An Efficient Re-rank and Fuzzy based Color & Edge Feature Extraction for CBIR

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Abstract: *Recently, feature extraction methods are in require today for Content Based Image Retrieval (CBIR) and object recognition applications. In previous decade, large database of image sets has grown quickly and will continue in future. Querying and Retrieval of these images in efficient way is needed in order to access the visual content from huge database set. Content based image retrieval (CBIR) gives the explanation for competent retrieval of image from these huge image databases the new propose system attribute is called "Edge Directivity Descriptor and Colour" and integrates in a texture information and histogram colour with re-ranking feature. CEDD feature extraction development consists of a HSV colour two-stage fuzzy-linking algorithm. This descriptor is apposite for correctly retrieving images even in deformation cases such as bend, smoothing and noise. Imperative feature of the CEDD is the low computational power needed for its extraction, in association to the requirements of the most MPEG-7 descriptors. The researchers are makes using WANG database which consists of 1500 images from 10 different classes. Experimental result explains that the proposed approach execute better in terms of precision compared to other existing methods.*

Keywords: *Content based image retrieval; Re-ranking, Fuzzy Linking Algorithm; Color & Edge Features.*

I. Introduction

Recently, with the rapid progress of digit devices and the Internet, the amount of multimedia data (e.g. images, videos) are explosively growing. These huge databases have created a significant challenges in terms of scalable parallel search in the direction of many multimedia applications, such as content based Multimedia retrieval (CBMR), and classification. With large image databases becoming a reality both in industrial and scientific domains, content-based image retrieval (CBIR) becomes an significant research area in computer vision and it largely relies on perform away with the appropriate characteristic quantities are describing the desired contents of images. To engagement, there has been important research within frequent domains that aims to develop the accuracy of CBIR and most of them are center on designing sophisticated low-level feature origin techniques to reduce the semantic gap between the visual features and the wealth of human semantics.

The multimedia inside are increasing explosively and the need for multimedia retrieval is happening extra and more frequently in our daily life. Appropriate to the difficulty of multimedia contents, image understanding is a complicated but interesting issue in this field. Remove valuable knowledge from a large-scale multimedia repository, so-called multimedia mining, has been newly considered by some researchers. Normally, in the growth of an image requisition system, semantic image retrieval relies deeply on the linked captions, e.g., file-names, categories, annotated keywords, and other manual imagery. Regrettably, this type of textual-based image retrieval always suffers from two problems: unfortunate automated annotation and high-priced manual annotation. On one hand, high-priced manual annotation cost is excessive in handling with a large-scale data set. On the other hand, regrettable automated annotation yields the imprecise results for semantic image retrieval.

A quantity of potent image retrieval technique has been newly proposed to deal with such harms over the past few years. Content-Based Image Retrieval (CBIR) is the foundation of current image retrieval methods. In general, the function of CBIR is to present an image theoretically, with a set of low-level visual features such as colour, shape, and texture. These conventional techniques for image retrieval are based on the computation of the similarity between the image query and users via a query by example (QBE) system. In spite of the control of the search strategies, it is very hard to optimize the retrieval worth of CBIR within only one query method. The unseen problem is that the extracted visual features are too various to capture the concept of the user's query. To answer such problems, in the QBE method, the users can pick up some ideal images to refine the image explorations iteratively. The feedback formula, called Relevance Feedback (RF), repeats until the user is pleased with the retrieval results.

One of the center research problems in multimedia retrieval is to look for an efficient space metric/function for computing comparison of two objects in content-based multimedia rescue tasks. Over the past decades, multimedia researchers have exhausted much effort in designing a variety of low-level feature representations and diverse distance actions. Discovery a good distance metric/function remainder an open dare for content-based multimedia rescue tasks cultivate now. In recent years, one capable direction to address this challenge is to discover distance metric learning (DML) by relating machine learning approaches to optimize expanse metrics from training data set or side information, such as historical logs of user consequence response in content-based image retrieval (CBIR) methods[19].

II. Related Work

These days, content-based image retrieval (CBIR) is the foundation of image retrieval organization. To be more advantageous, relevance opinion methods were integrated into CBIR such that more accurate results can be achieved by pleasing user's feedbacks into account. Still, presented relevance feedback-based CBIR techniques are usually request a figure of iterative feedbacks to fabricate cultured search results, especially in a large-scale image database. Distance metric learning (DML) is an significant method to progress parallel search in content-based image retrieval. In spite of being considered extensively, most existing DML techniques usually adopt a single-modal learning structure that learns the distance metric on either a solitary feature type or a shared feature space where multiple types of features are simply concatenated. Such single-model DML techniques suffer from some critical restrictions: (i) learning a distance metric on the combined high-dimensional feature space can be extremely time-consuming using the naive feature concatenation approach; and (ii) a number of features may considerably control the others in the DML assignment due to dissimilar feature representations[14].

The capability of fast comparison search at large scale is of large consequence to many Information Retrieval (IR) applications. A capable way to increase speed comparison search is semantic hashing which propose compressed binary codes for a large number of papers so that semantically parallel papers are mapped to analogous codes (within a short Hamming distance). Novel unsupervised Multi view Alignment Hashing (MAH) technique based on normalize Kernel Nonnegative Matrix Factorization (RKNMF), which can find a compressed representation discovery the hidden semantics and concurrently respecting the joint prospect distribution of data set. The depart scalable graph-based ranking technique called Efficient Manifold Ranking (EMR), trying to address the deficiency of MR from two main perceptions: scalable graph structure and capable ranking computation. Specially, we build an anchor graph on the database as a substitute of a traditional k-nearest neighbour graph, and propose a new form of adjacency matrix developed to speed up the ranking [18].

Appropriate to the volatile enhance of the multimedia inside in recent years, scalable assessment search has concerned major concentration in many large-scale multimedia applications. Along with the dissimilar corresponding search methods, hashing based predictable nearest neighbour (ANN) search has become very accepted suitable to its computational and storage space capability. Still, most of the available hashing method normally adopt a single modality or include multiple modalities only without increase the consequence of different features. Latent Semantic Sparse Hashing (LSSH) to perform cross-model equivalent search by employing Sparse Coding and Matrix Factorization. In rigorous, LSSH uses Sparse Coding to confine the applicable organization of images, and Matrix Factorization to study the latent format from text. This method, dubbed iterative quantization (ITQ), has associations to multi-class spectral clustering and to the orthogonal Procreates problem, and it can be used mutually with unsupervised data set embeddings such as PCA and supervised embeddings such as canonical correlation analysis (CCA).

The ensuing binary codes considerably break numerous other state-of-the-art techniques. A hierarchical feature collection and a multiview multilevel (MVML) learning for multiview image categorization, via embedding a newly proposed a new block-row regularized into the MVML structure. The block-row regularized concatenating an L2,1-norm regularized and Frobenius norm (F-norm) regularized is intended to perform a hierarchical feature selection. An additional exiting dubbed multi-view latent hashing (MVLH), to successfully incorporate multi-view data set into hash code learning. In particular, the binary codes are educated by the latent factors collective by multiple views from a combined kernel feature space, where the weights of dissimilar views are adaptively learned according to the reconstruction error with each analysis. The existing semi-supervised explanation advance by learning an optimal graph (OGL) from multi-cues (i.e., partial tags and multiple features) which can more precisely embed the relationships between the data set point [20].

III. Proposed Approach

The newly proposed system near the removal of a new low-level feature that holds, in one histogram, texture information and image colour. This element is planned for employ in query image indexing methods and query image retrieval. Our Experimental results illustrate that the proposed feature can add in accurate image query retrieval. Its major functionality is image-to-image matching and its future use is for still-image retrieval, where an image can consist of either a single rectangular frame work or randomly shaped, perhaps disconnected, regions. This characteristic is called "Colour and Edge Directivity Descriptor" and incorporates colour and histogram texture information. The proposed size image is incomplete to 54 bytes per image, rendering this descriptor apposite for employ in large-scale image databases. One of the majority considerable attribute is the low computational power wanted for its removal, in contrast with the wants of the mainly MPEG-7 descriptors.

The image factor connected with the removal of image colour in sequence is called Color element. Equally, the Texture element is the unit connected with the removal of image and texture information. The histogram is comprised through 6 regions, resolute by the Texture Unit. Each region is comprised by 24 individual regions, emanating from the Color Unit. In general, the final histogram includes $6 \times 24 = 144$ regions. In organize to form the histogram; firstly we divide the image in an accurately 1600 Image Blocks. This number was chosen in regulate to compromise between the computational power and the query image detail. Each Image Block feeds sequentially all the units. If we describe the bin that results from the Texture Unit as N and as M the bin that results from the Color Unit, then the Image Block is located in the productivity histogram position: $N \times 24 + M$.

In the Image and Texture Unit, the Image Block is divided into 4 regions, the Sub Blocks. The value of each Sub Block is the denoted by the significance of the luminosity of the image pixels that contribute in it. The luminosity standards are derivative from the alteration through the YIQ color spaceof tha image. Each Image Block is then clean with the 5 digital filter, and with the use of the pentagon's illustration it is secret in one or more texture type. Imagine that the organization resulted in the second bin, which identify NDE (Non-Directional Edge).

A. Indexing

Indexing is done using an completion of the manuscript designer boundary. A plain advance is to use the manuscript designer Factory, which generate manuscript designer instances for all obtainable features as well as admired combination of skin texture (e.g. all MPEG-7 features or all available features). A manuscript designer is essentially a binding for image features generate a Lucene manuscript from a Java defences Image. The signatures or vectors remove by the feature implementations are envelop in the papers as text. The manuscript output by a manuscript designer can be added to a Lucene index. Indexing techniques that are in use on large image databases, authenticate by performance figures: data partitioning, space partitioning, and distance-based methods. In space-partitioning index methods, the feature space is ordered like a tree.

Dataset partitioning index methods relate, with each point in feature space, a region that represents the neighbourhood of that vector. An R-tree is such a dataset partitioning collection to index hyper rectangular regions in M-dimensional space. The leaf nodes of an R-tree symbolize the minimum bounce rectangles of locate of feature vectors. An interior node is a rectangle surrounding the rectangles of all its children. An R.-tree is a variation which does not permit the minimum bounce rectangles in a join to be related.

B. Color Information

In, a unclear organization was newly proposed to manufacture a unclear linking histogram, which obtain the three channels of HSV as inputs, and figure a 10 bins histogram as an output. Each bin symbolizes a present color as follows: (0) Black, (1) Gray, (2) White, (3) Red, (4) Orange, (5) Yellow, (6) Green, (7) Cyan, (8) Blue and (9) Magenta. These colors were chosen based on mechanism that were obtainable in the history. The technique presented is further improved, by recalculating the input membership value restrictions and resulting in a superior mapping on the 10 present colors. These new boundary computation are support on the position of the vertical edges of images that symbolizes the channels H (Hue), S (Saturation) and V (Value).

The use of coordinate logic filters (CLF) is originate to be the most suitable between other edge uncovering methods for formative the fine dissimilarity and lastly take out these vertical edges. In the process followed, each pixel is restore by the result of the organize logic filter "AND" operation on its 3x3 neighbourhood. The result of this achievement, stresses the edges of the image. The entire edges are exported by calculating the dissimilarity between the original and the clean image. Based on these edges, the inputs of the methods are analysed as follows: Type is separated into 8 unclear areas. Their limitations are shown in figure 2(a) and are defined as: (0) Red to Orange, (1) Orange, (2) Yellow, (3) Green, (4) Cyan, (5) Blue, (6) Magenta and (7) Blue to Red. S is separated into 2 unclear regions as they emerge in figure 2(b). This channel describes the blind of a color based on white. The first area, in mixture with the location of the pixel in channel V, is used to define if the color is clear sufficient to be ranked in one of the grouping which are illustrate in H histogram, or if it is a blind of white or gray color.

The intend of a method that come up to these sunglasses is based on the determinations of the slight vertical edges emerge in images with even change from the complete white to the complete black through a color. The use of the organize logic filter "AND" was establish to be suitable for formative these vertical edges too. The standards of V and S from each pixel as well as the worth of the bin (or the bins) resultant from the unclear 10-bins unit comprise admission in the 24-bins unclear Linking method. So much the channels V as well as channel S are alienated into 2 regions as they emerge in figure 2(d). This method really undertakes to category the input block in one (or more) as of the 3 hue areas derivative after the vertical edge removal process explain over. These hues are labelled as follows: Dark Color (as Color is used the color that attributed by the first 10-Bins system) - Color and Light Color. In this method, a set of 4 TSK-like rules with unclear antecedents and hard consequents were used. The Multi contribute technique was also employed for the assessment of the consequent variables.

C. Texture Information

The 5 digital strains that were newly proposed by the MPEG-7 Edge Histogram Descriptor - EHD. These clean are used for the removal of the texture's in order. They are clever to describe the edges being current in their application region as one of the following kind: horizontal, vertical, 45-degree diagonal, 135-degree diagonal and non-directional edges. The size of their application region will be describe in segment 4 and it is called henceforth Image Block.

Each Query Image Block is constituted by 4 Sub Blocks. The average gray level of each Sub-Block at (i,j)th Image-Block is definite as a0(i,j), a1(i,j), a2(i,j), and a3(i,j). The filter coefficients for horizontal, horizontal, 45-degree diagonal, 135-degree diagonal, and non-directional edges are labeled as fv(k), fh(k), fd-45(k), fd-135(k), and fnd(k), equally where k=0…,3 represent the position of the Sub Block. The individual edge magnitudes mv(i,j), mh(i,j), md-45(i,j), md-135(i,j), and mnd(i,j) for the (i,j)th Image Block can be attain as follows:

$$m_v(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_v(k)\right| \quad (1)$$

$$m_h(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_h(k)\right| \quad (2)$$

$$m_{d-45}(i,j) = \left|\sum_{k=1}^{3} a_k(i,j) \times f_{d-45}(k)\right| \quad (3)$$

$$m_{d-135}(i,j) = \left|\sum_{k=1}^{3} a_k(i,j) \times f_{d-135}(k)\right| \quad (4)$$

$$m_{nd}(i,j) = \left|\sum_{k=1}^{3} a_k(i,j) \times f_{vnd}(k)\right| \quad (5)$$

Then the max is calculated:

$$max = MAX(m_v, m_h, m_{d-45}, m_{d-135}, m_{nd}) \quad (6)$$

and normalize all m.

$$m_v = \frac{m}{max}, m_v \; m_h = \frac{m}{max}, m_h, m_{d-45} = \frac{m}{max}, m_{d-45}, m_{d-135} = \frac{m}{max}, m_{d-135}, m_{nd} = \frac{m}{max}, m_{nd} \quad (7)$$

The production of the unit that sell overseas texture's information since each Image Block is a 6-area histogram. Each area communicate to a region as follows: EdgeHisto(0) Non Edge, EdgeHisto (1) Non Directional Edge, EdgeHisto(2) Horizontal Edge, Edge- Histo(3) Vertical Edge, EdgeHisto(4) 45-Degree Diagonal and EdgeHisto(5) 135- Degree Diagonal. The way that the system categorize the Image Block in an area is the following: to begin with, the method checks if the max value is greater than a given entrance. This threshold describe when the Image Block can be classified as Non-Texture Block (linear) or Texture Block.

D. Re-Ranking

Category list of results base on some comparison metric beside with a low-level query image feature. Still, sometimes you need a clean or re-ranking procedure to obtain position afterwards. Query Re-Ranking permit you to run a easy query (A) for matching papers and then re-rank the top N papers using the scores from a more composite query (B). While the costlier ranking as of query B is only practical to the top N papers it will have less crash on presentation then just using the composite query B by itself – the trade-off is that papers which score very low using the effortless query image A may not be measured during the re-ranking phase, Still if they would score very highly using query B.

Two query images can be comparable beginning a semantic view even if their expressions or illustration features are not equal: diverse expressions can be used to articulate the similar impression (synonymy), and numerous colors can symbolize the similar entityof image and texture. In addition, the identical declaration (or color) might have dissimilar connotation depending on the context (polysemy). Modelling honestly at the expression or illustration feature level would miss this uncertainty. Existing methods are based on the classification of a latent space where the papers are represent in a disambiguated structure.

$$\hat{q} = q * V$$

Previously a manuscript collection has been procedure, the comparison among an un annotated image $\hat{q}$ and the annotated image corpus is calculated in the latent space. q is first predictable by right multiplying by V, the terms uttered in the latent space basis, after ledge, the comparison between $\hat{q}$ and each row of U (representation of the compilation in the latent space) is calculate using the cosine measure. The annotation is then disseminating as of the ranked papers. Observations are less consistent as the comparison between papers reduces.

E. Image Retrieval

Previously we have take out color, texture and shape feature vectors beginning the query image, as glowing as the database images, we can use these feature vectors to calculate the comparison among images in order toward recover the most parallel DB images to the query. The parallel among a query image q and a DB image d is definite by a distance among them, denoted as (q, d), which is review according to the remove color, texture and shape features. Two images are equal when the distance value among them techniques zero and the comparison among them engrave as the expanse value among them enhance.

IV. EXPERIMENTAL RESULTS

Data set images beginning the WANG database have been worn. This database contains a large number of images of a diversity of inside variety from animal images to outdoor sports to natural images. These images have been pre-classified into dissimilar grouping each of size 100 by field professionals. Several researchers are of the estimation that the Corel database convenes all the supplies to assess an image retrieval method, appropriate to its huge size and heterogeneous material. For our experiment result, we have collected more than 1000 images to form database DB1. These images are together from ten different domains, namely, beaches, Africans, buses, buildings, dinosaurs, elephants, flowers, mountains, horses, and food. Each category has different images with resolution of either 256- 384 or 384 -256. For each user query, the system gathers database images with the minimum image matching distance computed. If the recovered image belongs to same type category as that of the query image, then we declare that the system has suitably identified the probable image, or else, the system has unsuccessful to discover the expected image.

The test image query is matched with matched database image dataset to identify high frequency regions. Precision is the fraction of recovered documents that are applicable to the search. Precision gets all retrieved documents into account, but it can also be appraised at a given cut-off rank, considering only the highest results arrived by the system.

$$precision = \frac{|\{relevant\ documents\} \cap \{retrieved\ documents\}|}{|\{retrieved\ documents\}|}$$

Recall in IR is the fraction of the documents that are applicable to the query that are productively retrieved.

$$recall = \frac{|\{relevant\ documents\} \cap \{retrieved\ documents\}|}{\{relevant\ documents\}}$$

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

Table 1. Different type Query Image Category comparison

Data Set	**MIR Flickr**		**NUS-WIDE**		**CEDD-Rerank**	
	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 show the comparison of edge histogram EMR and Proposed 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**	**CEDD-Rerank**
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 show the comparison of edge histogram EMR and Proposed system compared to two techniques the proposed fuzzy color extraction gives high image retrieval precision.

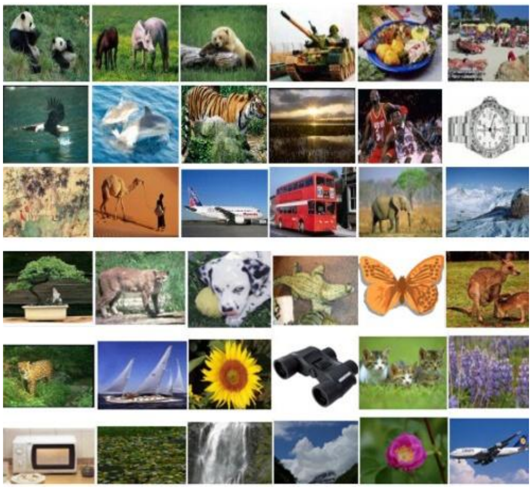

Fig 1: Some Sample Images from the Database

The WANG image database is a subset of 1,500 images of the Corel stock photo database which have been yourself selected and which form 10 classes of 150 images each. It can be considered comparable to common stock image retrieval tasks with numerous images from each grouping and a budding user having an image from a exacting category and seeming for comparable images which have e.g. cheaper royalties or which have not been worn by other media. The 10 classes are used for significance estimation: given a query input image, it is unspecified that the user is penetrating for images from the same class set, and therefore the remaining 149 images from the similar class are considered relevant and the images from all other classes are considered irrelevant

Fig 2: Query Image

Fig 3: First 9 retrieved images from the database

The fig 3 show the image retrieval based on CEDD give high performance for the query image with fast image matching.

V. Conclusion

The proposed system presents simple and fast feature removal techniques are in need today for Content Based Image Retrieval (CBIR) and object based recognition applications. In last decade, large database of query images has grown widely and will be continue in future. Image retrieval and querying of these image in efficient way is needed in order to process the visual content as of large database in image processing. Content based image retrieval (CBIR) gives the explanation for competent retrieval of query image as of these huge image query databases the newly propose system feature is called "Color and Edge Directivity Descriptor" and include in a histogram texture and color in sequence with re-ranking feature. CEDD feature removal procedure consists of a HSV color two-stage fuzzy-linking algorithm. This descriptor is suitable for exactly retrieving query images even in deformation cases such as noise, deformation and smoothing. Significant attribute of the CEDD is the low computational power needed for its removal, in assessment to the needs of the most MPEG-7 descriptors. The experiments are performed using WANG database images which consists of more than 1000 images from 10 dissimilar classes. Experimental result shows that the newly proposed approach performs better in terms of accuracy 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] N.Mahendran," Collaborative Location Based Sleep Scheduling with Load Balancing in Sensor-Cloud "International Journal of Computer Science and Information Security (IJCSIS), ISSN: 1947-5500, volume 14, Special Issue, October 2016, PP: 20-27.
[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] R Gomathi, N Mahendran, "An efficient data packet scheduling schemes in wireless sensor networks", in Proceeding 2015 IEEE international Conference on Electronics and Communication Systems (ICECS'15), ISBN: 978-1-4799-7225-8, PP:542-547, 2015
[19] S Vanithamani, N Mahendran, "Performance analysis of queue based scheduling schemes in wireless sensor networks", in proceeding 2014 IEEE international Conference on Electronics and Communication Systems (ICECS'14), ISBN: 978-1-4799-2320-5, PP: 1-6, 2014.
[20] P Kalaiselvi, N Mahendran, "An efficient resource sharing and multicast scheduling for video over wireless networks ",in proceeding 2013 IEEE international Conference on Emerging Trends in Computing, Communication and Nanotechnology (ICECCN'13), ISBN: 978-1-4673-5036-5, PP:378-383, 2013