Content Based Image Retrieval (CBIR) system. The existing technique searches the textual information regarding the images requiring users to describe database images. This task is tedious for large database.

In view of this, CBIR systems have been developed to address these shortcomings. CBIR attempts to retrieve a set of desired images from the database using visual features such as color [6, 17], shape [18], texture [6, 10], moment [15] and spatial relationships [7, 11, 14] that are present in the images.

Many research works have been carried on in image retrieval, such as Vector Quantization (VQ) [4, 21], Discrete Cosine Transform (DCT) [12], Discrete Wavelet Transform (DWT), Classified Vector Quantization (CVQ) [5] and Quadtree Classified Vector Quantization (QCVQ) [4].

Images can be indexed by the feature descriptors that consider spatial relationship, such as color histogram, Color Coherence Vector (CCV) [14] Color Auto Correlogram (CAC) [7] and Chromaticity Moment (CM) [13].

The focus of this paper is to build a universal CBIR system using quad tree segmentation based multiple instance learning SVM Classifier.

The rest of the paper is organized as follows. A comprehensive survey of CBIR is dealt in section 2. Section 3 describes the overview of the proposed framework. Section 4 is to provide particulars of experiments. Performance evaluation is tabulated in section 5. Finally, section 6 presents the conclusion.

2. Related Works

In this section, conventional image retrieval methods are discussed. CBIR using color histogram is proposed by Sharma *et al*. [17] Images are indexed using color histogram. The color histogram for an image is constructed by counting the number of pixels of each color and different color axes are divided into a number of bins. When indexing the image, the color of each pixel is found and the corresponding bin's count is incremented by one. This color histogram for image indexing includes only global distribution without considering spatial relationship between pixels.

An image indexing technique put forth by Pass *et al*. [14] using color coherence vector which involves comparison of number of coherent and incoherent pixels for each color. The computation of color

coherence vector involves blurring the image, discretization of color space and classification of pixel. This approach is based on initial pixel cluster not on updated cluster.

A color correlogram based CBIR is explained by Huang *et al*. [7] Correlogram was projected to index images expressing spatial correlation of pairs of color changes with distance. The extracted features from the images are fairly small. Though color correlogram does not work well in the compressed domain.

A codebook is used for vector quantization by Karnik and Shahane [8] involving codebook generation, encoding the images and decoding the images. The accuracy of the codebook determines the efficiency.

A new memory reduction method for CVQ is proposed by Dujmic *et al*. [5] the method decides the edgeness of the image. For each gray value in the image weight factor is determined, each edge block is binarized at last. Since the proposed approach is a pixel based operation the method suits for mass detection.

Bebis *et al*. [3] proposed the content based image retrieval using vector quantization. VQ allows us to retain the compressed database without storing the additional features for image retrieval. The generated VQ codebook serves as generative models representing the image while computing their similarity. Encoding an image with codebook of a similar image yields an effective representation on comparison with a codebook of a dissimilar image.

Schaefer proposed image retrieval technique that operates in the compressed domain of vector quantized images. VQ achieves compression, representing image blocks as codebook of prototype blocks. Images are coded with their own VQ codebook containing information in codebook itself. This paper states modified hausdorff distance as a novel method for compressed domain image retrieval.

An image indexing and retrieval technique is proposed by Teng and Lu [22] based on compressed image data using vector quantization. Capturing spatial relation pixel with indexing image is deployed in this paper.

Speeded Up Robust Feature (SURF) describing the novel scale and rotation invariant detector and descriptor is proposed by Bay *et al*. [2] interest points are detected and described using hessian matrix approximation and harr wavelet transformation respectively.

Structural shape representation and description techniques are proposed by Salih *et al*. [16] for analysing the retrieval accuracy of image retrieval. The user's sketch is opted for query input. If the user's sketch does not match with the shapes in the database, approximate representation is used.

Color and texture descriptor used in the proposed approach by Manjunath *et al*. [11] is not only used for similarity retrieval but also for the extraction, storage and representation. Color histogram descriptor is encoded by haar transform. Other color descriptors explained in this approach are color structure histogram, dominant color descriptor and color layout descriptor. Texture descriptor represents local edge distribution, homogenous texture region and compact descriptor.

Andrews *et al*. [1] proposed maximum pattern margin formulation and maximum bag margin formulation. The former leads to a mixed integer programming problem. The later is to expand the notion of a margin from individual patterns to sets of patterns margin problem. This is the proposed extensions of the SVM learning approach that results mixed integer quadrant problem that can be solved heuristically. The approach is the extension of SVM learning, the Quadratic Programming (QP) problem is solved by MIL-SVM using optimization heuristics approach.

2.1. Motivation

The former existing approaches emphasize on finding the best representation for different image features. Meagre representation work considers the invariance of geometric transformations in the image retrieval system. For the support of invariance of geometric transformation, SURF has been implemented in the current work. The computational load to manage large file collection stands as another problem. Thus MIL-SVM solves the problem of computational load.

In this paper, we propose a method that uses quad tree segmentation [4, 21] to extract smooth and high detail regions. Then, SURF [9, 20] feature extraction is used for extracting the features which are used for image classification. MIL-SVM [24] classifier for further classifying the images into several classes. The conventional VQ based method [4, 15] is not applicable for discriminative and powerful feature descriptors like scale-invariant feature transform. By contrast, the proposed method is applicable for scale invariant features and it also produces better image retrieval performance. In our simulations, we utilize the simplicity image database [23], which is a natural scene image database.

3. Proposed Work

The goal of the proposed system is to provide the system with an efficient image retrieval performance and the system which is applicable for scale invariant feature transform. Figure 1 depicts the overall process of the proposed system. The proposed system consists of the following phases: image segmentation using quad tree segmentation [4, 9, 25], extraction of features using SURF, classification of images using MIL-SVM, design of codebook using LBG algorithm, and measurement of Similarity between Query image and the Database image using Histogram Intersection (HI).
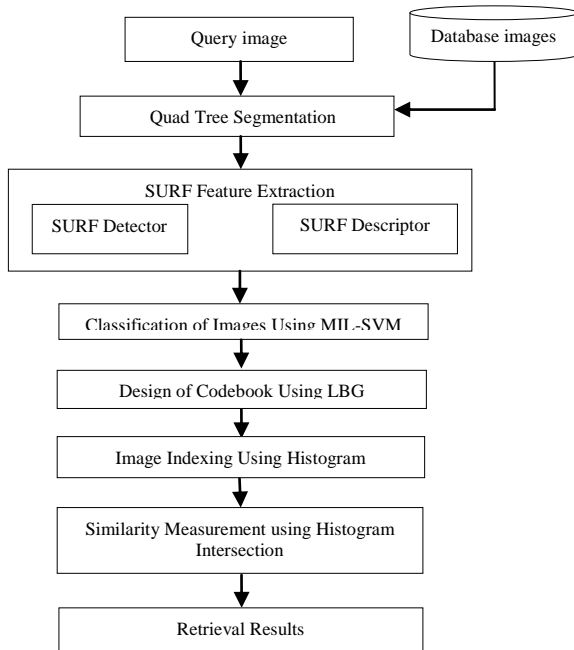
Figure 1. Overall process of the proposed system.

For a query image, quad tree segmentation is performed, which depends on the details of the blocks. The second stage is the feature extraction, which uses SURF [2, 18, 19] method for extracting the features. The third step is the classification of images using multiple instance learning SVM [1] from the extracted features of images. Fourth step is construction of codebook [8, 15, 17] using LBG algorithm. From the codebook, histogram [17] is constructed for each image in the database as well as query image. Finally histogram intersection [4] is calculated using the histogram for measuring the similarity between query image and the database image. Smaller value of histogram intersection indicates that the query image and the database image are more similar.

3.1. Quad Tree Segmentation

A quad tree [4, 9] is a tree data structure in which each internal node has four children. Quad trees are used to partition two-dimensional space by recursively subdividing into four quadrants or regions. Quad tree segmentation procedure is based on the variances of blocks in gray-level image information and it uses a hierarchical data structure for efficiently addressing variable block size regions.

The segmentation technique is summarized into following steps:

- A color image is first transformed into a gray level image.
- Gray level image is segmented uniformly into blocks of size 16x16.
- The splitting process is continued until the smallest block of size 4×4 is acquired or the variance of the block is not greater than a predefined threshold.

- The threshold of quad tree segmentation is determined as 2.5 based on the variances of blocks.

3.2. Feature Extraction

SURF technique [9, 18, 19, 25] has been developed for both the detection and description of local features. The main advantages of this technique are repeatability, distinctiveness, and robustness with less computation time. SURF is also referred as "Fast-Hessian" detector. The SURF technique is summarized into following steps:

- Interest point localization (SURF detector).
- Interest point descriptors (SURF descriptors).

Interest point localization (SURF detector): The interest points (their locations and sizes) are chosen automatically using a fast-hessian detector based on the determinant of the Hessian matrix shown in Equations 1, 2, and 3:

$$H(X,\sigma) = \begin{bmatrix} L_{xx}(X,\sigma) L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) L_{yy}(X,\sigma) \end{bmatrix} \qquad (1)$$

Where

$$L_{xx}(X,\sigma) = I(X) * \frac{\partial^2}{\partial x^2} g(\sigma) \qquad (2)$$

$$L_{xy}(X,\sigma) = I(X) * \frac{\partial^2}{\partial xy} g(\sigma) \qquad (3)$$

$L_{xx}(X, \sigma)$ is the convolution of the image with the second derivative of the Gaussian and similarly for $L_{xy}(X, \sigma)$ and $L_{yy}(X, \sigma)$. An integral image $I(x)$ shown in Equation 4 is an image where each point $x=(x, y)^T$ stores the sum of all pixels in a rectangular area between origin and x.

$$I(X) = \sum_{i=0}^{i \leq x} \sum_{j=0}^{j \leq y} I(x,y) \qquad (4)$$

Interest point descriptors (SURF Descriptors): in square region the SURF descriptors are calculated, centered on each interest point. 4×4 equal sub regions are derived from the original region. In each sub region, horizontal (d_x) and vertical (d_y) directions are measured from the Harr wavelet. Therefore, the underlying descriptor of each square is described by the vector $\vec{v}$ as in Equation 5.

$$\vec{v} = (\sum dx, \sum dy, \sum |dx|, \sum |dy|) \qquad (5)$$

As the region is divided into 4×4 sub regions, each feature point has 64 descriptors. Finally, the SURF descriptor is formed by normalizing the 64 descriptors to guarantee invariance to scale.

Feature extraction algorithm:

- Segmented image is taken as input.
- Apply SURF on the segmented images using Equation 1.

- The robust matching point vectors ($\vec{v}$ and $\vec{v}$) along with position vectors ($x1$, $y1$) and ($x2$, $y2$) are obtained.
- The interest points are calculated.

3.3. Multiple Instance Learning SVM

Multiple-Instance Learning (MIL) [1, 19] is a paradigm in supervised learning that deals with the classification of collections of instances called bags. Each bag contains a number of instances from which features are extracted. Classification consists of assigning a class label to a set of unclassified cases Algorithm overview: $X^{tr} = \{X_1, X_2, ..., X_n\}$ as the set of Images and $y^{tr} = \{y_1, y_2, ..., y_n\}$ as the label associated with each Image. An Image X_i contains m_i instances denoted by $X_{i,j}$ for $j = 1, 2, ..., m_i$. Different images can have different numbers of instances. Each instance $X_{i,j}$ is also associated with a label $y_{i,j}$ which is not directly observable Steps:

Input: Set of training Images ($X_1^+ ..., X_m^+ ..., X_1^- ..., X_m^-$).
Output: class label for each image.

1. Select a single instance in the training set to construct image level feature vector using Gaussian kernel based kernel density estimator using Equation 6.

$$ f(x) = \frac{1}{z \sum_i m_i} \sum_{y_i = -1} \sum_{j=1}^{m_i} exp(-\beta \parallel x - x_{ij}^- \parallel) \qquad (6) $$

Where $X_{i,j}^-$ denotes the jth instance from the ith negative bag and z is a normalization factor making $f(x)$ a proper density. An isotropic Gaussian kernel employed with the scale parameter β controlling the range of influence for training instances.

2. Compute the $P(x|\Omega_k)$, the class conditional distribution of training instances from the kth class using Equation 6.
3. Construct the Likelihood ratio value as defined in Equation 7 which is influenced in the jth instance of the ith image $x_{i,j}$.

$$ r(x_{ij}) = \frac{P(x_{i,j} / \Omega y_i)}{max^1 y_i p(x_{i,j} / \Omega_k)} \qquad (7) $$

Where $y_{i \pm} \{1, ..., c\}$ is the label for bag i.

4. The instance with largest Likelihood ratio value is selected for classification.
5. SVM classifier is trained using feature vector by solving the following single optimization problem shown in Equations 8 and 9.

$$ min(w_1, ..., w_c) = \sum_{j=1}^{c} \frac{1}{2} \parallel w_j \parallel^2 + c \sum_i l(y_i, f_i) \mid \qquad (8) $$

Where C = linear classifiers and $fi = [f_{i,1}, ..., fi, c]$ are the decision values returned by the c linear classifiers.

$$ l(y_i, f_i) = (1 - (f_i, y_i - max f_{i,j}))^2 \qquad (9) $$

The weight for the kth linear classifier is given by w_k and fi, $k = w_k^T x_i$ is the decision value returned by the kth classifier. A testing example is assigned label k if the decision value returned by the kth classifier is larger than those returned by other classifiers.

7. Repeat the above step until convergence.
8. Remove instances with small feature weights and update the classifier.

3.4. Codebook Design

For the purpose of Image Indexing codebook [4, 8, 15] is generated using Lindae-Buzo-Gray (LBG) algorithm. Steps in codebook design:

1. Some images from each class in the database training images are selected based on the classification method.
2. For each class of blocks, an initial vector is calculated by averaging all of the training vectors in a class to form a code vector for a sub codebook of size 1.
3. Splitting technique is used to produce two vectors from the initial code vector by adding and subtracting a threshold value ($\delta = 8$). To obtain the better retrieval results, the codebook should have a larger F ratio value [8]. F ratio is tested on threshold values such as 6, 8, and 10. And threshold 8 is chosen, as it gives higher F ratio value.
4. These vectors are served as initial vectors to generate the codebook of the next level. Therefore, if the size of the current codebook is N, then, at the next level, the size of the codebook becomes $2N$. This process is continued until the desired codebook size is achieved.

3.5. Image Indexing and Similarity Measure

Finally, image indexing [4] is done using the codebook generated. Each block in an image is encoded by the codebook to generate an index. Then, the frequencies of indices are counted to build an index histogram as the feature for each image in the database.

To compare the similarity of two images, the distance between their index histograms were calculated using HI. The HI [14] measure is denoted in Equation 10.

$$ d(Q,D) = \frac{\sum_{i=0}^{N-1} min\{HQ(i), HD(i)\}}{\sum_{i=0}^{N-1} HD(i)} \qquad (10) $$

Where, H_Q = Index histogram of a query image and H_D = index histogram of a database image.

4. Experimental Results

The proposed image retrieval framework is implemented using MATLAB 8.1.604 (R2013a) platform. The source of image database in the

proposed approach is from COREL photographs. Figures 2 and 3 shows the sample database images from COREL dataset and query image respectively.

Figure 2. Sample database images.

Figure 3. Query image.

The database holds 1018 color images of JPEG format, divided into ten classes as follows: Africans, beach, buildings, bus, dinosaur, elephant, flower, horse, mountain and food. Each class encapsulates 100 images of size 384*256 or 256*384. In the proposed approach the image is rescaled to 192*128 or 128*192. Figure 4 depicts the quad tree segmented image.
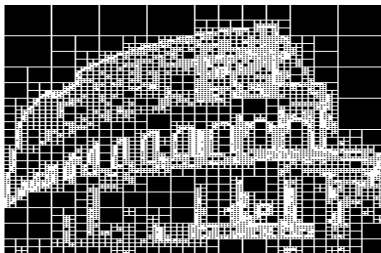

Figure 4. Quad tree segmented image.

A feature extraction of the query image has been depicted in Figure 5 The quad tree segmented image is deployed for feature extraction using SURF for the detection and description of local features. Interest point localization is computed based on the hessian matrix and Gaussian second order derivative.
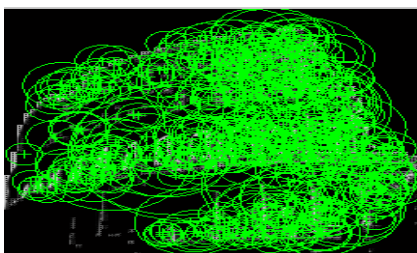

Figure 5. Features of a query image.

An image from the COREL dataset is the query image. For quad tree segmentation the query image is transformed to grey level image and segmented uniformly into blocks of size 16*16. Until the variance of the block is not greater than a threshold value 2.5, the segmentation process is continued.

Images are classified by MIL-SVM classifier, after performing feature extraction from the query image. Codebook is generated for the classified images using LBG algorithm. Codebook size is determined based on the number of classes. In our proposed approach the total codebook size is set as 1024. Figure 6 shows the retrieved result of a query image.
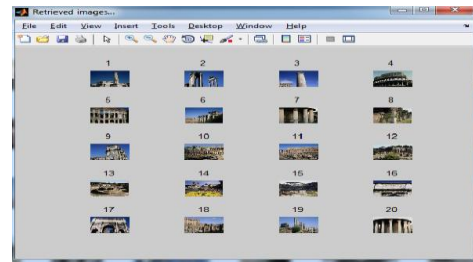

Figure 6. Retrieved result.

5. Performance Evaluation

The retrieval efficiency, namely precision and recall were calculated using natural color images from Corel image database. Precision is defined as the ratio of the number relevant images retrieved to the total number of retrieved images and recall is defined as the number of retrieved relevant images over the total number of relevant images available in the database. Standard formula for precision and recall is given in Equations 11 and 12.

Table 1 shows that the average precision for various categories of images in the database. For all the categories of images the proposed Quad tree Multiple Instance Learning (QMIL) produces the higher average precision compared with the existing QCVQ. The results shows that QMIL method produces 8.94% and 14.99% more gain than the existing method QCVQ in bus and flower databases. Thus on an average QMIL achieved 11.31% more gain than QVCE**.**

Table 1. Average precision comparison of different categories of images.

Category	QCVQ(Existing)	QMIL(Proposed)
Bus	74.31	83.25
Flower	78.22	93.21
Butterfly	77.63	81.64
Horse	62.50	84.30
Dinosaur	80.31	93.44
Car	70.21	81.22

The Precision vs. Recall graph (PR graph) is plotted represent the retrieval effectiveness. Table 2 illustrates the comparison of average precision between existing and proposed method.

Table 2. Avg precision comparison.

Method	Average Precision
Color Moments	30.12
CAC	44.33
CCV	59.22
VQ	67.11
QCVQ	74.50
Proposed QMIL	86.30

Figure 7 shows the average precision-recall graph of the retrieval results over 1,000 queries for existing systems and proposed system. In comparison with all the other existing methods the proposed QMIL system increases the average precision to 86.30%
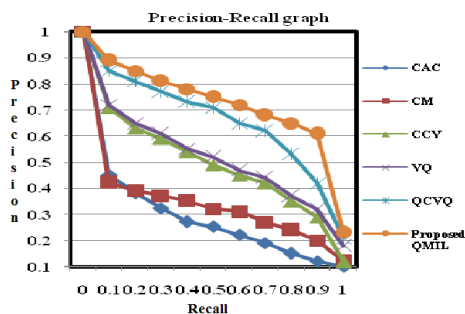

Figure 7. Precision-recall graph.

Figure 8 shows the comparison of mean average precision with existing systems and proposed system. The current system boosts the mean average precision to 86.30%.
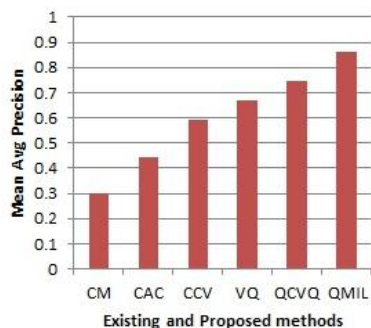

Figure 8. Comparison of mean average precision.

Figure 9 illustrates the comparison of average precision over various categories of images in the corel database. Based on these figures, it is evident that the proposed QMIL significantly improves the retrieval results interms of average precision on image database corel, as compared with the other existing methods.
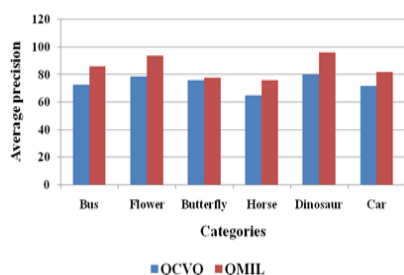

Figure 9. Comparison of average precision for different categories of images.

6. Conclusions

In this work, a robust technique named quad tree MIL-SVM has been implemented to improve the retrieval accuracy. The proposed approach using Quad tree segmentation avoids the problem of non-homogeneity of intra regions. Features are extracted SVM, to improve the classification accuracy. When the proposed system is compared with traditional CBIR. techniques it shows significant increase in retrieval accuracy. In future work, genetic algorithm can be Optimization (ACO), Particle Swarm Optimization (PSO) and Simulated Annealing (SA) can be used to improve the image retrieval performance further.

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