Research Article

Local mean differential excitation pattern for content based image retrieval

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Abstract

Effective and facile local texture feature descriptors assume a significant role in many image classification and retrieval tasks. However, conventional feature descriptors are impaired to capture salient image features like local inherent structure, orientation and edge information of the image. A typical local binary pattern (LBP)-like feature descriptors elicits information based on the gray level difference from each locality and consequently its value immensely susceptible to noise. To overcome a few deficiencies of traditional methods, the proposed research work acquaint with a lucid, novel, yet robust texture feature descriptor called local mean differential excitation pattern (LMDeP) for efficient content based image retrieval. The main strategy of LMDeP is to elucidate differential excitation using the mean of points over each angular and radial neighbor points. This enables the LMDeP to fetch robust features by skimming the noise effect of enticing neighbors over each local patch. LMDeP performance compared to the LBP variants on Corel-1 K and Corel-5 K datasets establish the superiority of proposed method to its counterparts.

Keywords Content based image retrieval · Differential excitation · Feature descriptor · Local binary pattern · Local mean differential excitation pattern · Texture classification

1 Introduction

Diversity in image acquisition mechanism has led to mutation in distinctive domains such as multimedia repositories, document registry, medicine, law enforcement and other such advancements. This led to the need for automated on demand information retrieval systems. Content based image retrieval systems (CBIR) emerged as a silver line technology to cater the needs of automated indexing and retrieval of images. The fundamental objective of CBIR system is to access and assemble images which are correlated to the visual inquiries from the open database based on content. Since, content is characterized by a diverse set of parameters, for example, texture, color, shape, position and region of interest and so forth. Evaluations of these parameters become difficult task. Further, a few image types like natural, satellite and medical images have their own distinct features. A few researchers have proposed many feature descriptors dependent on low level features like color, shape and texture. An adaptable image feature descriptor is the need of great importance as the available literature focus to the way that there is no single strategy available to manage such a diverse set of image types.

Real time applications like browsing, retrieving similar images on demand require a potent CBIR system, whose efficiency depends on the methodology adapted for feature description/representation. A feature is a substantial structure in an image. Features can vary from a single pixel to a group of pixels forming an edge or contour, and perhaps, it may be as large as object in the image. Identifying these significant structures in the image is called feature detection. A feature descriptor represents all or subset of feature points detected. Thus, the feature descriptor must have resilience against noise, illumination changes

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and variety of deformations. Features may alter from one domain to another domain of application, which raises the question of suitability. Thus, domain specific feature detector/descriptors attract the attention of the researchers in the present scenario. A handful feature descriptors have been suggested in the last decade. A wide survey of CBIR techniques has been reported in [1, 2].

The rest of the paper is arranged in the accompanying way. Section 2 talks about the related work on content based image retrieval, fundamental commitments of the paper. The propounded feature extraction methodology and similarity metric is provided in Sect. 3 and Experimental outcomes and discussion are carried out in Sect. 4. Section 5 finishes up the paper.

2 Related works

The search for lucid and powerful feature descriptors is the prevailing research field in image processing. This section provides a brief recap of progressive advancements in feature descriptors. Feature description based on low level features like color, texture and shape fundamentally attracted researchers, as they are easy to extract. A few number of feature descriptors have been suggested to extract low level features for expert image retrieval [3–9] in the recent times. Among, low level feature descriptors, texture feature descriptors are prominent and compelling features for image retrieval. Textures description is a wing of texture analysis that appeal to many industrial applications such as face recognition [10], textile inspection [11], object tracking [12],and identification of ceramic tiles and marble in granite industry etc [13].

The exemplary local texture pattern that was used in the past decade is local binary pattern(LBP) [14]. The LBP constructs the affiliation of center pixels with their P neighbors existed on a circle of radius R by encoding the sign of grey level difference between them to an 8 bit binary string. As a consequence of circular sampling, LBP lacks the robustness to noise and inability to mimic anisotropic structures. To overcome a few deficiencies associated with LBP several researches extend the LBP operator as depicted in [3, 15–17]. Tan and Trigg [18] propounded local ternary pattern (LTP) using ternary encoding to overthrow pattern susceptibility to noise.

The local patterns mainly focused on extracting the relation between the center pixels with its neighbors over a $n \times n$ local patch, where $n = 3$ in general and over looked the mutual relation among neighbors. Later, [5, 19] quoted the need for both sign and magnitude pattern for enriched discriminative power. Verma et al. [20] demonstrated the significance of counting the mutual affiliation of adjoining neighbors for revealing the rapport with the center pixels

considering two adjoining pixels at time. However, [5, 20] are based on the grey level difference and disregarded the original stimulus of intensity. Jabid et al. [21] devised a robust local pattern called local directional pattern (LDP) by considering edge data in different directions to encode local textures. LDP uses Kirsch masks to obtain edge data and it was appeared to be less prone to noise than the traditional LBP. Later, Chakraborti et al. [22] suggested a rotation invariant descriptor based on non linear fusion of LBP and LDP named as Local Optimal Oriented Pattern(LOOP). Chen et al. [23] introduced a robust descriptor based on differential excitation and orientation of gradient called Weber law descriptor(WLD) for texture image retrieval.

This research work proposes an original local feature descriptor entitled as local mean differential excitation pattern (LMDeP) for image retrieval. The salient feature of LMDeP is that it uses differential excitation instead of mere grey level difference to enumerate the relationship between center pixels and its neighbors. Further, the LMDeP consider the amalgamation of angular mean and radial mean of neighbors in the computation of differential excitation which endow to high discriminative power and high robustness to noise.

3 Proposed work

In this paper, an expert texture feature descriptor is proposed that uses consolidation of two local patterns inspired by LBP. First, being angular mean differential excitation (AMDeP) using average of intensity values over different angular directions and other is radial mean differential excitation pattern (RMDeP) using the mean of radial points at specified radius range. Both AMDeP and RMDeP are combined to form a unique feature descriptor labeled as local mean differential excitation pattern (LMDeP). LMDeP is competent enough to fetch potent and distinct features from noisy and traditional texture images. LMDeP profits by the accompanying things:

- Fundamentally, differential excitation [23] is a fraction of two terms. One being the grey level difference between focused pixel and its neighbors and other is original center pixel intensity itself. Utilizing differential excitation to extract local structure curtail any multiplicative noise associated with neighbor pixels.
- Further, proper choices of distance between radial and angular points empower LMDeP to subside noise effects on adjoining pixels.
- A few multi-scale descriptors based on LBP elicit large number of features by concatenating the feature vector of distinct neighborhoods which results in expanded length of feature vector. While, LMDeP obtains comple-

mentary information with considerably small dimension of feature vector.

The LMDeP is executed in two stages. First, obtain the angular mean of neighbor pixels with specified angular distance ($\Delta\emptyset$) and later, compute the differential excitation (δ) values for center pixel in eight directions. For example, the δ value for direction 1 i.e 0^0 with $\Delta\varphi = \pi/4$ designated as δ_1 is calculated as shown in Fig. 1a

$$\delta_1 = atan\left[\frac{Z - mean(a, b, c)}{Z}\right] \tag{1}$$

For example, as shown in Fig. 1c the center pixel values is $Z = 141$ (marked red in Fig. 1c) and the angular neighbors under consideration are a, b, and c are 148, 142, and 145 respectively in zero degree direction. Therefore, the differential excitation value in zero degree direction according to Eq. 1 is obtained as -1.62. Similarly, obtain $\delta_2, \delta_3, \ldots, \delta_8$ values for remaining seven directions. Now, the angular mean differential excitation pattern (AMDeP) is obtained by binary encoding δ values with given threshold and summing up to decimal values using predefined weights. The AMDeP for $R = 1, P = 8$ is computed using Eq. (2) as

$$AMDeP(Z) = \sum_{i=1}^{P} f(\delta_i) \times 2^{(i-1)} \tag{2}$$

where,

$$f(\delta_i) = \begin{cases} 1, & \text{for} \quad \delta_i > 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

The example angular pattern value computation is as shown in Fig. 1c. The AMDeP values ranges from 0 to 255, total 256 values. Obtain the histogram of AMDeP mapped image by considering each pixel in the given image as center pixel and designated as PTN1. In second stage, the radial mean values are obtained for specified range of R and compute the differential excitation values in eight directions nominated as $\delta_{r1}, \delta_{r2}, \ldots, \delta_{r8}$. The differential excitation for the center pixel Z in radial direction 1 as shown in Fig. 1b is obtained using Eq. (4) as

$$\delta_{r1} = atan\left[\frac{Z - mean(A, B, C)}{Z}\right] \tag{4}$$

Therefore, the radial mean differential excitation pattern (RMDeP) is obtained by thresholding and encoding the differential excitation values as given in Eq. (5). Where δ_{rj} represents differential excitation values in different directions as shown in Fig. 1c (differential matrix). Now, obtain radial pattern value by binary encoding δ_{rj} values and summing up to decimal values utilizing predefined weights

as shown in Fig. 1c. In the example, radial mean matrix computation using three radial neighbors are considered as shown in Fig. 1c.

$$RMDeP(Z) = \sum_{j=1}^{8} S(\delta_{rj}) \times 2^{(j-1)} \tag{5}$$

where,

$$S(\delta_{rj}) = \begin{cases} 1, & \text{for} \quad \delta_{rj} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

$S(\delta_{rj})$ is called threshold function. The histogram of RMDeP mapped image as is designated as PTN2. Now, concatenate PTN1 and PTN2 to form LMDeP feature vector. Hence, feature vector length is 1×512 for a given image.

4 Experimental results

To assess the performance of LMDeP, some established datasets with heterogeneous texture content are adapted. The adapted datasets in this work are Corel-1 K [22, 24] and Corel-5 K [22, 24] datasets. To demonstrate the noise robustness of LMDeP, the dataset images are contaminated with Gaussian noise with different signal to noise ratios. The outcomes showed that LMDeP outweigh some dominant strategies like local tetra patterns (LTrP), LDP and LOOP. Figure 2 shows example adapted textures with different SNR values.

4.1 Similarity metric

The d1 distance metric is used for similarity measurement between the query image and dataset images. The d1 distance function [5] for a feature vector of length L is defined as
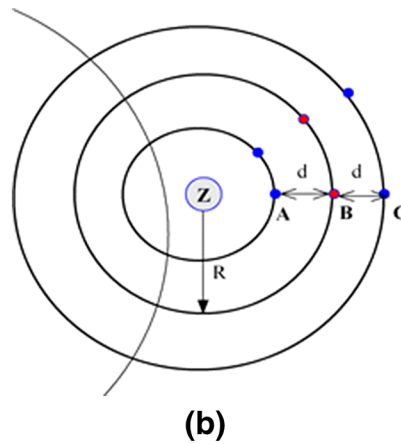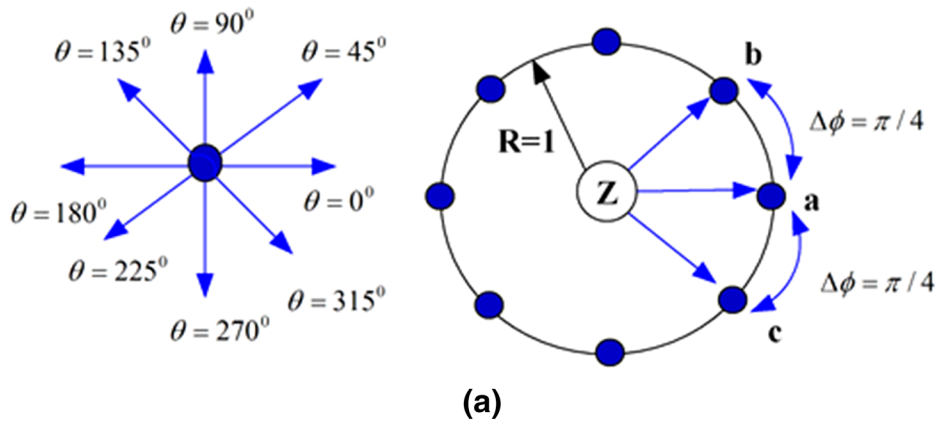
$$d_1(q, D_s) = \sum_{i=1}^{L} \left| \frac{f_{Dsi} - f_q}{1 + f_{Dsi} + f_q} \right| \tag{7}$$

where, f_{Dsi} stands for feature vector of ith image in the dataset and f_q stands for query feature vector.

4.2 Performance metric

The performance of LMDeP is evaluated compared to other strategies in terms of average precision rate (APR) and average recall rate (ARR) [5]. The precision and recall values are computed using Eqs. (8) and (9) for dataset with M number of images and m number of top matches as

$$\text{Precision} - p_i(m) = \frac{\text{Number of relevent images retrived} (T_r)}{\text{Total number of images retrieved} (T_{rr})} \tag{8}$$

(a)

(b)

(c)

◄**Fig. 1** Example pixel candidate's consideration for computing differential excitation. **a** Angular neighbor pixels for R = 1, $\Delta\varphi = \pi/4$. **b** Radial neighbour pixels for d = 1. **c** Example angular and radial pattern computation

$$recall - r_i(m) = \frac{\text{Number of relevent images retrived } (T_r)}{\text{Total number of images present in the databse } (T)} \quad (9)$$

The average precision for jth category $Ap_m(j)$ with M1 number of images are determined by using the formula

$$Ap_m(j) = \frac{1}{M_1} \sum_{i=1}^{M} p_i(m) \quad (10)$$

$$Average\ recall - Ar_m(j) = \frac{1}{M_1} \sum_{i=1}^{M} r_i(m) \quad (11)$$

The APR and ARR for a given dataset are computed as

$$APR = \frac{1}{M_2} \sum_{i=1}^{M_2} Ap_m(i) \quad (12)$$

$$ARR = \frac{1}{M_2} \sum_{i=1}^{M_2} Ar_m(i) \quad (13)$$

where, M2 stands for number of categories in the dataset, Ap_m stands for average precision per category and Ar_m stands for average recall per category.
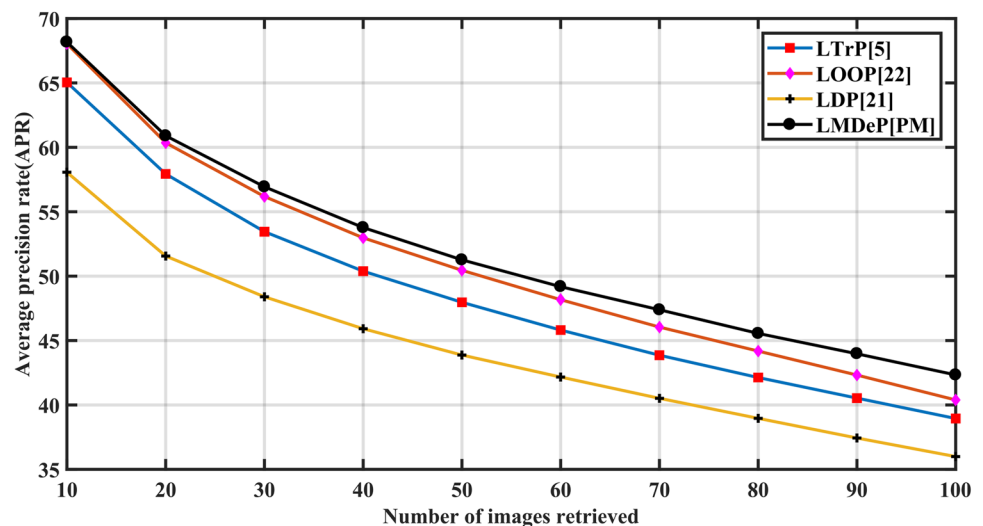
4.3 Experiment #1

The experiment #1 is conducted on Corel-1 K dataset. Corel-1 K is composed of 1000 images with ten classes and every class comprises of 100 images. For plotting the outcomes, each picture in the database is utilized as query picture. For each query picture the framework accumulates pictures from database with shortest d1 distance computed using Eq. (7). In those pictures some are significant to inquiry picture and some are non-important outcomes which don't match to query picture. Pictures which are of user concern are called relevant images and entire pictures retrieved for a given query are called retrieved images. The retrieval performance is computed in terms of precision which is the ratio of relevant images to retrieved images. Recall and precision values are computed using Eqs. (8)–(13). For each query picture the retrieved pictures are accumulated into groups of 10, 20, 30,…, 100. The efficiency of LMDeP compared to other strategies is depicted in Fig. 3 in terms of APR and ARR Vs number of images retrieved without noise. It is obvious from the outcomes that the proposed strategy out played
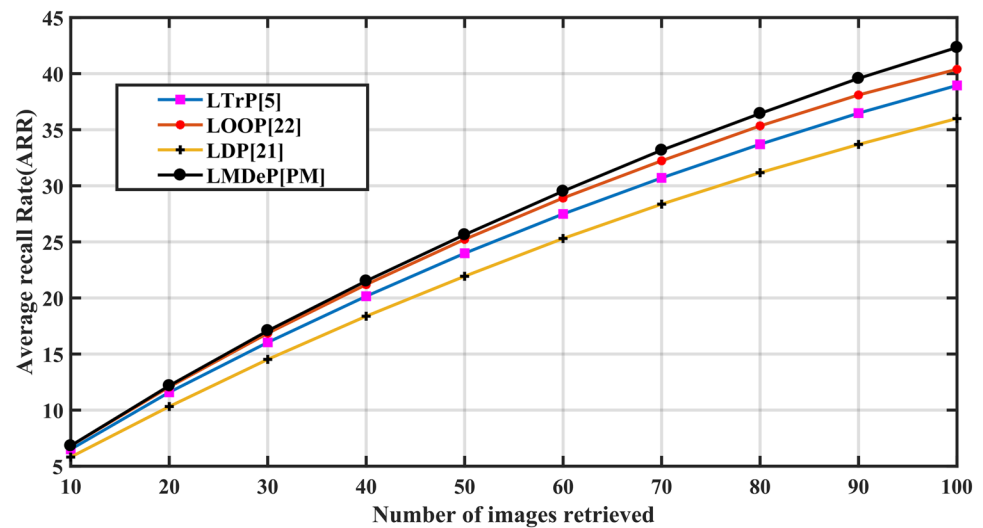
Fig. 2 An example of texture pictures with varying SNR values

No noise

SNR=20

SNR=15

SNR=2
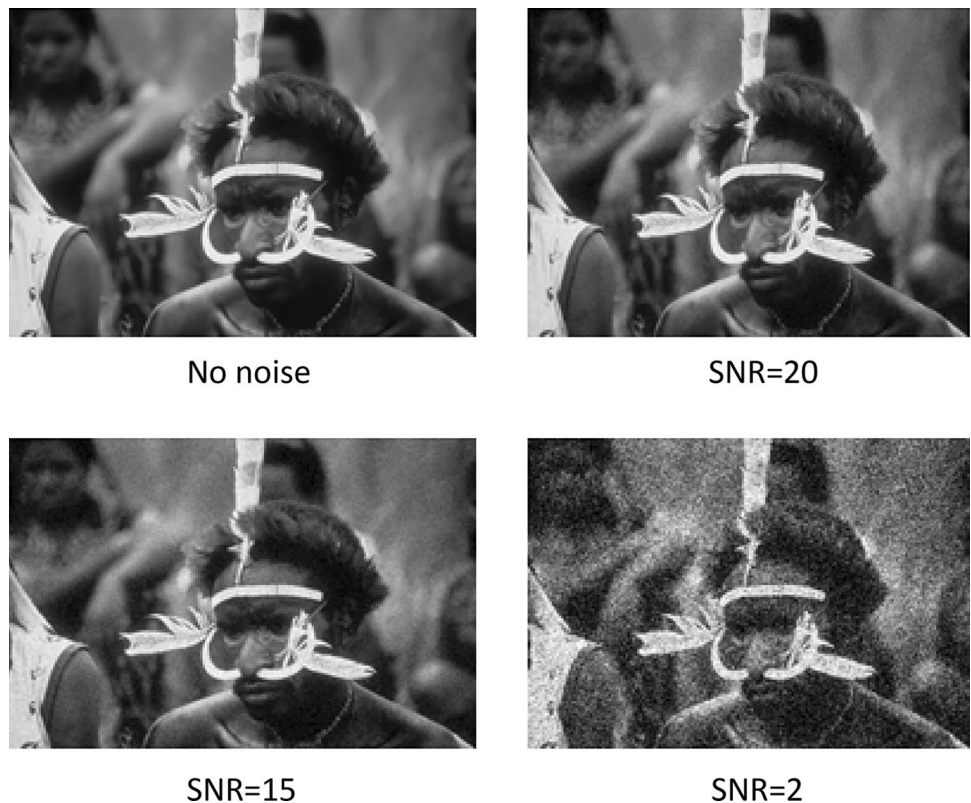
Fig. 3 Experimental results on Corel-1 K in terms of APR and ARR without noise (*PM- proposed method)

(a)

(b)

the current strategies. Tables 1 and 2 presents results on noise simulated dataset with different SNR values.

The following conclusions are drawn from the experimental results

- The APR has essentially enhanced from 60.05, 65.04, and 68% to 68.2% as contrasted with LDP, LTrP and LOOP individually on Corel-1 K dataset without addition of noise. As shown in Fig. 3a. LOOP initially performed comparable to LMDeP but as the number of

Table 1 ARR of different strategies on Corel-1 K dataset with different SNR values (m = 100)
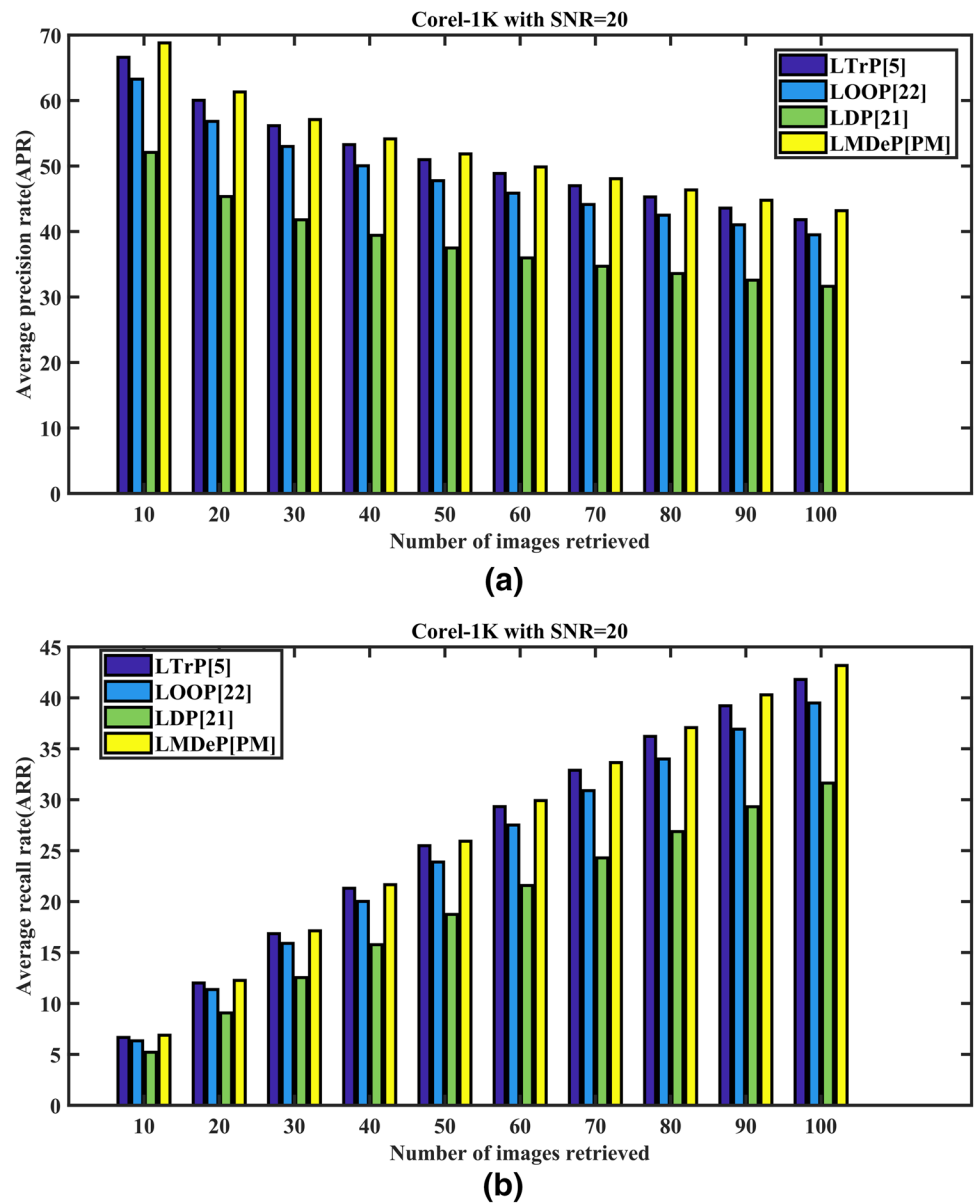
Strategy	SNR = 20	SNR = 15
LTrP [5]	41.803	38.67
LDP [21]	31.63	29.38
LOOP [22]	39.49	37.64
LMDeP [PM]	43.17	41.93

PM proposed method

Table 2 ARR of different strategies on Corel-5 K dataset with different SNR values (m = 100)

Strategy	SNR = 20	SNR = 15
LTrP [5]	19.91	19.41
LDP [21]	16.47	16.38
LOOP [22]	17.31	16.05
LMDeP [PM]	20.9	21.8

Fig. 4 APR and ARR results on Corel-1 K with noise SNR = 20

(a)

(b)

retrieved images increases LMDeP surpassed LOOP and remaining strategies.

- The Fig. 3b and Table 1 indicates that the LMDeP surpasses the remaining strategies in terms of ARR.
- The LMDeP likewise demonstrated noteworthy improvement compared to other methodologies in the presence of noise in texture images with varying SNR values on Corel-1 K dataset as shown in Table 1 and Fig. 4.

4.4 Experiment #2

The Corel-5 K picture database [24] comprises of five thousand pictures with fifty classes and every class is having

hundred pictures. The execution of proposed technique with other existing strategies is arranged in Table 2, Figs. 5 and 6.

The following conclusions are drawn from experimental results

- APR of LMDeP (46.15%) improved significantly compared to LDP (37.15%), LOOP (42.9%), and LTrP (44.4) on Corel-5 K dataset with m = 10 as shown in Fig. 5a.
- The retrieval performance of LMDeP surpasses remaining strategies with and without noise in texture images as shown in Figs. 5b, 6 and Table 2

Fig. 5 Experimental results on Corel-5 K dataset in terms of APR and ARR without noise (*PM-proposed method)
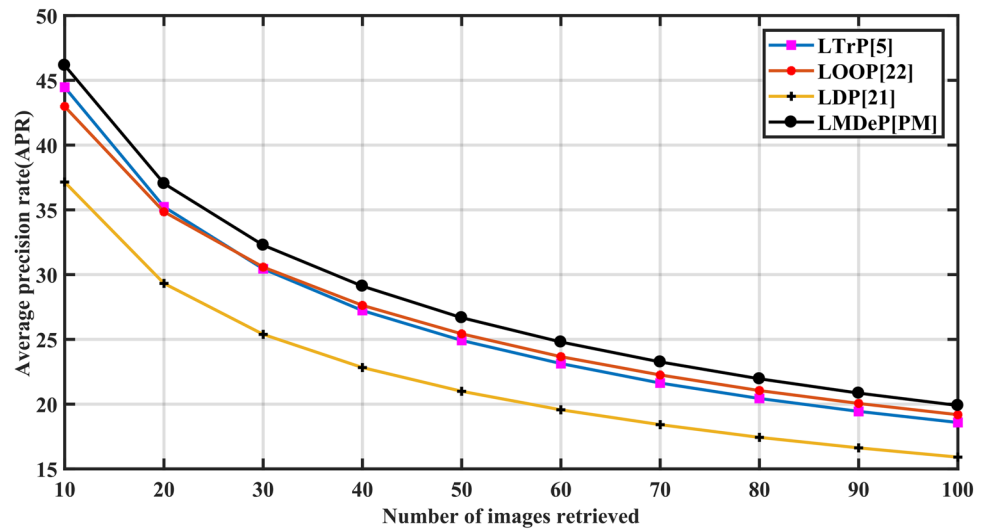
(a)
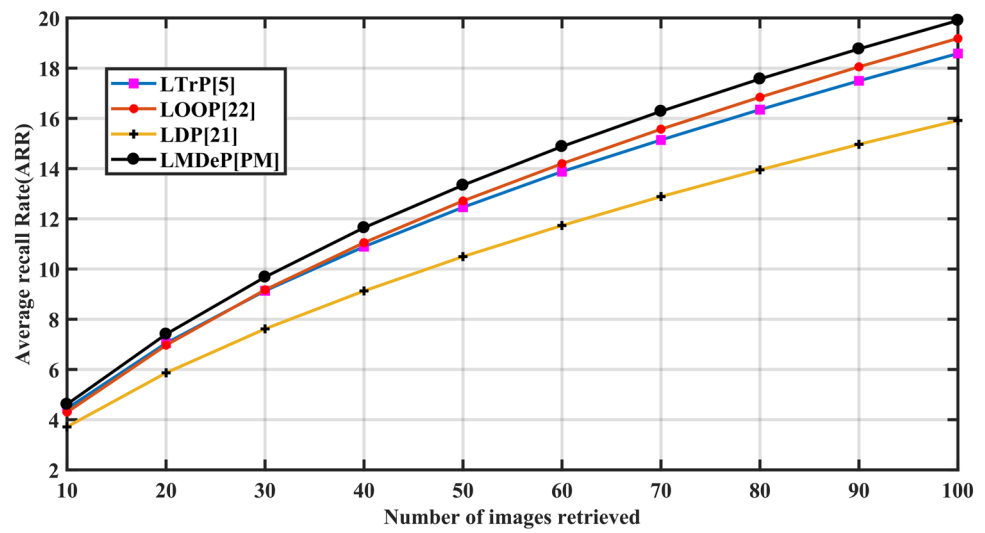
(b)

The trial results from Figs. 5 and 6 conclude that LMDeP surpasses various strategies in terms of APR and ARR on Corel-5 K dataset with or without noise.

5 Conclusion

In this work, a novel texture pattern which is robust to illumination variations and noise is presented. The proposed work integrated radial and angular point mean to extract local information structure. Utilizing mean of neighbor pixels and differential excitation to obtain relationship between focused pixels and its neighbors considerably reduced the effect of noise on texture pattern. The outcome imply that utilizing both radial and angular mean of points produces enriched score instead of using only gradient or edge data on natural and noisy textures. The retrieval results of proposed LMDeP outweighed the current strategies by 6.3, 3.4, and 1.95% on LDP, LTrP, and LOOP respectively on Corel-1 K dataset. LMDeP also showed significant improvement in precision rate by a factor of 9, 3.25, and 1.75% correlated with LDP, LOOP, and LTrP respectively on Corel-5 K dataset. In conclusion, LMDeP outperformed the state of the art strategies in terms of APR and ARR on benchmark datasets Corel-1 K and Corel-5 K. In this paper, only binary encoding is used for differential excitation values. Results can be further improved by considering ternary encoding or fuzzy encoding. Due to the potency of the proposed methodology, it is additionally appropriate for different pattern recognition applications like bio-medical image retrieval, texture retrieval, fingerprint recognition, and face recognition, etc.

Fig. 6 APR and ARR results on Corel-5 K with noise SNR=20

(a)

(b)
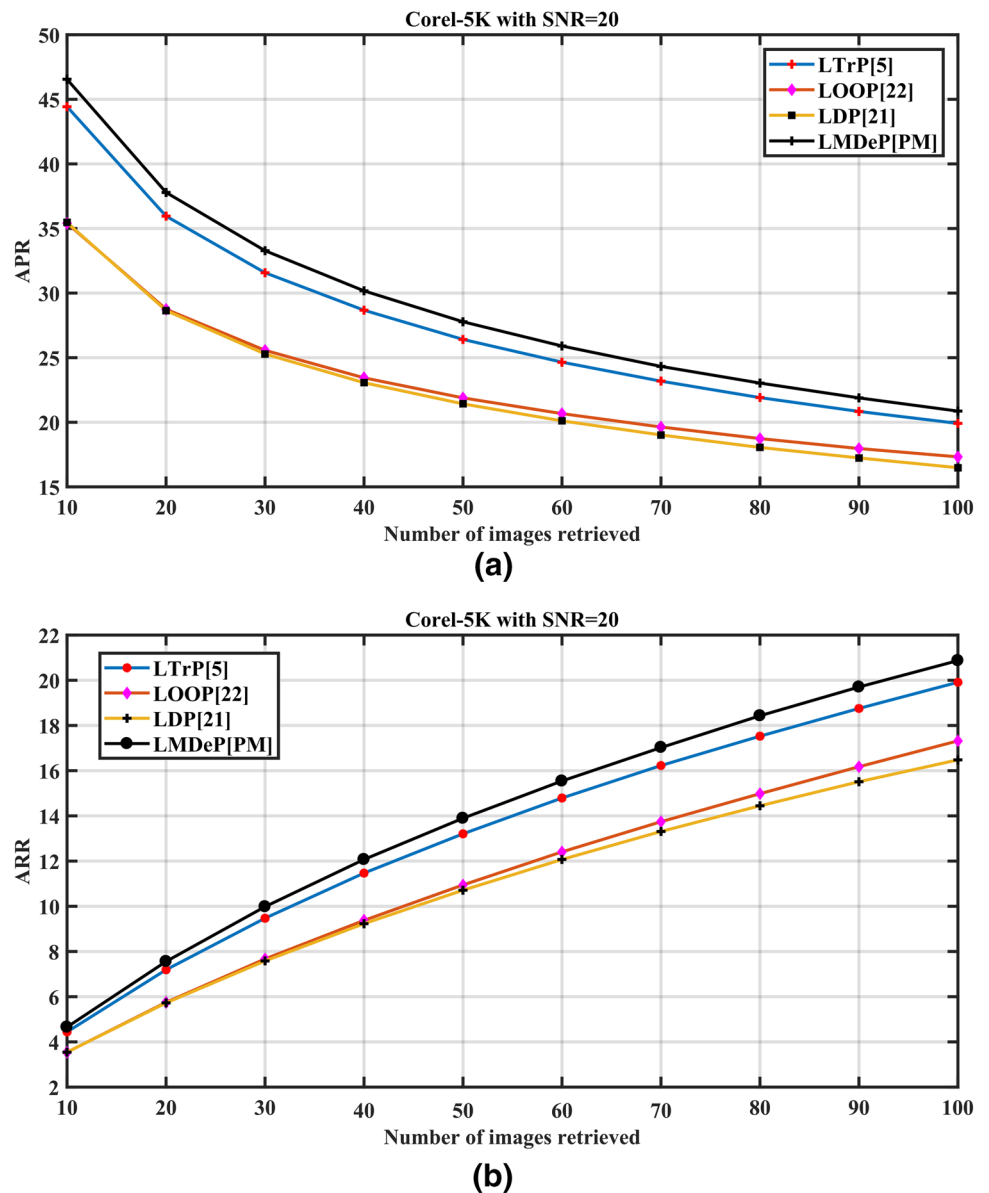
Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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