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Gaussian Density and HOG with Content Based Image Retrieval System – A New Approach

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Abstract**—**Content-based image retrieval (CBIR) uses the contents of images to characterize and contact the images. This paper focus on retrieving the image by separating images into its three color mechanism R, G and B and for that Discrete Wavelet Transformation is applied. Then Wavelet based Generalized Gaussian Density (GGD) is practical which is used for modeling the coefficients from the wavelet transforms. After that it is agreed to Histogram of Oriented Gradient (HOG) for extracting its characteristic vectors with Relevant Feedback technique is used. The performance of this approach is calculated by exactness and it confirms that this method is well-organized for image retrieval.

Keywords**—**Content-Based Image Retrieval (CBIR), Relevant Feedback, Histogram of Oriented Gradient (HOG), Generalized Gaussian Density (GGD).

I. Introduction

WORLD Wide Web (WWW) and Internet had developed extremely. An enormous amount of Image databases are added every minute and it need for effective and efficient image retrieval systems. A manual annotation of the images is too time-consuming and cannot keep up with the growth of data.

There are many features of content-based image retrieval but four of them are considered to be the main features. They are color, texture, shape, and spatial properties. Histograms are a commonly used technique, ranging from simple color histograms [2] to sophisticated histograms of local features [6] or histograms refined by smoothness information [3].

CBIR, also known as query by image and content based visual information retrieval is the application of computer vision. The complexity in image retrieval is of searching for digital images in large databases. In the CBIR system, the significance between a query and any target image is ranked according to a resemblance measure computed from the visual features. In CBIR each image that is stored in the database has its features extracted and compared to the features of the query image. It involves mainly two steps:

- Feature Extraction: The first step in this process is to extract the image features to a discernible extent. Feature is anything that is restricted and measurable. In an image noticeable features include objects, color, shape, corners, lines, spatial location, motion and texture. [12]
- Matching: The second step involves matching these features to yield a result that is visually similar. [11]

The design and development of effective and efficient CBIR systems are still a research problem, because the nature of digital images involves two well-known problems: the semantic gap and the computational load to manage large file collections. The semantic gap is required of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation [13]. It has linguistic and contextual consequences, and mainly depends on the domain knowledge to represent images. Alternatively, the computation load, when large image collections are managed, may create unreasonable use of CBIR systems [14].

In this paper a new algorithm of GGD combined with HOG is proposed. Here first the image components are separated based on R, G and B color components. Then image is subjected to feature extraction by wavelet coefficient based GGD and texture components are extracted for all the three components by HOG.

The paper can be organized as follows: Section II describes the related works involved in content based image retrieval, Section III describes the methodology used to retrieve the images, and Section IV describes Experimental results obtained by using proposed methodology.

II. Related Works

Wouwer et al. [15] employed generalized Gaussian density functions to represent texture images in the wavelet domain. The model parameters are estimated using a method of moment matching, and the similarity function is again defined as weighted Euclidean distances on extracted model parameters.

Vasconcelos and Lippman [16] recently took a similar approach where they introduced a probabilistic formulation of the CBIR problem as a common ground for several currently used similarity functions.

Wavelets analysis provides multiresolution and orientation representation of an image via subbands which offer a good representation that is consistent with the human visual system [1]. It has rapidly emerged as an efficient tool for image analysis, and, in the case of image retrieval, led to the formulation of three popular types of signatures, namely, energy signature [17], the generalized Gaussian distribution (GGD) signature [18], [17], and co-occurrence signature [17].

Patil et al. [19] put forwards an overview of the technical achievements in the research area of relevance feedback (RF) in content-based image retrieval (CBIR). It also covers the

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current state of art of the research in relevance feedback in CBIR, various relevance feedback techniques and issues in relevance feedback.

Dalal et al. [20] proposed a human detection algorithm using histograms of oriented gradients (HOG) which are similar with the features used in the SIFT descriptor. HOG features are calculated by taking orientation histograms of edge intensity in a local region. They are designed by imitating the visual information processing in the brain and have robustness for local changes of appearances, and position. Dalal et al. extracted the HOG features from all locations of a dense grid on a image region and the combined features are classified by using linear SVM. They showed that the grids of HOG descriptors significantly outer-performed existing feature sets for human detection. Ke et al. [21] applied Principal Components Analysis (PCA) to diminish the dimensionality of the feature vectors and tested them in an image retrieval application.

III. Methodology

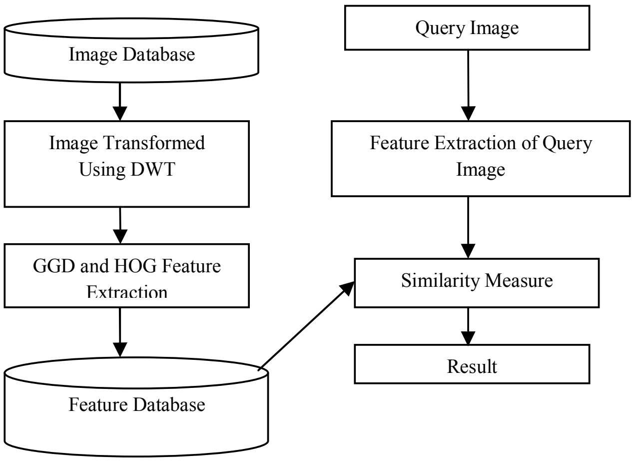


Fig. 1 Architecture of Proposed CBIR

Original Image (Horse)

Red Green Blue

Fig. 2 Separation of R, G & B component

A. Feature Extraction

Feature Extraction plays major role in retrieving. This provides images distinctive value which makes it's to differentiate with other type of images.

This proposed methodology utilizes two techniques:

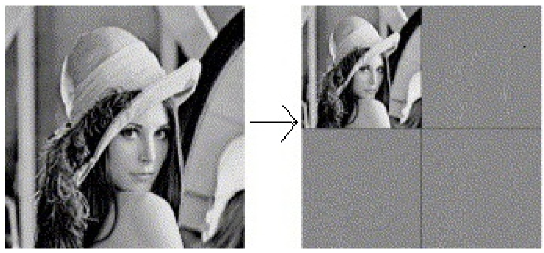
1. 1.DWT with GGD and
2. HOG based feature extraction for the images.

Each input image is separated into its three components Red, Green and Blue from the image. Sample of separation of R, G and B component is shown in above Fig. 2. This image is subjected to DWT individually and features values are extracted.

B. Discrete Wavelet Transform

Wavelets have newly emerged as an effectual tool to investigate texture information as they make available a natural partition of the image spectrum into multiscale and oriented subbands via efficient transforms [4]–[6]. Furthermore, since wavelets are used in major future image compression standards [7] and are also shown to be prominent in searching for images based on color and shape [8], [9], a wavelet-based texture retrieval system can be used effectively in combination with a compression system and retrieval systems using other image features

The discrete wavelet transform (DWT) is a linear adaptation that operates on data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale. [16]



(a) Input Image (b) Single Level DWT

Fig. 3 Single Level Image Transform Using DWT

Fig. 3 shows the single level transformation using DWT for input image, where H and L denotes high and low-pass filters respectively.

C. Generalized Gaussian Density Modeling of Wavelet Coefficients:

The Single Level DWT image is specified for GGD method. Mallat [10] initialized for a diversity of images, the allocation of all sub band wavelet coefficients emerge chosen alike in figure. Normally, the distributions were symmetrical about zero and had a sharp peak at zero. Mallat proposed modeling "typical wavelet coefficients" of the subbands by the GGD defined by

$$p(\omega; \alpha, \beta) = K e^{-\left(\frac{|\omega|}{\alpha}\right)^{\beta}} = \frac{\beta}{2\alpha\Gamma\left(\frac{1}{\beta}\right)} e^{-\left(\frac{|\omega|}{\alpha}\right)^{\beta}}$$

where $\Gamma(z) = \int_0^{\infty} e^{-t} t^{z-1} dt . z > 0$ is the Gamma function; α communicates to the width of the probability density function, and β corresponds to the shape of GGD. As β gets turn out to be sharper, and the height of the peak amplifies. These GGD parameters α and β can be predictable through instant estimation (ME) [19] or maximum probability estimation (MLE) [5]. They pass on $\{\propto B_m, \propto B_m\}$ $n = 1,2,\dots,3N_L$ as the GGD parameters of the subband B_n.

The fits are generally quite good. As a result, with only two parameters for the GGD, They can accurately capture the marginal distribution of wavelet coefficients in a sub band that otherwise would require hundreds of parameters by using histogram. This significantly reduces the storage of the image features, as well as the computational complexity in similarity measurement.

D. Histogram of Oriented Gradient (HOG)

The HOG are the familiarize descriptor used for extracting features for the images. The presentation counts occurrences of gradient orientation in restricted portions of an image.

HOG features have been initiated by Navneed Dalal and Bill Triggs [2] who have developed and experienced several variants of HOG descriptors, with differing spatial organization, gradient computation and normalization methods.

Currently the image is calculating the Gradient Orientation Histogram approximately the 16 x 16 pixel region of each significance points. Primarily, the region is separated in $4\ X\ 4$ sub-region, for each sub-region the 8-bin gradient direction $h(k), k = 0\ to\ 7$ are designed which forms a quality vector of size 128 dimension($4\ x\ 4\ x\ 8$). The gradient oriented histogram is computed using the most ordinary method is to be relevant the 1D centered point discrete derivative facade in both the horizontal and vertical directions. Particularly, this method requires filtering the grayscale image with the following filter kernels:

$$D_x = [\,-1\;0\;1\,]$$

$$D_y = [\,-1\;0\;1\,]^T$$

Subsequently, for the given an image say I, then acquire the x and y derivatives using a complication operation:

$$I_x = I * D_x \text{ and } I_y = I * D_y.$$

The magnitude of the gradient is $|G| = \sqrt{I_x^2 + I_y^2}$

The orientation of the gradient is given by:

$$\theta = \arctan\left(\frac{I_y}{I_x}\right)$$

Finally, combing all the Gradient orientation Histogram of the interest point's area together to form a feature vector of size 128-dimension.

These features and dwt features are combined and formed a feature vector. This feature vector is taken for the relevance feedback process.

E. Relevance Feedback

In relevance feedback-based approaches, a CBIR system studied from feedback provided by the user. Relevance feedback on the image retrieved in response to the initial query. This feedback is used consequently in improving the retrieval effectiveness [11], [12].

IV. Experimental Results

The Evaluation is performed to discover the relevant images for the given input query with reduced number of iterations. The experiment is done by using CORAL image Database with the software MATLAB.

Corel database [14] contains large amount of images of various contents ranging from animals and outdoor sports to natural images. These images are pre-classified into different categories of size 100 by domain professionals. Many researchers think that Corel database meets all the requirements to evaluate an image retrieval system, because of its large size and heterogeneous content.

The exactness of the image can be premeditated by the following formula which is expressed in %:

$$Accuracy = \frac{N - X}{N} * 100$$

where N is number of relevant images in the database which are recognized to the user and X is the number of irrelevant images in the database which are known to the user.

A. GGD Based Image Retrieval:

The initial input image is subjected to wavelet transformation and for that GGD algorithm is applied.

The input query is shown in the Fig. 5. Here in this bus is taken as query image.

Fig. 4 Input Query (Elephant)

Result using DCT:

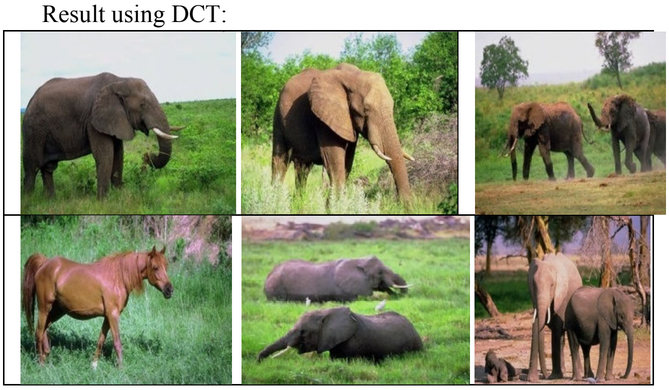


Fig. 5 Output image produced by using GGD image retrieval

Fig. 5 shows the result based on GGD wavelet coefficient. In this figure only one image are not extracted correctly for the query image building. The accuracy of the output images is 88%.

B. Combined GGD with HOG BASED Image Retrieval

Here the image retrieved from the database based on the combined algorithm of DWT and HOG based feature extraction.

The same query image of Fig. 5 building is given also for this process.

Result of DWT with HOG at first iteration:

Fig. 6 Output image before relevance feedback using texture-based image retrieval

Fig 6 exemplifies the output images based on GGD with HOG features for the user's input query image elephant. The output figure clearly shows that for elephant query image all the retrieved image is under the same category. So here next iteration is not required. If there is any image that can be corrected by using relevance feedback process.

The accuracy of the output images obtained in the first iteration is 96%.

C. Performance Evaluation

The Corel representation dataset consists of mainly six different images. The comparison accuracy of the query images to display these images before and after relevance feedback has been observed for combined DWT and HOG image retrieval. The accuracy before and after relevance feedback for this image retrieval is shown in Table I.

TABLE I
ACCURACY AND TIME COMPARISON OF COMBINED DWT AND HOG BASED IMAGE RETRIEVAL BEFORE AND AFTER RELEVANCE FEEDBACK

Query Image	Accuracy (%) without RF	Accuracy (%) with RF	Number of Iterations
BEACHES	78	86	2
BUILDING	68	78	2
DINOSAUR	94	98	1
ELEPHANT	96	98	1
FOOD	84	86	2
ROSE	92	96	2
AVERAGE	85	90	2

Table I illustrates that the average number of iteration for the six datasets is 2 and the maximum accuracy after relevance feedback is 90%.

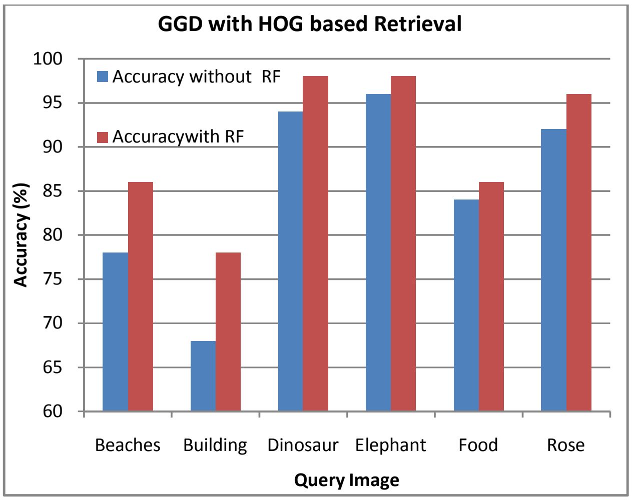


Fig. 7 Accuracy Comparison of the Combined GGD with HOG based image retrieval before and after relevance feedback

The evaluation result showed that the proposed method produces the nearly maximum accuracy for image retrieval.

V. CONCLUSION

This paper proposed a novel method based on GGD and HOG to extract the features of the Image. The traditional algorithm has some drawbacks in extracting the features. The GGD parameters are more meaningful in characterizing textures than the energy-based ones. In addition, the inferior result of the GGD shows that high-quality performance in retrieval independently. Then this is combined with HOG which is used to extract the features around the interest points. Then extracted features of the database is compared with the query image and based on that image is retrieved. The proposed statistical structure can be applied to other and more general retrieval technique. The GGD was used effectively here for modeling the coefficients from the wavelet transforms and wavelet frames. The performance of this method is evaluated using accuracy calculation. Thus this method out performs in image retrieval.

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