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Novel Directional Local Difference Binary Patterns (DLDBP) for Image, and Video Indexing and Retrieval

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***Abstract*—**In this paper, we propose a novel algorithm based on directional local difference binary patterns useful for content based image indexing and retrieval. The popular and successful method local binary patterns (LBP) codify a pixel, based on the neighborhood gray values around the pixel. Another flavor of LBP is, center symmetric local binary patterns (CS-LBP), which is the base method for our proposed novel algorithm. The proposed method is based on the directional difference between neighboring pixels. The four directional local difference binary patterns (DLDBP) in 0o, 45o, 90o, and 135o directions are proposed. Then, we apply our method on benchmark image database Corel-1k. The proposed DLDBP (Directional Local Difference Binary Patterns) can also be used to represent a video, using a key frame in the video. We apply the proposed directional local difference binary patterns (DLDBP) key frame based algorithm, on a video database, which consists of ten videos of airplane, ten videos of sailing boat , ten videos of car, and ten videos are of war tank. The performance of proposed DLDBP (Directional Local Difference Binary Patterns) is compared with CS-LBP (Central Symmetric Local Binary Patterns) method. The performance of DLDBP key frame based method is compared with volume local binary patterns (VLBP) method.

***Index Terms*—**Image, Indexing, Retrieval, Directional local difference binary patterns (DLDBP), LBP, CS-LBP, video, key-frame.

I. INTRODUCTION

In this present era, the availability of efficient cameras made it possible to have images easily. Due to which there are huge amounts of images present in image databases. This is where the demand for efficient indexing, and retrieval framework arises, to maintain the database. Content-based image indexing and retrieval (CBIR) methods depend on the features like color, shape, and texture, etc. The detailed literature survey on different existing CBIR methods can be found in [1-4].

Texture based methods, which are successful in pattern recognition applications have attained a great deal of interest by the research community. Ahmadian et al. proposed a method for texture classification based on wavelet transform in [5]. Image retrieval based on discrete wavelet transform can be found in [6]. The authors of [7] proposed image segmentation and texture based classification, using wavelet frames. Image retrieval based on gabor transform can be found in [8].

Texture based image retrieval using the combination of dual tree rotated complex wavelet filters and dual tree complex wavelet filters can be observed in [9-11]. ojala et al. in [12] introduced the popular texture based method known as local binary patterns (LBP), which has been successful in texture based pattern recognition tasks like, image retrieval, face detection, background modeling, and finger print recognition, etc. Rotational invariant LBP was proposed in [13]. An extended version of LBP meant for shape localization has been introduced in [14]. Li et al. in [15] have proposed a method for texture segmentation based on combined Gabor filter along with LBP features. Zhang et al. in [16] have proposed a method for face recognition using local derivative patterns. Subramanyam et al. in [17] have proposed directional local extrema patterns meant for content based image retrieval. Ibrahim S. I. Abuhaiba et al. [18] have proposed a novel image retrieval method based on global texture and local color features of the image. Hadis Heidari et al. [19] have introduced a method for image retrieval based on graphical processors units. K. Prasanthi Jasmine et al. in [20] have introduced a new framework meant for image retrieval based on color and wavelet transform features. A new algorithm useful for medical image retrieval based on generalized gamma distribution is proposed in the paper [21]. Another flavor of LBP is center symmetric local binary patterns (CS-LBP) was proposed in [22] for interest region description.

Main contributions of this paper are:

1. Directional local difference binary patterns in 0^o, 45^o, 90^o, and 135^o directions are proposed. The proposed method is different from CS-LBP.
2. Experiments are carried out on benchmark database Corel-1k, and results of our method are compared with CS-LBP method.
3. A novel video indexing and retrieval method based on DLDBP is proposed.

The rest of the paper is organized as follows; section 2 talks about related work. Section 3 discusses about the proposed methods. Section 4 projects the experimental work and results, and section 6 concludes the paper with future remarks.

II. Related Work

There are a number of texture based methods, which have been proposed in the past literature meant for CBIR. Among them, in this section, we are going to discuss about local binary patterns (LBP), center symmetric local binary patterns (CS-LBP), and volume local binary patterns (VLBP).

A. *Local binary patterns (LBP)*

Ojala et al. in [12] have proposed LBP method, which is a successful texture based routine, and it has been practical in some of the popular areas of research such as face identification, image retrieval, and object tracking, etc. LBP value is computed for a 3x3 square of an image by comparing the gray value of the center pixel with its neighborhood pixels as shown in the following equation (1).

$$LBP(I(C)) = \sum_{p=1}^{8} 2^{(p-1)} \times f_1\big(I(C) - I(N_p)\big) \qquad (1)$$

Where

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

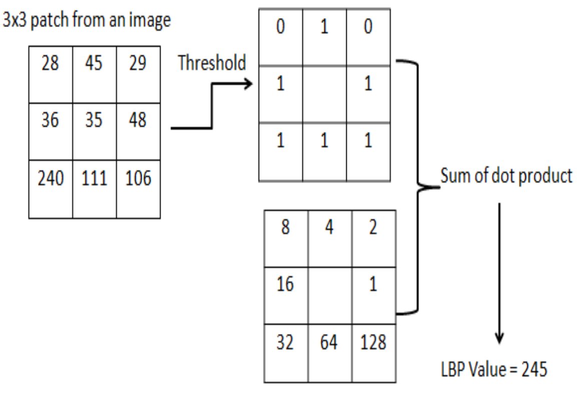


Fig.1. An example LBP value calculation

In the above equation I(C), and I(Np) signify gray value of the center pixel, and neighborhood pixel p respectively. Subsequent to computing LBP values for all the pixels in the image, extract a histogram, which will act as the feature vector of the image.

An example LBP calculation is as shown in figure, Fig.1.

B. *Center symmetric local binary patterns (CS-LBP)*

Heikkila et al. [18] have proposed center symmetric local binary patterns (CS-LBP) method, in contrast to finding difference between center pixel and each of the neighborhood pixels as in LBP, here, in CS-LBP, the difference between center symmetric pairs of pixels are computed, then, the resultant values will be compared with a predefined threshold value T, as shown in below figure, Fig.2.

$P_4(156)$	$P_3(215)$	$P_2(128)$
$P_5(128)$	$P_c(125)$	$P_1(56)$
$P_6(96)$	$P_7(211)$	$P_8(112)$

$$CS-LBP(P_c) = ((P_1 - P_5) > T) \times 2^0$$
$$+ ((p_2 - P_6) > T) \times 2^1$$
$$+ ((p_3 - P_7) > T) \times 2^2$$
$$+ ((p_4 - P_8) > T) \times 2^3$$
$$CS-LBP(125) = (0 + 2 + 4 + 8) = 14$$

Fig.2. An example finding CS-LBP for the center pixel

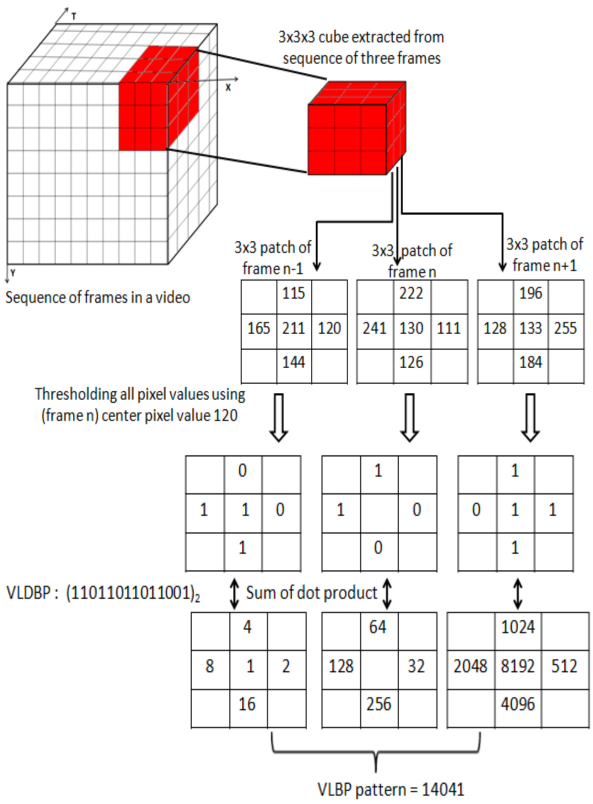


Fig.3. An example implementation of VLBP

As shown in figure Fig.2, the center symmetric local binary pattern for the center pixel is calculated using a predefined threshold value T, in our case T=0, 5, and 10. CS-LBP can be implemented easily, and an image can be represented with less number of texture patterns. CS-LBP is an interested region descriptor which has the strength of scale invariant feature transform (SIFT) combined with local binary patterns (LBP).

C. *Volume local binary patterns (VLBP)*

VLBP method has been proposed in [19], which is useful for dynamic texture extraction from a video. Texture features are extracted by using three sequential frames of the video as shown in below figure, Fig.3.

Detailed implementation of volume local binary patterns (VLBP) method can be found in [19].

III. Proposed Frameworks

In this section, we propose two novel frameworks based on DLDBP. Our proposed algorithm of texture extraction from an image has been inspired by the method CS-LBP. In contrast to comparing center semantic pairs of pixels as incase of CS-LBP, our proposed method ompares directional center symmetric pair of pixels. Our method computes directional local difference binary patterns in 0^o, 45^o, 90^o, and 135^o directions. For a pixel at position *(i , j)* in an image *I*, the DLDBP in all four directions as specified above can be computed with the help of following equations (2), (3), (4), and (5) respectively.

$$DLDBP0^o(i,j)=\sum_{p=1}^{8}2^{(p-1)}\times F1 \tag{2}$$

$$DLDBP45^o(i,j)=\sum_{p=1}^{8}2^{(p-1)}\times F2 \tag{3}$$

$$DLDBP90^o(i,j)=\sum_{p=1}^{8}2^{(p-1)}\times F3 \tag{4}$$

$$DLDBP135^o(i,j)=\sum_{p=1}^{8}2^{(p-1)}\times F4 \tag{5}$$

Where

$$F1=f(I(i,j-1)-I(i,j+1))$$
$$F2=f(I(i-1,j-1)-I(i+1,j+1))$$
$$F3=f(I(i-1,j)-I(i+1,j))$$
$$F4=f(I(i-1,j+1)-I(i+1,j-1))$$

And

$$f(x)=\begin{cases}1 & x>T\ (predefined\ threshold)\\ 0 & otherwise\end{cases}$$

The framework of the proposed DLDBP is as shown in below figure, Fig.4.

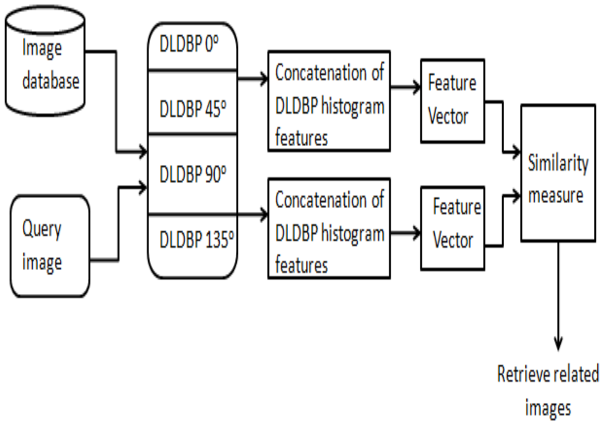
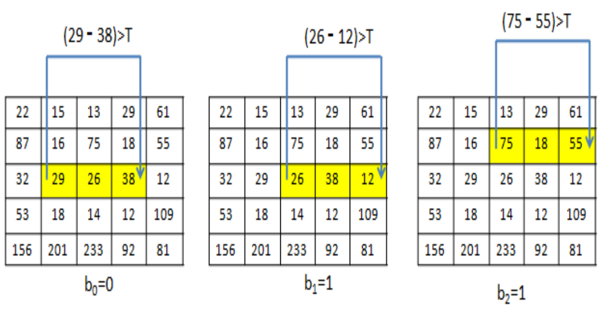


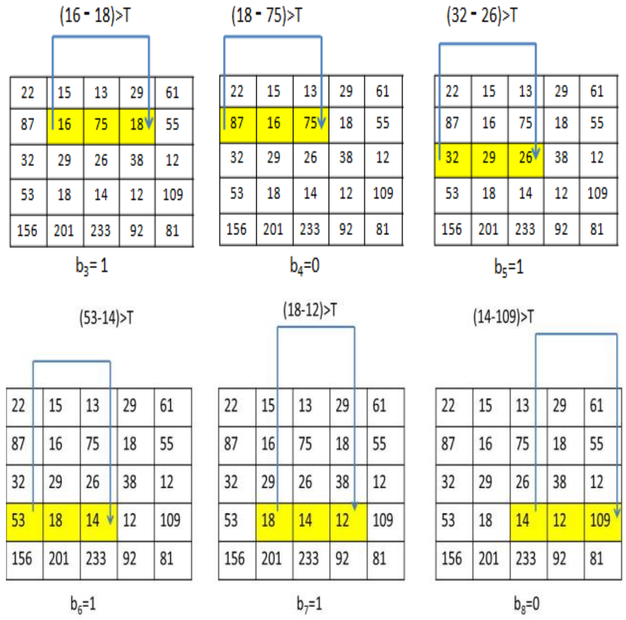
Fig.4. Framework of DLDBP

The initial step in our framework is for a pixel of the input image select the five by five neighborhood pixels around it then find the directional local difference binary patterns in all four directions 0^o, 45^o, 90^o, and 135^o using the equations 2, 3, 4, and 5 respectively. After applying the above procedure on all the pixels of the image, feature vector is obtained by concatenating the extracted directional local difference binary patterns. For the query image the feature vector of the query image is compared with pre-computed feature vectors of the images in the database using k-nearest neighbor search algorithm (k value is 10 for precision, and k value is 100 for recall) and relevant images are retrieved as output.

For threshold value T=0, an example of finding DLDBP in 0^o direction for 3x3 patch (highlighted in blue color) is as shown in below figure, Fig.5.

22	15	13	29	61
87	16(b_4)	75(b_3)	18(b_2)	55
32	29(b_5)	26(b_0)	38(b_1)	12
53	18(b_6)	14(b_7)	12(b_2)	109
156	201	233	92	81



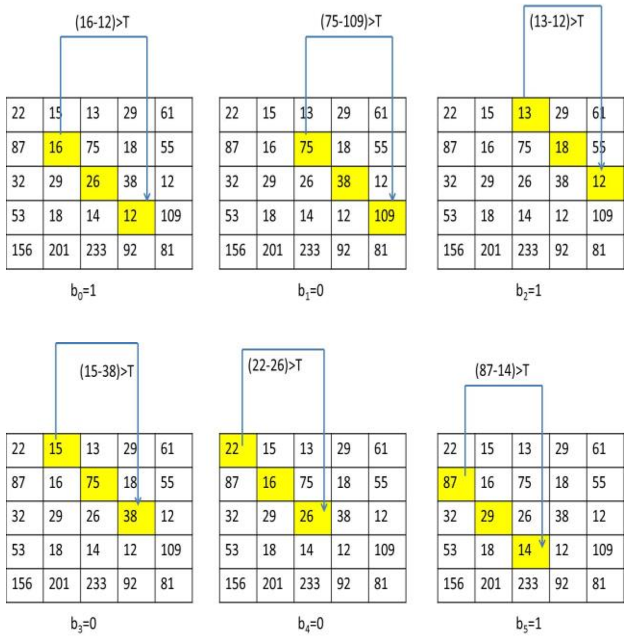


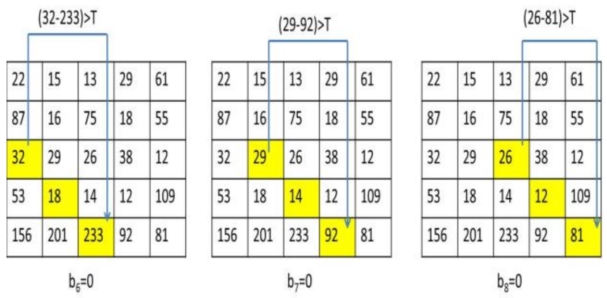
DLDBP 0° pattern = 011101110
DLDBP value = 238

Fig.5. An example calculation of DLDBP in 0° direction

For threshold value T=0, an example of finding DLDBP in 45° direction for 3x3 patch (highlighted in blue color) is as shown in below figure, Fig.6.

22	15	13	29	61
87	16(b_4)	75(b_3)	18(b_2)	55
32	29(b_5)	26(b_0)	38(b_1)	12
53	18(b_6)	14(b_7)	12(b_2)	109
156	201	233	92	81



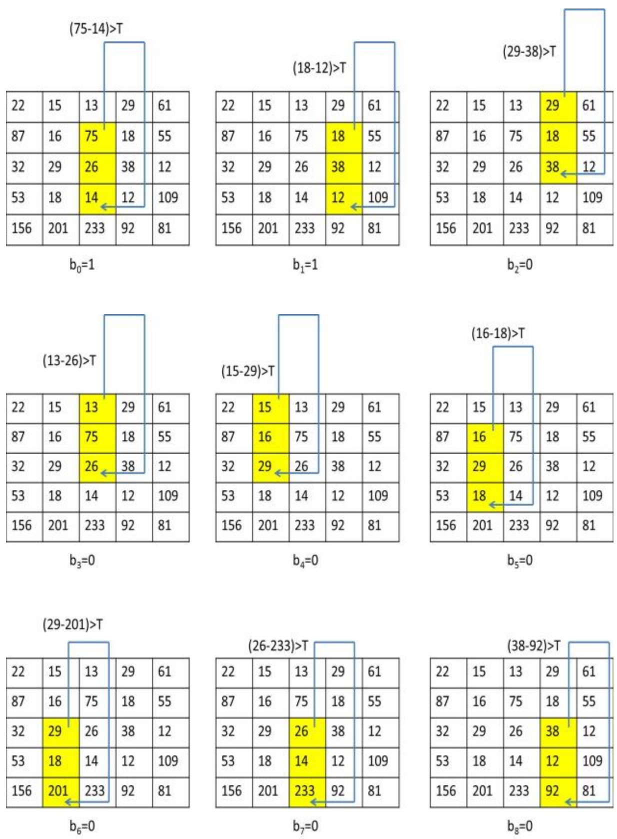


DLDBP 45° pattern = 000100101
DLDBP value = 37

Fig.6. An example calculation of DLDBP in 45° direction

For threshold value T=0, an example of finding DLDBP in 90° direction for 3x3 patch (highlighted in blue color) is as shown in below figure, Fig.7.

22	15	13	29	61
87	16(b_4)	75(b_3)	18(b_2)	55
32	29(b_5)	26(b_0)	38(b_1)	12
53	18(b_6)	14(b_7)	12(b_2)	109
156	201	233	92	81



DLDBP 90° pattern = 000000011
DLDBP value = 3

Fig.7. An example calculation of DLDBP in 90° direction

For threshold value T=0, an example of finding DLDBP in 135° direction for 3x3 patch (highlighted in blue color) is as shown in below figure, Fig.8.

22	15	13	29	61
87	16(b_4)	75(b_3)	18(b_2)	55
32	29(b_5)	26(b_0)	38(b_1)	12
53	18(b_6)	14(b_7)	12(b_2)	109
156	201	233	92	81

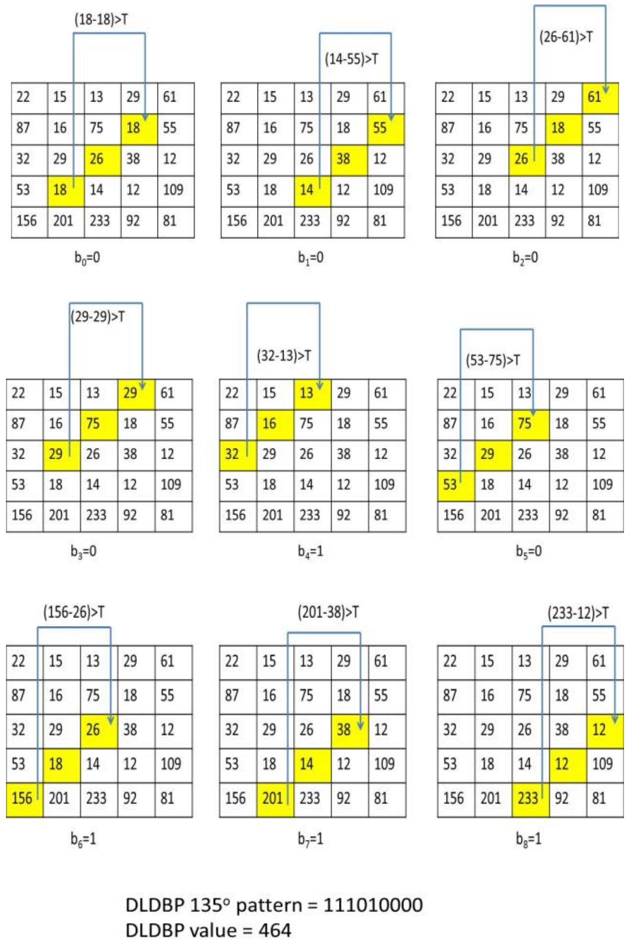


Fig.8. An example calculation of DLDBP in 135° direction

After calculating DLDBP for all the pixels in an image, the image is represented by using histogram calculated with the following equation.

$$H_{DLDBP}(l) = \sum_{j=1}^{N1} \sum_{k=1}^{N2} h(DLDBP(j,k),l)$$
$$l \in [1,2,3,........,255] \qquad (6)$$

Where

$$h(x,y) = \begin{cases} 1 & x = y \\ 0 & otherwise \end{cases}$$

As shown in above equation the histogram is calculated for DLDBP, we ignore zero patterns for having accuracy in retrieval of similar images. That is histogram is calculated for the values from one to two hundred and fifty five (1-255).

An example image from the Corel-1k dataset and the resultant images after applying the proposed directional local difference binary patterns in 0°, 45°, 90°, and 135° method are as shown in below figure, Fig.9.

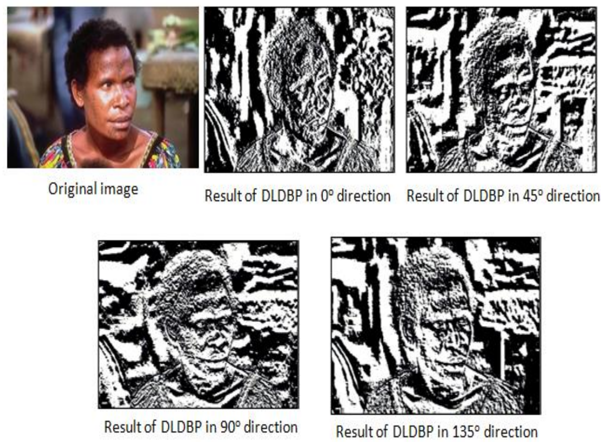


Fig.9. Example DLDBP feature maps

The framework of our proposed DLDBP method is as shown in figure, Fig.4, and the proposed DLDBP algorithm is presented below:

Step 1: For an input Gray scale image

Step 2: Compute directional local difference binary patterns in 0°, 45°, 90°, and 135° directions for all the pixels in the image.

Step 3: Separate histograms are constructed in 0°, 45°, 90°, and 135° directions using equations (2), (3), (4), and (5) respectively.

Step 4: Feature vector is constructed by concatenating all the histograms obtained in step 3.

Step 5: Query image feature vector is compared with the feature vectors of images in the database using k-nearest neighbor search method.

Step 6: Best matched images are retrieved.

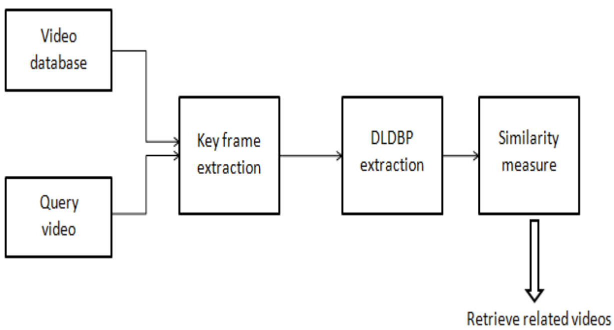


Fig.10. Video indexing and retrieval framework

Our video indexing, and retrieval framework is as shown in figure Fig.10. Initial step in the framework is, from the input video extract twenty key frames using histogram based method as presented in below algorithm:

Step 1: For the input video, convert each frame from RGB to equivalent gray scale frame.

Step 2: Compute the histogram of each gray scale frame.

Step 3: Find out the mean histogram of all the histograms computed in step 2.

Step 4: Find out the twenty nearest histograms to mean histogram using k-nearest neighbor search method.

Step 5: Declare the nearest histogram frames as key frames of the video.

As shown in the figure Fig.10, the next step is to find the DLDBP for the selected twenty key frames, and concatenate the DLDBP of all the twenty key frames of the video to form the feature vector of the video.

Our video database consists of ten airplane videos, ten sailing boat videos, ten car videos, and ten war tank videos. For each video in the database, the same procedure of finding key frames and extracting DLDBP is followed. A snap shot of our video dataset is as shown in figure, Fig.11.

Fig.11. A snapshot of video dataset

IV. Experimental Results

We have performed our experiments and tested the proposed method of DLDBP on Corel-1k database. The corel-1k database consists of one thousand images of ten different classes of images; each class type consists of one hundred images. We have evaluated our proposed video indexing and retrieval algorithm on the video database available at [20]. The retrieval performance is evaluated using precision and recall. Precision and Recall are calculated using following equations.

$$precision = \frac{T_p}{T_p + F_p} \tag{7}$$

$$recall = \frac{T_p}{T_p + F_n} \tag{8}$$

Where T_p stands for True positive, F_p stands for False positive, and F_n stands for False negative.

Table 1. Precision (n=10) (%) based on top ten images retrieved for the query image with threshold value T = 0, 5, and 10

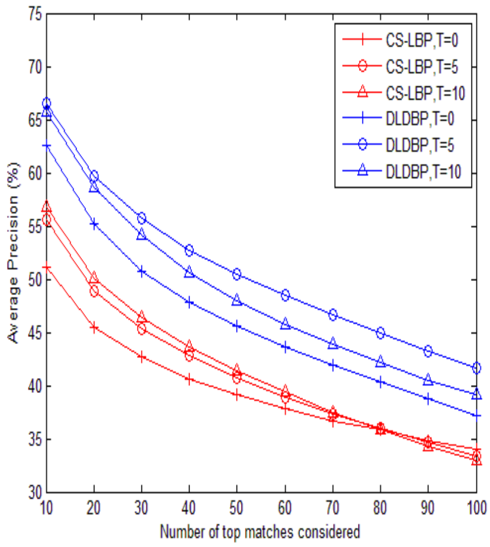
Category	CS-LBP			DLDBP		
	T=0	**T=5**	**T=10**	**T=0**	**T=5**	**T=10**
Africans	50.7	50.7	51.7	46.7	65.1	65.5
Beaches	46.4	46.7	46.2	54.8	50.3	45.7
Buildings	34.2	34.5	35.4	54.9	55.2	51.5
Buses	56.3	78.6	81.0	91.7	91.8	88.5
Dinosaurs	95.5	94.7	93.7	96.2	95.0	92.6
Elephants	34.6	37.5	37.8	42.9	50.8	52.1
Flowers	76.5	85.9	90.4	77.3	83.7	85.9
Horses	64.5	61.8	59.8	75.4	72.1	71.6
Mountains	26.7	32.5	32.8	35.9	43.0	41.5
Food	25.6	32.5	39.3	49.4	58.0	61.7
Average value	**51.10**	**55.54**	**56.81**	**62.52**	**66.50**	**65.66**

Table 2. Recall (n=100) (%) based on top hundred images retrieved for the query image with threshold value with threshold T = 0, 5, and 10

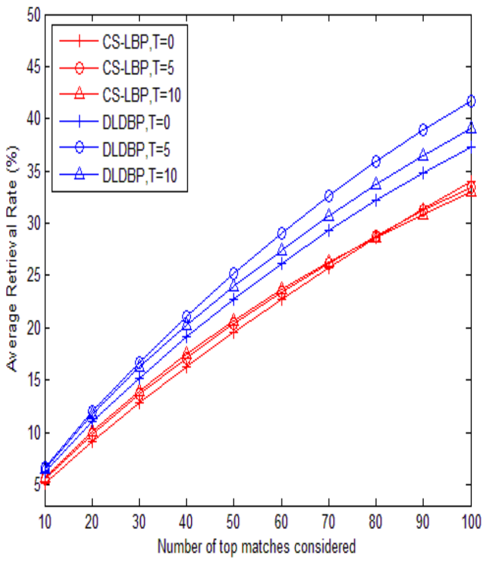
Category	CS-LBP			DLDBP		
	T=0	**T=5**	**T=10**	**T=0**	**T=5**	**T=10**
Africans	32.60	30.04	26.36	29.10	37.59	33.56
Beaches	29.66	26.22	25.28	27.15	29.03	27.02
Buildings	19.04	17.39	18.12	25.53	24.39	24.08
Buses	41.09	45.23	46.77	63.95	68.35	64.71
Dinosaurs	88.35	76.61	69.00	79.42	75.14	66.11
Elephants	18.76	19.38	20.99	22.19	24.64	27.09
Flowers	45.17	46.70	47.98	43.82	52.96	47.82
Horses	33.16	34.02	32.63	33.16	41.86	38.08
Mountains	16.32	19.77	20.32	21.28	28.29	27.08
Food	15.74	18.82	22.71	26.71	34.48	34.74
Average value	**33.99**	**33.42**	**33.02**	**37.23**	**41.67**	**39.03**

The results we have obtained after applying the proposed DLDBP method and existing CS-LBP on corel-1k dataset are as shown in above tables Table1 and Table 2. Precision is calculated based on top ten images retrieved for the query image, and recall is computed based on top hundred images retrieved for the query image. On an average our proposed method have achieved precision of 66.5%, and recall of 41.67% with the threshold value T=5.

Comparison of average precision and average recall results of proposed DLDBP and that of existing CS-LBP method are as shown in below graphs in figure, Fig.12.



(a)



(b)

Fig.12. Comparison of proposed method DLDBP with existing method CS-LBP in terms of (a) average precision (b) average retrieval rate on the benchmark database Corel-1k.

Our proposed video indexing and retrieval frameworks results are as shown below. As discussed above our proposed algorithm is applied on a video database of forty videos (airplane, sailing boat, car, and war tank), which are available at [20].

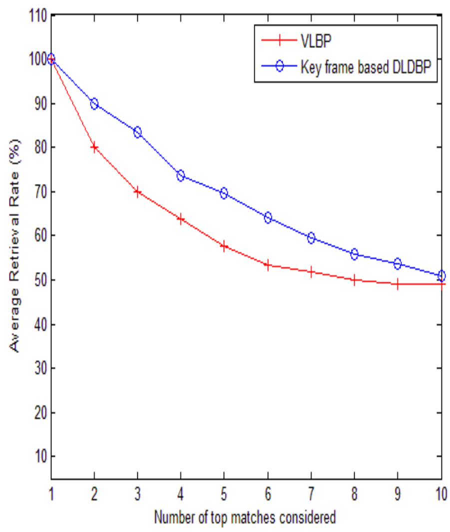
Table 3. Precision (n=5) (%) based on top five videos retrieved for the query image with threshold value T=5.

Category	VLBP	Key frame based DLDBP
Airplane	70	84
Sailing boat	50	68
Car	62	68
War tank	48	58
Average value	**57.5**	**69.5**

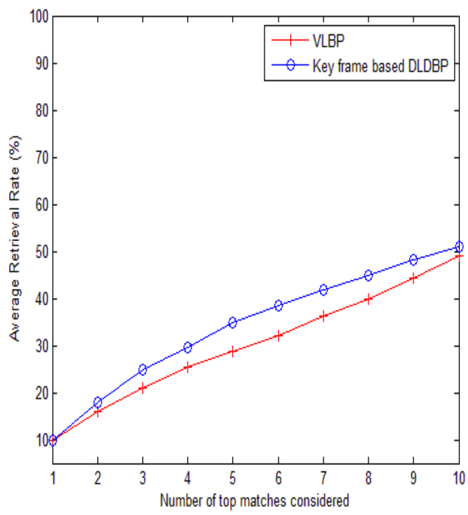
Table 4. Recall (n=10) (%) based on top ten videos retrieved for the query image with threshold value T=5.

Category	VLBP	Key frame based DLDBP
Airplane	52	58
Sailing boat	48	52
Car	56	55
War tank	40	39
Average value	**49**	**51**

The average precision and average retrieval recall results of, video indexing and retrieval framework of key frame based DLDBP, for different numbers of top matches are as shown in the following graphs in figure Fig.13. On an average our proposed algorithm has achieved 69.5% precision and 51% recall.



(a)



(b)

Fig.13. Comparison of proposed video indexing and retrieval method, key frame based DLDBP with existing method VLBP in terms of (a) average precision (b) average retrieval rate

V. Conclusion

In this paper, a novel image indexing and retrieval framework called directional local difference binary patterns (DLDBP) has been proposed, and as well as a framework meant for video indexing and retrieval using key frame based DLDBP has been introduced. Experiments are carried out on benchmark image database Corel-1k and compared the results with existing central symmetric local binary patterns method. Also, we have evaluated the video indexing and retrieval framework on a database available at [20], and compared the results with the existing volume local binary patterns (VLBP) method. Compared to existing methods our proposed methods have shown reasonably good results. As our future work we will try to improve the proposed algorithms performance by introducing Gabor filters.

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