

Binary & Local Features Extraction on Content based Image Retrieval

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Abstract— Content Based Image Retrieval (CBIR) is a technique for retrieving images from large digital image databases. CBIR depends on extracting visual features such as color, texture and shape of an image. These features are extracted automatically without any human intervention. In this paper, visual word integration of SURF and FREAK feature descriptors are performed. Then for checking similarity deep neural network is trained and finally performance analysis is done for showing the results.

Key words: Content Based Image Retrieval (CBIR), Speeded up Robust Feature (SURF), Fast Retina Keypoint (Fast), Deep Neural Network (DNN)

I. INTRODUCTION

The use of digital images is increasing day by day in almost every sphere of life including business, medical images, and satellites images. In order to extract valuable information from these images proper analysis manipulating, sorting, indexing, searching from databases should be done [1] as the produced data is very large and manual retrieval of images and the analysis is very time consuming and not very efficient [2]. The previous work[3 4] uses text based image retrieval technique in which annotation is given manually to all images in the databases and then similar image are retrieved based on the similarity between the annotation of images. This is not an efficient method of image retrieval so content based image retrieval technique is used[3].

In CBIR, the commonly used image representation, mainly based on global and local features [4], are extracted automatically using feature extraction algorithm.

CBIR system have two main steps, the first step involves the pre-processing that includes noise removal, image enhancement and deblurring of images from the image database after then features from images are extracted from the image database and are stored in feature database [5]. The second step involves the similarity measures, in which user query image features are matched with the stored feature database that gives the best possible match according to the user query image. In the proposed paper the late fusion (visual word integration) of SURF and FREAK is done. SURF is selected for local feature extraction from image as SURF is faster in computation and invariant to rotation, blur, warp transform and illumination changes in images. FREAK is used for binary feature extraction. Late fusion of FREAK and SURF integrates the performance of both feature descriptors for effective image retrieval.

II. RELATED WORK

Domonkos, Tamas, 2016 [11] proposed an end to end supervised learning framework for fast retrieval of images that learns probability based semantic level similarity and feature level similarity concurrently.

Anusha, Veeraswamy, Anitha, 2017 [8] proposed content based image retrieval using enhanced gabor wavelet for increasing the retrieval efficiency. Gabor wavelet transform is widely concentrated on the combination of features of plane wave and gabor function to form non-orthogonal function.

Dhanraj, Bamnote, 2017 [9] proposed content based image retrieval using hybrid approach of features such as texture and color. Color feature is extracted through color histogram and texture feature is extracted through Haar wavelet transformation. The combination of these features is robust to scaling and translation of objects in an image.

Rahmaniansyah, Harsa, Yoga, 2017 [10] proposed a method that involves combination of HSV color feature extraction and Gray level co-occurrence matrix texture feature extraction methods. In this method similar images are retrieved from databases based on Euclidean distance.

III. PROPOSED METHODOLOGY

In CBIR, late fusion of binary and local features are done. For binary feature extraction Fast Retina Keypoint (FREAK) feature descriptor is used as the performance of FREAK is efficient for the problems that are based on classification. For local feature extraction Speeded up Robust Feature (SURF) feature descriptor is used. SURF feature descriptor provides better performance for extracting interesting points from images and are robust to translation, scaling, rotation and small distortion in image.

SURF feature descriptor shows good performance in anti-noise which can be extended from 64 dimensions to 128 dimensions and thus make the descriptor more specific for extracting important details from images

Local and binary descriptors are used for describing information of images in a high-dimensional feature space by using keypoints which describes the important details of images. The late fusion (visual word integration) is based on the selecting of proper features which improves the effectiveness of image retrieval. And for checking similarity between query image and database images the training of DNN (deep neural network) is done.

The framework of the proposed CBIR method is shown as below:

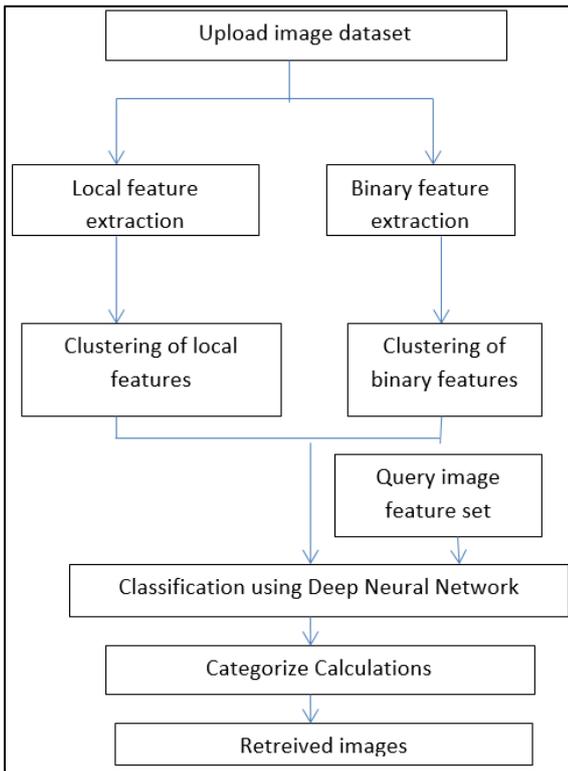


Fig. 1: Proposed Flowchart

- 1) Read the image dataset.
- 2) Extract local features using SURF method and binary features using FREAK method from images.
- 3) Cluster the local and binary features by using K-means clustering method to form codebook. Separate codebook are constructed for binary and local features.
- 4) Late fusion of both binary and local features are done.
- 5) Extract the features from query image.
- 6) Classify features from feature database.
- 7) Categorize calculations for images based on both query and database image.
- 8) The images with best possible match are shown.

Fig. 2: The Algorithm

IV. IMPLEMENTATION & RESULTS

The data set used in the proposed method is Corel 1000 image dataset, 10 classes are used from dataset from which 70% of the images from each class are selected for training and 30% for testing. The set of images selected for training are used for the constructing codebook and performance for retrieving images is evaluated by using the images from test dataset. Image retrieval performance is affected by the size of the codebook. When size of the codebook increases its also results in an increment of the retrieval precision.

Clustering of local and binary features of an image is done by using k-means clustering algorithm.

Precision and Recall is used to determine the performance of our proposed system. Precision determines the number of correctly retrieved images, and is given by equation (1) as

$$\text{Precision} = R/T \tag{1}$$

Where R is the number of relevant images similar to query and T is the number of images retrieved by system in response to user query.

Recall is used for measuring the performance and is given by following equation (2).

$$\text{Recall} = R/C \tag{2}$$

Where C is the total number of images in that class of images. Mean Average Precision (MAP) is obtained for top 15 retrievals. Table I presents the numerical values of MAP:

TABLE I: MAP as a function of codebook size (late fusion of FREAK and SURF)

Codebook size and feature % used	50	100	200	300	400
25%	65.52	68.43	73.24	73.54	73.64
50%	66.43	68.56	72.45	73.98	73.16
75%	68.93	70.15	72.98	72.46	73.48
Mean	66.96	69.05	72.89	73.32	73.42

The results and comparisons presented in Table I indicate that the best MAP is obtained from the proposed last fusion on a codebook of size 400 with a value of 73.42%.

Following fig. 3 shows the mean average precision (MAP) as a function of codebook size.

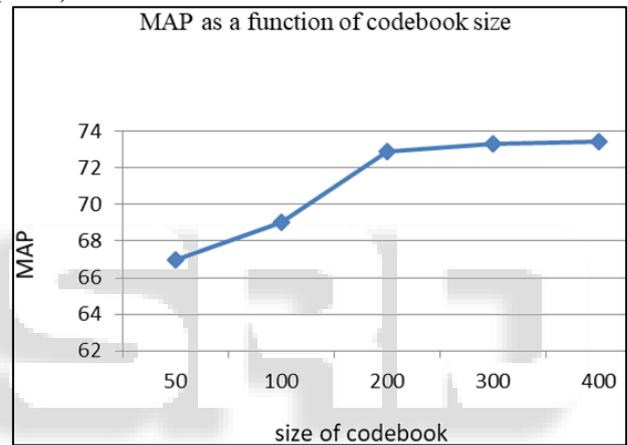


Fig. 3: MAP As A Function of Codebook

Now, precision and recall based on the user query, similar images are retrieved from database is calculated. Table II and Table III shows the calculation of precision and recall of proposed framework and an existing SIFT-LBP Algorithm.

Name of class	Proposed Framework	SIFT-LBP Algorithm [10]
Africa	65.94	57
Beach	62.98	58
Buildings	68.25	43
Buses	93.54	93
Dinosaurs	98.84	98
Elephants	80.04	58
Flowers	92.08	83
Food	82.34	53
Horses	72.67	68
Mountains	60.94	46
Mean	77.76	65.70

Table 2: Calculation of Precision of Proposed Framework & SIFT-LBP Algorithm

Name of class	Proposed Framework	SIFT-LBP Algorithm [10]
Africa	65.94	57
Beach	62.98	58
Buildings	68.25	43
Buses	93.54	93
Dinosaurs	98.84	98
Elephants	80.04	58
Flowers	92.08	83
Food	82.34	53
Horses	72.67	68
Mountains	60.94	46
Mean	77.76	65.70

Africa	12.89	11.40
Beach	12.35	11.60
Buildings	14.60	8.60
Buses	19.20	18.60
Dinosaurs	22.23	19.60
Elephants	14.08	11.60
Flowers	18.78	16.60
Food	17.05	10.60
Horses	12.54	13.60
Mountains	11.84	9.20
Mean	15.54	13.14

Table 3: Calculation of Recall of Proposed Framework and SIFT-LBP algorithm

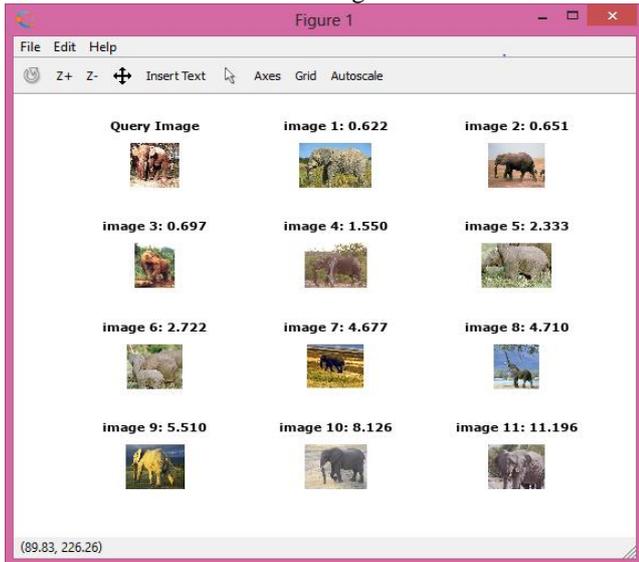


Fig. 4: Retrieval Result on the basis of Similarity Measures for the Class "Elephant"

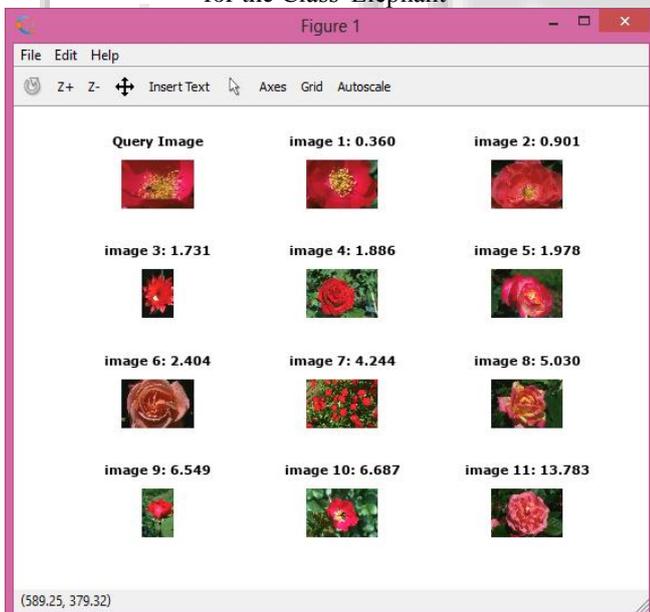


Fig. 5: Retrieval Result on the basis of Similarity Measures for the Class "Flowers"

V. CONCLUSION & FUTURE SCOPE

The method for Content-based image retrieval in this paper is based on late fusion (visual word integration) of binary and

local descriptor for retrieving the similar images. FREAK is selected as it has good computation time and shows good performance in recognition ability. For local feature extraction SURF is selected as it is robust to change in translation, scaling, rotation, and small distortions.

After feature extraction, neural network is trained based on the features of images in the database so that when a query image is given by a user, it retrieves and displays the images which are relevant and similar to query image from the database. The results show a considerable improvement in terms of precision and recall.

Future scope includes implementing the CBIR system with highly efficient deep learning neural network by using convolutional neural network this work can be extended by integrating color feature with SURF algorithm for retrieval accuracy.

REFERENCES

- [1] Mohamadzadeh, Sajad, and Hassan Farsi. "Content-based image retrieval system via sparse representation." *IET Computer Vision* 10.1 (2016): 95-102.
- [2] Kekre, H., et al., Improved Shape Content Based Image Retrieval Using Multilevel Block Truncation Coding.
- [3] Kekre, H., S.D. Thepade, and A. Maloo, Extended Performance Appraise of Image Retrieval Using the Feature Vector as Row Mean of Transformed Column Image.
- [4] Fadaei, Sadegh, Rassoul Amirfattahi, and Mohammad Reza Ahmadzadeh. "New content-based image retrieval system based on optimised integration of DCD, wavelet and curvelet features." *IET Image Processing* (2016)
- [5] Pourreza, Alireza, and Kouros Kiani. "A partial-duplicate image retrieval method using color-based SIFT." *Electrical Engineering (ICEE), 2016 24th Iranian Conference on. IEEE*, 2016.
- [6] Anusha, Veeraswamy. "Content Based Image Retrieval using Enhanced Gabor Wavelet Transform". *International Conference on Computer* (2017).
- [7] Dhanraj, Bamnote. "Multilevel Haar Wavelet Transform in Content Based Image Retrieval". *International Conference on vision, image and signal processing* (2017).
- [8] Rahmani Ansari, Harsa. "Color and Texture Feature Extraction on Content Based Image Retrieval". *International Conference on science* (2017).
- [9] Domonkos, Tamas. "Fast Content Based Image Retrieval using Convolutional Neural Network and Hash Function". *IEEE International Conference on Systems* (2016).
- [10] J. Yu, Z. Qin, T. Wan, and X. Zhang, "Feature integration analysis of bag-of-features model for image retrieval," *Neurocomputing*, vol. 120, pp. 355–364, 2013.