

Novel Class Addressed by an Image Retrieval

G.Sangeetha¹

Post Graduate Student., Dept. of ECE
Parisutham Institute of Technology and Science
Affiliated to Anna University, Chennai., Tamilnadu
Email id: sangeetha120185@gmail.com¹

M.Vasudevan²

Assistant Professor., Dept. of ECE
Parisutham Institute of Technology and Science
Affiliated to Anna University, Chennai, Tamilnadu
Emailid:vasudevan.m247@gmail.com²

Abstract— For the purpose of content based image retrieval, Image classification is important one help to improve the retrieval speed and accuracy of the retrieval process. In this research user query as image. There are two types of query. One is common query and another one is novel query. Common query means it is in predefined dataset. Novel query means it isn't dataset. That novel query is hidden class. In this research address the problem of hidden class using Bag of Words(BOW) classifier. Using BOW classifier can get more relevant images. In existing system image classification used Support Vector Machine Classifier. Finally compare the image classification and error rate for both classifiers.

Keywords—CBIR, Hidden class, SVM, BOW

I. INTRODUCTION

Research on content based image retrieval has gained tremendous momentum during the last decade. A lot of research work has been carried out on image retrieval. The automatic retrieval of the images from a database, based on the color and shape present. Since then, the term has widely been used to describe the process of retrieving desired images from a large collection of database on the basis of syntactical image feature. Content-based image retrieval (CBIR) is an active research area. The aim of various CBIR systems is to search images by analyzing their content. Images are normally described by their low-level features such as color, texture and shape. In the literature, a significant amount of research has been conducted relating to CBIR. However, the robustness of CBIR systems has not been sufficiently investigated even though the topic of robustness has been explored extensively in traditional information retrieval. We have already identified and addressed unclear queries as a problem of robustness. However in this paper; we will study the hidden class problem of CBIR systems employing image classification as pre-processing. The application of image classification techniques into a CBIR system results in a user's queries being answered with images in predefined classes, thus helping to improve retrieval accuracy and speed. However, in a large-scale image collection, some images classes may be unseen. We call these hidden classes as opposed predefined classes. The existence of hidden classes severely affects the retrieval accuracy of image classification based CBIR systems. There are two approaches that can address the problem of robustness.

One approach is detecting hidden classes at the stage of pre-processing in order to avoid the problem of hidden classes when answering a query. The second approach is to take hidden classes into account when answering a query because different retrieval strategies can be adopted for different queries. We decided upon the second approach because it is too difficult to detect hidden classes during pre-processing without extra information. Under the query-by-example (QBE) paradigm

There are three problems that arise due to hidden classes. When considering hidden classes, a user's queries can be divided into two categories; a common query and a novel query. Fig. 1 illustrates a hidden class, common query and novel query. A common query can be answered using a predefined image class because relevant images of the common query have been gathered in this class. A novel query is associated with a hidden class and it cannot be answered using any predefined image classes.

The first problem is how to identify whether a query is a common or novel query. This determination will influence the retrieval strategy. The second problem is how to predict a relevant predefined image class for a common query. The third problem is how to perform image retrieval for a novel query if it is not associated with any predefined image class. The solutions to these problems will result in a new retrieval scheme that can manage the problem of hidden classes. In this paper, we aim to address the critical problem of hidden classes in CBIR systems. Our major contributions are summarized as follows:

We develop a novel query detection technique to determine

- ① Whether a user's query is a common or novel query, therefore making it feasible to consider hidden classes in the retrieval process.
- ② Develop a self-adaptive retrieval strategy. For a common query, a relevant predefined image class will be predicted and the within images are ranked. For a novel query, a new method is proposed to filter out the irrelevant images before image ranking.

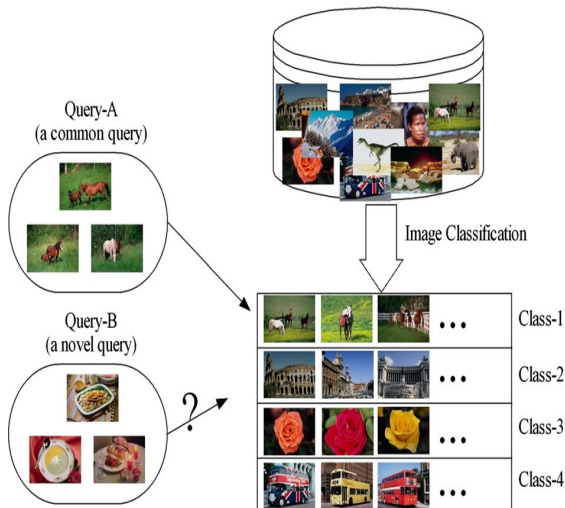


Fig. 1. Illustration of the problem of hidden classes.

II. SYSTEM ARCHITECTURE

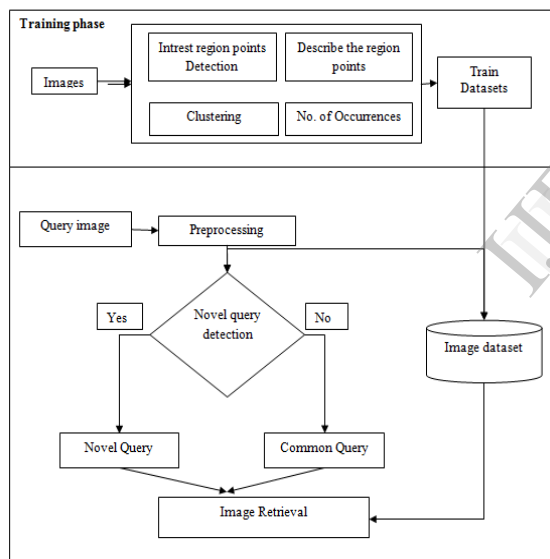


Fig: 2 System Architecture

In that system architecture there are two phases. One is training phase and another one is testing phase. Training phase in the sense train a dataset. Train the dataset through Intrest point detection, describing the image, clustering and find no. of occurances. After train the dataset, Testing phase in the sense give query image. For that query image once again train those things. Then check whether that query image is common query or novel query. This check using similarity measure of distance measurement. Then retrieval the relevant image.

A. Intrest Point Detection:

The algorithm of intrest point detection is Scale-space extrema detection. It is used to find where the intrest points, which is called key points.

i) Laplace of Gaussian (LOG)

ii) Difference of Gaussian (DOG)

- ⊕ Image is convoluted with Gaussian filters at different scales.

$$L(x,y,k\sigma) = G(x,y,k\sigma) * I(x,y)$$

- ⊖ Subtracting of different scales.

$$D(x,y,\sigma) = L(x,y,k_1\sigma) - L(x,y,k_2\sigma)$$

Key point:

Here $L(x,y,k\sigma)$ is blurred image. Comparing each pixel in the DOG image to its eight neighbors at the same scale and nine corresponding neighboring pixels in the each of neighboring scale. If the pixel value maximum or minimum among all compared pixels it is selected as a candidate key point.

Key point Localization:

Scale space extrema detection produces too many key point candidates. Some of which unstable. This information allows points to be rejected that have low contrast. Discarding low contrast keypoints. To discard, the value of second order Taylor expansion $D(X)$ is computed. If $D(X) < 0.03$ the candidate key point is discarded. Otherwise it is kept.

Eliminate Edge Responses:

Eliminate the key point poorly determined location. but have high edge responses. This is done by Hessian Matrix,

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

$$H \propto D(\text{Curvature of } D)$$

$$\text{Tr} - \text{Trace of } H - \text{Tr} = D_{xx} + D_{yy}$$

$$D - \text{Determinant} - D = D_{xx}D_{yy} - D_{xy}^2$$

$$R = \text{Tr}(H)^2 / \text{Det}(H)$$

If R for a candidate key point is larger than $(r_{th} + 1)^2 / r_{th}$, the key point is poorly localized and hence rejected. This is used to corner detection.

Orientation Assignment:

Each key point is assigned one or more orientations based on local image gradient directions. The Gaussian smoothed image $L(x,y,\sigma)$ at the key point scale σ is taken. For an image sample $I(x,y)$ at scale σ , the gradient magnitude $m(x,y)$ and orientation $\Theta(x,y)$ are pre computed using pixel differences.



Fig: 3 Interest point detection



Fig: 4 Key point

Fig.4.1.keypoint

Fig.4.2.keypoint localization

Fig.4.3.Eliminating edge responses

B.Descriptor:

Using SIFT descriptor to describe the image. First a set of orientation histograms is created on 4x4 pixel neighborhoods. These histograms are computed from magnitude and orientation values of samples in a 16 x 16 region around the key point such that each histogram contains samples from a 4 x 4 sub region of the original neighborhood region. The magnitudes are further weighted by a Gaussian function with equal to one half the width of the descriptor window.



Fig: 5 Descriptor

C.Clustering:

K- means clustering.

Partition n observations into k clusters in which each observation belongs to the cluster.

Given set of observations $(x_1, x_2, x_3, \dots, x_n)$ where each observation is a d-dimensional real vector means clustering aims to partition the n observations into k sets $(k \leq n), S = \{s_1, s_2, \dots, s_k\}$ so as to minimize the within cluster sum of squares.

$$\underset{s}{\operatorname{argmin}} \sum_{i=1}^k \sum_{x_j \in s_i} \|x_j - \mu_i\|^2$$

Where μ_i is the mean of points in S_i .

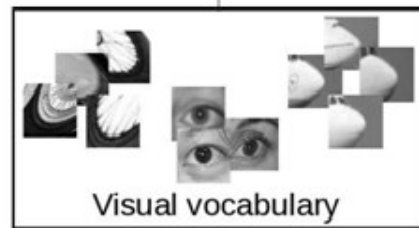


Fig:6.Clustering

D.No. Of Occurances:

The ratio between the particular occurrences to total no. of occurrences.

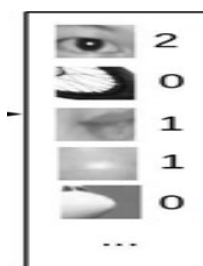


Fig: 7. Occurrences

III. TESTING PHASE

A. Similarity Measure:

It is used to check whether the query is common query or novel query.

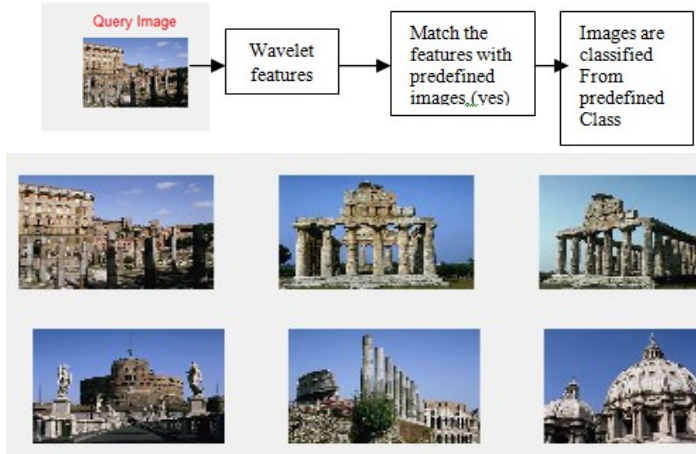
B.Distance Measurement

$$d_{i,j}(d,q) = (\sum_i |d_i - q_i| / k) / k$$

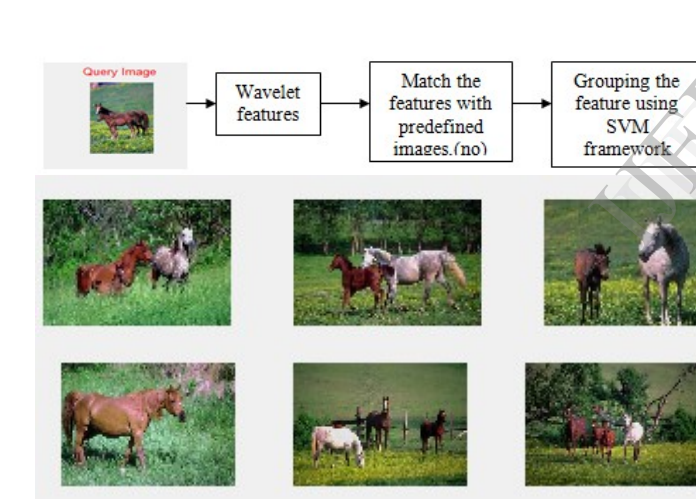
Here the d and q value is datapoints of dataset images and query images. The value of k is minimum and maximum means provide poor performance. medium that means 2 good performance.

IV. SIMULATIONS AND EXPERIMENTAL RESULTS

A. Results-Common Query



B. Results-Novel Query



C. Performance Measures:

The most common evaluation measures used in IR are precision and recall .usually presented as a precision vs. recall graph.

Precision = No. relevant documents retrieved / Total No. documents retrieved
Recall = No. relevant documents retrieved / Total No. relevant documents in the collection

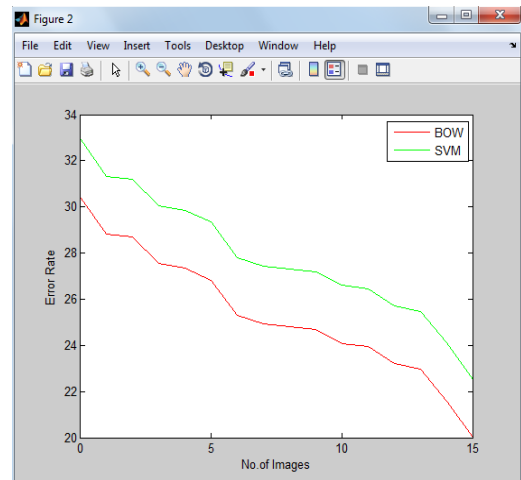
Error rate calculation:

Error Rate = 2 * (Precision + Recall) / (Precision * Recall)

ACCURACY

No. of relevant images retrieved = 6
 Total no. of images retrieved = 7

Total no. of images in this collection = 100
 Precision value = 0.85
 Recall value = 0.14
 For that the above value corresponding error rate graph.



SPEED

S.NO	SUPPORT VECTOR MACHINE FRAMEWORK	BAG OF WORDS FRAMEWORK	SECS (SVM)	SECS (BOW)
1.	Common query 	Common query 	2 SEC	1 SEC
2.	Novel query 	Novel query 	3 SEC	1 SEC

V. CONCLUSION

In this paper, we identified and addressed a new robustness problem of hidden classes which severely affected the performance of content-based image retrieval (CBIR) systems employing image classification. We observed that, because of hidden classes, the queries can be separated into two categories; either a common query or a novel query. In the proposed scheme, novel query detection was developed to determine whether a query was a novel query or a common query. A self-adaptive strategy was proposed to conduct image retrieval for different types of queries. Therefore, the problem of hidden classes can be addressed from the perspective of query answering. A number of experiments carried out on two real-world image datasets. Compared to the conventional scheme, SVM scheme, the BOW can achieve over a 10% improvement in its retrieval performance thus helping to significantly improve user's experience in top ranked

images. Improve the retrieval speed and accuracy by using any classifier and also can do retrieval of video and audio content.

REFERENCES

- [1] T. Sikora, The MPEG-7 visual standard for content description-an overview, IEEE Trans. Circ. Syst. Video Technol. 11 (6) (2001) 696–702.
- [2] H. Qi, K. Li, Y. Shen, W. Qu, An effective solution for trademark image retrieval by combining shape description and feature matching, Pattern Recogn. 43 (6) (2010) 2017–2027.
- [3] A.W.M. Smeulders, M. Worring, S. Santini, A. Gupta, R. Jain, Content-based image retrieval at the end of the early years, IEEE Trans. Pattern Anal. Mach. Intell. 22 (12) (2000) 1349–1380.
- [4] R. Datta, D. Joshi, J. Li, J.Z. Wang, Image retrieval: ideas, influences, and trends of the new age, ACM Comput. Surv. 40 (2) (2008) 5:1–5:60.
- [5] V. Vapnik, The Nature of Statistical Learning Theory, Springer-Verlag, 1995.
- [6] J.C. Burges, A tutorial on support vector machine for pattern recognition, Data Min. Knowl. Disc. 2 (2) (1998) 121–167.
- [7] D. Ashok Kumar Department of Computer Science
V.S.S Government Arts College , Pulankurichi Study on CBIR based by Color Histogram, Gabor and Wavelet Transform.
- [8] A. Vailaya, M.A.T. Figueiredo, A.K. Jain, H.-J. Zhang, Image classification for content-based indexing, IEEE Trans. Image Process. 10 (1) (2001) 117–130.
- [9] A. Bosch, X. Munoz, R. Marti, Which is the best way to organize/classify images by content?, Image Vision Comput 25 (6) (2007) 778–791.
- [10] Segmentation and histogram generation using the HSV color space for Image retrieval ,Shamik Sural, GangQian Dept. of Computer Science and Engineering.