Content-Based Image Retrieval Using Local Derivative Laplacian Co-occurrence Pattern

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Abstract. For accessing images from huge repository in an easy manner, the images are required to be properly indexed. Content-Based Image Retrieval (CBIR) is a field which deals with finding solutions to such problems. This paper proposes a new multiresolution descriptor namely, Local Derivative Laplacian Co-occurrence Pattern (LDLCP) for CBIR. Gray level image is subjected to four-level Laplacian of Gaussian filtering in order to perform multiresolution processing of image. Local Derivative Pattern descriptors of resulting four-level filtered image is computed to extract local information from the image. Finally, the Gray-Level Co-occurrence Matrix is used for constructing feature vector. Corel-1K and Corel-5K datasets have been used to test the proposed descriptor and its performance is measured using precision and recall metrics.

Keywords: CBIR · Image retrieval · Laplacian of Gaussian · Local Derivative Pattern · Gray-Level Co-occurrence pattern

1 Introduction

Capturing the images is quite easy nowadays resulting in huge repository of different types of images. For an easy access, proper organization of images is very important. To solve such problems, image retrieval systems play an important role. Image retrieval systems are categorized broadly into two classes-Text-Based Image Retrieval (TBIR) systems and Content-Based Image Retrieval systems (CBIR). TBIR systems use keywords to retrieve relevant images from dataset. But such systems are not considered to be very efficient as manual annotation of huge repository of images is needed, and retrieval of visually similar images is difficult. In CBIR systems, the image itself is provided in the form of query from which features are extracted. This results in construction of a feature vector of that particular image which is then matched with other images in the repository. Based on similarity measurement, visually similar images get retrieved [1].

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The primary features, which include colour, texture, and shape, have been extensively used for constructing feature vector. Many feature descriptors [2, 3] have been used to extract colour features from image. For extracting texture features Gabor transform [4] and local patterns [5–8] have been extensively used. Similarly, shape features have been extracted using polygonal structures and moments to construct feature vector [9].

Construction of feature vector using single feature proved to be insufficient due to complex structure of image. This limitation shifted the trend of CBIR techniques towards combination of primary features [10]. The combination of features has been mostly exploited on single resolution of image. An image consists of varying level of details and for extracting such details, single resolution processing of image proves to be insufficient. This drawback is overcome by making use of multiresolution processing of image which analyzes and interprets an image at multiple scales. Processing of images at more than one resolution has an important advantage of detecting those features at a particular level which were left undetected at previous level [11]. This paper proposes a multiresolution feature vector Local Derivative Laplacian Co-occurrence Pattern (LDLCP). It exploits multiple resolutions of image to extract local information by computing Local Derivative Pattern descriptor of Laplacian of Gaussian of image using three different filters of size 3×3, 5×5, and 7×7 and different values of standard deviation. Construction of feature vector has been performed using Gray-Level Cooccurrence Matrix (GLCM). The proposed descriptor efficiently extracts directional local information at multiple resolutions of image.

The remaining sections of the paper is organized as follows- Sect. 2 discusses Related work, Sect. 3 discusses briefly about LDP, LoG, and GLCM. The Proposed Method is discussed in Sect. 4. Section 5 describes Experiments and Results and finally, Sect. 6 concluding the paper.

2 Related Work

Image feature descriptors play a significant role in extraction of discriminating features. Local feature descriptors such as LBP [5], LTP [6], and LDP [7] have been extensively used for feature extraction. While these feature descriptors extract low level features, there are many features descriptor such as HID [12] which extract high level features from the image along with low level features. These feature descriptors have been mostly exploited using single resolution of an image for feature extraction. Processing an image using only single resolution for feature extraction proves to be insufficient as image contains complex details. For overcoming this limitation, feature descriptors which utilize multiple resolutions of image to extract features have been introduced. Srivastava and Khare [13] proposed a multiresolution descriptor which combined Local Spatial Binary Pattern and Gaussian filtering technique for construction of feature vector. The method proposed in [14] computed wavelet coefficients of LBP descriptor image. Another descriptor Wavelet Correlogram which combined wavelet transform and colour correlogram for image retrieval is proposed in [15]. Multiresolution feature descriptors extract features by utilizing multiple resolutions of image. This proves to be advantageous as features which were left undetected in previous levels get detected at another level. This paper proposes a novel multiresolution feature descriptor, Local Derivative Laplacian Co-occurrence Pattern (LDLCP).

3 Laplacian of Gaussian, Local Derivative Pattern, and Gray-Level Co-occurrence Pattern

3.1 Laplacian of Gaussian

Laplacian is a measure of second derivative of an image. Laplacian is used for detecting edges in an image. The Laplacian *L(x, y)* of an image having intensity value *I* can be mathematically expressed as-

$$L(x, y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \tag{1}$$

However, the original form of Laplacian is not used for detecting edges in the image because of its sensitivity to noise. The segmentation operation becomes complicated because the magnitude of Laplacian generates double edges. Due to this, it is unable to detect edge direction. In order to overcome this drawback, the image is first blurred using Gaussian filter. The degree of blurring is determined by standard deviation σ. The equation that combines both these filters is called Laplacian of Gaussian and is mathematically expressed as-

$$LoG = -\frac{1}{\pi\sigma^4}[1 - \frac{x^2 + y^2}{2\sigma^2}]e^{\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

LoG filtering has a number of important applications apart from removing noise from image. One of the most important applications is multiresolution processing of image. The multiresolution processing of image is performed through convolution operation between kernels of different size and image thereby resulting in a series of images at different resolutions. These images can be further used for extracting features to construct feature vector for retrieval.

3.2 Local Derivative Pattern

Local Derivative Pattern (LDP) is a local feature descriptor which encodes higher-order derivative information in different directions unlike LBP which encodes *(n-1)*th order derivative direction variations on the basis of binary coding function [7]. It extracts information in multiple direction which represent various distinctive relationships. LDP extracts more discriminative information as it encodes more distinguishing relationships among intensity values in a local region.

3.3 Gray-Level Cooccurrence Matrix

GLCM computes how frequently pixel pairs located adjacently having specific values and at specific directions occur in an image [16]. Such information are not provided by other features such as histogram.

3.4 Advantages of Local Derivative Laplacian Cooccurrence Pattern

Advantages of the proposed descriptor can be summarized as follows-

1. Multiresolution processing of image extracts features at more than one scale. Due to this, undetected features at a particular scale are detected at another scale.
2. The proposed descriptor extracts local information from image through LDP which encodes higher-order derivative information unlike LBP
3. LoG filtering of image at multiple levels help in removal of noise which may cause local pattern descriptors to vary.
4. Although LoG filtering extracts features at multiple scales of image, it fails to extract directional information. LDP descriptor extracts local information at four different orientations (0^0, 45^0, 90^0, and 135^0). Combination of LoG with LDP perform extraction of local directional information at more than one level of resolution of image.
5. Construction of vector through GLCM provides spatial distribution details which are not provided by other features such as histogram.

4 The Proposed Method

The proposed method consists of the following steps –

1. Application of Laplacian of Gaussian on gray scale image.
2. Computation of Local Derivative Pattern descriptor of resulting filtered image.
3. Construction of GLCM of LDP descriptors.
4. Similarity Measurement.

4.1 Laplacian of Gaussian (LoG) Filtering

Application of LoG filters results in multiresolution processing of gray scale image. Image decomposition into multiple resolutions gather varying discriminative details. LoG filter is applied on grayscale image by performing convolution operation between grayscale image and LoG filter. In the proposed method, in case of level 1, the kernel size is considered 3×3, and standard deviation value as 1; for level 2, size of kernel is considered as 5×5, and standard deviation value as 1.25; for level 3, size of kernel is considered as 7×7, and standard deviation value as 1.5; and for level 4, size of kernel is considered as 9×9, and standard deviation value as 1.75.

4.2 Computation of LDP Descriptors

The next step of the proposed method is computation of second order LDP descriptor of resulting filtered images. The resulting descriptor are then stored in four separate matrices. Second order LDP extracts local information at multiple orientations.

4.3 Construction of Gray-Level Co-occurrence Matrix (GLCM)

GLCM of resulting second order LDP descriptors is constructed in the next step. GLCM acts as feature vector to retrieve visually similar images. In the proposed method, GLCM for 0^0 angle and distance 1 has been considered for constructing feature vector and rescaled to size 8×8.

4.4 Similarity Measurement

Similarity measurement serve the purpose of retrieving images that are visually similar to the query image. Let $(f_{Q1}, f_{Q2}, ..f_{Qn})$ be the set of query images and let $(f_{DB1}, f_{DB2}, ..f_{DBn})$ be the set of database images. Then, the similarity between query image and database image is computed using the following formula-

$$Similarity(S) = \sum_{i=1}^{n} \left| \frac{f_{DBi} - f_{Qi}}{1 + f_{DBi} + f_{Qi}} \right|, \; i = 1, 2, \ldots, n \tag{3}$$

5 Experiment and Results

To carry out the experiment using the proposed method, images from the two datasets, namely Corel-1K [18] and Corel-5K [19] datasets are considered. There are of 1000 images in Corel-1K dataset which are divided into 10 categories, each containing 100 images. Corel-5K datasets consist of 5000 of images divided into 50 categories, each containing 100 images. In case of Corel-1K dataset, the size of each image is either 256×384 or 384×256. In case of Corel-5K dataset, the size of each image is either 127×187 or 187×127.

In order to ease the computation process, the resizing of each image of Corel-1K dataset has been done to size 256×256 and to size 128×128 of Corel-5K dataset. For experimentation purpose, each image in the dataset is considered as query image.

5.1 Performance Evaluation

Precision and recall metrics have been used to evaluate the proposed method. Precision metric is defined as the ratio of total number of relevant images retrieved to the total number of images retrieved. The mathematical expression of precision can be expressed as

$$P = \frac{I_R}{T_R} \tag{4}$$

where I_R denotes total number of relevant images retrieved and T_R denotes total number of images retrieved. Recall metric is defined as the ratio of total number of relevant images retrieved to the total number of relevant images in the database. The mathematical expression of recall can be expressed as

$$R = \frac{I_R}{C_R} \tag{5}$$

where I_R denotes total number of relevant images retrieved and C_R denotes total number of relevant images in the database. In this experiment, $T_R = 10$ and $C_R = 100$.

5.2 Retrieval Results

Application of LoG with different values of standard deviation and filter size produce four smoothed images. LDP descriptors of resulting smoothed images is computed which results in four LDP matrices. The construction of feature vector is performed by computing GLCM of each of these matrices separately. In order to perform similarity measurement, each of these feature vectors are used separately resulting in four sets of similar images. Union of these sets of similar images results in final sets of similar images. The computation of recall is done by counting total number of relevant images in the dataset. In order to compute precision value, counting of top n matches is performed for each set, followed by computing union of these sets for producing final set. For the computation of precision, top n matches in the final set are considered. The relevant image set of previous level along with the relevant image set of that level is considered to obtain relevant image set for the current level.

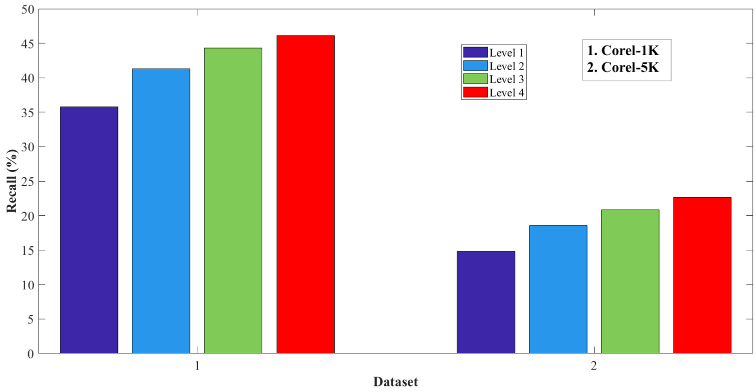
For four levels of resolution, average precision and recall values can be observed in Table 1 and Table 2 for Corel-1K and Corel-5K datasets. The plot between average values of precision and dataset, and recall and dataset for four levels of resolution is shown in Fig. 2 for Corel-1K and Corel-5K datasets. There is a surge in the precision and recall values as the level of resolution increases, which can be observed from Table 1, Table 2, and Fig. 1. The proposed method exploits more than one resolution of image because of which the features that are not detected at a particular level get detected at another level of resolution. This phenomenon results in surge in precision and recall values.

Table 1. Average Recall and Precision values of the Proposed Method for Corel-1K dataset.

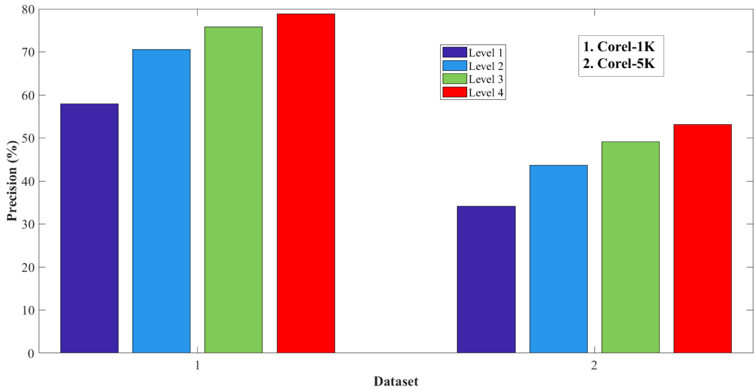
Level of resolution	Recall (%)	Precision (%)
Level 1	35.79	57.89
Level 2	41.31	70.52
Level 3	44.33	75.79
Level 4	46.13	78.80

Table 2. Average Recall and Precision values of the Proposed Method for Corel-5K dataset.

Level of resolution	Recall (%)	Precision (%)
Level 1	14.83	34.18
Level 2	18.57	43.59
Level 3	20.87	49.14
Level 4	22.69	53.16



(a)



(b)

Fig. 1. (a) Average Recall vs. Dataset (b) Average Precision vs. Dataset

5.3 Performance Comparison

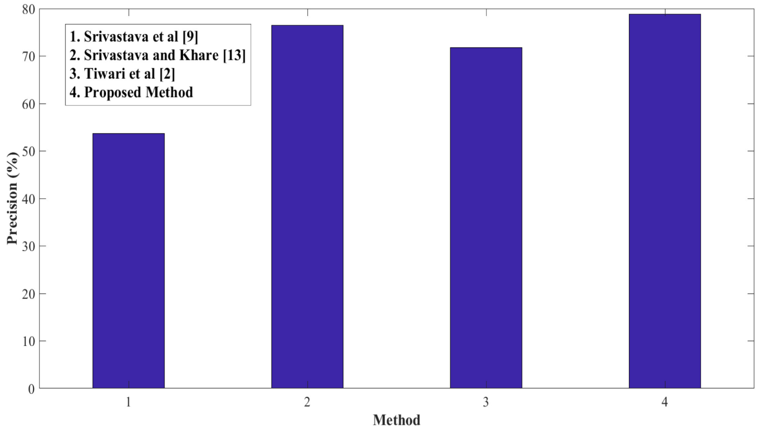
For testing the efficiency of the proposed descriptor LDLCP, its performance has been compared with some of the such as Srivastava et al. [9], Srivastava and Khare [13], Zeng et al. [17], Tiwari et al. [2], Vipparthi and Nagar [8], in terms of precision. These methods combine multiple features at single resolution of image. Single resolution processing does not prove to be efficient for extracting discriminating details present in the image. Hence, these methods fail to produce high retrieval accuracy. The proposed descriptor constructs feature vector by extracting local information at more than one scale of image. Therefore, the proposed descriptor produces better retrieval accuracy in terms of precision metric than some of the other state-of-the-art CBIR methods. Table 3 and Table 4 show with other CBIR techniques in terms of precision on Corel-1K and Corel-5K datasets respectively. Figure 2 demonstrates performance comparison in terms of precision on Corel-1K and Corel-5K datasets. The results shown in Table 3, Table 4, and Fig. 2 clearly demonstrate the effectiveness of the proposed method in comparison to other CBIR techniques in terms of precision metric.

Table 3. Performance comparison of the Proposed Method with other state-of-the-art methods on Corel-1K dataset

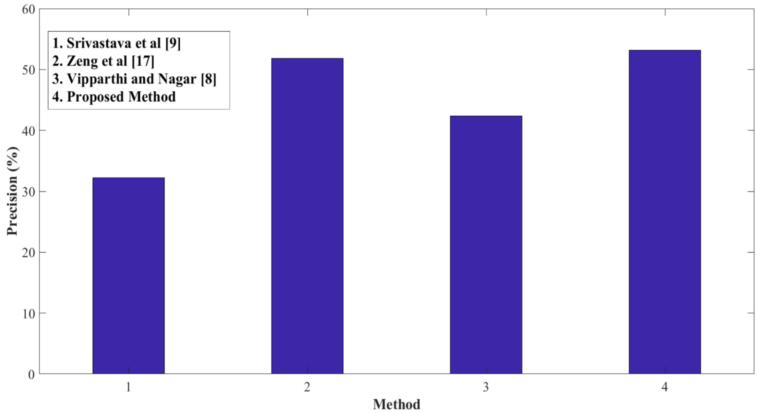
Method	Precision (%)
Srivastava et al. [9]	53.70
Srivastava and Khare [17]	76.46
Tiwari et al. [2]	71.78
Proposed method	**78.80**

Table 4. Performance comparison of the Proposed Method with other state-of-the-art methods on Corel-5K dataset

Method	Precision (%)
Srivastava and Khare [9]	32.18
Zeng et al. [17]	51.80
Vipparthi and Nagar [8]	42.40
Proposed method	**53.16**



(a)



(b)

Fig. 2. Performance comparison of the Proposed Method with other state-of-the-art CBIR techniques in terms of precision on (a) Corel-1K dataset (b) Corel-5K dataset

6 Conclusion

A novel descriptor Local Derivative Laplacian Co-occurrence Pattern (LDLCP) is proposed in this paper. The proposed descriptor integrates multiresolution processing of image with local pattern descriptor for constructing feature vector to perform retrieval. Multiresolution processing of gray scale image was performed using Laplacian of Gaussian (LoG) filter followed by extraction of local information from the filtered image using Local Derivative Pattern (LDP). Finally, the construction of feature vector was carried out using GLCM. A significant advantage of the proposed descriptor is that it exploits image at more than one scale to extract features so that the features that do not get detected at one level get detected at another level. The proposed descriptor utilizes second order Local Derivative Pattern which efficiently extracts local information at different orientations. Performance measurement of the proposed method was carried out using precision and recall metrics. The proposed method has better performance than some of the other CBIR methods as demonstrated by experimental results. Use of other multiresolution techniques such as contourlet transform along with efficient local feature descriptors to improve retrieval accuracy can further improve the performance of the proposed method. Also, incorporating intelligent techniques such as deep learning can help in extracting semantic features.

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