ISSN (Online): 2456-5717

International Journal of Advanced Research in Basic Engineering Sciences and Technology (IJARBEST)
Vol.4 Issue.3 March 2018

An Efficient Semantic Based Image Retrieval Using Low-Level and High-Level Features

[1]M.Sudharsan, [1]S.Gowtham, [1]N.Ezhil Yohaventhan, [1]V.Venkatesh, [2]N.Sumathi

[1]UG Scholar, Computer Science and Engineering, Dr.Mahalingam college of Engineering and Technology, Pollachi, India

[2]Associate Professor, Computer Science and Engineering, Dr.Mahalingam college of Engineering and Technology, Pollachi, India

***Abstract*: The proposed system aims at an automatic image search and retrieval system that works best even in its average and worst-case scenarios. This system incorporates a new indexing technique along with few other feature extraction techniques. The objective of this project is to reduce the number of iterations and improve image retrieval accuracy. The proposed system has an image re-ranking strategy based on the multimedia information available on the product databases. The proposed system can annotate the photos with free text and rate of quality. Indexing is finished utilizing a usage of the Document Builder interface. The quick image retrieval supported document builder factory, which creates document builder instances for all accessible features moreover as standard combinations of features (e.g. all MPEG-7 features or all available features). The proposed low-level feature extraction techniques used in the image retrieval are scalable color, color layout, edge histogram and dominant color. The image retrieval can be done based on both text and image-based input. The content-based image retrieval can be achieved by using the visual color layout descriptors and scalable color. It is outlined within the MPEG-7 standard and the relevance image is retrieved by looking for a similar semantic graph. Semantic analysis has become a vigorous analysis topic aimed at partitioning the gap between low-level image features and high-level semantics that could be a promoting approach to image understanding. The Web Ontology Language OWL offers an expensive syntactic structure of semantics for image syntactic depiction during which distinctive ontologies need to specific learning of conditions, diverse content by OWL ontology mapping associated with high reusability. The proposed semantic-based re-ranking list of results based on the semantic relationship between the image feature similarity metric along with a low-level image features. The filtering or re-ranking method to take place subsequently. Query Re-Ranking permits to run a simple query (A) for matching documents then re-rank the highest N images exploitation the scores from an additional complex query (B). The experiments are performed using WANG database which consists of 1000 images from 10 different classes. The experimental result shows that the proposed approach performs better in terms of precision compared to other existing systems.**

***Keywords*: Content-based image retrieval; color layout, edge histogram; Color & Edge Features.**

I. INTRODUCTION

Recently, with the rapid advances in digit devices and the Internet, the amount of multimedia data (e.g. images, videos) are explosively increasing. These huge databases have posed a significant challenge in terms of scalable similarity search to many multimedia applications, such as content-based multimedia retrieval (CBMR), and classification. With large image databases becoming a reality both in scientific and industrial domains, content-based image retrieval (CBIR) becomes a very important analysis space in computer vision and it mostly depends on extracting the acceptable characteristic quantities describing the specified contents of images. To date, there has been significant research within numerous domains that aims to improve the accuracy of CBIR and a large portion of them are concentrating on planning refined low-level feature extraction algorithms to reduce the semantic hole between the visual features and the abundance of human semantics.

The multimedia contents are developing violently and the requirement for multimedia retrieval is happening increasingly oftentimes in our day by day life. Because of the multifaceted nature of multimedia contents, image understanding is a troublesome yet fascinating issue in this field. Removing profitable learning from an expansive scale multimedia repository, supposed multimedia mining, has been as of late concentrated by a few researchers. Typically, in the development of an image requisition system, semantic image retrieval relies heavily on the related captions, e.g., file-names, categories, annotated keywords, and other manual descriptions. Unfortunately, this sort of text-based image retrieval dependably experiences two issues: high-priced manual explanation and inappropriate automated annotation. On one hand, expensive manual annotation cost is restrictive in adapting to a huge scale informational collection. On the other hand, inappropriate automatic annotation yields the distorted results for linguistics image retrieval.

Various effective image retrieval algorithms have been proposed to manage such issues in the course of recent years. Content-Based Image Retrieval (CBIR) is the mainstay of current image retrieval systems. In general, the purpose of CBIR is to present an image conceptually, with a set of low-level visual features such as color, texture, and shape. These conventional approaches for image retrieval are based on the computation of the similarity between the user's query and images via a query by example (QBE) system. In spite of the power of the search strategies, it is extremely hard to improve the retrieval quality of CBIR inside just a single query process. The concealed issue is that the separated visual features are excessively assorted, making it impossible to catch the idea of the user's query. To tackle such issues, in the QBE framework, the users can get some favored images to refine the image investigations iteratively. The criticism methodology, known as Relevance Feedback (RF), rehashes until the point when the user is satisfied with the retrieval results.

One of the core research issues in multimedia retrieval is to look for a powerful separation metric or function for processing similarity of two objects in content-based multimedia retrieval assignments.The multimedia analysts have spent much exertion in planning an assortment of low level feature portrayals and diverse distance measures. Finding a good distance metric/work remains an open test for content-based multimedia retrieval undertakings till now. Lately, one promising bearing to deliver this test is to investigate distance metric learning (DML) by applying machine learning procedures to streamline separate measurements from preparing information or side data, such as verifiable logs of client pertinence input in content-based image retrieval (CBIR) systems.

II. RELATED WORK

Nowadays, content-based image retrieval (CBIR) is the mainstay of image retrieval systems. To be more profitable, relevance feedback techniques were incorporated into CBIR such that more precise results can be obtained by taking user's feedback into account. However, existing relevance feedback-based CBIR methods usually request a number of iterative feedbacks to produce refined search results, especially in a large-scale image database. Distance metric learning (DML) is an important technique to improve similarity search in content-based image retrieval. Despite being studied extensively, most existing DML approaches typically adopt a single-modal learning framework that learns the distance metric on either a single feature type or a combined feature space where multiple types of features are simply concatenated. Such single-modal DML methods suffer from some critical limitations: (i) some type of features may significantly dominate the others in the DML task due to diverse feature representations; and (ii) learning a distance metric on the combined high-dimensional feature space can be extremely time-consuming using the naive feature concatenation approach.

The ability of fast similarity search at large scale is of great importance to many Information Retrieval (IR) applications. A promising way to accelerate similarity search is semantic hashing which designs compact binary codes for a large number of documents so that semantically similar documents are mapped to similar codes (within a short Hamming distance). Novel unsupervised Multiview Alignment Hashing (MAH) approach based on Regularized Kernel Nonnegative Matrix Factorization (RKNMF), which can find a compact representation uncovering the hidden semantics and simultaneously respecting the joint probability distribution of data. The exiting scalable graph-based ranking model called Efficient Manifold Ranking (EMR), trying to address the shortcomings of MR from two main perspectives: scalable graph construction and efficient ranking computation. Specifically, anchor graph can be built on the database instead of a traditional k-nearest neighbours graph and design a new form of adjacency matrix utilized to speed up the ranking.

Due to the explosive growth of the multimedia contents in recent years, scalable similarity search has attracted considerable attention in many large-scale multimedia applications. Among the different similarity search approaches, hashing based approximate nearest neighbours (ANN) search has become very popular owing to its computational and storage efficiency. However, most of the existing hashing methods usually adopt a single modality or integrate multiple modalities simply without exploiting the effect of different features. Latent Semantic Sparse Hashing (LSSH) to perform cross-modal similarity search by employing Sparse Coding and Matrix Factorization. In particular, LSSH uses Sparse Coding to capture the salient structures of images, and Matrix Factorization to learn the latest concepts from the text. This algorithm, dubbed iterative quantization (ITQ), has connections to multi-class spectral clustering and to the orthogonal Procrustes problem, and it can be used both with unsupervised data embedding such as PCA and supervised embedding such as canonical correlation analysis (CCA).

The resulting binary codes significantly outperform several other state-of-the-art methods. a hierarchical feature selection and a Multiview multilabel (MVML) learning for Multiview image classification and block-based embedding are proposed a new block-row regularizer into the MVML framework. The block-row regularizer concatenating a Frobenius norm (F-norm) regularizer and an L2,1-norm regularizer are designed to conduct a hierarchical feature selection. The dubbed multi-view latent hashing (MVLH), to effectively incorporate multi-view data into hash code learning. Specifically, the binary codes are learned by the latent factors shared by multiple views from a unified kernel feature space, where the weights of different views are adaptively learned according to the reconstruction error with each view. The existing semi-supervised annotation approach by learning an optimal graph (OGL) from multi-cues (i.e., partial tags and multiple features) which can more accurately embed the relationships among the data points.

Hashing methods, such as locality sensitive hashing (LSH) and its variants, have been widely used to achieve fast approximate similarity search by trading search quality for efficiency. However, most existing hashing methods make use of randomized algorithms to generate hash codes without considering the specific structural information in the data. In this paper, a novel hashing method has been proposed, namely, robust hashing with local models (RHLM), which learns a set of robust hash functions to map the high-dimensional data points into binary hash codes by effectively utilizing local structural information. Compared with existing hypergraph learning methods, the proposed method has a regularizer on the hyperedge weights and simultaneously optimizes labels and hyperedge weights. In this way, the effects of different hyperedges can be adaptively modulated. For those hyperedges that are informative, higher weights will be assigned. The tree-based algorithm is easy to implement, requiring a kd-tree as the only major data structure. The practical efficiency of the filtering algorithm has been established. Outline some matrix factorization approaches for co-clustering polyadic data (like publication data) using non-negative factorization (NMF). web image dataset created by NUS's Lab for Media Search. The dataset includes: (1) 269,648 images and the associated tags from Flickr, with a total of 5,018 unique tags; (2) six types of low-level features extracted from these images, including 64-D color histogram, 144-D color correlogram, 73-D edge direction histogram, 128-D wavelet texture, 225-D block-wise color moments extracted over 5x5 fixed grid partitions, and 500-D bag of words based on SIFT descriptions; and (3) ground-truth for 81 concepts that can be used for evaluation.

III. PROPOSED APPROACH

The proposed system presents the extraction of a new low-level feature that contains, in one histogram, color and texture information. This element is intended for use in image retrieval and image indexing systems. Experimental results show that the proposed feature can contribute inaccurate image retrieval. Its main functionality is image-to-image matching and its intended use is for still-image retrieval, where an image may consist of either a single rectangular frame or arbitrarily shaped, possibly disconnected regions. This feature is called “Color and Edge Directivity Descriptor” and incorporates color and texture information in a histogram. The proposed size is to 54 bytes per image, rendering this descriptor suitable for

ISSN (Online): 2456-5717

International Journal of Advanced Research in Basic Engineering Sciences and Technology (IJARBEST)
Vol.4 Issue.3 March 2018

use in large image databases. One of the most important attributes of the is the low computational power needed for its extraction, in comparison with the needs of the most MPEG-7 descriptors.

The unit associated with the extraction of color information is called Color Unit. Similarly, the Texture Unit is the unit associated with the extraction of texture information. The histogram is constituted by 6 regions, determined by the Texture Unit. Each region is constituted by 24 individual regions, emanating from the Color Unit. Overall, the final histogram includes $6 \times 24 = 144$ regions. In order to shape the histogram, firstly the image in 1600 Image Blocks are separated. This number was chosen in order to compromise between the image detail and the computational power. Each Image Block feeds successively all the units. The bin can be define from the results from the Texture Unit as N and as M the bin that results from the Color Unit, then the Image Block is placed in the output histogram position: $N \times 24 + M$.

In the Texture Unit, the Image Block is separated into 4 regions, the Sub Blocks. The value of each Sub Block is the mean value of the luminosity of the pixels that participate in it. The luminosity values are derived from the transformation through the YIQ color space. Each Image Block is then filtered with the 5 digital filters, and with the use of the pentagon's diagram, it is classified into one or more texture categories. Assume that the classification resulted in the second bin, which defines NDE (Non-Directional Edge).

In the Color Unit, every Image Block is transported in the HSV color space. The mean values of H, S, and V are calculated and they constitute the inputs of the fuzzy system that shapes the fuzzy 10-bins histogram. Assume that the classification resulted in the fourth bin, which dictates that the color is red. Then, the second fuzzy system (24- Bin Fuzzy Linking), using the mean values of S and V as well as the value of the bin (or bins) expense from the previous system, calculates the hue of the color and shapes the fuzzy 24-bins histogram. Assume again that the system classifies this block in the fourth bin which dictates that color is the dark red. The combination of the 3 fuzzy systems finally will classify the block in the 27 bins $(1 \times 24 + 3)$. The process is repeated for all the blocks of the image. At the completion of the process, the histogram is normalized in the interval {0-1}.

A. Relevance Feedback

The photos can be annotated with free text and rate of quality. Pre-existing metadata like EXIF or IPTC tags inside images is loaded and converted to MPEG-7. Here the second

ISSN (Online): 2456-5717

International Journal of Advanced Research in Basic Engineering Sciences and Technology (IJARBEST)
Vol.4 Issue.3 March 2018

panel, the semantic description panel, is shown. It offers a tool for visual creation of MPEG-7 based semantic descriptions using a drawn directed graph. On the feature extraction panel, the low-level descriptors that are automatically extracted are shown. Extracted MPEG-7 descriptors are Color Layout, Scalable Color and Edge Histogram. This component allows the user to define a graph with minimum one to maximum three nodes and two possible relations. An asterisk is used as a wildcard. A search graph which only contains one node with a word defining this node will return each MPEG-7 document wherein a semantic object containing the specified word is found.

B. Indexing

Indexing is finished utilizing a usage of the Document Builder interface. A simple approach is to use the Document Builder Factory, which creates Document Builder instances for all available features as well as popular combinations of features (e.g. all MPEG-7 features or all available features). A Document Builder is basically a wrapper for image features creating a Lucene Document from a Java Buffered Image. The signatures or vectors extracted by the feature implementations are wrapped in the documents as text. The document output by a Document Builder can be added to a Lucene index. Indexing methods that are in use on large image databases, substantiated by performance figures: space partitioning, data partitioning, and distance-based techniques. In space-partitioning index techniques, the feature space is organized like a tree.

Data partitioning index techniques associate, with each point in feature space, a region that represents the neighborhood of that vector. An R-tree is such a data partitioning structure to index hyper rectangular regions in M-dimensional space. The leaf nodes of an R-tree represent the minimum bounding rectangles of sets of feature vectors. An internal node is a rectangle encompassing the rectangles of all its children. An R.-tree is a variant which does not allow the minimum bounding rectangles in a node to overlap.

C. Feature Extraction

- Scalable color

The Scalable Color Descriptor is a Color Histogram in HSV Color Space, which is encoded by a Haar transform. Its binary representation is scalable in terms of bin numbers and bit representation accuracy over a broad range of data rates. The Scalable Color Descriptor is useful for image-to-image matching and retrieval based on the color feature. Retrieval accuracy increases with the number of bits used in the representation.

ISSN (Online): 2456-5717

International Journal of Advanced Research in Basic Engineering Sciences and Technology (IJARBEST)
Vol.4 Issue.3 March 2018

- Color Layout

This descriptor effectively represents the spatial distribution of color of visual signals in a very compact form. This compactness allows visual signal matching functionality with high retrieval efficiency at very small computational costs. It provides image-to-image matching as well as ultra-high-speed sequence-to-sequence matching, which requires so many repetitions of similarity calculations. It also provides very friendly user interface using hand-written sketch queries since this descriptor captures the layout information of color feature.

- Edge Histogram

The edge histogram descriptor represents the spatial distribution of five types of edges, namely four directional edges and one non-directional edge. Since edges play an important role for image perception, it can retrieve images with similar semantic meaning. Thus, it primarily targets image-to-image matching (by example or by sketch), especially for natural images with non-uniform edge distribution. In this context, the image retrieval performance can be significantly improved if the edge histogram descriptor is combined with other Descriptors such as the color histogram descriptor. Besides, the best retrieval performances considering this descriptor alone are obtained by using the semi-global and the global histograms generated directly from the edge histogram descriptor as well as the local ones for the matching process.

- Dominant Color

This color descriptor is most suitable for representing local (object or image region) features where a small number of colors are enough to characterize the color information in the region of interest. Whole images are also applicable, for example, flag images or color trademark images. Color quantization is used to extract a small number of representing colors in each region/image. The percentage of each quantized color in the region is calculated correspondingly. A spatial coherency on the entire descriptor is also defined and is used in similarity retrieval.

ISSN (Online): 2456-5717

International Journal of Advanced Research in Basic Engineering Sciences and Technology (IJARBEST)
Vol.4 Issue.3 March 2018

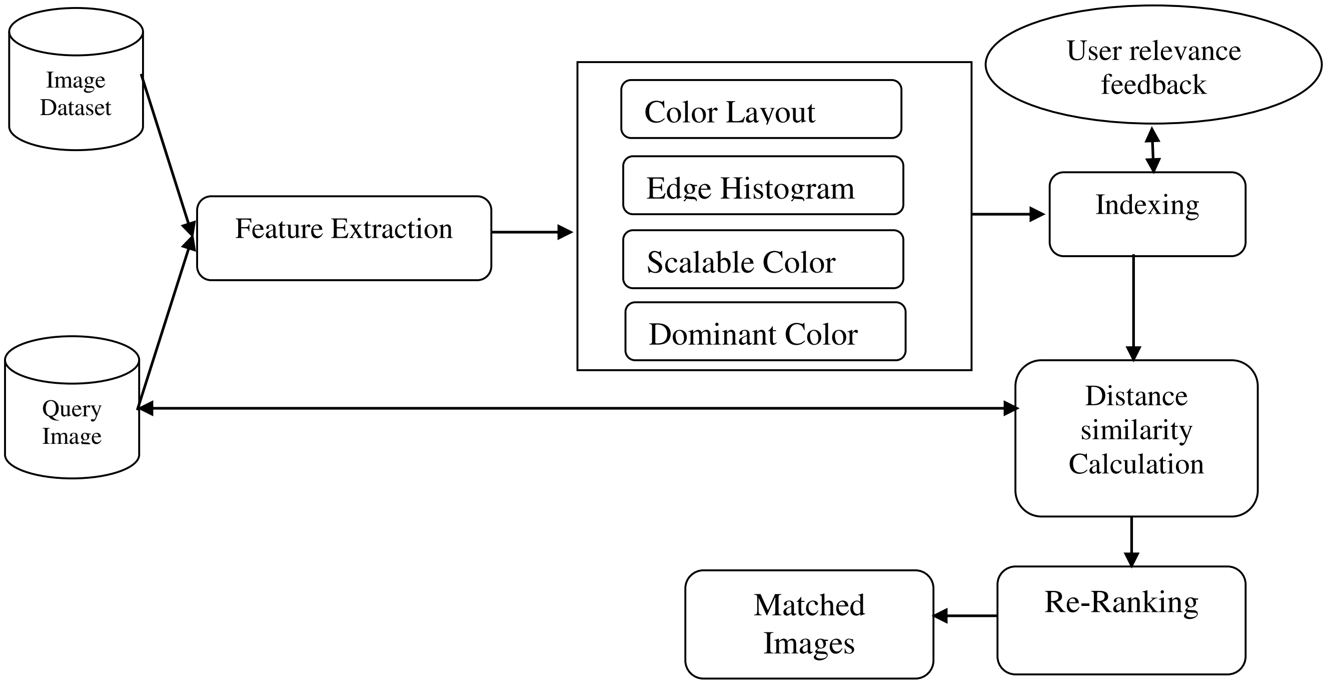

Fig. 1. Overall flow diagram of proposed system

D. Re-Ranking

Ranked list of results based on some similarity metric along with a low-level image feature. However, sometimes the need for filtering or re-ranking process can take place afterward. Query Re-Ranking permits to run a simple query (A) for matching documents and then re-rank the top N documents using the scores from a more complex query (B). Since the costlier ranking from query B is only applied to the top N documents it will have less impact on performance than just using the complex query B by itself – the trade-off is that documents which score very low using the simple query A may not be considered during the re-ranking phase, even if they would score very highly using query B.

Two images can be similar from a semantic viewpoint even if their words or visual features are not identical: different words can be used to express the same concept (synonymy), and several colors can represent the same object. Furthermore, the same word (or color) might have different meanings depending on the context (polysemy). Modelling directly at the word or visual feature level would miss these ambiguities. Existing approaches are based on the definition of a latent space where the documents are represented in a disambiguated form.

$$\hat{q} = q * V \quad (1)$$

Once a document collection has been processed, the similarity between an unannotated image $\hat{q}$ and the annotated image corpus is measured in the latent space. q is first projected by right multiplying by V, the terms expressed in the latent space basis, after projection, the similarity between $\hat{q}$ and each row of U (representation of the collection in the latent space) is computed using the cosine measure. The annotation is then propagated from the ranked documents. Annotations are less reliable as the similarity between documents decreases.

E. Image Retrieval

CBIR Retrieval gives the user the ability to retrieve annotated photos. Due to the fact, that this is experimental software the retrieval mechanism is file system based. All MPEG-7 documents found by CBIR Retrieval in a specified directory and in further subdirectories are searched.

Four different ways to search for a matching photo:

1. Searching through an XPath statement
2. Defining search options through textboxes with various options
3. Content-based image retrieval using the visual descriptors Color Layout and Scalable Color defined in the MPEG-7 standard.
4. Searching for a similar semantic description graph

Once the color, texture and shape feature vectors have been extracted from the query image, as well as the database images, the feature vectors is used to measure the similarity between images in order to retrieve the most similar DB images to the query. The similarity between a query image q and a DB image d is defined by a distance between them, denoted as $D\ (q,\, d)$, which is assessed according to the extracted color, texture and shape features. Two images are equivalent when the distance value between them approaches zero and the similarity between them decreases as the distance value between them increases.

For the measurement of the distance of RF with color feature between the images, Tanimoto coefficient has been selected.

$$\mathrm{T_{ij}} = \mathrm{t}(\mathrm{x_i}, \mathrm{x_j}) = \frac{\mathrm{x_i^T x_j}}{\mathrm{x_i^T x_i} + \mathrm{x_j^T x_j} - \mathrm{x_i^T x_j}} \quad (2)$$

Where xT is the transpose vector of x. In the absolute congruence of the vectors, the Tanimoto coefficient takes the value 1, while in the maximum deviation the coefficient tends to zero

IV. Experimental Results

Images from the WANG database has been used. This database consists of a large number of images of various contents ranging from animals to outdoor sports to natural images.

ISSN (Online): 2456-5717

International Journal of Advanced Research in Basic Engineering Sciences and Technology (IJARBEST)
Vol.4 Issue.3 March 2018

These images have been pre-classified into different categories each of size 100 by domain professionals. Some researchers are of the opinion that the Corel database meets all the requirements to evaluate an image retrieval system, due to its large size and heterogeneous content. For the experiment, the 1000 images has been collected to form database DB1. These images are collected from ten different domains, namely, Africans, beaches, buildings, buses, dinosaurs, elephants, flowers, horses, mountains, and food. Each category has images with a resolution of either 256 384 or 384 256. For each query, the system collects database images with the shortest image matching distance computed. If the retrieved image belongs to the same category as that of the query image, then the system has appropriately identified the expected image, or else, the system has failed to find the expected image. The performance of each technique is measured by calculating its Average Image Retrieval Precision (IRP) and recall value as given

$$\text{IRP} = \frac{\text{No of relevent images Retrieved}}{\text{Total No of images Retrieved}} \quad (3)$$

$$Recall = \frac{No\ of\ Relevent\ images\ Retrieved}{No\ of\ Relevent\ images\ in\ the\ database} \quad (4)$$

The test image is matched with the matched database to identify high-frequency regions. Precision is the fraction of retrieved documents that are relevant to the search. Precision takes all retrieved documents into account, but it can also be evaluated at a given cut-off rank, considering only the topmost results returned by the system.

$$precision = \frac{\left|\{relevant\ images\} \cap \{retrieved\ images\}\right|}{\left|\{retrieved\ images\}\right|} - (5)$$

Recall in information retrieval is the fraction of the documents that are relevant to the query that are successfully retrieved.

$$recall = \frac{\left|\{relevant\ images\} \cap \{retrieved\ images\}\right|}{\{relevant\ images\}} - (6)$$

Our experiments on a 101-category image database, each category having 50 images. The categories include field, sea, sunset, white rose, red rose, and sunflower. The performance measure of the algorithms proposed is done with the calculation of the precision-recall.

Table 1. Different type Query Image Category comparison

Data Set	MIR Flickr		NUS-WIDE		RF with color feature	
	IRP	Recall	IRP	Recall	IRP	Recall
Butterfly	33	30	45	40	56	50
Sunrise	22	20	67	60	56	50
Rose	67	60	45	40	45	40
Car	45	40	67	60	33	30
Building	78	70	67	60	56	50
Flag	11	10	67	60	78	70
Tree	56	50	67	60	56	50
Average	46	40	61	54	54	56

Table 1 shows the comparison of edge histogram semantic-assisted visual hashing and RF with color feature system compared to two techniques the proposed fuzzy color extraction gives high accuracy average.

Table 2. Comparison of Existing Feature Extraction Technique with proposed system

Query image category	% Image Retrieval Precision value for Existing System		% Image Retrieval Precision value for Proposed system
	MIR Flickr	NUS-WIDE	RF with color feature
Butterfly	30	20	56
Rose	44	30	45
Car	40	10	33
Building	45	20	56
Tree	50	10	56
Average IRP value	40	20	**49**

Table 2 shows the comparison of edge histogram EMR and Proposed system compared to two techniques the proposed fuzzy color extraction gives high image retrieval precision.

Fig 2 Some Sample Images from the Database

The WANG database is a subset of 1,000 images of the Corel stock photo database which have been manually selected and which form 10 classes of 100 images each. The WANG database can be considered similar to common stock photo retrieval tasks with several images from each category and a potential user having an image from a particular category and looking for similar images which have e.g. cheaper royalties or which have not been used by other media. The 10 classes are used for relevance estimation: given a query image, it is assumed that the user is searching for images from the same class, and therefore the remaining 99 images from the same class are considered relevant and the images from all other classes are considered irrelevant

Fig 3: Query Image

Fig 4: First 9 retrieved images from the database

The fig 3 shows the image retrieval based on RF with color feature give high performance for the query image with fast image matching.

V. CONCLUSION

In this proposed system there is three low-level feature extraction techniques are used. They are color, scalable and edge histogram. During the retrieval process, the user's high-level query and perception subjectivity are captured by dynamically updated weights based on the user's feedback. The search in text-based MPEG-7 descriptors is based on the keywords, quality assessments. Automatic extraction of low-level features and existing metadata is also supported. The proposed graph-based data model for MPEG-7 based semantic metadata and an indexing technique are used. The high-level feature extraction stored in an XML file. The experimental result shows the better performance compare with existing algorithm. The experiments are performed using WANG database which consists of 1000 images from 10 different classes. The experimental result shows that the proposed approach performs better in terms of precision compared to other existing systems.

REFERENCES

[1] J.-H. Su, W.-J. Huang, P. S. Yu, and V. S. Tseng, "Efficient relevance feedback for content-based image retrieval by mining user navigation patterns." IEEE Trans. Knowl. Data Eng., vol. 23, no. 3, pp. 360–372, 2011.
[2] P. Wu, S. C. H. Hoi, P. Zhao, C. Miao, and Z. Liu, "Online multi-modal distance metric learning with application to image retrieval," IEEE Trans. Knowl. Data Eng., vol. 28, no. 2, pp. 454–467, 2016.
[3] D. Zhang, J. Wang, D. Cai, and J. Lu, "Self-taught hashing for fast similarity search," in Proc. Int. ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2010, pp. 18–25.
[4] L. Gao, J. Song, F. Zou, D. Zhang, and J. Shao, "Scalable multimedia retrieval by deep learning hashing with relative similarity learning," in Proc. ACM Int. Conf. Multimedia (MM), 2015, pp. 903– 906.
[5] J. Cheng, C. Leng, P. Li, M. Wang, and H. Lu, "Semi-supervised multi-graph hashing for scalable similarity search," Comput. Vis. Image Underst., vol. 124, no. 0, pp. 12–21, 2014.
[6] J. Zhou, G. Ding, and Y. Guo, "Latent semantic sparse hashing for cross-modal similarity search," in Proc. Int. ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2014, pp. 415–424.
[7] X. Zhu, Z. Huang, H. T. Shen, and X. Zhao, "Linear cross-modal hashing for efficient multimedia search," in Proc. ACM Int. Conf. Multimedia (MM), 2013, pp. 143–152.
[8] Y. Gong, S. Lazebnik, A. Gordo, and F. Perronnin, "Iterative quantization: A procrustean approach to learning binary codes for large-scale image retrieval," IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 12, pp. 2916–2929, 2013.
[9] X. Zhu, Z. Huang, H. Cheng, J. Cui, and H. T. Shen, "Sparse hashing for fast multimedia search." ACM Trans. Inf. Syst., vol. 31, no. 2, p. 9, 2013.
[10] X. Zhu, X. Li, and S. Zhang, "Block-row sparse multiview multilabel learning for image classification," IEEE T. Cybernetics, vol. 46, no. 2, pp. 450–461, 2016.
[11] X. Shen, F. Shen, Q.-S. Sun, and Y.-H. Yuan, "Multi-view latent hashing for efficient multimedia search," in Proc. ACM Int. Conf. Multimedia (MM), 2015, pp. 831–834.
[12] L. Liu, M. Yu, and L. Shao, "Multiview alignment hashing for efficient image search," IEEE Trans Image Process., vol. 24, no. 3, pp. 956–966, 2015.
[13] B. Xu, J. Bu, C. Chen, C.Wang, D. Cai, and X. He, "Emr: A scalable graph-based ranking model for content-based image retrieval." IEEE Trans. Knowl. Data Eng., vol. 27, no. 1, pp. 102–114, 2015.
[14] L. Gao, J. Song, F. Nie, Y. Yan, N. Sebe, and H. T. Shen, "Optimal graph learning with partial tags and multiple features for image and video annotation," in Proc. IEEE Int. Conf. Computer Vision and Pattern Recognition (CVPR), 2015, pp. 4371–4379.
[15] J. Song, Y. Yang, X. Li, Z. Huang, and Y. Yang, "Robust hashing with local models for approximate similarity search," IEEE T.Cybernetics, vol. 44, no. 7, pp. 1225–1236, 2014.
[16] J. Yu, D. Tao, and M. Wang, "Adaptive hypergraph learning and its application in image classification," IEEE Trans Image Process.,vol. 21, no. 7, pp. 3262–3272, 2012
[17] T. Kanungo, D. M. Mount, N. S. Netanyahu, C. D. Piatko, R. Silverman, and A. Y.Wu, "An efficient k-means clustering algorithm: Analysis and implementation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 881–892, 2002.
[18] M. Sachan and S. Srivastava, "Collective matrix factorization for co-clustering," in Proc. Int. Conf.WorldWideWeb (WWW), 2013, pp. 93–94.
[19] N. Rasiwasia, J. Costa Pereira, E. Coviello, G. Doyle, G. R. Lanckriet, R. Levy, and N. Vasconcelos, "A new approach to cross-modal multimedia retrieval," in Proc. ACM Int. Conf. Multimedia (MM), 2010, pp. 251–260.

ISSN (Online): 2456-5717

International Journal of Advanced Research in Basic Engineering Sciences and Technology (IJARBEST)
Vol.4 Issue.3 March 2018

[20] T.-S. Chua, J. Tang, R. Hong, H. Li, Z. Luo, and Y. Zheng, “Nuswide: A real-world web image database from national university of singapore,” in Proc. ACM Int. Conf. Image and Video Retrieval (CIVR), 2009, pp. 48:1–48:9. 2010, pp. 251–260.