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[Sharma* *et al.*, 7(1): January, 2018]
IC™ Value: 3.00

ISSN: 2277-9655
Impact Factor: 4.116
CODEN: IJESS7

IJESRT
INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

SURVEY PAPER ON CONTENT BASED IMAGE RETRIEVAL USING AUGMENTED K-MEANS CLUSTERING ALGORITHM

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DOI: 10.5281/zenodo.1135378

ABSTRACT
In this paper, we are surveying the different ways through which we can access the content of any image. As processors become increasingly powerful, and memories become increasingly cheaper, the deployment of large image databases for a variety of applications have now become realizable. Databases of art works, satellite and medical imagery have been attracting more and more users in various professional fields for example, geography, medicine, architecture, advertising, design, fashion, and publishing. "Content-based" means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, or descriptions associated with the image

I. INTRODUCTION
Image retrieval is the processing of searching and retrieving images from a huge dataset. As the images grow complex and diverse, retrieval the right images becomes a difficult challenge. For centuries, most of the images retrieval is text-based which means searching is based on those keyword and text generated by human's creation.[1] The text-based image retrieval systems only concern about the text described by humans, instead of looking into the content of images. Images become a mere replica of what human has seen since birth, and this limits the images retrieval. This may leads to many drawbacks which will be state in related works.

For decades, text in a given language has been set to order, to categorize and to search from, be it manually in the ancient Bibliotheke, or automatically Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. To overcome those drawbacks of text-based image retrieval, content-based images retrieval (CBIR) was introduced [2][3]. With extracting the images features, CBIR perform well than other methods in searching, browsing and content mining etc.

The need to extract useful information from the raw data becomes important and widely discussed. Furthermore, clustering technique is usually introduced into CBIR to perform well and easy retrieval. Although many research improve and discuss about those issues, still many difficulties hasn't been solved. The rapid growing images information and complex diversity has build up the bottle neck. Interpretation of what we see is hard to characterize, and even more so to teach a machine such that any automated organization can be possible. Yet, over the past decade, ambitious attempts have been made to make machines learn to understand, index and annotate images representing a wide range of concepts, with much progress.

II. LITERATURE SURVEY
Xianwang et al, [14] have developed a novel framework for low level feature and high level feature. To tackle the issues in leveraging low-level features (eg. Color) and high-level features (attributes) of clothing. To improve search quality by using re-ranking approach exploiting clothing attributes, including the type of clothing, sleeves, patterns, etc. The attributes have better robustness to clothing variations, and carry semantic meanings as high-level image representations.

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Theo et al, [15] has been proposed from color invariant edges which shape invariant features are computed. Color and shape invariant method are combined into a unified high-dimensional invariant feature set for the discriminatory object search.

Lingyang et al, [16] are retrieving the near duplicate images with large area of duplicates region, since the spatial structure of the near duplicate images could be described by the COP consistency.

Gaurav et al, [17] a reasonably accurate and fast color segmentation technique that leverages the strengths of region-based and edge-based segmentation. Also, a new parametric relevance feedback algorithm is explicitly utilizes information about non relevant examples.

Guo-Dong et al, [18] a content based image retrieval for the constrained similarity measure. The constrained similarity measure takes consideration for the perceptual similarity between images and improves the retrieval performance.

Issam El-Naqa et al, [19] a learning machine-based framework for modelling human perceptual similarity for content-based image retrieval. They are evaluated for retrieval of clinical mammograms containing clustered microcalcifications.

Hao et al, [20] have shown that Online Multiple Kernel Similarity (OMKS) significantly surpasses the state-of-the-art linear and nonlinear metric learning techniques for image similarity search.

Qianni et al, [21] a strategy for multifeature-based retrieval of history images database. The multifeature fusion model is a suitable model for feature combination based on multiple query images that are associated with the keyword in concern.

Hatice et al, [22] a weighting scheme inspired by IR theory, retrieval performance of the CBIR system is better than the traditional image-level retrieval. Its retrieval accuracy for all seven subtypes. There are two challenging diseases are inter reading and intra reading semantic variations. Both intra slide semantic variations, and inter subtype are visual similarities.

Dimitris et al, [23] a scheme involves block-based low level feature are extracted from images to form higher level clustering of the feature space. An expectation-maximization algorithm is clustering of the feature space that uses an iterative approach to automatically determine the number of clusters.

Md Mahmudur et al, [24] the probabilistic outputs of a multiclass support vector machine (SVM) classifier. SVM classifier is used for prediction of the query and database images are exploited. The image category information is utilized directly to filter out irrelevant images and adjust the feature weights in a linear combination of similarity matching.

Hayit et al, [25] the medical image retrieval for GMM-KL framework as a localized statistical framework. The similarity image matching measure for GMM-KL framework combines a continuous and probabilistic and region-based image representation scheme.

Jorma et al, [26] the self-organizing CBIR system named PicSOM and shown that MPEG-7-defined content descriptors can be successfully used. To implement relevance feedback, the PicSOM system is based on using SOMs from the user of the system.

Zhong et al, [27] a novel method for the feature subspace extraction. The progressive learning capability is the new feedback approach. This approach is based on a Bayesian classifier and treats positive and negative feedback examples with different strategies. They have proposed a new relevance feedback approach by integrating a feature subspace extraction process into a Bayesian feedback process in content-based image retrieval.

Lining et al, [28] a geometric optimum experimental design (GOED) a novel active learning method to select multiple representative samples in the database. The main problem in GOED can be small-sized training data. The Kernel Hilbert space has the geometric structure of unlabeled samples and to enhance the retrieval performance.

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Impact Factor: 4.116
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Igor et al, [30] to represent the information contained in the original images for geometrical constraints of the trace transform that can be optimized. The dimensionality reduction in terms of the mean and kurtosis value pairs of frequency coefficients has demonstrated. The results have a very robust set of features in terms of precision.
Mina et al, [31] a medical decision support system. The medical decision making system has been designed with normal and finding two certain abnormalities. The techniques used to find images with tumor and image of multiple sclerosis are the gray level co-occurrence matrices (GLCM). The supervised learning method like principal component analysis (PCA), and support vector machine (SVM) which help in classifying the normal images, and abnormal images.

Yang et al, [32] have a generalized brain state in a box (gBSB) based hybrid neural network. Using Hybrid neural network can store and retrieve large-scale patterns combining the pattern decomposition concept and pattern sequence storage and retrieval.

Esther et al, [33] to retrieve brain image using soft computing technique. The shape features are extracted using 2-D Zernike moment. The soft computing technique of Extreme Learning Machine is used with different distance metric measures like Euclidean, Quasi Euclidean, City Block, Hamming distance. The Fuzzy Expectation Maximization Algorithm is used to remove the non-brain portion of the MRI Brain image.

Rajalakshmi et al, [34] a relevance feedback method using a diverse density algorithm is used to improve the performance of content- based medical image Retrieval. The texture features are extracted based on Haralick features, Zernike moments, histogram intensity features and run -length features. The hybrid approach of branch and bound algorithm and artificial bee colony algorithm using brain tumor images.

Ahmed et al, [35] the efficacy of different types of features such as texture, shape and intensity for segmentation of Posterior- Fossa tumor. The four different techniques like PCA, boosting, KLD and entropy metrics demonstrate the efficacy of 249 real MRI of ten pediatric patients.

Murala et al, [36] a new image retrieval algorithm for local mesh pattern using biomedical image retrieval. The significant improvement for retrieval performance LBP with gabor transform and domain methods.

Manjunath, et al, [37] an image retrieval method using gabor texture feature. To measure the similarity of image. The retrieval performance of the texture is useful for region based retrieval.

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Table 1: Different Techniques, Dataset, Advantages & Disadvantages

S.No	Title	Author	Year	Dataset	No of Images	Method	Advantage	Disadvantage
1	Remote Sensing Image Retrieval with Global Morphological Texture Descriptors	Erchan Aptoula	May 2014	Land cover	2100 images	Mathematical Morphological	Execution time is lower	Description of irrelevant content
2	Trace Transform Based Method for color image domain identification	Igor et al,	April 2014	Corel , Geneye	1000 images, 1003 images	DITEC	Efficient, Robust, Accuracy	Recall and F-score measure have not been compared
3	Geometric Optimum experimental Design for Collaborative Image Retrieval	Lining et al,	February 2014	Small Scale Image	3139 images	GOED & CiR	Effective, to Achieve better performance	To difficult in small sized training data
4	Personal Clothing retrieval on Photo Collections by color attributes	Xianwang et al,	December 2013	Clothing database, Consumer photos	12823 images, 26324 images	Bags of visual words	It Improves retrieval efficiency and Robust	It has a Scalability Issue
5	Robust Spatial Consistency Graph Model for Partial Duplicate Image retrieval	Lingyang et al,	December 2013	Web Images	1 Million images	COP- Combined Orientation Position	Efficient, Robust, Effective and Increases speed	It is a Poor PR performance in over domination
6	Relevance feedback in CBIR Bayesian framework,feature subspaces and progressive learning	Zhong et al,	August 2013	Corel database	10000 images	PCA- principal component analysis	It is speed, reduces the memory and improve the retrieval accuracy	One positive example for each iteration
7	Histology Image retrieval in optimized Multifeature space image	Quianni et al,	January 2013	Histology database	20,000 images	Multiobjective learning method	More precise results, fusion model for each keyword	Direct linear multifeature retrieval did not bring significant improvement
8	Online Multiple Kernel Similarity Learning for visual search	Hao et al,	January 2012	Indoor database	15620 images	OMKS- Online Multiple Kernel Simiarity	It is more flexible and efficient	Learning similarity function for ranked image
9	A learning based similarity fusion & filtering approach for biomedical image retrieval using SVM classification & relevance feedback	Md Mahmudur et al,	July 2011	Biomedical images	5000 images	Similarity fusion approach	It is Efficient and effective	Linear search time without filtering is twice
10	CBIR system for human brain magnetic resonance image indexing	Mina et al,	October 2010	Human brain dataset	120 images	GLCM, PCA, SVM	It is easy to operate, non invasive,& inexpensive It is accurate & robust	There is an increase in image database, it requires fresh trainage each time

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Impact Factor: 4.116
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III. CONCLUSION

In past years, content-based image retrieval (CBIR) has been focused on research in image processing, low-level feature extraction, etc. CBIR systems should provide the semantic gap between low level feature and semantic retrieval. The method, advantages and disadvantages of the several approaches in content based image retrieval are discussed. Some other related issues and retrieval performance metrics are also discussed. In future, Humans aim to use the higher level feature in everyday life. The low level feature image is automatically extracted from the current computer vision techniques. In a general setting, the low-level features do not have a direct link to the high-level concepts. Some off-line and on-line processing need for semantic gap. The supervised learning, unsupervised learning, or the combination of the two is achieved in off-line processing. Neural network, genetic algorithms, fuzzy logic and clustering are such learning tools needed [39, 40, 41, 42]

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Sharma, M., Vidwans, A., & Bisen, A. S.. SURVEY PAPER ON CONTENT BASED IMAGE RETRIEVAL USING AUGMENTED K-MEANS CLUSTERING ALGORITHM. *INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY*, *7*(1), 41-46.