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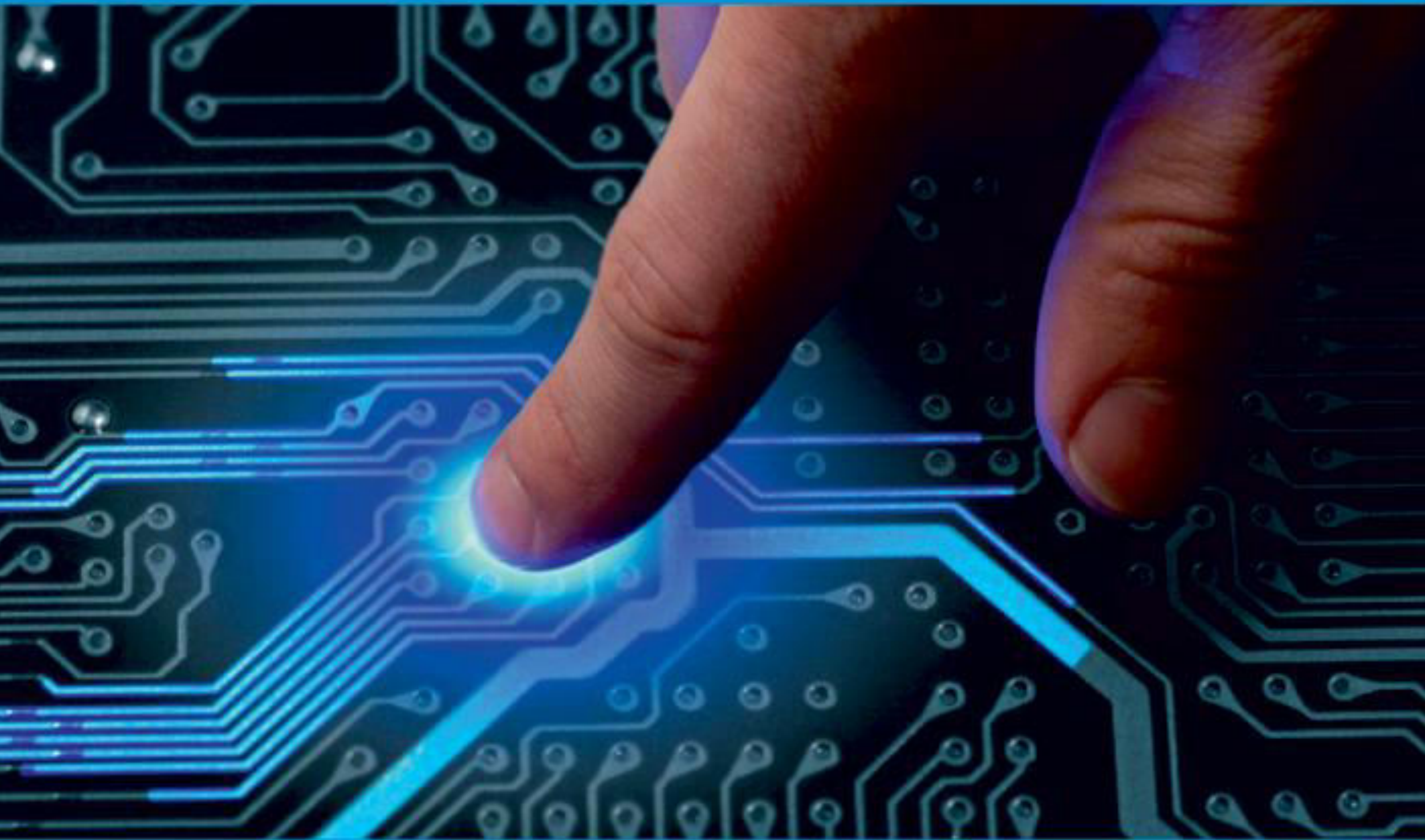

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Evaluating Image Retrieval Methods: A Comparative Analysis

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ABSTRACT: Image retrieval systems play a crucial role in a variety of applications, from digital asset management to medical imaging and security. This paper presents a comparative analysis of current image retrieval methods, focusing on their effectiveness, efficiency, and applicability across different contexts. We systematically evaluate several prominent techniques, including content-based image retrieval (CBIR), semantic-based retrieval, and hybrid approaches that combine multiple methodologies. The evaluation criteria encompass retrieval accuracy, computational complexity, and user interaction effectiveness. Through a series of experiments and case studies, we assess the performance of these methods using benchmark datasets and real-world scenarios. Our analysis highlights the strengths and limitations of each approach, providing insights into their suitability for specific applications. The findings aim to guide practitioners and researchers in selecting the most appropriate image retrieval method based on their needs and constraints. This study contributes to the understanding of image retrieval technologies and their impact on information retrieval systems.

KEYWORDS: Digital communication, Image retrieval, text-based image retrieval, content-based image retrieval.

I. INTRODUCTION

Image retrieval [10] is a computer technique for browsing, searching and retrieving images from a large database of digital images. Originally, TBIR techniques are using some keywords of the images to retrieve the target images. It is a manually image annotation technique. However, manual image annotation is expensive and time consuming, even mistaken. With the consideration of these questions, more and more researchers paid more attention to do some research on automatic image retrieval system. Content-based image retrieval [9] is an automatic image retrieval system. It extracts the feature vectors of all images in the database and then compares the feature vector of the query image to that of all the other images in the database for finding the nearest images.

Due to the development of large number of image databases, the exhaustible search is not generally well-suited. Feature space structuring methods such as clustering is necessary for organizing feature vectors of all images in order to facilitate and accelerate further retrieval. Clustering [3] aims to split a collection of data into clusters so that objects belong to the same cluster and dissimilar objects are in different clusters. Because the feature vectors only capture low-level information such as texture, color or shape of image or of a part of an image, there is a semantic gap between the low-level semantic features and high-level semantic concepts expressed by the user. The clustering technique fills the semantic gap to improve the performance of image retrieval. So, clustering methods are incrementally built to facilitate the image retrieval process.

In this article, an overview of previous researchers associated with the image retrieval using different approaches and algorithms are proposed. The main intension of this article is studying detailed information on different approaches and algorithms utilized for image retrieval. In addition, their limitations are addressed to further improve the image retrieval process effectively.

II. SURVEY ON IMAGE RETREIVAL TECHNIQUES

A novel clustering-based geometrical structure retrieval (C-GSR) method [11] was proposed for man-made target in synthetic aperture radar (SAR) images. Based on the Scattering Centers (SCs) coordinates and types of SAR images, SCs were grouped. From this, it C-GSR estimated the geometric structure of targets. Each peak in SAR image was assumed as a single SC and extracted both polarization and frequency features for classification. After that, SCs were clustered by using density-distance-based clustering algorithm. The geometric structure equivalent to each canonical scatterer was retrieved by manipulating the coordinates of SC related to the corresponding clusters.

Based on Convolutional Neural Network (CNN) a method [4] was presented for wafer map image retrieval. In the semiconductor manufacturing, rare event detection is critical to maintain high yield. For image retrieval, a binary code for each wafer map was generated from an output of fully connected layer with sigmoid activation. The CNN was trained by

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using theoretically generated data where rare defect patterns were included to the CNN model and yet achieved reasonable classification accuracy.

An interactive sketch-based image retrieval system called MindCamera [12] was proposed. In MindCamera system, a novel method of contour extraction was adopted to filter out backgrounds and textures from the images. By doing contour extraction, a high quality line-drawings dataset is formed. A Gradient Field Histogram of Gradient (GF-HOG) was used to include spatial information to Bag of Visual Words (BoVW). Then, a feedback of the sorted result was provided to combine the semantics which improved the precision of MindCamera.

Correlated Primary Visual Texton-Histogram Features (CPV-HF) [7] was proposed for content-based image retrieval. The CPV-HF was combined the visual content and semantic information of the image by finding correlation among the local spatial structure, color, intensity and texture orientation information of an image. For texture image analysis, box-shaped structural elements were designed according to the texton theory. Then, the local spatial structure, color, intensity and texture orientation features were represented by correlated attributes of the co-occurrence matrix. The co-occurrence matrix and histogram added necessary semantic information to image retrieval system.

An unsupervised multicode hashing method [8] was proposed for accurate and scalable remote sensing image retrieval. It signified each image with primitive cluster sensitive hash codes. The hashing method comprised of two steps is characterization of images by descriptors of primitive-sensitive clusters and description of multi-hash codes from the descriptors of the primitive-sensitive clusters. Finally, multi-hash code matching was employed to retrieve the images.
Dynamic kernel with deep CNN [14] was proposed for image retrieval. A dynamic match kernel was constructed by adaptively computing the matching thresholds between candidate images and query based on pairwise distance among deep CNN features. It was independent to the global appearance of the retrieved images. The dynamic kernel influenced the semantical similarity as a constraint for determining the matches. As a result, a semantic-constrained retrieval framework was proposed by combing the dynamic match kernel. It focused on matching patches between the filters and relevant images and removed the ones for irrelevant pairs.

A personalized Sketch-Based Image Retrieval (SBIR) system [5] was proposed by using CNN and deep transfer learning. Initially, the personalized SBIR incorporated a deep full CNN as a general model. Then, fine-grained image semantic feature was obtained by applying transfer learning. With the consideration of the images selected by the user in history and pre-trained general model, a personalized model training dataset was constructed. In addition to this, the user history feedback with the current hand-drawn image was combined as the input of the transfer learning model. It optimized the distribution of features in vector space, in order to that the neural network learned the personalized information.

Table 1. Comparison of Different Image Retrieval Techniques

Ref. no.	Year	Methods Used	Merits	Demerits	Performance Metrics
[11]	2017	Clustering-based geometrical structure retrieval	Accurately retrieve the geometric structure	Performance of C-GSR method depends on the selection of cutoff distance	Retrieved size (for Cylinder_0 canonical scatterer) = 19.5 Real size of Cylinder_0 canonical scatterer = 20 Retrieved size (for Dihedral_0 canonical scatterer) = 29.5 Real size of Dihedral_0 canonical scatterer = 30
[4]	2018	Convolutional Neural Network	Achieved reasonable classification accuracy	CNN cannot be trained well without having enough number of dataset and it is difficult to have enough data size in some cases	Retrieval error rate (test dataset) = 0.36% Retrieval error rate (real wafers) = 3.7% Retrieval time = 0.13 sec/wafer map
[12]	2018	MindCamera	High average precision	Feedback is affected by the accuracy of tags	Average precision (@ top 25 returned images) = 0.892
[7]	2018	Correlated	Enhance correlation	Low retrieval accuracy for	Accuracy and Recall(@

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		Primary Visual Texton-Histogram Features	strength with finer and more compact edge information	HSV color space	40 intensity level, 85 texture orientation quantization level, for RGB color space) = 61.85% and 7.42% Accuracy and Recall(@ 40 intensity level, 85 texture orientation quantization level, for HSV color space) = 57.81% and 6.93%
[8]	2018	Unsupervised multicode hashing method	Does not required any labeled annotated image	By increasing hash bits (b), both the retrieval time and the amount of memory required for storing the hash codes increase	Recall (@b=8) = 61.12% Time (@b=8) = 10×10^{-4}s Storage (@b=8) = Complexity (@b=8) = 0.061 KB Recall (@b=32) = 65.29% Time (@b=32) = 41×10^{-4}s Storage (@b=32) = Complexity (@b=32) = 0.068 KB
[14]	2018	Dynamic match kernel with DCNN	More effective	Additional time required for extracting deep features and calculating dynamic threshold	Mean Average Precision (mAP) (for Holidays dataset, fc_7 layer)= 87.92% Mean Average Precision (mAP) (for DupImages dataset, fc_7 layer)= 89.43%
[5]	2019	Personalized Sketch-Based Image Retrieval	Has strong generalization ability	Once the data relationship or data volume cannot meet the requirements, personalized SBIR will cause poor training results	Mean Average Precision (MAP) = 0.6449
[2]	2019	heterogeneity- aware multi resolution Local Binary Pattern	Preserve more texture information	Low F1 measure	Balanced Accuracy (BAC) = 0.8613 F1 measure = 0.7665
[13]	2019	Deep learning framework	High accuracy	Mostly misidentification is occurred in those images with multiple categories of features	Average error rate = 10.08% Time/second = 5.12 s Time efficiency = 0.176 Classification accuracy = 98.56%

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[1]	2019	Multi-modal procedure	It is based on known concepts but combined very judicious and effective way	The weak point of multi-modal procedure is the automatic choice of relevant images	P@20 (for First flickr images) = 0.4 P@20 (for text-based cluster images) = 0.4 P@20 (for visual cluster images) = 0.4 C@20 (for First flickr images) = 0.2727 C@20 (for text-based cluster images) = 0.3636 C@20 (for visual cluster images) = 0.5455

A heterogeneity-aware multi resolution Local Binary Pattern (hmLBP) [2] was proposed for retrieval of histopathology images. It was explicitly aware of the heterogeneity of local texture patterns through heterogeneity- based weighting. The LBP histograms were extended by using both homogeneity and the second moment of local neighborhoods. It had the capability to capture the polymorphism in the input histopathology images. The texture features were extracted from different resolution of histology image and texture features were combined together to form the final feature vector. Then, compact binary codes were extracted using rotation invariant binary codes which reduced feature vector dimensionality and comprised the vast majority of texture patterns. Finally, the histogram bins were weighted through counted LBP codes.

A deep learning framework [13] was proposed for fabric image retrieval. The idea of the deep learning framework was that the binary code and features for representing the image was learned by a deep CNN. The novel framework used a hierarchical search strategy that included the fine-level retrieval and coarse-level retrieval. Initially, the coarse-level retrieval was performed using binary codes and the then fine-level retrieval was performed using high-dimensional features.

A multi-modal procedure [1] was proposed for social image retrieval. The multi-modal procedure consisted of two steps are Formal Concepts Analysis (FCA) and Hierarchical Agglomerative Clustering (HAC). The FCA was used to arrange the text content of the images based on the concepts covered by the images. In the HAC, clustering was carried out that used to determine the topics addressed by the images. In order to estimate a relevance measurement for all the images in the dataset, an adaptive multi-modal relevance feedback algorithm was used. At last, the images were ranked by choosing the highest probability image at each text cluster. It generated a diverse and relevant ranked list.

III. CONCLUSION

In this article, a detailed review of image retrieval based on methods was presented. It shows all the researchers expressed various methods for image retrieval in order to enhance performance of image retrieval than the traditional methods. Based on the analysis, it is known that the multi-modal procedure [1] has better performance than the other methods. The main challenge of multi-modal procedure is to select the relevant and non-relevant images as closely as possible to behavior of human, which is still far from being achieved. Deeper analysis of clustering techniques could help to tackle this problem.

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