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# IR-HF-WED: IMAGE RETRIEVAL USING HYBRID FEATURE EXTRACTION WITH WEIGHTED EUCLIDEAN DISTANCE

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ABSTRACT. Attributable to the fast development of image acquisition and storage modernization, image retrieval plays a key role in different applications such as Medical Imaging, Visual Data Mining etc. Due to high storage complexity Image Retrieval needs complex algorithms to retrieve images in efficient and fast manner. Image Retrieval technique using Hybrid Feature Extraction with Weighted Euclidean Distance (IR-HF-WED) is proposed to reduce the time complexity and increase the accuracy. Multiple features are extracted using Color Co-occurrence Matrix (CCM), Histogram of oriented Gradient (HoG), Compound Local Binary Pattern (CLBP) and Difference Between Pixels of Scanned Patterns (DBPSP). The proposed algorithm is tested and analyzed by comparing with Absolute Distance (AD), Euclidean Distance (ED), Cross Correlation (X) distance matching techniques and it is found that IR-HF-WED outperforms with respect to Precision and Recall compared to the [1, 2].

## 1. INTRODUCTION

Advancements in solid state electronics have led to increase in the number of digital devices like mobile phones, digital cameras etc. A huge number of digital images are captured through them for analysis, storing and indexing large data in a digital database is a challenge [1]. For big data applications, retrieval of data plays a vital role, however this process has to be accurate and

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efficient for the analysis to be performed on the retrieved data at latter phase. Thus, considering an application that is designed for image analysis, retrieval of images is a major task that is poised with challenges like real-time retrieval, feature extraction quality and retrieval cost [3].

Traditionally, image retrieval methods are divided in-to two types as: Text-Based Image Retrieval (TBIR), and Content-Based Image Retrieval (CBIR). TBIR [4] uses metadata to find the relevant image and the metadata are indexed and stored in a large-database, whenever a query is placed in search bar, the search engine gazes into the index and if any matches are found it will exhibit the matching pictures to the request for its significance without considering any characteristics of the images. Although it takes less time to respond but it is impossible to annotate each and every image in the database and also there is an additional storage cost incurred due to the use of metadata.

The CBIR derives features of the images and indexes them. It retrieves the color, shape, texture, motion etc., and stores the retrieved features in the form of vectors called descriptors. To retrieve local features from the images CBIR extracts low-level visual features from the images. A typical CBIR system should be able to understand the query and it should be aware of the content where it is being utilized [5].

*Motivation:* In a large scale image search, the descriptors of the images are mapped with other images. The distance among the images are determined to build image correlation score that is used to find similarity of two given images. Image equalization is then used for image comparison that is usually bound to linear complexity. Due to the uncertainty in quantization error, irrelevant pictures may have the equivalent visual words and they lead to image mismatch and thus false positive result occurs to a given query. There is a need for an efficient algorithm to improve the accuracy and processing time of CBIR [2,6].

*Contributions:* The main contributions are:

(i) The Retrieval time of a model is reduced comparatively with respect to the existing systems [1,2].
(ii) The Precision of a model is increased compared to existing system [1].

*Organization:* The paper is organized as follows: A brief description of research work on image retrieval techniques is presented in section 2. The algorithm and proposed system is explained in section 3. Results are analysed in section 4. Conclusions are presented in section 5.

## 2. Related work

In this section, the publications that are related to the image retrieval technique for big data applications are reviewed.

Yue et al., [5] proposed a strategy to extract the image color and texture feature using CBIR. In this method to meet the visual requirements images are transformed from Red Green Blue (RGB) to Hue Saturation Value (HSV). Then image Color Histogram (CH) and the texture features are extracted through co-occurrence matrix and are utilized for image retrieval. Elalami et al., [7] presented a model to retrieve images from the database that uses the features which increases the retrieval rate and reduce the computation time. In this method, for extracting respective texture and color features, 3D CH, the Gabor filter and genetic algorithm is utilized in substituting the numerical features with nominal features to represent numerical domain intervals using discrete values. Finally, preliminary and deep reduction functions are used in selecting the matched features from the original feature set. Precision of the system is increased.

Gao et al., [8] devised a retrieval method based on cross-region matching. The query image is related with other images in the database through different locations and scales. It follows the probabilistic ranking technique to sort the images. Further, Liu et al., [9] conceptualized an image retrieval method that utilizes neighbor reversibility correlation. In this method, the image has highest neighbor reversibility correlation is ranked ahead of other images in the list. Hence, needs more computation time. To avoid this, inside subspace learning neighbor reversibility correlation is used to transform the image from their global feature into low dimensional representation.

Rao et al., [10] illustrated the use of Local Quantized Extrema Patterns (LQEP) for feature description. It is a combination of Local Quantized Patterns (LQP) and Directional Local Extrema Patterns (DLEP). The LQP accumulates the directional association among the center and neighbor pixels. DLEP, accumulates the directional information depending upon the local extrema in the directions of $0°$, $45°$, $90°$, $135°$. Initially, directional quantization information of the image is collected using LQP and the quantized information using DLEP, directional extrema computed. Finally, the feature vector is generated through integrating color histogram with LQEP. However, precision of the model is comparatively less. Similarly, Shamna et al., [11] developed a CBIR method through visual words for spatial matching of the images. It uses Skip Similarity Index to find spatial similarity among the medical images. The correlation between significant visual words required to be increased for accurate retrieval process.

Yasmin et al., [12] suggested image retrieval method dependent over color, edge and inner pixel features. In this method initially, the whole image is decomposed into small matrix and then they are classified based on the image pixels, further edge detection is applied. Then images that exhibit same color feature is clustered to reduce the query response time.

## 3. Proposed Image Retrieval System

3.1. **Background.** The CBIR was suggested for about decade, the necessity of image databases, users interaction, image similarity learning, the semantic gap with the image features, the problem of computation and image analysis are the main issues involved in CBIR and need to be considered for an improvement. The existing image retrieval system necessitates manual annotation and classification over the image database, the query is processed with TBIR. Thus, the non-standard description and manual intervention are the drawbacks of such development methods. Accordingly, with increasing development in the size of the digital images, browsing and searching of unannotated images in image database is conquering importance. To overcome the understanding of images, the proposed method extracts hybrid features, which uses Weighted Euclidean distance that measures similarity between images to accomplish high precision in image retrieval.

3.2. **Problem Statement.** Develop an Image Retrieval model to efficiently retrieve the images from the database.
*Objectives:*

(i) To reduce the retrieval time and
(ii) To enhance the retrieval accuracy

The objective is to propose an efficient, accurate image retrieval method by developing an improved visual similarity search which uses a nearness function that efficiently measures images similarity by higher precision value. This work proposes a new and efficient framework for retrieving relevant images from the database in a faster way without compromising the accuracy. The enhanced feature extraction technique is modelled using several features *viz.*, Grey Co-occurrence Matrix (GCM), CCM, DBPSP, CLBP and the HoG.

The proposed system is conceptualized as three modules namely, the pre-processing, feature extraction and the retrieval module. In the initial module, the image undergoes the pre-processing operations to meet the visual requirements as required by the remaining modules. Then, the image features are extracted in the feature extraction module. Finally, the images are matched based on the extracted features through precision, recall and retrieval time. The extracted features are further combined to reduce the image retrieval time. For reuse, a separate database is maintained where the images are stored along with its extracted features. Then, the developed model is evaluated.

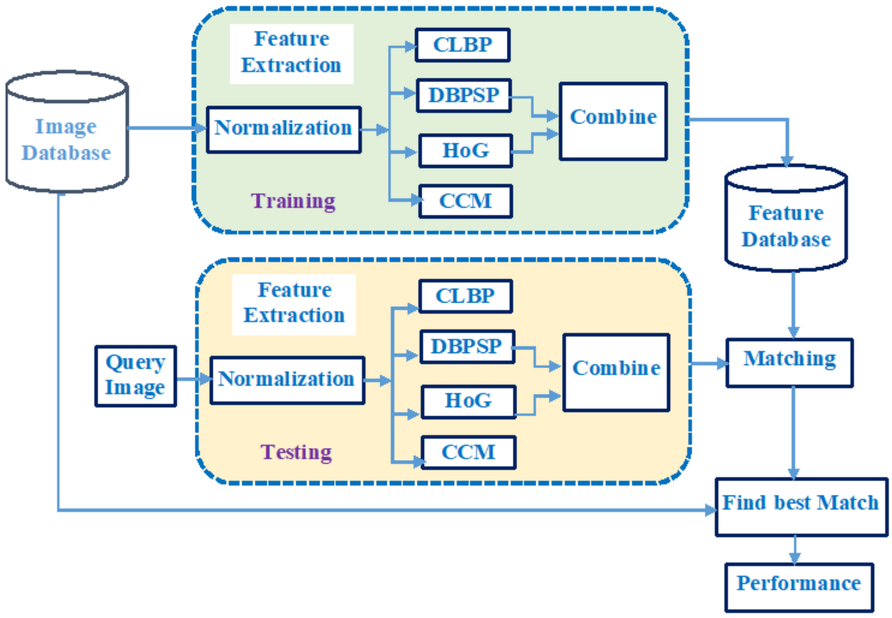


FIGURE 1. Proposed System Architecture

3.3. **System Architecture.** In this work, RGB colour images are considered as input and images are stored in the database as different classes. These images are normalized to increase the clarity of image and then the image features are extracted using GCM, CCM, DBPSP, CLBP and HoG. The query image is normalized with the above-mentioned feature extraction methods. Then the best matching images are searched from the database for the extracted images for the query image. The performance of the framework is analysed by the time taken for retrieving the best matched images from the dataset as the query image is shown in the Figure 1.

3.4. **Feature Extraction.** The IR-HF-WED uses hybrid features which are extracted from RGB colour images. Each feature gives specific information. For example, CLBP produces the local texture information and CCM produces the colour information. The different features which are extracted in the proposed method is as follows:

3.4.1. *Colour Co-occurrence Matrix (CCM)*. CCM [13] is represented by the 3-dimensional matrix, colours of any pair are alongside the 1D and 2D and the spatial distance alongside the 3D. CCM is named as a streamlined technique for representing the colour pairs count which presents among neighbouring pixel displayed in a picture. For every pixel, both horizontal and vertical neighbours are considered. CCM is utilized to decide the probability of co-occurrence among two motifs $(x, y)$ and $(x+\delta x, y+\delta y)$. The absolute number of co-occurring motifs of scan pattern sets $(u, v)$ which incorporates the distance from $(x, y)$ on the $x$-coordinates in $\delta x$ and on the $y$-coordinates in $\delta y$ is controlled through Equation (3.1) and Equation (3.2):

$$M_i(u, v) = M_i(u, v|\delta x, \delta y), \tag{3.1}$$

$$M_i(u, v) = M_i(P_i[x, y], P_i[x + \delta x, y + \delta y]),$$

$$m_i(u, v) = \frac{M_i(u, v)}{N_i}. \tag{3.2}$$

Here, $P_i[N_x, N_y]$ is Co-occerence Matrix, $N$ is Dimension, $(x, y)$ is Pixel, $(x + \delta x, y + \delta y)$ are the Coordinates of Adjacent Pixel, $M(u, v)$ is Motif Scanned Pattern Pair, $(\delta x, \delta y)$ is Spatial Offset.

3.4.2. *Difference Between Pixels of Scanned Pattern (DBPSP).* DBPSB computes pixel difference in all direction within motifs of a scanned pattern. The $\Delta(x, y)$ is the total difference of pixel value of any coordinates - $(x, y)$ in an image. It is similar to produce six scanned patterns motifs, these may possibly individually appear as per $\Delta^1(x, y)$, $\Delta^2(x, y)$, ... , $\Delta^6(x, y)$ within the accompanying equations [14]:

$$\begin{aligned}
\Delta^1(x, y) &= |PX_1 - PX_2| + |PX_2 - PX_3| + |PX_3 - PX_4|, \\
\Delta^2(x, y) &= |PX_1 - PX_3| + |PX_3 - PX_2| + |PX_2 - PX_4|, \\
\Delta^3(x, y) &= |PX_1 - PX_3| + |PX_2 - PX_4| + |PX_4 - PX_2|, \\
\Delta^4(x, y) &= |PX_1 - PX_2| + |PX_2 - PX_4| + |PX_4 - PX_3|, \\
\Delta^5(x, y) &= |PX_1 - PX_4| + |PX_4 - PX_3| + |PX_3 - PX_2|, \\
\Delta^6(x, y) &= |PX_1 - PX_4| + |PX_4 - PX_2| + |PX_2 - PX_3|.
\end{aligned}$$

Here, $\Delta^1(x, y)$ is the difference of aggregate pixel value of all directions of $i^{th}$ motif number of any coordinates - $(x, y)$ of an image. Then, Equation (3.3) is used for computing the appearance rate of $\Delta(x, y)$ in the complete image:

$$f_i = \frac{1}{N_i} \sum_{j=1}^{N_i} \Delta^i j(x, y). \tag{3.3}$$

Here, $i$ is motif number, $N_i$ is total appearance of $i^{th}$ motif number of an complete image.

3.4.3. *Histogram of oriented Gradient (HoG).* The descriptor extracts the distribution of image gradients information in different orientations for an object detection. HoG feature extraction consists different computations which are created by SIFT descriptor. HoG feature extraction is carried out by passing the input image to square root or the log of gamma correction function and then the image gradient computation is performed in three channels by simple $1 - D$ centred $[-1, 0, 1]$ masks in horizontal and vertical fields. The gradient magnitudes are computed with all the three-color channels. Gradient orientations are calculated and is classified into nine orientations, which provides color invariance to a large extent. The next stage is to compute normalization for normalizing the overall response before entering the next stage. The regularized block descriptors are denoted as HoG descriptors.

3.4.4. *Compound Local Binary Pattern (CLBP)*. The LBP operator executes the image pixels as a result of thresholding an *n*n* neighbourhood matrix of each pixel with the value of central pixel and concatenating outcomes mathematically to frame a number for evaluating each pixel in the query image [13]. For that a binary code is obtained and is named as binary pattern. That binary pattern developed is symbolized as texture characteristics of the image. The Architecture may get rid of information of magnitude of difference between central and the neighbour gray values in a local neighbourhood may outcome in the production of inconsistent codes.

The CLBP operator is applied on all the image pixels by computing CLBP all patterns in-to the correlative CLBP sub-patterns, results two binary codes for every pixel of an image leads to compound local binary patterns. The histograms achieve through two-encoded images and are later united towards framing a spatially joined histogram called as CLBP - Histogram.

3.5. **Matching through Weighted Euclidean Distance.** Matching is an important process in image retrieval system. Distance computing algorithms are used for matching query image with the images in database. This section explains about different distance calculating algorithms [1]. The Equation (3.4) is used to compute the relationship among the two feature vectors, Equation (3.5) computes Euclidean Distance among two feature vectors.

$$d(q, x_j) = \sum_{i=1}^{i=m} |x_{ij} - q_i|, \tag{3.4}$$

$$d(q, x_j) = \sqrt{\sum_{i=1}^{i=m} (x_{ij} - q_i)^2}. \tag{3.5}$$

The Cross Correlation, Minimum Mean Distance(MMD) and Statistical Measures are used in the Equation (3.6), (3.7) and (3.8) respectively for matching:

$$r(q, x_j) = \frac{\sum_{i=1}^{i=m} x_{ij} q_i}{\sqrt{|\sum_{i=1}^{i=m} (x_{ij}^2)|}\sqrt{|\sum_{i=1}^{i=m} (q_i^2)|}}, \tag{3.6}$$

$$z_j = \frac{\sum_{i=1}^{i=m} x_{ij}}{m}, \tag{3.7}$$

$$s_j = \sum_{i=1}^{i=m} [\frac{Max(x_{ij}, q_i)}{Max(x_{ij}, q_i)} - 1]^2. \tag{3.8}$$

The Weighted Euclidean Distance algorithm produces maximum accuracy by computing distance among two vectors as shown in Equation (3.9), Equation (3.10) and Equation (3.11):

$$d(q, x_j) = \sqrt{\sum_{i=1}^{i=m} \rho_i (x_{ij} - q_i)^2}, \tag{3.9}$$

$$\rho_i = \frac{n}{\sum_{j=1}^{n} (x_{ij} - \bar{z}_i)^2}, \tag{3.10}$$

$$\bar{z} = \frac{\sum_{n}^{j=1} x_{ij}}{n}, \tag{3.11}$$

where, $x_{ij}$ is the image feature from the database, $q_i$ is the query input feature, $\rho_i$ is the weight used for feature, $i$ and $\bar{z}$ is an average of the image features in the database.

## 4. Results and discussion

To justify the proposed framework, we have compared the proposed model with the following existing frameworks Yang et al., [1] and Elalami et al., [2]. The following section gives the detailed analysis.

4.1. **Dataset.** In the proposed work, WANG Dataset [1] is used for analysing image retrieval system performance. WANG database has 10 classes each of the class has 100 pictures; totally it has 1000 images with the dimension of 384x256, among 1000 images 900 are used towards training and 100 images for testing.

4.2. **Retrieval Time of a Model.** The retrieval time is a main factor in image retrieval system, Accuracy is reliably proportionate with the number of features, so use of more features the processing time will increase. The Table 1 shows that the proposed method has an upright balance amongst retrieval time. It is achieved by reusing the extracted features and reducing the dimension of the extracted features helped to reduce the retrieval time.

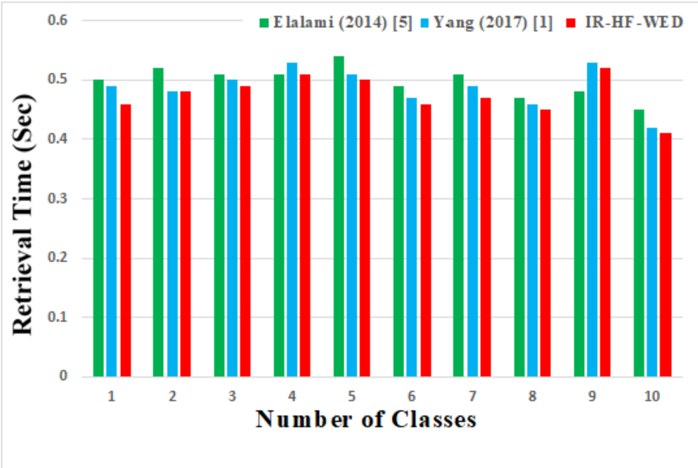


FIGURE 2. Specific comparisons in Wang Dataset

4.3. **Retrieval Time and Number of Features.** The proposed framework is implemented using MATLAB and compared with Yang et al., [1] and Elalami et al., [2]. The Table 1 shows various retrieval time for the WANG database. The Figure 2 shows the Specific comparisons in different databases for different methods. The Figure 3 and Figure 4 justifies proposed scheme has higher precision over [1] and [2].

TABLE 1. Retrieval Time Performance for Wang Database

| **Number of Features** | **10** | **20** | **30** | **40** | **50** | **60** | **70** | **80** | **90** | **100** |
|---|---|---|---|---|---|---|---|---|---|---|
| Elalami *et al.*, [2] [2014] | 0.50 | 0.52 | 0.51 | **0.51** | 0.54 | 0.49 | 0.51 | 0.47 | **0.48** | 0.45 |
| Yang *et al.*, [1] [2017] | 0.49 | **0.48** | 0.50 | 0.53 | 0.51 | 0.47 | 0.49 | 0.46 | 0.53 | 0.42 |
| IR-HF-WED | **0.46** | **0.48** | **0.49** | **0.51** | **0.50** | **0.46** | **0.47** | **0.45** | 0.52 | **0.41** |

4.4. **Precision v/s Number of Features.** To improve the precision, the proposed system extracts a large number of features, this section explains the impact of extracted features with respect to precision. The Figure 3 shows association among precision *v/s* number of features. From the Figure 4, it is clear that the precision increases when the number of features increases.

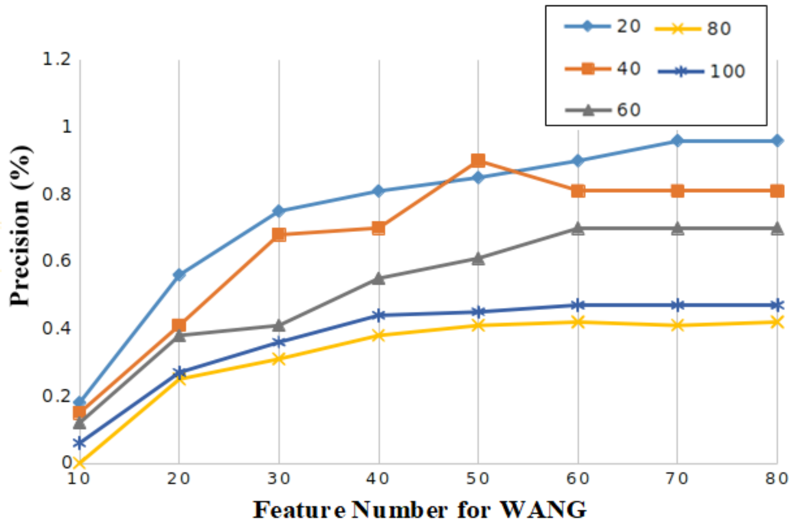


FIGURE 3. Precision *v/s* Number of Features

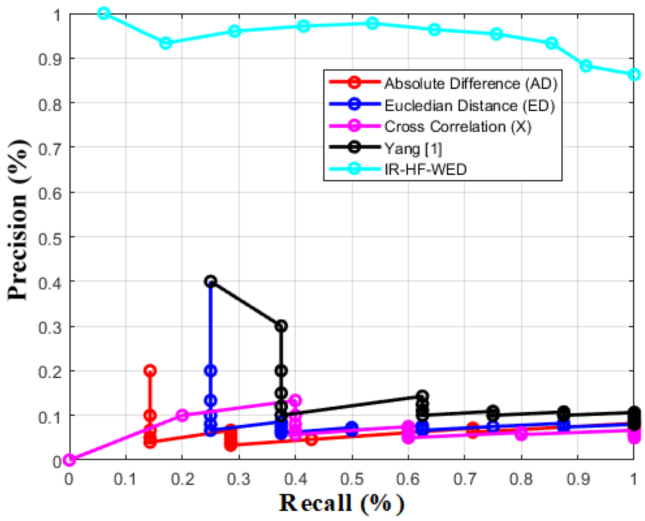


FIGURE 4. Precision *v/s* Recall

4.5. **Precision v/s Recall.** This section explains about the effect of distance matrices on precision. In this framework, several distance matrices like ED, WED, Manhattan Distance, MMD, Statistical Measure and Cross Correlations are used. The Figure 4 shows the effect of distance matrices on precision and demonstrate that whatever the distance metrics applied precision will increase with the increase in training data regardless of distance matrices.

## 5. CONCLUSIONS

The Image Retrieval method using Hybrid Feature with Weighted Euclidean Distance (IR-HF-WED) is implemented and validated. The Retrieval method performance is related with traditional techniques and the results are verified. The Precision of IR-HF-WED is improved due to the hybrid combination of feature extraction and matching. In IR-HF-WED, the matching quality is improved by adding weight in Euclidean Distance for perfect matching. Similarly, the time complexity is reduced by selecting features by giving proper weightage for the corresponding features.

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