Novel Framework of Semantic Based Image Reterival by Convoluted Features with Non-Linear Mapping in Cyberspace

Virender Singh, Rajeev Gupta

ABSTRACT---In Image Information Retrieval System, finding an effective image is challenging problem. In this problem, main challenge is researcher's work on texture, color and shape but they ignore semantic relation between these features. In some research emphasis on region base semantic which not only reduces the precision of image retrieval. But region base semantic features uses low-level features and high-level semantic concept to increase the ambiguity in features. In proposed approach find the low-level features and non-linear mapping, to find that use convolution and mapping by poling concept. In polling, parts combine the features of three different layers and find semantic relation by polling concept which reduces the ambiguity of features.In experiment, our emphasis on fruit image retrieval and comparison with color base and region base semantic features approaches but proposed approach shows significant improvement in precision, recall and f-score.

Keywords—

I. INTRODUCTION

As the accessability of digital images are increasing, automatic image retrieval tools are providing able means to the users to operate through them. Although there are established methods which allowed the users to post queries and get results, but there is less retrieval accuracy because of the built-in complication of the images for users to describe exactly[1]. Image searches are supported in content based image retrieval on the basis of some characterisitics like shape, color and texture. For some users, using these features are difficult thats why they use keywords for serach. Combined approach of keyword and content-based get benefitted from both examples. In this approach, a query can be started with adding some keywords. After that, image system use feaures of images with their explanation note for multimodal query refinement [2].

There are two types mainly i.e., text-based and content based. The text descriptors annotated the images manually in text based approachs. This system was used by a database management system for retrieval of images. But text based approaches have some limitations like abundant labour is needed for manual annotation. Another big disadvanatge is inappropriate annotation because it is done by humans. After seeing these limitations, content-based image retrieval is introduced. Images are ordered as per their visual content like color, shape and texture [4]. After these researches, one research challenge remains for image and video retrieval community i.e., semantic analysis of scenes. The main reason for this is underdeveloped techniques of organizing, indexing and retrieving data of digital images. The thing that creates fast processing in high-level semantic content for searching and retrieval of iamge is the semantic gap between the user's understanding and representation of image in computer [5]. The techniques which reduce the semantic gap are divided into five categories: (i) use of machine learning tools to collaborate low-level features with highlevel semantics. (ii) Introduction of relevance feedback into retrieval loop to undestand the user's demand. (iii) To define the ontology for image explanation, domain knowledge is explored. (iv) Multiple sources are used like Web for textual information and visual content of images. (v) For the support of semantic-based image retrieval, sematic templates are generated. Apart from these techniques there are some tools like Artifical vector machines (ANN), Support Vector Machines (SVM) and Bayesian networks (BN) are also used for the study of iamge semantic [6].

To deal with problems of image retrieval many algorithms have been proposed. But for current image retrieval systems, Content-based Image retrieval is the chief support. The motive of CBIR is to display an image with features like color, texture etc. These approaches are based on computing the analogy of query of user and images with QBE system. But it has problem that it is not an easy task to optimize the CBIR's retrieval quality in one query process. The main issue is that the features which are dra out are different which cannot understand the concep of user's query. So for this problem, preferred images are picked by user to refine the image explorations. There is a Relevance feedback which is a feedback procedure, it repeats till the user is not satisfied from the results [8].

II. RELATED WORK

Lu Ye et al [1] had proposed a relevance feedback technique, I find. For achieving high accuracy with less number of feedback redundancies , semantic and low level features were combined. It also introduced semantic and low level feature based relevance feedback scheme. The characteristic which differentiate the semantic and low-level feature was twofold. It also used the simple machine learning technique to undersatnd the queries of users. **Chang Edward et al [2]** had provided a CBSA procedure which provided images with semantically labels. Firstly, it used a bit percentage of manually labeled data to train a BOM-OPC ensemble. All the images are processed with ensemble and the output of the ensemble was mapped to

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Virender Singh, Research Scholar, MMICT & BM, MMDU, Mullana, Ambala Haryana, India. (seh_74@yahoo.co.in)

Rajeev Gupta, Assistant Professor, MMICT & BM, MMDU, Mullana, Ambala Haryana, India. (rajeev.gupta@mmumullana.org)

probabilities. Each image was defined with bundle of words. The values of probablity presented the image's relevancy. **Lehmann Thomas M. et al [3]** presented an comprehensive appraisal of different methods which categorized the medical images automatically. The method which uses the data mining for medical was automatic categorization and it as essential for medical uses such as case-based reasoning. It also reviewed the existing features which were used in medical applications. **Liu Ying et al [4]** had reviewed the technical attainment in high-level semantic-based image retrieval. It included the features of low-level image and derived the high-level semantic features. It also provided the useful insights to decrease the gap of semantic by obtaining salient low-level features. **Singhai Nidhi et al [7]** had discussed the techniques of content-basedimage retrieval techniques. These techniques were also analyzed and compared. From the survey, it was retrieved that most of the systems used color and texture features, some used shape feature and other used layout features. It also used fuzzy logic for the improvement of system. The fuzzy interference assimilated the features in CBIRsystem and follow the requirements of users. **Su Ja-Hwung et al [8]** proposed Navigation-Pattern based Relevance Feedback (NPRF). NPRF used the discovered navigation patterns and query refinement strategies of three types i.e., Query Point Movement (QPM), Query Expansion (QEX) and Query Reweighting (QR) to gather the information according to user's intention effectively. **Clinchant Stephane et al[9]**introduced a set of techniques which were called semantic combination. These techniques overwhelmed the conceptual barrier. When it was comapred with late fusion, the performance shows improvement over two datasets but there was no improvement in others.**Cinar Hatice et al [10]** designed theCBIR system. It was used for microscopic images which had images of one or more diseases. It used many approaches for classification and retrieval of microscopic images, which were not easy for classification. **Singha Manimala et al [11]** presented the content-based image retrieval which used properties such as texture, color called WBCHIR. The color histogram and texture features were extracted using wavelet transformation. After that integration of these features were constructed for scaling of objects in an image. **Zhang Hanwang et al [12]** had presented a novel attribute-augmented Semantic Hierarchy. It presented the organization of semantic concepts into many levels of semantic and augments. Every concept had a aspects which explained the facts of concepts and also play role of intermediate bridge between the concept and low-level visual content. For retrieval of images, hierarchical semantic similarity function was used to distinguish the likeness of semantic. Experimental results showed that effectiveness of AASH in bridging the semantic and intention gaps had better results than CBIR approaches. **Bi Ahmad Alzu et al[13]** presented a detailed review of CBIR approach. It showed some new things like pre-processing of image, features extraction, features indexing and set the benchmarks for datasets etc. Li Xuelong et al presented a novel joint binary codes learning method. It combines the properties of images to latent semantic features with minimum encoding loss which is called Latent Semantic Minimal Hashing. **Zhu Lei et al [14]** proposed an SAVH, effective hashing framework. It combined the extra segregated into the new visual codes and functions. It also had an advantage that offline learning influenced the semantics which were in the text, on the other side online hashing only needs one input i.e., visual images. **Singh et al** [15] In this research review createapplicationsoftware thatcouldanalyzethecomplexsystem,whichcouldbematerialized ifthere ishigherdegreeofmutualrelationshipatdifferentlevelssuch ascontextinformation takenintoaccount.**Gupta et al[16]** proposed framework is to develop application software that could analyze the complex system, which could be materialized if there is higher degree of mutual relationship at different levels such as context information taken into account.

III. PROPOSED APPROACH

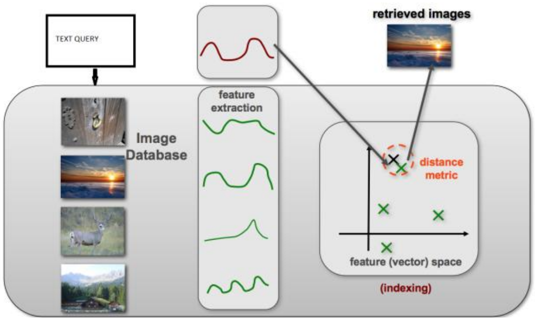

Fig3.1 Architecture of image retrieval

Flowchart:

1). Input the image
2). Send the image to ConvolutionLayerof 64 X 64, 128 X128, 128 X128.
3). After convolution layer, apply 64 vector and 28 vector on respective images and also extract low-level features.
4). Then apply convolution on output of 64 and 128 vectors and send them for semantic in Pooling Layer.
5). After semantic analysis, non-linear mapping is done.
6). After mapping, output the feature vector.
7). And then convolution of feature vector and query image is done.
8). At last analysis of Precision, recall and F-measure is done.

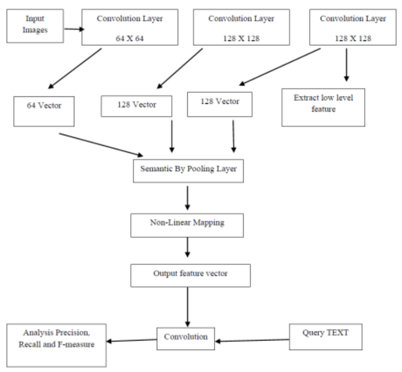

Fig3.1 Proposed methodology flowchart

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Input: Images for training.
Output: Semantic Low level features

While (I>N)
Begin
$S^{(N)}_{I} = -(y\text{-}a^{N}_{I}) . f' (z^{(N)})$ (1)
$S^{(N)}_{I}$ = gradient of I Image out of N Image.
y = Learning constant (0.4).
f' = Transpose activation function.
$z^{(N)}$ = Input by convolution.
$f' (z^{(N)})$ = Convolution (64,128,128).
End.
While (I>L) (L= Layers)
Begin
L= 1,2,3
$\delta^{(l)} = ((W^{(l)})' \, \delta^{(l+1)}) . f'(z^{(l)}))$ (2)
$\delta^{(l)}$ = Layer wise gradient.
$W^{(l)}$ = Convolution vector weights in Transpose form.
$\delta^{(l+1)}$ = gradient (l+1) form.
$f'(z^{(l)})$ = output of layer wise convolution.
End
$V^{(N)} = \sum_{i=0}^{N} \quad \delta^{(N}{}_{I}{}^{)} . \delta^{(l)}$ (3)
$V^{(N)}$ = feature vector.

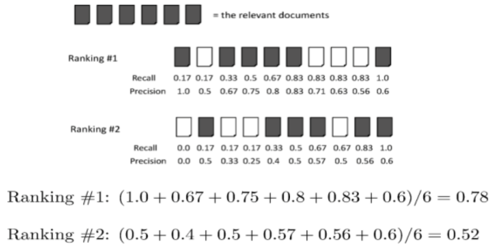
Input :feature vector
Output: query analysis

While (I>Q) Q: query
Begin
$V^{(N)}$ = feature vector
$X^{(N)} = I^{(N)} © \sum_{i=1}^{N} V (N)$ (4)
$I^{(N)}$ = feature vector of query
$V^{(N)}$ = feature vector of database image
End
$T = Max (X^{(N)})$
if (Image $\geq$ T)
Begin
Collect Image
End
Analysis, Precision, Recall and F measure

IV. EXPERIMENT AND RESULT ANALYSIS

1. Dataset

To evaluate the method and compare it with the state-of-the-art method, 10 classes of the Corel dataset are selected and then tested it in the experiments. Totally there are 1000 general-use images in the image database and each class has 100 images on the same topic like fruit and combined fruit and other images (Airplane, Bicycle, Bird, Butterfly, Car, Cat, Chicken, Clock, Cow, Deer, Dog, Dolphin, Elephant, Flower, Giraffe, Hedgehog, Horse, Lion, Moon, Motorcycle, Panda, Pig, Rabbit, Sakura, Ship, Snake, Tiger, Train and Turtle). The size of the image is either 256 x 384 or 384 x 256. To further evaluate this method comprehensively, the dataset called Natural is manually collected from Flickr,which has 9 classes and each class has at least 200 images.



Experimental analysis use the semantic-based four approaches. From these four approaches, one proposed approach based on CNN lower features which semantically related by layers shows in fig.1. In this approach, collect the lower level featuresfrom three layers and connect them with pooling layer and then map the high-level semantic features. These features are used for matching between query image and database images. In CNN based approach, convolution of lower level features andnon-linear featuresmapping the performance of precision and recall. Table 1 shows the different type of images precision and recall in average ten rounds.

Type OF Images	PRECISION	RECALL	F-SCORE
APPLE	**72.34**	**70.34**	**70.23**
BANANA	**69.13**	**67.67**	**69.45**
MANGO	**70.23**	**71.23**	**70.34**
GRAPES	**60.13**	**70.45**	**68.56**
STRAWBERY	**59.34**	**60.13**	**60**
GUAVA	**78.56**	**75.34**	**75.45**
COMBINED FRUITS	**56.67**	**54.34**	**53.45**
ORANGE	**70.56**	**67.89**	**69.89**
OTHER IMAGES	**71.34**	**70.34**	**67.89**
AVERAGE	**67.58**	**67.52**	**67.25**

Table 1 CNN Based performance on Precision, recall,and F-score

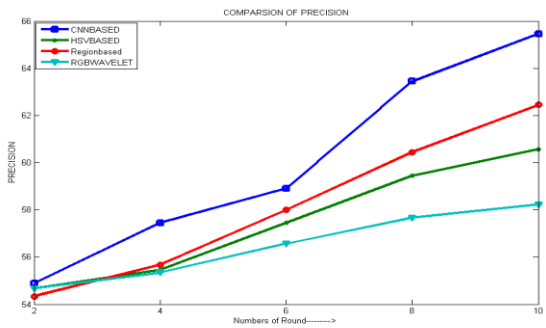


Fig.1 Comparison of average precision in proposed(CNNBASED) and other approaches

Fig. 1 depicts the comparison of wavelet-based, HSV color based, region based and CNN based approaches. In first approach, transformation in discrete wavelet is used but ignore the continuous features but also uses the RGB color system. In second approach, HSV color format is used and still use wavelet transformation. These both methods find the discrete semantic feature and ignore the non-linear and

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continuous features which reduces the precision from other two approaches which work on continuous features. The analysis of third approach i.e., region-based approach which finds the different regionsand finds the semantic relation of continuous region but this approach ignores the non-linear features. In the fourth approach which is proposed called Convolution Neural Network finds the continuous feature and polling approach map low-level features to non-linear mapping using sigmoid activation function in eq. (2).

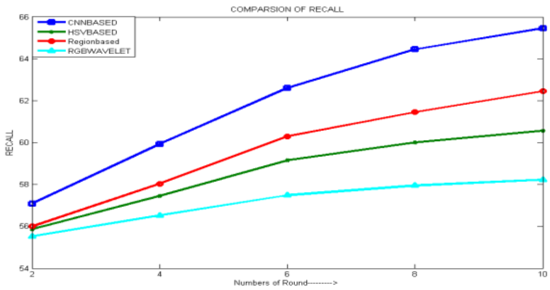

Fig. 2 Comparison of average recall in proposed(CNNBASED) and other approaches

Fig. 2 presents the comparison of recall of proposed and existing approaches. In this comparison, recall increases when the round increases but significant improvements in CNN-BASED proposed approach because of non-linear and continuous feature mapping. The mapping semantic relation increases the improvement of semantic low-level features, its impact on query run increases semantic base feature matching and also improves the precision and recall.

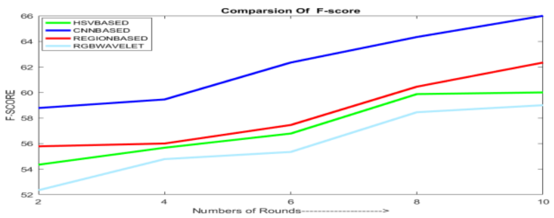

Fig. 3 Comparison of average F-score in proposed(CNN BASED) and other approaches

V. CONCLUSION

This paper presents the analysis of semantic feature based image retrieval. In analysis, proposed approach convoluted low-level features and use three layers of convoluted features space pooling by non-linear manner. In proposed approach find the linear and non-linear semantic features mapping by sigmoid function. In experimental analysis, comaprison of semantic based region features and color base features (RGB, HSV) with convoluted semantic mapping features in different number of queries is done. In graphs analysis on 2 to 10 queries and performance involvement of all approaches is used to take the average performance of precision, recall and f-score but CNN used approach shows the significant performance.

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