Context Re-Ranking in Sketch Based Image Retrieval

Durga Prasad Kalasapati, Manjunathachari Kamsali, Giri Prasad Mahendra Nanjappa

Abstract: Image retrieval based on the sketch-based descriptor is focused in this paper. The retrieval operation based on the sha pe details defined in a sketch input is used for image region descriptor and a distance based mapping approach is developed for image retrieval in a database system. The search overhead, decision accuracy and feature representation is constraint to such sketch based approach, hence in this paper, a context re-ranking model based on feedback modeling is proposed. The approach has an advantage of faster retrieval performance compared to the conventional retrieval system. The validation is made with the simulation result developed for the proposed approach over the conventional benchmark approach.

Index Terms: Sketch based image retrieval, context feature, re-ranking, feedback modeling.

I. INTRODUCTION

Image retrieval has become a basic need in current developing applications, which extend from e-learning system to e-commerce, security, medical, geo mapping etc. The development in this arealso enormous and various algorithms, system, approaches and architectures are upcoming rapidly to offer best quality of services. In the process of image recognition various approaches of image representation and coding were developed. Image recognition has emerged into new area of applications, such as e-learning, medical diagnosis, authentication and security, mining, industrial applications etc. With development of new technologies in imaging, images are now captured at very high resolutions, and each detail of the image could be extracted at a very finer level to represent the image. However the representing coding, such as shape, color, textures was extracted from the content based on feature descriptors used. It is hence observed that the performance of an image retrieval system mainly depends on the representing features. Among all these representative features, shape is observed to be a simpler and distinct representative feature for an image sample. To derive the shape feature edge based feature descriptors were proposed.
A double exponential derivative function (DODE) for edge based shape representation is outlined in [1].The approach is a enhance modeling of image shape representation, wherein a DODE filter is applied over the bounding contour to derive exact shape of an image.

Revised Manuscript Received on 30 January 2019.
***** Correspondence Author
Durga Prasad Kalasapati*, Department of ECE, JNTUA, Ananthapuramu, A.P, India.
Manjunathachari Kamsali, Department of ECE,GITAM University Hyderabad, Telangana, India.
Giri Prasad Mahendra Nanjappa, Department of ECE, JNTUA, Ananthapuramu, A.P, India.

In [2] to derive edge features, a combination of invariant moments and edge direction histogram is proposed. In various approaches, moments are used as a shape descriptor to define the shape feature. For the video application in [3] an angular radial transformation (ART) for region oriented shape description is presented. This approach has a independent component analysis is using Zernike moments.
A whitening Zernike operator is used in the shape representation. Where in edge based approaches are the simplest mode of shape representation, in most of the image representation, edge operators derive coefficients out of the bounding regions. These extra information's result in computational overhead, making the system slower in process. To derive more precise shape description, contour based coding was developed. A contour based learning approach is defined in [4]. The approach of contour is a bound region growing method where the outer bounding region is extracted via a region growing approach to derive image representation. In [5], a binary image is defined to a closed contour, where each contour represents a chain code for edge description. To calculate the similarity of the two images, the distance in each contour is measured with each of the image in the database using a string matching technique. The average distance is the sum of the maximum matching of each image and the highest matching is declared as the final similarity. The methods of the contour-based are mainly Polygonal approximation, Fourier descriptors [6], wavelet descriptors, or scale space [7, 8], wherein the region-based methods are mainly geometric moment invariants, and orthogonal moments [9]. In addition to the edge and contour based coding various other approaches such as In [10], a graphical structure representing multiple object images, using the individual objects spatial relation forming a connectivity graph is presented. In [11] an effective design that develops the shape descriptor using shape context (SC) is proposed. This descriptor defines the modeling of a histogram based on the attached attribute of each boundary that describes the relative distribution of the remaining points. In [12] shapes using a geometric pattern of a polar transforming is proposed.
Shape distinct vertices for matching are extracted and the comparison is used as parameters to reduce the difference in distance from the center. In [13], a recovery method based on the descriptor of the local shape form and the base index of similarity is used. A regional local feature, called scale invariant feature transform (SIFT) [14], which calculate the histogram of local oriented distributions around the feature point is proposed. However the contour based or the other techniques such as graph based, context based etc. defines the overall bounding contour, wherein the variations in the feature coefficients are very large.

Each projection in the contour region is taken as a feature, which leads to large feature data set. To overcome the problem of large feature vectors, curvature coding has emerged in recent past. A curvature based scale space representation is presented in [3]. A very effective representational approach has been outlined in [6], where the edges are defined and used for all curves and curvatures in an image.

A Multi scale convexity concavity (MCC) is represented as various scales can be obtained using Gaussian kernels. The curvature of each boundary point was defined based on relative moment of a contour point based on previous scale level. The approach of curvature coding, results in lower feature descriptors for image retrieval. However in such coding, features are extracted based on a thresholding of the curvature plot, and values with higher magnitude are selected. This approach of feature selection process discards the lower variational information considering as noise. However in various image samples curvature with variations existing for a lower time period exist. So, this assumption of feature selection process minimizes the descriptive features relevancy wrt. image representation. To overcome this issue, in this paper a new coding approach, by the linearization of curvature coding and normalization process is proposed. The linearization process results in the representation of curvature information into a 1-D plane, which is then processed for feature representation, based on Empirical coding. This proposed approach improves the selection of feature relevancy, in terms of selectivity, where features are selected based on variation density rather to magnitudes.

II. IMAGE RETRIEVAL

In the process of image retrieval various coding approaches were developed in past. These developed approaches were developed based on the content information's of the sample. In the image retrieval system, approaches developed based on the sample content information, called as content-based image retrieval (CBIR). In the last decade, a number of research has been developed on the content-based image retrieval (CBIR). The goal of the CBIR is to provide images or image information based on the content of an image. The system uses a descriptive features, such as color, shape, or texture in the retrieval process. Here a query equivalent image is retrieved from the data base images. Due to the rapid rise in digital image repositories, various technologies have been recently investigated to store, browse, and retrieve images. Conventional system, Illustrate using a traditional approach image through image recovery and then use text-based data base management system to develop a retrieval system.The image retrieval systems are computed with basically the content features of the image namely color, or shape recognition. To achieve the objective of image retrieval, the operation is performed in two operational stages, training and testing. A Basic operational architecture for such a system is shown in Fig. 1. Conventional retrieval system uses a single cue such as shape, texture, or color which is extracted from the image as a feature vector.

a) Color Feature

The selected color space has to be discretized and number of times each discrete color appears has to be counted. Selection of appropriate color space and the quantization of the selected color are the key issues.

b) Texture Feature

Texture can act as a vital cue for image classification. Texture classification is particularly useful to classify the images consisting of scenes containing pictures of wood, grass, etc. instead of color and shape. It is very hard to define a texture.

As large databases are considered, a combination of texture and color can be used extract multiple features for querying the database. In various approach [10-22], image features are combined for the representation of image data in retrieval system.

c) Shape Features

One of the most popular techniquesof this kind in the research community is the shape feature. Very Retrieval by appearance is another method for giving interesting results. In this technique either whole-image matching or matching on selected parts of an image is considered.   is considered in part matching. On the other hand, the technologies used in the local edge structure are processed with the whole image. The advantage of the above techniques is to describe an image that describes in detail for every level. While the content of the expression may appear on a different guises, it is very useful in the natural scene that avoids the demand of the image as part of a prior information for retrieval. This leads to a problematic issue despite of recent developments in image coding techniques.

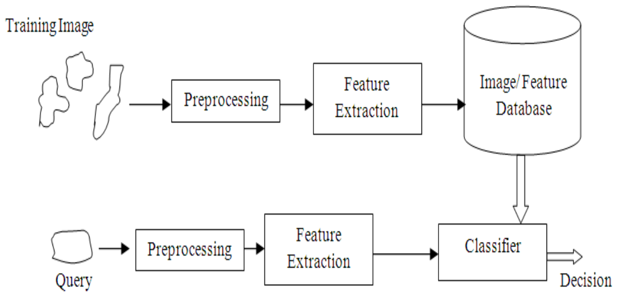

Fig. 1: Model of a Sketch based image retrieval system

In such system the samples are preprocessed for filtration, and dimensional uniformity. The pre-processed samples were then processed for feature extraction. These features are the descriptive details of each test sample or training sample which are stored onto dataset for further processing. The accuracy of these feature descriptors defines the processing accuracy of the system. in the image retrieval approach, various approaches of image retrieval systems were developed. Among different approaches of retrieval sketch based image retrieval (SBIR) has its advantage of simpler computation and lower computing overhead. A basic model of SBIR is presented in Fig. 1.

III. SKETCH BASED RETRIEVAL SYSTEM

Sketch Based Image Retrieval (SBIR) is a recent research area, there are many issues and challenges related to the design and design of a SBIR system, which is based on an independent hand sketch.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The use of current methods explains how to use specific descriptor to handle the lag between a sketch and a color image for efficient retrieval. The Edge Histogram Descriptor (EHD) has been suggested as one such approach for image retrieval. The idea is to extract regional descriptor of five different edges from the content of an image. A sketch is a free hand drawing that includes a set of strokes, but there is no texture and color features. In SBIR application,

the input is a simple sketch that represents one or more objects in the image. Although a large number of multimedia image recognition are developed primarily based on content features, attention has been increased on SBIR over the past few years. This interest applies to the emerging touch screen technology that allows users to draw a query directly on the screen and allow a user to perform a simple and accessible process.Sketch based image retrieval (SBIR) was observed in QBIC and Visual SEEK Systems. In this system the user provides color sketches and blocks in the drawing area. In a SBIR application, the user operates on a drawing area where a free hand sketch input is given. SBIR application are now applied in daily life usage such as medical diagnosis, digital library, search engines, crime recording, geographical information, art galleries, remote sensing systems etc [4]. Features are used as a measure of representation for image retrieval. Each feature has more than one representative. The shape and texture for image retrieval with graphical rough edges are the most commonly used features describing edge-based features as a histogram of features. While the Edge based feature extraction methods used by the Fourier descriptor to identify image retrieval, these methods only apply to features for limited images that contain high variant edges. Extracting the edge-based features of the shape information is difficult, because extensive feature representing edges reflect shape of the image are highly effective to external noise interference. With the motive of improving the accuracy of retrieval in SBIR, the images are processed in feature extraction and mapping. However, the search overhead is large and hence, needed to be optimized. IN this need, a relevant feedback logic based re-ranking system called “Smart Sketcher” is presented [23]. This system input is an image collection of up to thousands of pictures, usually trained with a keywords called tags such as "air", "tree", "boat" etc. in SBIR, the user expresses these tags by drawing a rough sketch and presents images that match for the given original image. The system interact with the developed approach workflow supporting further queries based on the previous query passed. It is been designed to retrieve images that match to the accuracy at a short time with fewer search overhead. In the search, Final output is a list of images that match the user's sketch input. The main component of SmartSketcher is a re-ranking technology that helps improve the functionality of the free retrieval system and helps the user to resolve the problem of wrong classification. Common SBIR methods developed the nearest neighbors by calculating a similarity score on low-level features. In most of the SBIR applications, user does not pass a accurate and detailed input sketches, and the input question boxes are also limited in resolution. As a result, there is a significant effort to browse the search results and select the images that match the query. So one important factor of SBIR system is to refer the results of semantic meaningful features to give higher retrieval accuracy. The feature based regrouping helps to rearrange the data with representation through a deep analysis in a larger image database. In the conventional SBIR system, the first semantic features were compared and given for the query sketch to K-semantic clusters or using k-means clustering for classification. For a true match images for a given test query, the best match results are sorted top. The goal of the approach is to re-rank the results such as the image with higher matching is ranked higher in the cluster.

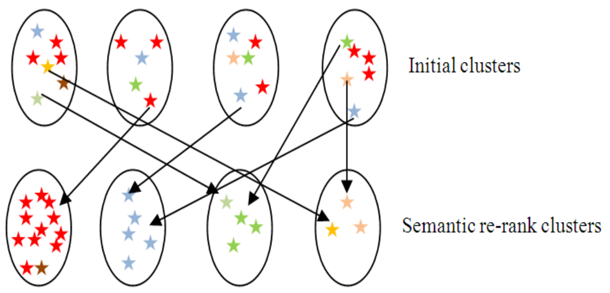

Fig. 2: **Schematically re-ranking in SBIR application [23]**

To achieve this, each member in the cluster is based on the average equivalent similarity. If there is a image in SBIR is higher, the specific approach will rank the observing image to a desired cluster. The image is deployed on individual clusters based on scores of original identities. However, the sequence of semantic similar features is the limitation to such clustering. In many, a case the feature vectors will be sharing a high degree of similarity in the image detail, which will, leads to misclassification model. To overcome the stated issue in this paper, a semi supervised clustering for unlabeled features vector is developed.

IV. CONTEXT RE-RANKING MODEL

In the development of a optimal clustering operation, a semi-supervised context re-ranking (SSCR) approach is developed. it has a significance of higher clustering performance due to the consideration of label and un labeled dataset together. The distance measure is a Euclidian approach and K-mean clustering gives the lower computational complexity, however, the class diversity and attribute variation is not been considered in this approach in distance measure. The supervised algorithm creates a models in associated labels or outputs in the training datasets paired with the input sample. On the other hand, algorithms in unsupervised approach takes into consideration similarities to group input into a cluster. Labeling and semi-supervised models are used to make the final database. Semi-supervised classification techniques can be used to designate self-training, co-mapping, or multi-view studies, generative models, and graphical edge based methods. The proposed SSCR model increases the learning process of its local learning models given by,

1) Utilizing unlabeled data
2) Adding training data to each separate clusters. For examples images of the same category are likely to be brought together in the Euclidean space. The detection performance in the SSCR's increases.

1) The K-Mean creating multiple random layers of cluster is given a diversity monitoring.
2) identifying the difficult and simple classification samples and
3) develop the final prediction of a test sample based on the majority vote for a query.

Data instances are provided for different clusters during different initialization parameters. In this approach a K-mean clustering is
defined where each layer is defined with a random parameter (i.e., seed). Here the feature point may be defined at different clusters of different layers. Clusters of different layers overlap, but may have non-existent data, and clusters interact with each other in the same layer, and may contain data from one or more classes.

For example, consider the dataset with two classes. In this case a layer is defined as a set of K-Mean cluster algorithms based on a set of initial parameters (ie. seeds). Thus, a data point will leads to different clusters of different layers based on the distance. Clusters in the same group are complementary to each other (ie non-overlapping). However, clusters may be overlapping in different layers with no common values. Therefore, clusters in different layers can be used for different base classifiers. This distinction is used to create a classification model of the entire database.

Randomized K-Means Algorithm produces multiple layers of SSCR. A training approach is developed for all layers in SSCR model and each layers go to a K-cluster formation. The function of each layer of the clusters may have different classes or different data points. This suggests that a cluster is defined as atomic when the cluster holds a common feature value, while the meanings of a non-atomic cluster is defined as a cluster with different class labels. The SSCR builds local learning models in clusters as a result each layer indicate the dependencies of the data on the other cluster. It basically creates binary commentators on non-atomic clusters and remembers the category label in the atomic clusters.

The K-Mean Clustering Algorithm is quite widespread because of its simplicity and easy implementation. However, the efficiency of K-mean depends on the initialization parameters. The SSCR exploits this object to provide diversity in the basic classification. It generates a local learning model on generated overlapping in each layer in a non-identical clusters. For a set of instance a_1, a_2, ... a_n in a space of K cluster, the K-mean algorithm optimizes the objective function defined as,

$$F(a_1, a_2, \dots \dots a_3) = \sum_{k=1}^{K} \sum_{a \in c} \|a - \bar{a}\|^2 \qquad (1)$$

Here, a is the cluster data of ith cluster, and $\bar{a}$ is the mean of the cluster defined by,

$$\bar{a} = \frac{1}{n} \sum_{a \in c} a \qquad (2)$$

For the distance evaluation, in a K-mean algorithm, Euclidean distance metric is been used defined by,

$$dist(a, c) = \sqrt{\sum_{i=1}^{n} (a_i - c_i)^2} \qquad (3)$$

Although the Euclidean distance works well with the homogenous data distribution, all the attributes in this method is treated equally. Such an approach is limited when the data patterns are observed to have a differentiate patterns. Similarly, deployment of such measures may result in a low performance until the K-Means Algorithm is iterated for the required iterations. Therefore, when used to measure distance learning, different attributes have a stronger effect on the different content of data and the iteration overhead will be large. To minimize the overhead, weight values are assigned to each parameter, based on class label. In this paper, a information gain ratio (IGR) is used as an attribute of weight, reflecting the attributes and importance of the attribute in finding a class type, the IGR parameter is defined as,

$$IGR = \frac{En(I) - En(I|a_i)}{En(a_i)} \qquad (4)$$

Here, En reflect the entropy factor of the observing class I with attributes a_i. The Entropy value is given by,

$$En(I) = -\sum_{i=1}^{n} P(C_i) log_2\big(P(C_i)\big) \qquad (5)$$

where P(.) is the probability operator and *i* is an index of the probabilities in a given input. The proposed weighted Euclidian distance Ed for an attribute in a class C is given as,

$$Ed(C, a) = \sqrt{\sum_{i=1}^{d} W_i (C_i - a_i)^2} \qquad (6)$$

Here,W_i is the allocated weight for the class i, which is defiend as a function of the IGR for the jth attribute given as,

$$W_i = IGR(C, a_i) \qquad (7)$$

The computed weight is fed back and a new cluster with updated weight is performed until the IGR is maximized. These features are grouped in cluster, gives a faster search performance. due to semantic cluster attributes the distance measure is made faster by selecting the cluster based on cluster center. The search overhead is decreased by the number of cluster derived.

V. SIMULATION RESULTS

For the evaluation of the proposed approach, the Acer data set is used. The Acer dataset is used for the present research areas. to evaluate the performance of the different models this data set is particularly been used for real time variations modeling. To test the developed system, a k-fold test analysis is performed. where for the simulation of the developed approach, 4-fold test is applied. The whole of the data set in this case is transformed randomly into 2 dataset, where one half is used for testing and other half for training. In 3 fold , 1/3rd data is used as test value and a similar 1/4th value in 4-fold, remaining values are used as training values. The parameters evaluated are the accuracy (Acc), false alarm rate (FAR), detection rate (DR) (sensitivity), and Matthew's correlation coefficient (Mcc). The parameters are given as,

The accuracy is given by,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (8)$$

The detection ratio is defined as a ratio of true classification over an aggregate of true positive over false negative value

$$DR = \frac{TP}{TP + FN} \qquad (9)$$

FAR is the ratio of FP to sum of TN and FP given as,

$$FAR = \frac{FP}{TN+FP} \qquad (10)$$

Here,

TABLE 1: Measuring parameters

TP (True Positive)	number of correctly classified images
TN (True Negative)	number of correctly classified negative data
FN (False Negative)	number of intrusions incorrectly classified as normal
FP (false positive)	number of normal traffic incorrectly

The confusion matrix for the developed system is defined as,

TABLE 2: Confusion Matrix

Type	Detected Normal	Detected Variations
Normal	TP	FP
Variations	TN	FN

The observations obtained are given as;

TABLE 3: Observation table for the developed Approach

Samples	Method	Accuracy(%)	DR	FAR	Mcc	TT(s)
S1	SSCR	99.85	0.72	0.285319	0.72	0.347383
	Smart Sketcher [23]	99.22	0.58	0.242766	0.58	0.138035
	HoG[17]	99.08	0.92	0.458809	0.91	0.125998
S2	SSCR	99.52	0.60	0.405255	0.60	0.259342
	Smart Sketcher [23]	99.13	0.88	0.542915	0.87	0.147938
	HoG[17]	99.05	0.72	0.287872	0.72	0.162521
S3	SSCR	99.76	0.72	0.247319	0.73	0.358719
	Smart Sketcher [23]	99.25	0.90	0.541915	0.85	0.147317
	HoG[17]	99.04	0.92	0.475809	0.88	0.142396
S4	SSCR	99.74	0.72	0.241319	0.72	0.366849
	Smart Sketcher [23]	99.56	0.90	0.585915	0.87	0.178043
	HoG[17]	99.48	0.92	0.456809	0.91	0.152812

TABLE.4.Search Overhead for variations

Edge noise	SSCR	Smart Sketcher [23]	HoG [17]
0.1	0.33	0.64	0.73
0.3	0.34	0.66	0.77
0.5	0.37	0.69	0.7
0.7	0.23	0.61	0.72

The obtained retrieval observations for different variations on the Acer dataset were observed and the result derived are as illustrated below,

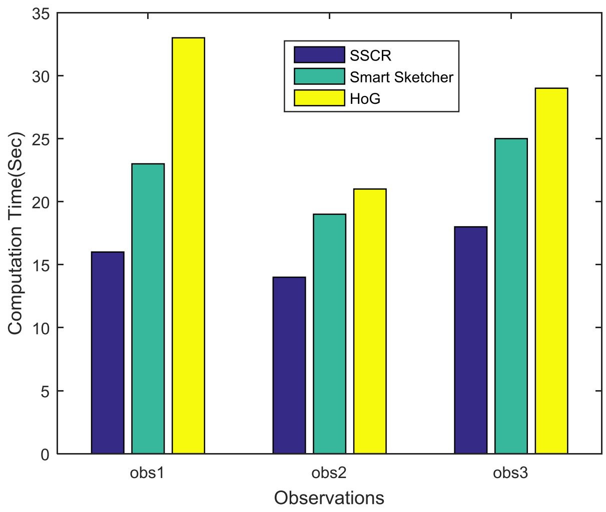

Fig. 3. Computation Time over different test observations

Fig.3 shows the Comparative analysis between the proposed and conventional approaches with respect to the Computational Time (Sec) for various observations. Compared to the conventional approaches, Smart Checker and HoG, the proposed SSCR has less retrieval time which results in the less computational time. On an average the proposed SSCR is attained a reduced computational time of 34 Sec and 18 Sec compared to the conventional approaches, Smart Checker and HoG respectively.

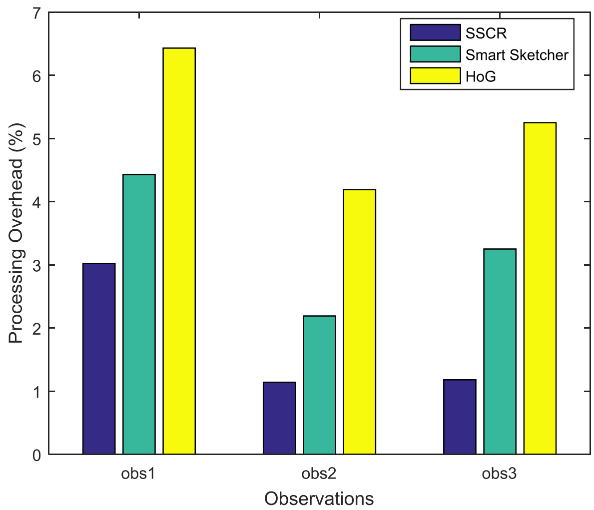

Fig. 4. Processing Overhead

Fig..4 shows the Comparative analysis between the proposed and conventional approaches with respect to the Processing Overhead (%) for various observations. As it can be seen from the above figure, the processing overhead of proposed SSCR is less compared to smart checker and HoG. Due to the reduction of the features, the processing overhead is reduced and it is approximated on an average as 4.5 %. Furthermore, it is much reduced when compared to the conventional approaches and it is figured as 6% and 11.5% from smart checker and HoG respectively.

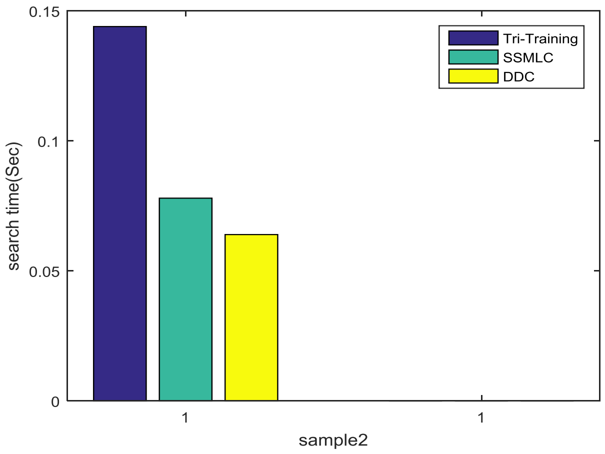

Fig. 5. Search overhead plot host

Fig.5 illustrates the Tri-Training and SSMLC techniques in comparison to the proposed DDC for host sample. The iteration count is shown in comparison with Tri-Training and SSMLC DDC retrieval accuracy is improved, and the iteration count and computational time has been increased. Compared with Tri-Training and SSMLC, DDC has 32 iterations low in count.

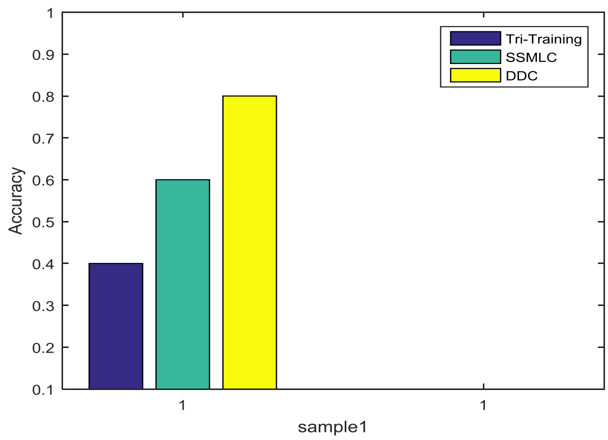

Fig. 6. Accuracy plot for the developed approach in Host type

Fig.6 illustrates the Accuracy details of proposed DDC. compared with Tri-Training and SSMLC, the proposed approach has higher Accuracy. Compared with Tri-Training and SSMLC, DDC has 20% increased Accuracy and 10% when compared with LDA.

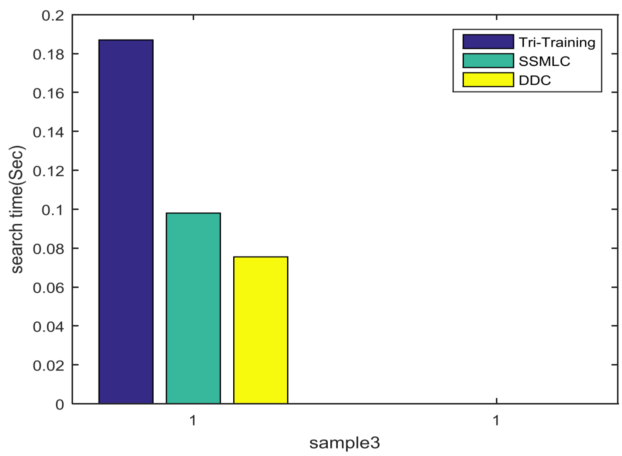

Fig. 7. Search plot content type

Fig 7.Illustrates the iteration count details of the content sample for the proposed DDC along with earlier Tri-Training and SSMLC techniques. Compared with Tri-Training and SSMLC, the DDC has increased iteration count which reduces computational time along with retrieval accuracy.

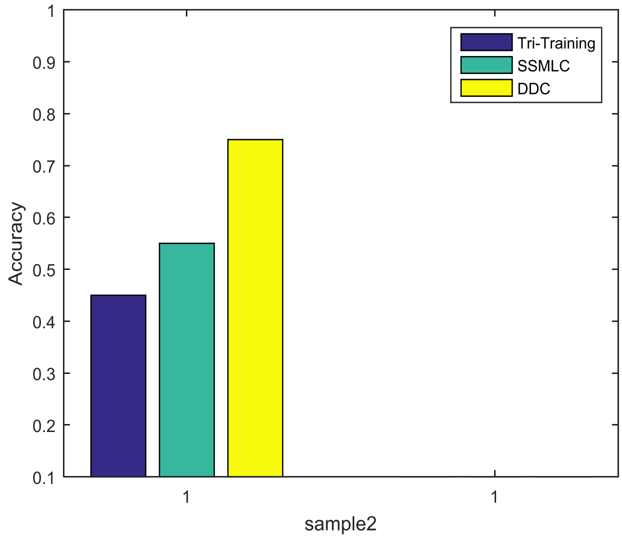

Fig. 8. Accuracy plot for the developed approach in content type

Fig 8. illustrates the Accuracy details of proposed DDC. compared with Tri-Training and SSMLC, the proposed approach has increased Accuracy. Compared with Tri-Training and SSMLC, DDC has 24% increased Accuracy and 15% when compared with LDA.

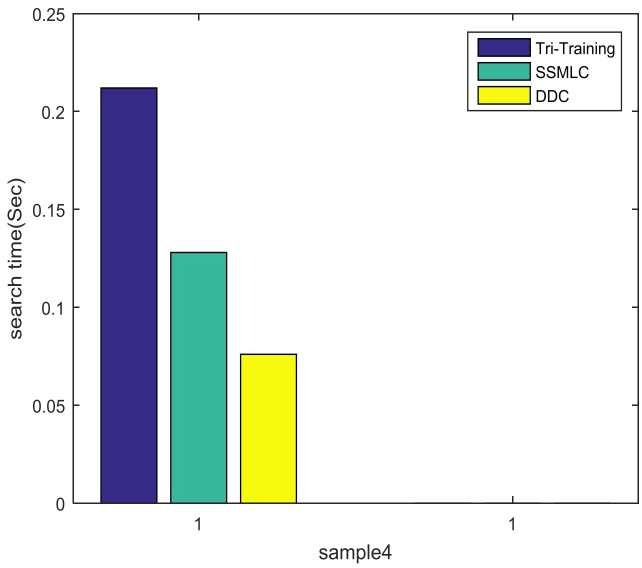

Fig. 9. Search plot service type

The increased iteration count for service sample using DDC along with Tri-Training and SSMLC is shown in Fig.9. The proposed approach has increased iteration count when it is compared with earlier approaches. Compared with Tri-training and SSMLC, the proposed DDC has a reduced search time of 0.14 Sec and 0.05 Sec respectively.

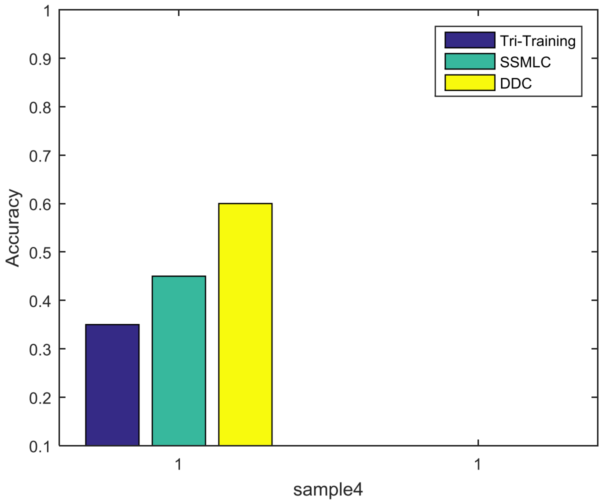

Fig. 10. Accuracy plot for the developed approach in service type

The Accuracy of proposed DDC is less compared with Tri-Training and SSMLC for service sample. The details are represented in fig.10. Compared with earlier approaches, DDC has 17% increased Accuracy.

VI. CONCLUSION

This paper outlines a new approach to feature clustering in SBIR application using semantic re-ranking logic. the approach, present a information gain ratio in feature description in cluster formulation. In the approach of conventional cluster formulation, each of the cluster is defined based on the minimal distance vector. These distance vectors are mean distance of each feature with its cluster value. However, the clustering of un labeled class and its retrieval based on the cluster based system is outlined as a semi supervised feedback relevance in SBIR application. The result obtained illustrated an considerable improvement in the retrial accuracy and system precision in comparison to the HoG based and the Smart Sketcher system. The performance evaluation carried out with respect to the classification accuracy and computational time had shown an efficient performance in the effective retrieval of sketch images. On an average the DDC method attained an increment in the classification accuracy of 25% and 16% when compared with the conventional approaches, Tri-Training and SSMLC respectively. Similarly, the computational time is reduced and it is in the order of 34 Sec and 18 Sec compared to the conventional approaches.

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AUTHORS PROFILE

K. Durga Prasad, has completed his graduation from Institute of Engineers (AMIE) INDIA, Calcutta in 2001. Completed MTech from JNTUH, Hyderabad in DIgital systems and computer electronics in May 2005. Currently Pursuing Phd from JNTUA, Anantapuramu Andhra Pradesh.

Dr. K. Manjunathachari has obtained his graduation from Gulbarga University in June 1991.Completed his MTech in Digital systems and computer science from JNTUH, Hyderabad in August 1996. Completed his Phd in Image processing from JNTUK Kakinada in March 2010..

Dr. M. N. Giriprasad has obtained his BTech from JNTUCE, Anantapur in 1982. Completed his MTech from SVU College of Engineering Tirupathi in 1994. Completed his Phd from JNTU Hyderabad in 2003.