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Performing content-based image retrieval using rotated local binary pattern and multiple descriptors

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Feature Extraction

Similarity Measure

A B S T R A C T

Images have been viewed as a powerful medium for displaying visual information in numerous applications. Content-based retrieval and querying the indexed collections are required to access visual information. Content image retrieval is an efficient means of retrieving similar images from large repositories which require high speed and accuracy. The extraction of features is imperative for efficient results. Following research work aimed at colors and texture extraction for enhancing image metadata. The proposed technique was evaluated on WANG datasets using MATLAB. WANG consists of one thousand images of flowers, buildings and forest. Each category consists of one hundred images of size 187x126 or 126x187 in JPEG format. The features were extracted using RGB and HSV. Rotated Local Binary Patterns were used and distances between images was obtained using Euclidean algorithm. The results showed high accuracy and precision.

1. Introduction

The growth in computerized devices has elevated development in the multimedia industry. This significant growth has benefited diverse domains of science and social science in terms of visual contents of large amounts of digital data. The digital data may consist of images, image data involves raw images and information obtained through computer-assisted or automated image analysis [1]. The utilization of digital cameras has increased dramatically. In this decade, advanced transformation in imaging and transmission of digital images have been observed [2-3].

Newspapers, image providers and organizations are currently utilizing digital images in their databases. Images usually contain an abundance of touchy data. The search and retrieval of images in tiny databases is simple, but the database becomes enormous. Moreover, images are sorted based on keyword, making text-based search efficient for locating a particular image [4].

However, images in the databases are poorly labeled and sometimes unlabeled. Moreover, it is quite difficult to process images in a large sized repository [3]. Researchers have identified a variety of methods to capture, process, store, and transmit images from image repositories. The research area for viewing, browsing and restoring digital images of a large database is Image Retrieval (IR). The most common techniques of IR from image repositories are text-based retrieval and content-based retrieval [5-6].

Handling gigabytes of unlabeled and unstructured images over the web and in network computing systems, requires efficient and effective techniques [5]. Accurate and reliable information about retrieved images is inadequate, which makes it difficult to create an efficient image retrieval system [7].

Text based retrieval is time consuming and a difficult task (ibid). In addition, consistency is a major problem in manual tagging considering that a human annotator can neglect a meaningful image description and interpretation. Although a significant amount of research has been conducted yet the retrieval of images using text-based approach remains problematic task [5, 8].

In order to overcome the issues and challenges in text-based image retrieval, researchers have identified intelligent IR methods. Content-Based Image Retrieval (CBIR) is viewed as a standout among the best strategies for getting to visual data [9]. The CBIR is used to fix retrieval issues in identifying images in image repositories [10]. CBIR implies search on the basis of image content rather than using metadata [11]. It works on color, shape, texture, or other contents derived from the image and uses those contents to cluster images homogeneously. It implies searching for an image's real content. Images are to be retrieved by applying query on the image [12-13].

Moreover, most search engines operate entirely on image metadata and produce trash while CBIR works on the actual content to generate outcomes [14]. This technique uses content of images instead of using keywords that rely on humans. CBIR extracts the image's characteristics and then retrieves it [15]. The most significant part is to identify the silent information in the image which can help in bringing more accurate results [16-17].

2. CBIR Challenges and Issues

The in-depth analysis of literature revealed that CBIR is facing following challenges [18-21].

1. Understanding needs of users and behavior of information seeking.
2. Extraction of features from image repository according to the user's query.
3. Matching queries with images stored in the repository.
4. Noise removal of images stored in the repository.
5. Assessing the stored images by content.
6. Bridging the semantic gap in image retrieval.

3. Proposed Solution

A genetic algorithm is proposed to reduce the gap between outcomes of retrieval, it used the HSV method and luminance section isolated. Moreover, it has utilized surface highlights like entropy dependent on grey level co-occurrence in edge histogram. Furthermore, this procedure is compared with others methods and received better results. Numerous techniques have been developed to reduce this gap. The extraction of features is necessary for efficient results. To assess and analyze issues in achieving perfect extraction, multiple techniques have been proposed based on the user's needs [22-23].

In this research, a system is introduced to extract features on the basis of colors and in finding more accurate retrieval. The main contribution of this research is to design systems and improve CBIR for most effective retrieval. The objective is to extract features (color, texture) from images and fuse them together by applying RGB, HSV histograms and rotated local binary pattern method to improve the retrieved information. Fig. 1 depicts the basic flow of proposed CBIR for image retrieval.

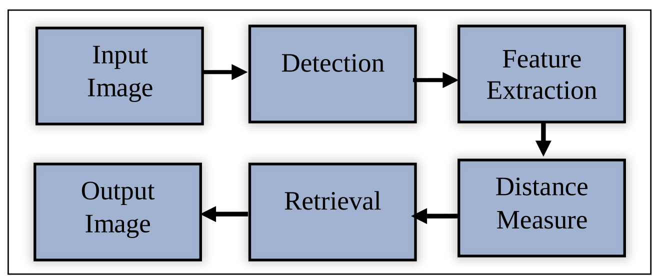

Fig. 1. Basic flow of proposed CBIR

Images representation is made by using appropriate feature vector space, the vector space provides meaningful information of picture properties. Feature selection acts as an important aspect in representing greater accuracy of the image. The essential parts of the CBIR framework are extracting attributes, storing images, specifying vector quantities and estimating closeness of the images [14, 24]. The input image is a Query Image (QI) selected by the user; it is used to extract similar content from the database. Database is created in the preprocessing step. Firstly, QI is submitted, image characteristics and features are extracted. The extracted features follow multiple steps. The steps are discussed later in this paper. After initial QI processing, features are grouped together and stored in an array. The scheme extracts descriptors of the color and texture of all images in the repository the same way as QI. The features vectors are then compared to obtain similar images. The extracted features value is compared with the QI value. When the distance is small, the retrieved image is similar to QI. The main focus to achieve is to enhanced precision. The research focuses on retrieving images that are similar to QI. The detailed work flow of the proposed system is shown in Fig. 2.

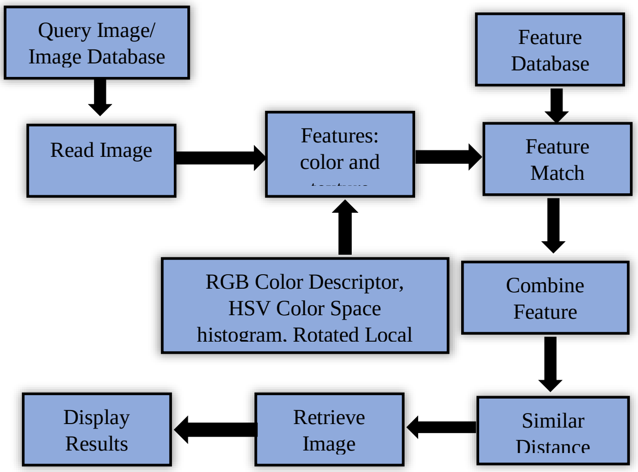

Fig. 2. Workflow of Proposed CBIR using Rotated Local Binary Pattern

3.1 Image Pre-Processing

Fig. 3 shows steps involved in image processing. The first step image is provided as an input. In second step, RGB color histogram is extracted. Then it is converted into a HSV color space. The "rgb2hsv" function is used for converting the RGB image into HSV.

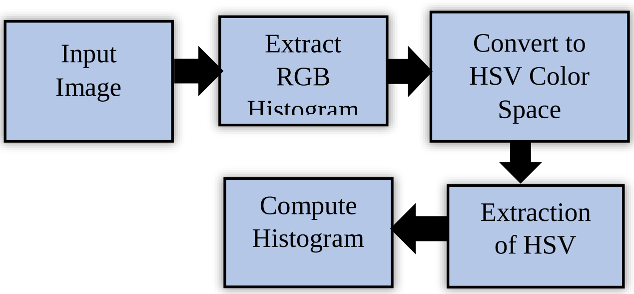

Fig. 3. Steps of Image Processing

3.1.1 Color histogram descriptor

A color histogram shows the number of pixels in a color area list containing hues. An image histogram is generated by discretizing colors of image in various containers and number of pixels in each container. Once extracted, a histogram is created using bits representing each component of the RGB pixel. When pixels of various colors are processed in an image, the color space into a specific number of little intervals are separated. Each interval is known as a bin. The histogram consists of 48 bins with a small range of pixel values defined by each bin. The value stored in each bin indicates pixel number within the image range [18]. These ranges depict the RGB element's intensity levels. The values in each bin are normalized by dividing the total amount of pixels in the image. The values of a color histogram show statistical distribution of colors [7, 25].

3.1.2 HSV (hue, saturation, and value) color space descriptor

HSV color space is used to detect an object with specific color and reduce influence of light intensity from outside [9].

The amount of gray in the color is between 0 and 100 percent saturation. When saturation is reduced to zero, a gray attenuation effect will be created. The selection of HSV color begins with the selection of one of the available tones. The tones are then adjusted for shades and brightness.

3.2 Processing Steps

In this research, the Rotated Local Binary Pattern (RLBP) Descriptor for feature extraction is used.

3.2.1 Rotated local binary pattern (RLBP)

The RLBP works for both rotated images and normal images. It chooses the middle of the image encircled by eight neighbors and determines the direction of dominance and moves the pixel in that direction. Every pixel value is assigned a weight. The weights at which pixel values are higher than the center are added to determine the total value. RLBP only looks at the pixel weight and utilizes it during the procedure [26-27]. The primary concept behind the enhanced RLBP is to prepare bit adjustments in order to eliminate the noise in the image and to make the findings more precise.

Using built-in features of MATLAB, different characteristics are obtained from both QI and images in the image repository. The QI pixel values, as well as images, are indexed in the repository. An array is kept where the image list is stored. After storing these values, the next step is to find pixel values exist both in the QI and in the images data set.

3.2.2 Texture descriptor

The descriptor of the texture characterizes textures or areas of image. It observes homogeneity of the region and histograms of the boundaries. They are designed to capture the general characteristics of textures in order to describe texture similarity. It can detect the boundaries of objects that are characterized more by texture than by intensity [25, 27]. The algorithm being utilized is texture classified. RLBP classifies the texture element in the image.

3.3 Similarity Comparison

The repository contains various techniques for calculating similarity between vectors of QI feature and vectors of image feature. Euclidean distance (Eq. 1) is used in this research for its higher accuracy, the formula calculates the similarity between the QI feature vector and the Database Image.

$$\text{ED (QI-DBI)} = \sqrt{\sum(QI - DBI)^\wedge 2} \qquad (1)$$

3.4 Retrieval Process

In the recovery process, the following steps are performed.

Step 1: Input the QI
Step 2: Extract features by utilizing RLBP and Local Binary Patterns (LBP)
Step 3: Collect relevant images from the repository
Step 4: Read the images individually
Step 5: Extract characteristics using the above-mentioned techniques
Step 6: Compare the QI with the images of the database by Euclidean distance.
Step 7: Save the results.
Step 8: Sort the results.
Step 9: Display the images that match. The search is based on similarity instead of the precise match.

4. Experiment Results and Discussion

The strategy is tested on a Wang dataset consisting of 1000 different content pictures. These images were pre-characterized into 10 different sizes of 100 categories. The ten distinct image classes were used. The images are either 187x126 or 126x187 in JPEG format. MATLAB is a powerful tool that offers strong numerical assistance for sophisticated algorithm execution. Moreover, MATLAB offers many features for image processing and deep learning. Image processing toolbox provides many built-in libraries to extract color, texture features in the image. For implementation of the system, this research utilized tools and built-in libraries in MATLAB.

4.1 Experimental Results for RGB, HSV, RLBP

4.1.1 Performance parameters

To evaluate the performance, relevant images were retrieved in response to query image. The effectiveness of CBIR is assessed by calculating values of precision and recall. The resulting images were determined by distance between a query image and images from the Euclidean.

4.1.1.1 Precision: Precision was used to determine the number of relevant images retrieved in response to query image and shows the image retrieval system's specificity. It is the fraction of retrieved images that are relevant to the input image.

$$\text{Precision} = \frac{number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ images\ retrieved}$$

4.1.1.2 Recall: Recall is the ratio of correct images retrieved to the total number of images of that class in the dataset. It is the fraction of images relevant to the query that are retrieved successfully.

$$\text{Recall} = \frac{Number\ of\ relevant\ images\ retrieved}{Number\ of\ relevant\ images\ in\ the\ database}$$

Table 1

Evaluation of Precision and Recall Measurements

Classes	Semantic	Precision	Recall
1	Dinosaurs	0.99	0.86
2	Ducks	0.98	0.94
3	Flowers	0.61	0.58
4	Horses	0.99	0.98
5	Mountains	1	0.87
6	Food	0.97	0.80
7	Buses	1	0.88
8	Building	0.96	0.78
9	Cards	1	0.87
10	Humans	0.99	0.85

4.1.1.3 Graph representation: The y-axis represents the retrieval percentage while x-axis represents the number of classes.

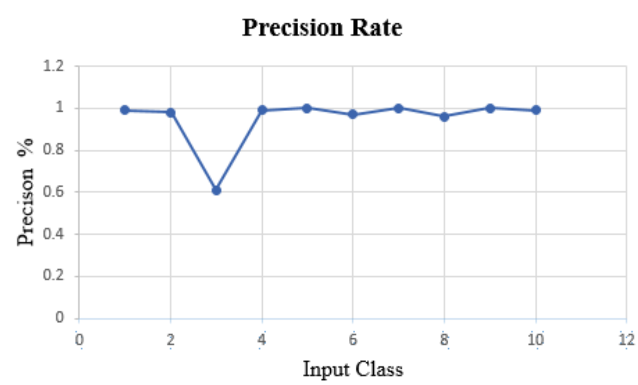

Fig. 4. Precision Rate

Overall Precision (OP) = (Total Precision ÷ Total number of classes) x 100, total Precision = 9.49 and total number of classes =10; therefore OP =94.9%.

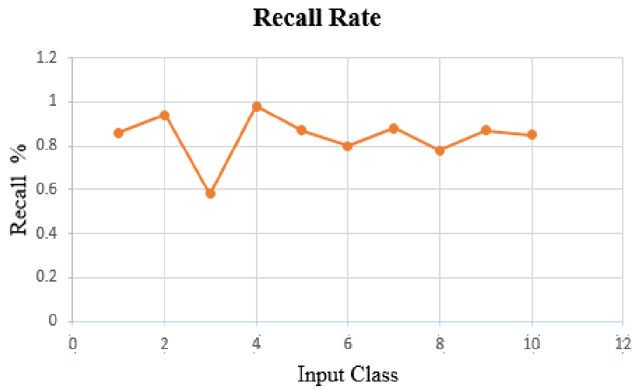

Fig. 5. Recall Rate

The graphical representation depicts that combining RGB + HSV + RLBP provides better results. Lowest results were achieved from class 3 but overall, 94.9% precision (OP) is achieved.

4.1.1.4 Research synthesis: In this section, different CBIR techniques are compared with proposed techniques based on RLBP. The comparison was performed based on color and texture characteristics to represent images. The maximum average accuracy attained is nearly 95%. Table 2 demonstrates that the suggested RLBP scheme works considerably better than other schemes. The rotated local binary when combined with color histograms gave much higher results as compared to previous works.

5. Conclusion

Owing to the development of the internet, digital media has risen significantly. Image retrieval systems play a significant role in extraction and management from image repositories. Content-based image retrieval provides and processes images based on resemblance to the query image. Many proposed techniques use gray scale images. The proposed technique works by extracting image features and then comparing those characteristics for similarity measures.

Colored images are used to extract the RGB color that is converted to HSV color space. Histogram method is used. Textures are extracted using a rotated algorithm. Both methods are combined to achieve better results.

Euclidean distance is used to discover the similarity metric between the images. WANG image repository is used containing one thousand images in ten classes. The images are categorized by sorting algorithm according to similarity.

The performance was evaluated by calculating the Precision and Recall matrices. The efficiency is improved through the extraction and integration of color and texture in one feature vector. Afterwards, similarity between the images is calculated. The experimental results showed significance of proposed system and increased average precision retrieval accuracy of 94.9%. The color extraction technique with LBP for texture was also implemented resulting in better results.

Table 2

Comparative Study Analysis

Authors (Year)	Techniques	Descriptors	Results
Kokare et al., (2004)	Cosine modulated wavelet transform	Texture	74.78%
Yue et al., (2011)	HSV color space GLCM.	Color Texture	50%
Mounika et al., (2016)	RGB histogram Grid coding, Principal component analysis	Color	61%
Apostol, (2015)	LBP Intensity Histogram	Texture Color	54.28% 31.42%
Benco et al., (2014)	GLCM Gabor filters	Texture	80%
Vikhar and Karde, (2017)	Edge Histogram Descriptor Gabor wavelet	Texture	60%
Kumar and Shukla, (2017)	co-occurrence matrix wavelet movements	Texture Edges	77.7%
(Alsmadi, 2017)	memetic algorithm	Shape Edges	76.5%
(Islam et al., 2017)	fuzzy rough set model	Color Structure descriptors	84%
Annrose and Seldev Christopher, (2018)	GLCM dominant color descriptor color	Texture Shape Color	81%
Annrose et al., (2018)	LBP GLCM	Texture	83.18%
Proposed Technique	RGB HSV RLBP LBP Euclidean Distance	Color Texture	94.9%

6. Future Work

Though high precision and accuracy was achieved using color and texture, however it is insufficient to depict and explain images. The results showed that some of the retrieved images do not match to the query image. The need is to reduce semantic gap and to indulge more features of the image. In order to gain greater accuracy between low-level and high-level features, it is required to work on semantic gap for its reduction.

7. References

[1] M. Paulin, M. Douze, Z. Harchaoui, J. Mairal, F. Perronin, and C. Schmid, “Local convolutional features with unsupervised training for image retrieval”, Proceedings of the IEEE International Conference on Computer vision, pp. 91–99, 2015.

[2] L. Zhu, J. Shen, L. Xie, and Z. Cheng., “Unsupervised visual hashing with semantic assistant for content-based image retrieval”, IEEE Transactions on Knowledge and Data Engineering, vol. 29, no. 2, pp. 472–486, 2016.

[3] M. E. Elalami, “A novel image retrieval model based on the most relevant features”, Knowledge-Based Systems, vol. 24, no. 1, pp. 23–32, 2011.

[4] Z. Zhang, F. Zhou, S. Qin, Q. Jia, and Z. Xu, “Privacy-Preserving Image Retrieval and Sharing in Social Multimedia Applications”, IEEE Access, vol. 8, pp. 66828–66838, 2020.

[5] L. Piras, and G. Giacinto, “Information fusion in content based image retrieval: A comprehensive overview”, Information Fusion, vol. 37, pp. 50–60, 2017.

[6] W. Li, L. Duan, D. Xu, and I. W.-H. Tsang., “Text-based image retrieval using progressive multi-instance learning”, IEEE International Conference on Computer Vision, pp. 2049–2055, 2011.

[7] J. Yue, Z. Li, L. Liu, and Z. Fu, “Content-based image retrieval using color and texture fused features”, Mathematical and Computer Modelling, vol. 54, no. 3–4, pp. 1121–1127, 2011.

[8] Y. Liu, D. Xu, I. W. Tsang, and J. Luo, . “Textual query of personal photos facilitated by large-scale web data”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 5, pp. 1022–1036, 2010.

[9] S. Kumar, and A. K. Shukla, “Design and analysis of CBIR system using hybrid PSO and K-mean clustering methods”, International Journal of Current Engineering Technology, vol. 7, pp. 397–401, 2017.

[10] I. Dimitrovski, D. Kocev, S. Loskovska, and S. Džeroski, “Improving bag-of-visual-words image retrieval with predictive clustering trees”, Information Sciences, vol. 329, pp. 851–865, 2016.

[11] B. Mounika, Y. Sowmya, S. Pasala, and A. Sravani, “Content-based image retrieval using color”, International Journal of Appllied Engineering Research, vol. 11, no. 6, pp. 4331–4334, 2016.

[12] M. N. Munjal, and S. Bhatia, “A novel technique for effective image gallery search using content based image retrieval system”, IEEE International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), pp. 25–29, 2019.

[13] P. Vikhar, and P. Karde, “Improved CBIR system using edge histogram descriptor (EHD) and support vector machine (SVM)”, IEEE International Conference on ICT in Business Industry and Government, pp. 1–5, 2016, pp. 1–5.

[14] A. Latif, et al., “Content-based image retrieval and feature extraction: A comprehensive review”, Mathematical Problems in Engineering, doi: 10.1155/2019/9658350, 2019.

[15] M. K. Alsmadi, “An efficient similarity measure for content based image retrieval using memetic algorithm”, Egyptian Journal of Basic and Applied Sciences, vol. 4, no. 2, pp. 112–122, 2017.

[16] S. Wei, L. Liao, J. Li, Q. Zheng, F. Yang, and Y. Zhao, “Saliency inside: learning attentive CNNs for content-based image retrieval”, IEEE Transactions on Image Processing, vol. 28, no. 9, pp. 4580–4593, 2019.

[17] A. J., and S. R., “A faster secure content-based image retrieval using clustering for cloud [Formula presented]”, Expert Systems with Applications, vol. 189, no. March 2021, p. 116070, 2022.

[18] N. Soni, and L. Pinjarkar, “Content Based Image Retrieval (CBIR): Review and Challenges”, International Journal of Engineering Sciences and Research Technololgy, vol. 6, no. 6, pp. 171-174, 2017.

[19] H. Wang, D. Mohamad, and N. Ismail, “Approaches, Challenges and Future Direction of Image Retrieval”, Journal of Computing, vol. 2, no. 6, pp. 193–199, 2010.

[20] S. M. Islam, M. Banerjee, S. Bhattacharyya, and S. Chakraborty, “Content-based image retrieval based on multiple extended fuzzy-rough framework”, Applied Soft Computing, vol. 57, pp. 102–117, 2017.

[21] N. Keisham, and A. Neelima, "Efficient content-based image retrieval using deep search and rescue algorithm", Soft Computing, vol. 26, no. 4, pp. 1597–1616, 2022.

[22] K. N. Sukhia, M. M. Riaz, and A. Ghafoor, "Content-based retinal image retrieval.pdf", IET Image Processing, vol. 13, no. 9, pp. 1525–1534, 2019.

[23] M. Benco, R. Hudec, P. Kamencay, M. Zachariasova, and S. Matuskal, "An advanced approach to extraction of colour texture features based on GLCM", International Journal of Advanced Robotic Systems, vol. 11, no. 1, pp. 1-8, 2014.

[24] J. Annrose, and C. Seldev Christopher, "An efficient image retrieval system with structured query based feature selection and filtering initial level relevant images using range query," Optik, vol. 157, pp. 1053–1064, 2018.

[25] S. Kodituwakku, and S. Selvarajah, "Comparison of color features for image retrieval", Indian Journal of Computer Science and Engineering, vol. 1, no. 3, pp. 207–211, 2004.

[26] R. Mehta, and K. Egiazarian, "Dominant Rotated Local Binary Patterns (DRLBP) for texture classification", Pattern Recognition Letters, vol. 71, pp. 16–22, 2016.

[27] O. A. B. Penatti, E. Valle, and R. D. S. Torres, "Comparative study of global color and texture descriptors for web image retrieval", Journal of Visual Communication and Image Represention, vol. 23, no. 2, pp. 359–380, 2012.

