

## CONTENT BASED IMAGE RETRIEVAL USING LOCAL DERIVATIVE PATTERNS

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### ABSTRACT

A new image indexing and retrieval algorithm known as local derivative pattern (LDP<sub>16\_2</sub>) is proposed in this work. LDP<sub>16\_2</sub> histograms are used as features of each image in the data base. LDP<sub>16\_2</sub> encodes the higher order derivative information which contains more detailed discriminative features. This property made it a powerful tool for feature extraction of images in the data base. Improved results in terms of retrieval efficiency and computational complexity are observed over recent work based on LBP<sub>16\_2</sub> (Local Binary Patterns) features based CBIR system and LBP correlogram features based CBIR system. The distance measures viz. city block distance, Euclidean distance, Canberra distance and  $d_1^2$  distance are used as similarity measures in the proposed CBIR system. Superiority of  $d_1^2$  distance is observed over other distances in terms of average retrieval rate.

**Keywords:** *High Order Local Patterns, Texture, Local Derivative Patterns (LDP<sub>16\_2</sub>), Local Binary Patterns (LBP<sub>16\_2</sub>), Image Retrieval, Histogram.*

### 1. INTRODUCTION

#### 1.1. Motivation

Recently, with the advances in various multimedia technologies, such as high speed network, compression and new digital image sensor technologies, large image databases are being created by scientific, educational, medical, industrial and other applications. These large volumes of the images make difficult for a user to browse through the entire database. Therefore, an efficient and automatic procedure is a need for indexing and retrieving images from databases [1]. Traditionally, two approaches are used to retrieve the images: text based and content based approaches. In text based approaches, images are first annotated either manually or with the help of machine and then retrieved using traditional text retrieval techniques. Manual annotation is a cumbersome and expensive task for large image databases and often subjective in nature. Similarly the first hurdle in machine annotation is the proper segmentation of image itself. As a result, it is difficult for the traditional text-based methods to retrieve a variety of images from database. In order

to resolve this problem, a new technique known as content based image retrieval (CBIR) evolved. CBIR is a technique which uses visual contents of an image such as color, shape and texture to search images from large image databases.

Content Based Image Retrieval (CBIR) is an important research area for manipulating large multimedia databases and digital libraries. High retrieval efficiency and less computational complexity are the desired characteristics of CBIR system. CBIR finds applications in advertising, medicine, crime detection, entertainment, and digital libraries. Computational complexity and retrieval efficiency are the key objectives in the design of CBIR system [2]. However, designing of CBIR system with these objectives becomes difficult as the size of image database increases. CBIR based on color, texture, shape, and edge information are available in the literature [3, 4, 5, 6, 7]. Features of an image should have a strong relationship with semantic meaning of the image. CBIR system retrieves the relevant images from the image data base for the given query image, by comparing the features of the query image and images in the database. Relevant images are

retrieved according to minimum distance or maximum similarity [8] measure calculated between feature of query image and every image in the image data base.

CBIR systems can be based on many features, viz., texture, color, shape and edge information. Texture contains important information about the structural arrangement of surfaces and their relationship to the surroundings. Varieties of techniques are developed for texture analysis [9, 10]. Most of the textural features are obtained from the application of a local operator, statistical analysis, or measurement in transform domain. In [11] color distribution and quantization is used for color image retrieval. Shape features are computed assuming that images contain only one shape. Shape features include: modal matching [12], histograms of edge directions [13], and matching of shape components such as corners, line segments or circular arcs [14].

Recently Fu et al., [15] have proposed CBIR system based on features obtained by multi resolution LBP correlogram. Local binary patterns are used for texture feature extraction. This algorithm is tested on Brodatz data base and MIT Vistex data base [16, 17]. In the proposed method LDP and MLDP histograms are used as features vector to represent every image in the image data base. LBP actually encodes the binary result of the first order derivative among Local neighbors by using simple threshold function, which is incapable of describing more detailed information. LDP over comes these limitations and represents information in higher order local patterns. Hence the proposed method based on LDP is giving better performance in terms of computational complexity and retrieval efficiency over LBP feature based CBIR system

## 1.2. Related Work

The recently proposed local binary pattern (LBP) features are designed for texture description. Ojala et al. proposed the LBP [18] and these LBPs are converted to rotational invariant for texture classification [19]. Pietikainen et al. proposed the rotational invariant texture classification using feature distributions [20]. Ahonen et al. [21] and Zhao et al [22] used the LBP operator facial expression analysis and recognition. Heikkila et al. proposed the background modeling and detection by using LBP [23]. Huang et al. proposed the extended LBP for shape localization [24]. Heikkila

et al. used the LBP for interest region description [25]. Li et al. used the combination of Gabor filter and LBP for texture segmentation [26]. Zhang et al. proposed the local derivative pattern for face recognition [27]. They have considered LBP as a non directional first order local pattern, which are the binary results of the first-order derivative in images.

## 1.3. Main Contribution

To improve the performance in terms of retrieval accuracy and computational complexity, in this paper, we considered local derivative patterns (LDP\_16\_2). Two experiments have been carried out on Corel database and MIT VisTex databases for proving the worth of our algorithm. The results after being investigated shows a significant improvement in terms of their evaluation measures as compared to LBP\_16\_2, and other existing transform domain techniques.

The organization of the paper as follows: In section I, a brief review of image retrieval and related work is given. Section II, presents a concise review of Local Binary Patterns. Section III, presents the local derivative patterns and proposed system framework. Experimental results and discussions are given in section IV. Based on above work conclusions are derived in section V.

## 2. LOCAL BINARY PATTERNS (LBP)

The LBP operator introduced by Ojala et al. [18] as shown in Fig. 1. For a given center pixel in the image, a LBP value is computed by comparing it those of its neighborhoods:

$$LBP_{P,R} = \sum_{i=0}^{P-1} 2^i \times f(g_p - g_c) \quad (1)$$

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (2)$$

Where  $g_c$  is the gray value of the center pixel,  $g_i$  is the gray value of its neighbors,  $P$  is the number of neighbors and  $R$  is the radius of the neighborhood.

Example	Binary Pattern	Weights	LBP value																																				
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$LBP = 8 + 16 + 32 + 64 + 128 = 248$

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Figure1. LBP calculation for 3×3 pattern

Figure2 shows the examples of circular neighbor sets for different configurations of  $(P, R)$ .

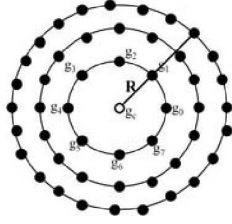


Figure2. Circular neighborhood sets for different  $(P, R)$

### 3. LOCAL DERIVATIVE PATTERNS (LDP)

#### 3.1. Local Derivative Patterns (LDP)

Baochang Zhang et al. proposed the LDP operator for face recognition [27]. In this scheme, LBP is conceptually regarded as the nondirectional first-order local pattern operator; because LBP encodes all-direction first-order derivative binary result while LDP encodes the higher-order derivative information which contains more detailed discriminative features that the first-order local pattern (LBP) cannot obtain from an image.

Given an image  $I$ , the first-order derivatives along  $0^\circ, 22.5^\circ, 45^\circ, 67.5^\circ, 90^\circ, 112.5^\circ, 135^\circ$  and  $157.5^\circ$  directions are denoted as  $I'_\alpha$ , where  $\alpha=0^\circ, 22.5^\circ, 45^\circ, 67.5^\circ, 90^\circ, 112.5^\circ, 135^\circ$  and  $157.5^\circ$ . Let  $g_c$  be a center point in  $I$ , and  $g_p$ ,  $p=1, 2, \dots, 16$  be the neighboring point around  $g_c$ . The eight first-order derivatives at  $g_c$  can be written as:

$$I'_{0^\circ}(g_c) = I(g_c) - I(g_1); \quad (3)$$

$$I'_{22.5^\circ}(g_c) = I(g_c) - I(g_2); \quad (4)$$

$$I'_{45^\circ}(g_c) = I(g_c) - I(g_3) \quad (5)$$

$$I'_{67.5^\circ}(g_c) = I(g_c) - I(g_4) \quad (6)$$

$$I'_{90^\circ}(g_c) = I(g_c) - I(g_5) \quad (7)$$

$$I'_{112.5^\circ}(g_c) = I(g_c) - I(g_6) \quad (8)$$

$$I'_{135^\circ}(g_c) = I(g_c) - I(g_7) \quad (9)$$

$$I'_{157.5^\circ}(g_c) = I(g_c) - I(g_8) \quad (10)$$

The second-order directional LDP,  $LDP_\alpha^2(g_c)$ , in  $\alpha$  direction at  $g_c$  is defined as

$$LDP_\alpha^2 \{ f(I'_\alpha(g_c), I'_\alpha(g_1)), f(I'_\alpha(g_c), I'_\alpha(g_2)), \dots, f(I'_\alpha(g_c), I'_\alpha(g_{16})) \} \quad (11)$$

where  $f(\dots)$  is a binary coding function determining the types of local pattern transitions. It encodes the co-occurrence of two derivative directions at different neighboring pixels as

$$f(I'_\alpha(g_c), I'_\alpha(g_p)) = \begin{cases} 0, & \text{if } I'_\alpha(g_c) * I'_\alpha(g_p) > 0 \\ 1, & \text{if } I'_\alpha(g_c) * I'_\alpha(g_p) \leq 0 \end{cases} \quad (12)$$

$$p = 1, 2, \dots, 16$$

The more details of the LDP is available in [27].

#### 3.2. Magnitude of LDPs

The magnitude LDPs are calculated by using the first order derivatives in  $\alpha$  direction at  $g_c$  is defined as:

$$MLDP_\alpha^2(g_c) = \{ \bar{f}(I'_\alpha(g_c), I'_\alpha(g_1)), \bar{f}(I'_\alpha(g_c), I'_\alpha(g_2)), \dots, \bar{f}(I'_\alpha(g_c), I'_\alpha(g_8)) \} \quad (13)$$

Where  $\bar{f}(\dots)$  is a binary coding function determining the types of local pattern transitions. It encodes the co-occurrence of two derivative directions at different neighboring pixels as

$$f(I'_\alpha(g_c), I'_\alpha(g_p)) = \begin{cases} 0, & \text{if } I'_\alpha(g_c) \leq I'_\alpha(g_1) \\ 1, & \text{if } I'_\alpha(g_c) > I'_\alpha(g_1) \end{cases} \quad (14)$$

$$p = 1, 2, \dots, 16$$

Further, these binary coded is converted into gray values by multiplying with weights as shown in Figure 1.

The uniform LBP/LDP pattern refers to the uniform appearance pattern which has limited discontinuities in the circular binary presentation. In this paper, the pattern which has less than or equal to two discontinuities in the circular binary presentation is considered as the uniform pattern and remaining patterns considered as non-uniform patterns.

Fig. 3 shows all uniform patterns for  $P=8$ . The distinct values for given query image is  $P(P-1)+3$  by using uniform patterns.

After identifying the LP (LBP/LDP) pattern of each pixel  $(j, k)$ , the whole image is represented by building a histogram:

$$H_s(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f(LP_{P,R}^{u2}(j,k,l); l \in [0, P(P-1)+3]) \quad (15)$$

$$f(x,y) = \begin{cases} 1 & x=y \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

Where the size of input image is  $N_1 \times N_2$ .

### 3.3. Proposed System Framework (LDP\_16\_2)

In this paper, we proposed the new technique by considering the neighboring pixels for image retrieval. The algorithm for the proposed image retrieval system is given below:

*Algorithm:*

*Input: Image; Output: Retrieval results.*

1. Load the input image and convert it into gray scale.
2. Perform the first order derivatives along  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$  directions.
3. Calculate the second order LDPs in  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$  directions using Eq. (7).
4. Calculate the LDP histograms in  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$  directions using Eq. (11).
5. Form the feature vector by concatenating the both LDP and MLDP histograms.
6. Calculate the best matches using Eq. (17).
7. Retrieve the number of top matches.

### 3.4. Similarity Measurement

In the presented work  $d_l^2$  similarity distance metric is used as shown below:

$$D(Q, I_l) = \sum_{i=1}^{Lg} \left| \frac{f_{I,i} - f_{Q,i}}{1 + f_{I,i} + f_{Q,i}} \right|^2 \quad (17)$$

where  $Q$  is query image,  $Lg$  is feature vector length,  $I_l$  is image in database;  $f_{I,i}$  is  $i^{th}$  feature of image  $I$  in the database,  $f_{Q,i}$  is  $i^{th}$  feature of query image  $Q$ .

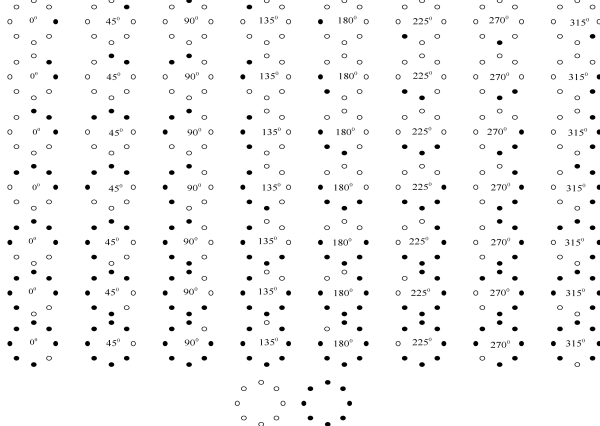


Figure3. Uniform patterns when  $P=8$ . The black and white dots represent the bit values of 1 and 0 in the  $S_{LP}$  operator.

## 4. EXPERIMENTAL RESULTS AND DISCUSSIONS

For the work reported in this paper, retrieval tests are conducted on two different databases (Corel 1000, and MIT VisTex) and results are presented separately.

### 4.1 Database DB1

Corel database [28] 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. Some researchers think that Corel database meets all the requirements to evaluate an image retrieval system, because of its large size and heterogeneous content. In this paper, we collected the database DB1 contains 1000 images of 10 different categories (groups  $G$ ). Ten categories are provided in the database namely *Africans*, *beaches*, *buildings*, *buses*, *dinosaurs*, *elephants*, *flowers*, *horses*, *mountains* and *food*.

Each category has 100 images ( $N_G = 100$ ) and these have either  $256 \times 384$  or  $384 \times 256$  sizes. Fig. 4 depicts the sample images of Corel 1000 image database (one image from each category).

The performance of the proposed method is measured in terms of average precision and average recall by Eq. (18) and (19) respectively.

$$\text{Precision}[P(I_q, n)] = \frac{\text{No. of Relevant Images Retrieved}}{\text{Total No. of Images Retrieved}} \quad (18)$$

$$\text{Recall}[R(I_q, n)] = \frac{\text{No. of Relevant Images Retrieved}}{\text{Total No. of Relevant Images in Database}} \quad (19)$$

where  $I_q$  is the query image and  $n$  is number of top matches considered.

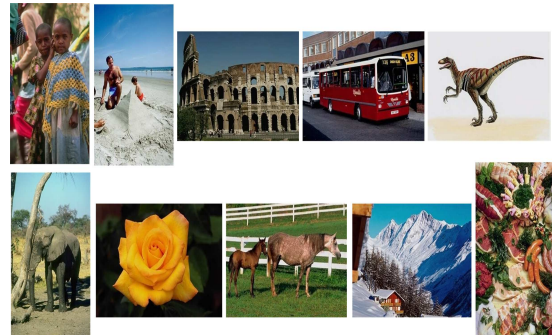


Figure4. Sample images from Corel 1000 (one image per category)

Table I and II summarizes the retrieval results of the proposed method LDPM (LDP\_P\_R+MLDP\_P\_R), LDP\_P\_R, LBP\_P\_R and other transform domain methods (WC and GWC) in terms of average retrieval precision and

recall respectively. From Table I, Table II, and Fig. 5, it is clear that the proposed method showing better performance compared to LBP\_P\_R, LDP\_P\_R and other transform domain methods in terms of average retrieval precision and recall.

TABLE I RESULTS OF ALL TECHNIQUES IN TERMS OF PRECISION ON DB1 DATABASE

Category	WC [11]	GWC[8]	LBP_8_1	LBP_16_2	LDP_8_1	LDP_16_2
Africans	57.7	52.9	61.8	64.4	62.4	66
Beaches	49.3	42	55.4	54.3	59.4	58
Buildings	50.9	47.8	65.4	63.3	73.1	66
Buses	87.1	88.3	96.7	96.4	97.5	95.4
Dinosaurs	74.6	96.2	98.4	96.7	96.2	96.6
Elephants	55.7	65.9	46.3	50.7	54.4	60
Flowers	84.3	75.5	92.2	92.5	90.3	89.1
Horses	78.9	73	76.7	79.1	77.2	75.8
Mountains	47.2	35.2	41.9	43.3	39.6	44.3
Food	57.1	63.2	68.6	66.2	84.1	76.9
Total	64.3	64.1	70.3	70.7	73.42	72.81

TABLE II RESULTS OF ALL TECHNIQUES IN TERMS OF RECALL ON DB1 DATABASE

Category	WC [11]	GWC[8]	LBP_8_1	LBP_16_2	LDP_8_1	LDP_16_2
Africans	31.1	33.2	38.1	37.6	37.57	39.83
Beaches	28.6	26.2	35.4	29.6	37.42	33.79
Buildings	30.5	26.5	33.7	29.6	38.03	35.53
Buses	64	65.1	70.5	74.2	76.32	65.55
Dinosaurs	28.8	65	75.1	67.9	77.78	72.26
Elephants	30.7	37	25.4	25.4	28.91	30.25
Flowers	65.3	50.4	65.6	66	64.04	64.62
Horses	39.9	39.5	42.2	43.4	43.36	37.56
Mountains	25.1	20.1	26.9	24.6	25.1	25.55
Food	36.4	43.1	37.2	35	48.75	42.7
Total	38	40.6	44.9	43.3	47.72	44.76

TABLE III RESULTS OF ALL TECHNIQUES IN TERMS OF AVERAGE RETRIEVAL RATE ON DB2 DATABASE

T1: DT-CWT; T2: DT-RCWT; T3:T1+T2

GGD&KLD	T1	T2	T3	LBP_8_1	LBP_16_2	LDP_8_1	LDP_16_2
76.57%	80.78	75.78	82.34	82.23	81.2	85.03	81.01



TABLE IV RESULTS OF PROPOSED METHOD WITH DIFFERENT DISTANCE MEASURES IN TERMS OF AVERAGE RETRIEVAL RATE ON DB2 DATABASE

Distance	City Block (L1)	Euclidian (L <sub>2</sub> )	Canberra	d <sub>1</sub> <sup>2</sup>
LDPM_8_1	87.13%	80.50%	87.11%	<b>87.31%</b>
LDPM_16_2	88.12%	79.61%	88.13%	<b>88.22%</b>

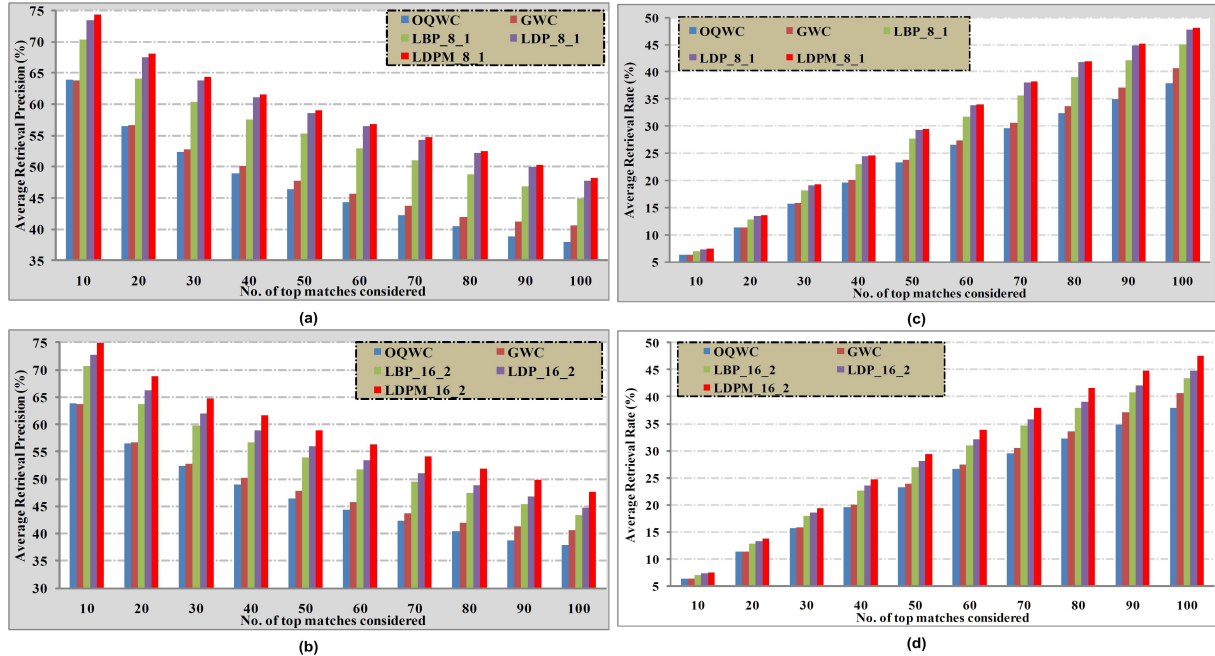


Figure5. Comparison of proposed method (LDPM) with other existing methods in terms: (a)–(b) average retrieval precision, (c)–(d) average retrieval rate

#### 4.2. Database DB2

The database DB2 used in our experiment consists of 400 different textures [29]. The size of each texture is 512×512. Each 512×512 image is divided into sixteen 128×128 non-overlapping sub-images, thus creating a database of 640 (40×16) images. The performance of the proposed method is measured in terms of average retrieval rate (ARR) is given by Eq. (20).

$$ARR = \frac{1}{|DB|} \sum_{i=1}^{|DB|} R(I_i, n) \Big|_{n=16} \quad (20)$$

The database DB2 is used to compare the performance of the proposed method LDPM (LDP\_P\_R+MLDP\_P\_R) with, LBP\_P\_R, LDP\_P\_R, GGD & KLD [14], DT-CWT [18], DT-RCWT [18], and DT-CWT+DT-RCWT. Table III summarizes average retrieval rate of all methods. From Table III and Fig. 6, it is evident that the proposed method LDPM\_P\_R (87.31%/88.22%) is outperforming the T1 (80.78%), T2 (75.78%), T3 (82.34%), LBP\_P\_R (82.23%/81.2%) and LDP\_P\_R (85.03%/81.01%).

The results of the proposed method are also compared with the different distance measures as shown in Table IV. From Table IV, it is found that the d12 distance is outperforming

(87.31%/88.22%) the L1 distance (87.13%/88.12%), L2 distance (80.5%/79.6%), and Canberra (87.11%/88.13%).

#### 5. CONCLUSIONS

A new image indexing and retrieval algorithm is proposed in this paper by considering the LDP\_16\_2 features. Two experiments have been carried out on Corel database and MIT VisTex for proving the worth of our algorithm. The results after being investigated shows a significant improvement in terms of their evaluation measures as compared to LBP\_16\_2 and other existing transform domain techniques.

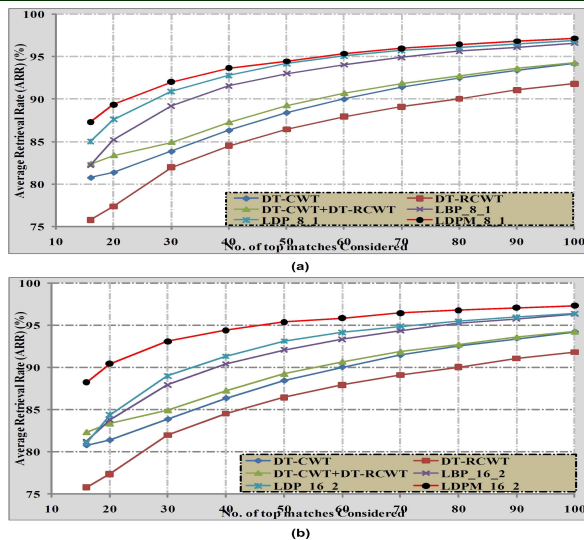


Figure6. Average retrieval precision of DB2 database according to no. of top matches considered

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