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AN EFFICIENT HYBRID FEATURE DESCRIPTOR FOR CONTENT BASED IMAGE RETRIEVAL

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ABSTRACT

In recent days the content-based image retrieval plays an important role in image retrieval and has achieved great development. This paper proposes a novel diagonal direction feature descriptor for content based image retrieval (CBIR). In Existing Local Tetra pattern, the relationship between the referenced pixel and its neighbors are encoded using first order derivatives only in vertical and horizontal direction. The image retrieval results are further improved by considering diagonal pixels for derivative computation in addition to vertical and horizontal direction. The proposed system includes the following phases 1) Pre-processing of an image using resize method and calculation of the direction of a pixel by computing the first order derivatives along with 0°, 90° and 45° 2) Derivation of Local Octa Pattern from the direction 3) Construction of Magnitude Pattern using magnitude of first order derivatives 4) Calculation of feature vector on combining LOP and magnitude pattern and then similarity is measured. Experimental results show the proposed method is capable of effectively retrieving relevant images thus providing superior performance than several existing approaches.

Keywords: *Feature Vector, Local Tetra Pattern (LTrP), Local Octa Pattern (LOP), Local Binary Pattern.*

1. INTRODUCTION

The fast expansion of worldwide network and improvements in information technology leads to an explosive progress of multimedia databases and digital libraries used in application sectors such as scientific, educational, medical, and industrial and agriculture etc. The ultimate aim of content based image retrieval process is to extract the desired image data of the user more accurately. This demands an effective tool that allows users to search and browse efficiently through a large collection [1]. Content-based image retrieval (CBIR) is one of the most accepted solutions for above mentioned applications.

The CBIR utilizes image's visual contents such as color, texture, shape, faces, spatial layout, etc., for the representation and indexing of the image database [2]. It is difficult for an algorithm to choose the best image in various illumination changes from large collection. The survey of various image mining techniques is presented in [3]. The image retrieval performance is further optimized using an evolutionary approach [4]. Texture[5] plays an important role in identifying ceramic tiles and marble pattern in industrial applications. Saadatmand Tarzjan has explained about Gabor wavelet correlogram used in texture based image retrieval for CBIR [6]. The shape [7] of the objects characterized in images is one of the weightiest properties used in CBIR and in recognition tasks. This is due to the fact that the shape is relevant for identifying an object. Anjali Goyal described shape based retrieval and demonstrated its performances measures [10].

The remainder of this paper is organized as follows. Section 2 discussed the related works on content based image retrieval. Section 3 presents the proposed octa pattern framework and describe the methods for the experiment. Experimental results are discussed in section 4 and Finally Section 5 is concluded with the direction of future work.

2. RELATED WORKS

A keyword based approach is influenced by subjective decision on image content and is difficult to change a keyword based system. Therefore, new techniques are required to

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overcome such limitations [8], [9]. Color histograms are used in computer vision and have multiple number of computational advantages, and they are also sensitive to both illumination changes and quantization errors. The colors of similarity can be quantized into different number of bins, since conventional methods assign every pixel into a bin. Fuzzy approach can overcome this issue on assigning a pixel into a bin of each histogram with a degree of association through functions of fuzzy-set membership described in[16].

Contour-based descriptions concentrate only on boundary lines; hence, they are not suitable for complex shapes consisting of several disjoint regions such as clipart, emblem, trademark etc., Region-based methods consider the whole area of the object and are most suitable for complex shapes [11], [12]. Commonly, region-based methods use moment for shape description. Regular moments store redundant information. Since low-order moments cannot describe the shape accurately the high-order moments are desirable [13].

Baochang Zhang proposed a novel high-order local pattern descriptor, local derivative pattern (LDP), for face recognition [14], [16]. LDP is a general framework to encode directional pattern features based on local derivative variations. The n th-order LDP is proposed to encode the (n-1) th-order local derivative direction variations, which can capture detailed information than the first-order local pattern used in local binary pattern (LBP). Different from LBP[15] encoding the relationship between the central point and its neighbours, the LDP templates extract high-order local information by encoding various distinctive spatial relationships contained in a given local region. Both gray-level images and Gabor feature images are used to evaluate the comparative performances of LDP and LBP.

A novel image indexing and retrieval algorithm using local tetra patterns (LTrPs) for content-based image retrieval (CBIR) was proposed in [17]. The standard local binary pattern (LBP) and local ternary pattern (LTRP) encode the relationship between the referenced pixel and its surrounding neighbours by computing grey-level difference.

The proposed method encodes the relationship between the referenced pixel and its neighbours, based on the directions calculated using the first-order derivatives in vertical and horizontal directions. [18] uses the Multi Wavelet decomposition scheme and color correlogram, which yield improved retrieval performance. Through combination of Multi wavelet decomposition and color correlogram increase the number of features, which improves the retrieval accuracy. To support the fast retrieval of relevant images from image databases feature extraction plays an important role in content-based image retrieval.

In [19] a new approach was introduced for image indexing called wavelet correlogram. According to this approach, wavelet coefficients are computed first to decompose space-frequency information of the image. These directional sub bands enable the user to compute the image spatial correlation in a more efficient way, while taking into consideration the semantic image information. Quantization step is then applied before computing directional autocorrelograms of the wavelet coefficients. Finally, index vectors are constructed using these wavelet correlograms.

3. PROPOSED SYSTEM

The goal of the proposed system is to detect the most relevant images from the databases. In the proposed method, the LOP includes Local Derivative Pattern (LDP), Local Binary Pattern (LBP) and Local Tetra Pattern (LTrP). The LOP is able to encode the images with eight distinct values as it is able to extract more detailed information. LTrP encodes the relationship between the center pixel and its neighbours based on directions that are calculated with the help of (n-1) th-order derivatives. LOP encodes the relationship based on the direction of the centre pixel and its neighbours, which are calculated by combining (n-1)th order derivatives of the $0^{\circ},90^{\circ},45^{\circ}$ directions. Feature vector is obtained using the direction of pixel and magnitude patterns. Based on the pixel direction the octa pattern is calculated and histogram also constructed. Similarly the histogram for magnitude pattern is constructed and these two histograms are combined to form the feature vector. For a given query image the system retrieves the similar images from the database.

The proposed system includes Pre-processing and direction of pixel which uses the preprocessing technique named resize and calculated the first order derivatives along with $0^{\circ},90^{\circ},45^{\circ}$. Extractions of pattern using LOP and

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LBP used to classify each pixel using octa direction and separate into binary patterns. Extraction of magnitude pattern is collected using magnitudes of derivatives. Finally, Hybrid method is established to extract the feature of an image by combining LOP, LBP and magnitude pattern which are used to improve the performance.

3.1 Preprocessing and Direction of Pixel

Pre-processing is the technique of enhancing data images prior to computational processing. The proposed system uses the pre-processing technique called image resize to reduce the image retrieval time.

Given image I, the first-order derivatives are denoted as $I^1_{0^\circ}(g_p)$, $I^1_{90}(g_p)$ and $I^1_{45}(g_p)$ where g_p denotes neighboring pixels of an image along with 0°, 90° and 45° directions. Based on vertical, horizontal and diagonal direction pixel values, the first order derivatives are calculated for each pixel. The first-order derivatives along 0°, 90° and 45° directions are denoted as

$$I^1_{0^\circ}(g_c) = I(g_h) - I(g_c) \qquad (1)$$

$$I^1_{90}(g_c) = I(g_v) - I(g_c) \qquad (2)$$

$$I^1_{45}(g_c) = I(g_d) - I(g_c) \qquad (3)$$

Let g_c denotes the center pixel and g_h, g_v, g_d denotes horizontal, vertical and diagonal neighbourhood of center pixels respectively.

Steps:
Input: Query image;
Output: Direction of pixel values.

i) Load and resize the image and convert into gray scale values.
ii) Based on vertical, horizontal and diagonal direction of pixel values the first order derivatives for each pixel is calculated.
iii) Based on the first order derivatives value of pixel, the direction of every pixel can be calculated as

$$I^1_{Dir}(g_c) = \begin{cases} 1, & I^1_{0^\circ}(g_c) \geq 0 \text{ and } I^1_{90^\circ}(g_c) \geq 0 \text{ and } I^1_{45^\circ}(g_c) \geq 0 \\ 2, & I^1_{0^\circ}(g_c) < 0 \text{ and } I^1_{90^\circ}(g_c) \geq 0 \text{ and } I^1_{45^\circ}(g_c) \geq 0 \\ 3, & I^1_{0^\circ}(g_c) < 0 \text{ and } I^1_{90^\circ}(g_c) < 0 \text{ and } I^1_{45^\circ}(g_c) \geq 0 \\ 4, & I^1_{0^\circ}(g_c) \geq 0 \text{ and } I^1_{90^\circ}(g_c) < 0 \text{ and } I^1_{45^\circ}(g_c) \geq 0 \\ 5, & I^1_{0^\circ}(g_c) \geq 0 \text{ and } I^1_{90^\circ}(g_c) \geq 0 \text{ and } I^1_{45^\circ}(g_c) < 0 \\ 6, & I^1_{0^\circ}(g_c) < 0 \text{ and } I^1_{90^\circ}(g_c) \geq 0 \text{ and } I^1_{45^\circ}(g_c) < 0 \\ 7, & I^1_{0^\circ}(g_c) < 0 \text{ and } I^1_{90^\circ}(g_c) < 0 \text{ and } I^1_{45^\circ}(g_c) < 0 \\ 8, & I^1_{0^\circ}(g_c) \geq 0 \text{ and } I^1_{90^\circ}(g_c) < 0 \text{ and } I^1_{45^\circ}(g_c) < 0 \end{cases} \qquad (4)$$

Where, $I^1_{0^\circ}(g_c)$ – Value of center pixel in the horizontal direction, $I^1_{90^\circ}(g_c)$ – value of the center pixel in vertical direction, $I^1_{45^\circ}(g_c)$ – value of the center pixel in diagonal direction. From (4), it is obvious that the possible direction for each center pixel can be either 1, 2, 3, 4, 5, 6, 7, 8 and finally, the image is converted into eight values, i.e., directions.

3.2 Local Octa Pattern(LOP)

The LOP is able to encode the images with eight distinct values as it is able to extract more detailed information. LOP encodes the relationship between the center pixel and its neighbours based on directions that are calculated with the help of (n-1)th order derivatives. The second-order $LOP^2(g_c)$ is defined as [14].

$$LOP^2(g_c) = \{f_3\left(I^1_{Dir}(g_c), I^1_{Dir}(g_1)\right), \ldots\ldots f_3\left(I^1_{Dir}(g_c), I^1_{Dir}(g_p)\right)\} \qquad (5)$$

$$f_3\left(I^1_{Dir}(g_c), I^1_{Dir}(g_p)\right) = \begin{cases} 0 & , I^1_{Dir}(g_c) = I^1_{Dir}(g_p) \\ I^1_{Dir}(g_p), & else \end{cases} \qquad (6)$$

LOP encodes the relationship based on the direction of the center pixel and its neighbours, which are calculated by combining (n-1)th - order derivatives using 0°, 90° and 45° directions.

Input: Direction of pixel values
Output: 8-bit Octa pattern

i) Select a pixel and consider it as a center pixel.
ii) Choose its 8 neighbouring pixels around it.
iii) Compare the center pixel value with neighbour pixel values.
iv) If the neighbour pixel value matches the centre pixel value replace it with ‘0’. Otherwise retained the same neighbour pixel value.
v) Finally, it gives 8-bit octa pattern for each pixel.

From (4) and (5), we get 8-bit octa pattern for each pixel. Then separate all patterns into eight parts based on direction of center pixel. Finally, the octa patterns for each part (direction) are converted to seven binary patterns. The Local Binary Pattern (LBP) is an operator for image description based on the signs of differences of adjacent pixels. It is fast to compute and varied with unvaried grey-scale changes of the image. Hence the direction of the center pixel $I^1_{Dir}(g_c)$obtained using (5) be “1”; then, LOP^2 can be defined by segregating it into seven binary patterns. Every octa pattern separates into 7 binary patterns based on direction of pixel values. Similarly, the other seven octa patterns for remaining seven directions (parts) of center pixels are converted to binary patterns. Thus, obtained 56 (8 * 7) binary patterns.

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3.3 Magnitude pattern

Although the sign component extracts more useful information as compared with the magnitude constituent, exploiting the combination of sign and magnitude mechanisms can provide better clues, which are not evident in any one individual constituent. This concept has motivated to propose the 57th binary pattern by using the magnitudes of horizontal and vertical first-order derivatives.

Input: Query image;

Output: Magnitude pattern

i) Select a pixel and choose the adjacent pixel in horizontal and vertical position, Calculate the difference between a pixel and adjacent pixels.
ii) Similarly, choose its 8 neighbouring pixels around it, calculate difference between all the neighbouring pixels and its adjacent pixels.
iii) Compare the difference of a pixel value and the difference 8 neighbouring pixel values.
iv) If the difference value of a pixel is lesser than the difference value of neighbouring pixels means it gives '1' as a magnitude pattern value
v) If the difference value of a pixel is greater than the difference of the neighbouring pixels it gives '0' as a magnitude pattern value

For the local pattern with neighbourhoods, 2^P variations of LBPs are possible, resulting in the feature vector length of 2^P. The computational cost of this feature vector is very expensive. Permissible to decrease the computational cost, the system used the uniform patterns [18]. The uniform pattern refers to the uniform presence pattern that has limited incoherence in the circular binary representation. In this paper, those patterns that have less than or equal to two incoherence in the circular binary image are referred to as the uniform patterns, and the residual patterns are referred as non-uniform. Thus, the distinct uniform patterns for a given query image would be P(P-1)+2. The possible uniform patterns for P=8 can be seen in [18]. After identifying the local pattern (the LBP, the LTRP, the LDP, or the 57-binary-pattern form LOP), the whole image is represented by construction of a histogram.

3.4 Feature vector and query matching

Extracting the feature vector from the combined 57 (8*7 + Magnitude LBP) binary pattern using histograms. Measure the similarity and retrieve the most relevant matches. Calculate the feature vector for every image in the database. Compare the query image with the images in the database using

$$D(Q, DB) = \sum_{i=1}^{L_g} \left| \frac{f_{DB_{j,i}} - f_{Q_i}}{1 + f_{DB_{j,i}} + f_{Q_i}} \right| \qquad (7)$$

Where, $f_{DB_{j,i}}$ is the ith feature of jth image in the database DB and f_{Q_i} is the feature of query

And finally, select top-matched images by measuring the distance between the query image and the images in the database.

Fig. 2. Shows an example to obtain the magnitude patterns. For the magnitude pattern, the bit is coded with "1" when the magnitude of the focus pixel is less than the magnitude of its neighbour, or else "0.

4. EXPERIMENTAL RESULTS

The performance of the proposed technique is tested on the Corel dataset of 1018 variable size images spread across different categories such as Bus, Dinosaur, Elephant, Flowers, Horse, car, Buildings, etc. as shown in fig 3. The proposed Local Octa pattern has the following stages namely Preprocessing of both database and query images, direction of pixel, Extraction of magnitude pattern using LOP, Feature vector construction using magnitude pattern and direction. Fig 4.shows the query image preferred by the user.

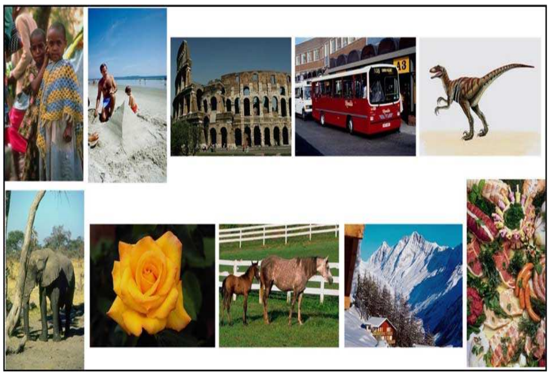

Figure 3: Categories of Images in Corel Databse

4.1 Direction of Pixel

Fig .5 shows the direction of each pixel of query image based on Octa class. From the first order derivatives the direction of pixel is obtained using equation (4). The direction of pixel contains either 1,2,3,4,5,6,7, or 8. Thus the image is transformed into eight values directions.

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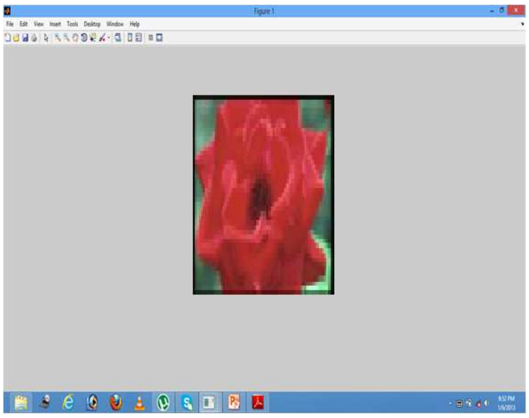

Figure 4: Input Query

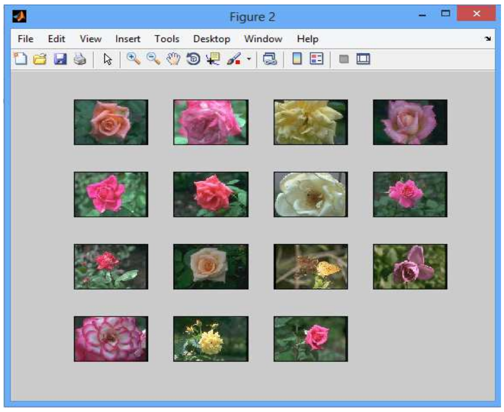

Figure 9 : Retrieval Result Obtained by LOP for a Query Image (Rose)

4.2 Local Octa Pattern

The Local Octa pattern is generated based on the direction of the center pixel and its neighbours as shown in fig.6. It was calculated by combining (n-1)th order derivatives using 0°, 90° and 45. Thus LOP is able to encode the images with eight distinct values for the extraction of more detailed information from the images of the database.

4.3 Magnitude pattern

The magnitude of both central and neighbourhood pixels are computed. When the magnitude of central pixel is lesser than the magnitude of pixels of neighbourhood 1 is assigned else 0 as a magnitude pattern values as illustrated in fig.7.

4.4 Construction of feature vector database

Convert the magnitude pattern into decimal values and apply Fourier descriptor for the extraction of feature vectors. Similarly, convert 56 binary patterns into decimal values and construct their feature vector. The system calculates the similarity between the query image and the database image, retrieving the top ranked images and displaying them for the user. The feature vector database is shown in fig.8.and relevant images are shown in fig 9.

Table 1and Table II shows the performance of the proposed system and Existing systems. We measured the effectiveness of the system using two retrieval statistics precision and recall. The definition of the precision and recall are given in (7) and (8).

$$P = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} \quad (7)$$

$$Q = \frac{\text{Number of relevant images retrieved}}{\text{Total Number of relevant images in the database}} \quad (8)$$

Table 1: Average precision and recall for categories of images

Method	Average Precision	Average Recall
LBP	70.25	44.13
LDP	71.92	45.41
LTrP	73.57	48.79
LOP	85.30	51.87

Table 2 :Precision and Recall for database

Categories	Performance	
	Precision(%)	Recall(%)
Bus	86	43
Flower	94	47
Elephant	78	39
Horse	76	38
Dinosaur	96	48
Car	82	41

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Fig 10, Fig 11 and Fig 12 Shows the graph illustrating the retrieval performance of the LOP vs LTRP. It indicates that proposed system outperform than the Existing methods due to its diagonal Derivatives in addition to Horizontal and vertical Directions.

5. CONCLUSION

In this paper, we have put forth an approach named LOP for CBIR. The Octa encodes the images based on the direction of pixels calculated by horizontal, vertical and diagonal derivatives. The proposed system includes pre-processing and direction of pixel calculated using first order derivatives along with0°, 90° and 45°.Extraction of pattern using LOP and LBP are used to classify each pixel using octa direction. Magnitude pattern is extracted using magnitudes of derivatives. Finally, Hybrid method is established to extract the feature of an image by combining LOP, LBP and magnitude pattern which is used to improve the performance. The performance analysis shows that the proposed method improves the retrieval result from 74.75%/48.79% to 85.30%/51.87% in terms of average precision/average recall on Corel database. Results can be further improved by considering the enhanced Fourier Descriptor in addition to horizontal, vertical and diagonal directions.

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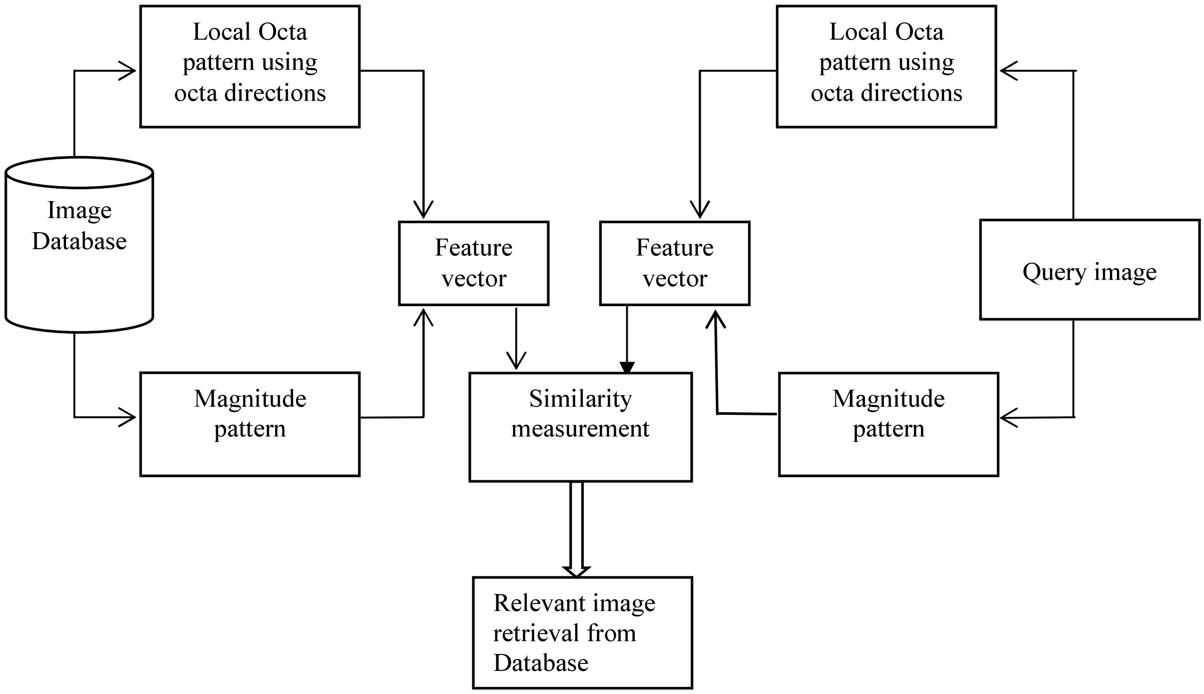

Figure. 1: Overview of the Proposed Model

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10th August 2014. Vol. 66 No.1

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137	138	132	135	138
125	127	130	134	124
134	125	124	125	122
133	131	134	129	122
152	147	152	147	144

137	138	132	135	138
125	127	130	134	124
134	125	124	125	122
133	131	134	129	122
152	147	152	147	144

137	138	132	135	138
125	127	130	134	124
134	125	124	125	122
133	131	134	129	122
152	147	152	147	144

137	138	132	135	138
125	127	130	134	124
134	125	124	125	122
133	131	134	129	122
152	147	152	147	144

$\sqrt{(125-124)^2+(130-124)^2}$ = 6.08 $\sqrt{(125-124)^2+(130-124)^2}$ = 6.08 $\sqrt{(125-124)^2+(130-124)^2}$ = 6.08

$\sqrt{(125-124)^2-(130-124)^2}=9.48$ $\sqrt{(124-134)^2-(135-134)^2}=10.04$

$\sqrt{(134-130)^2-(132-130)^2}=4.47$

137	138	132	135	138
125	127	130	134	124
134	125	124	125	122
133	131	134	129	122
152	147	152	147	144

137	138	132	135	138
125	127	130	134	124
134	125	124	125	122
133	131	134	129	122
152	147	152	147	144

137	138	132	135	138
125	127	130	134	124
134	125	124	125	122
133	131	134	129	122
152	147	152	147	144

$\sqrt{(125-124)^2+(130-124)^2}$ = 6.08 $\sqrt{(125-124)^2+(130-124)^2}=6.08$

$\sqrt{(125-124)^2+(130-124)^2}=6.08$

$\sqrt{(130-127)^2-(138-127)^2}=11.40$ $\sqrt{(124-125)^2-(127-125)^2}=2.23$

$\sqrt{(125-131)^2-(134-131)^2}=6.70$

Figure. 2: Magnitude Pattern Generation

Magnitude Pattern = 1 1 0 1 0 1 1 1

Journal of Theoretical and Applied Information Technology
10th August 2014. Vol. 66 No.1

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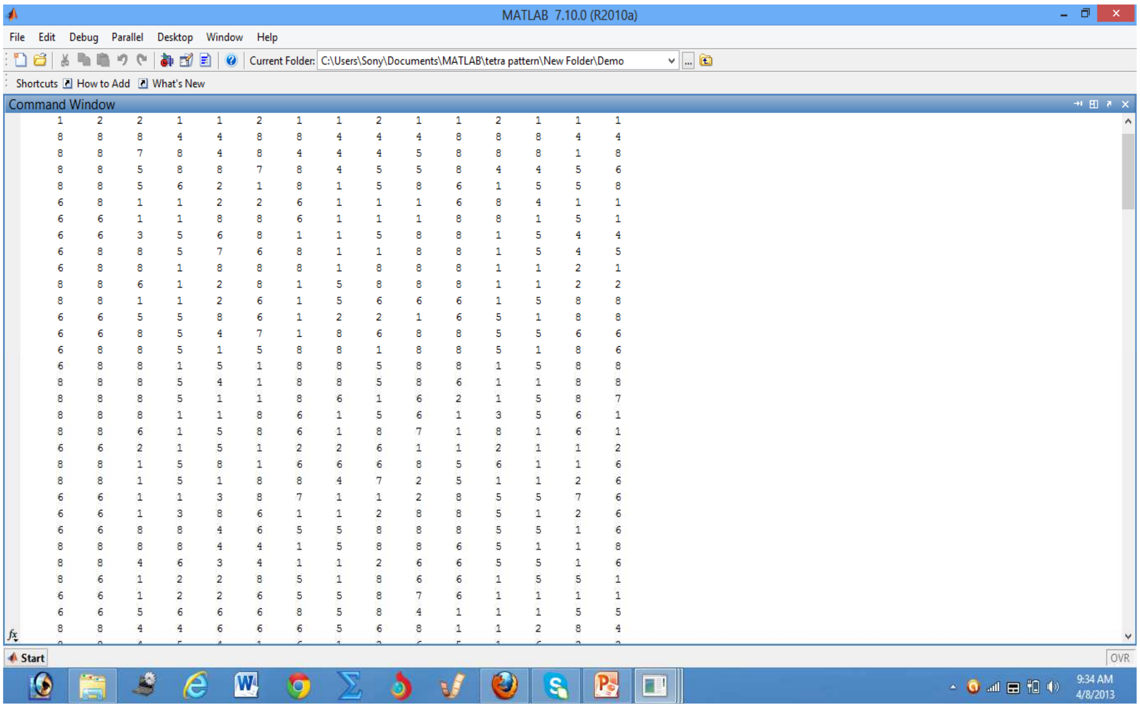

Figure.5: Direction of Pixel of a Query Image

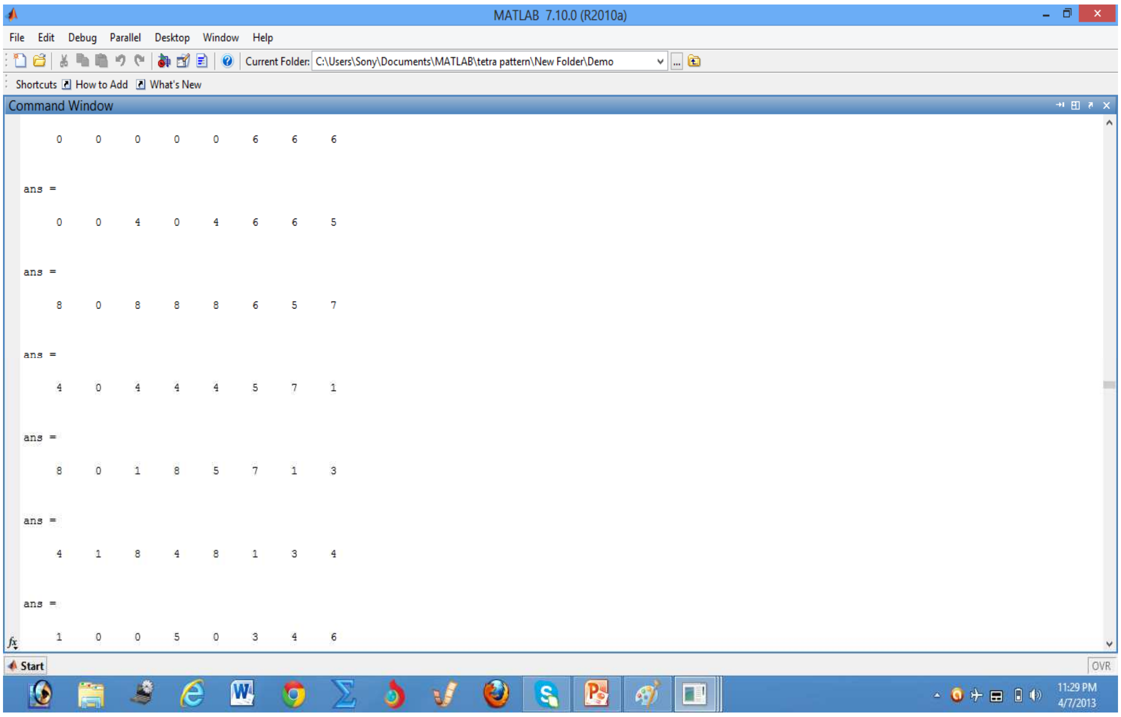

Figure. 6: Construction of Octa Pattern

Journal of Theoretical and Applied Information Technology
10th August 2014. Vol. 66 No.1

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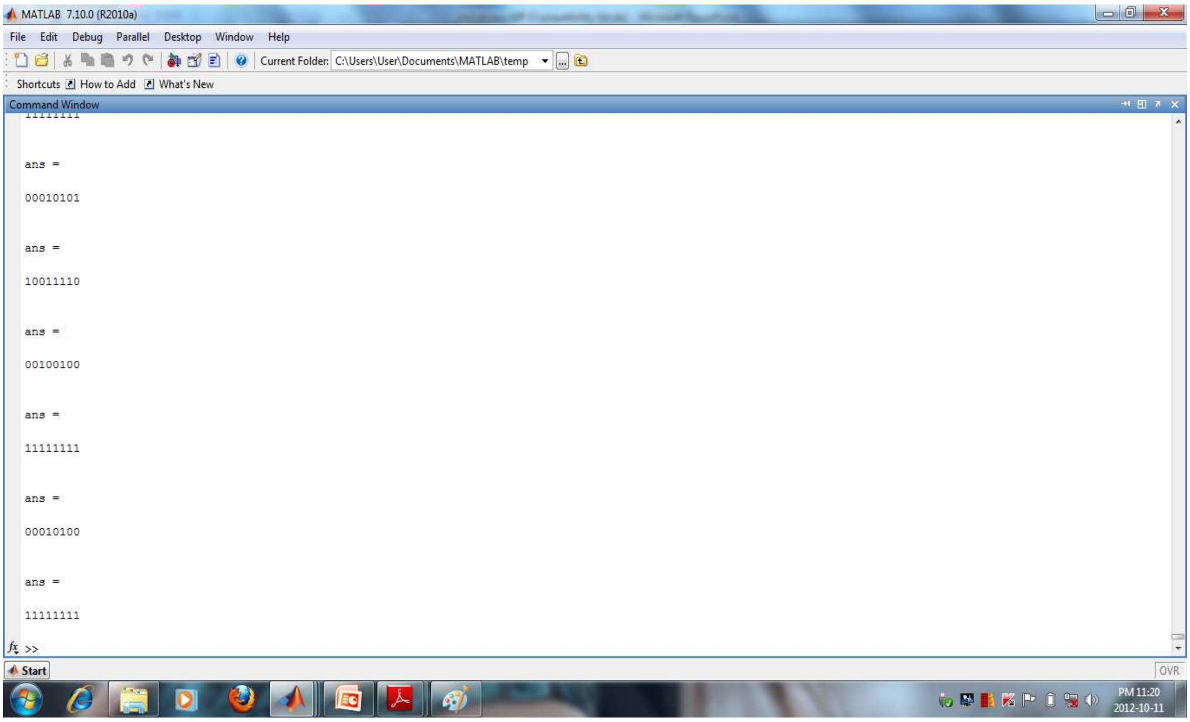
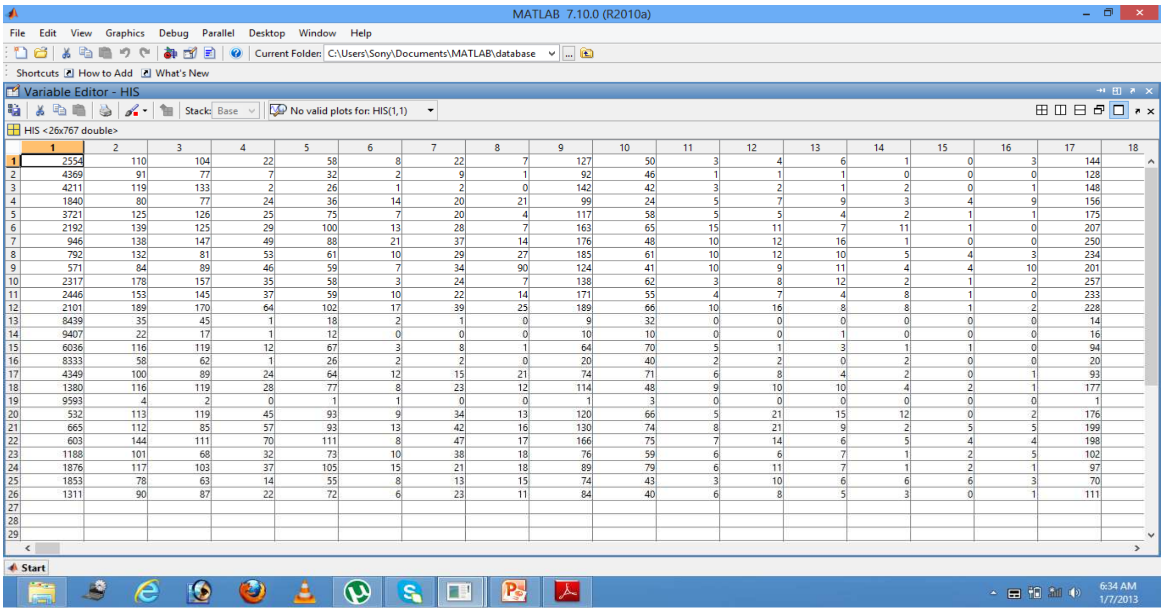


Figure.7: Magnitude Pattern



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
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2	4369	91	77	7	32	2	9	1	92	46	1	1	1	0	0	0	128	
3	4211	119	133	2	26	1	2	0	142	42	3	2	1	2	0	1	148	
4	1840	80	77	24	36	14	20	21	99	24	5	7	9	3	4	9	156	
5	3721	125	126	25	75	7	20	4	117	58	5	5	4	2	1	1	175	
6	2192	139	125	29	100	13	28	7	163	65	15	11	7	11	1	0	207	
7	946	138	147	49	88	21	37	14	176	48	10	12	16	1	0	0	250	
8	792	132	81	53	61	10	29	27	185	61	10	12	10	5	4	3	234	
9	571	84	89	46	59	7	34	90	124	41	10	9	11	4	4	10	201	
10	2317	178	157	35	58	3	24	7	138	62	3	8	12	2	1	2	257	
11	2446	153	145	37	59	10	22	14	171	55	4	7	4	8	1	0	233	
12	2101	189	170	64	102	17	39	25	189	66	10	16	8	8	1	2	228	
13	8439	35	45	1	18	2	1	0	9	32	0	0	0	0	0	0	14	
14	9407	22	17	1	12	0	0	0	10	10	0	0	1	0	0	0	16	
15	6036	116	119	12	67	3	8	1	64	70	5	1	3	1	1	0	94	
16	8333	58	62	1	26	2	2	0	20	40	2	2	0	2	0	0	20	
17	4349	100	89	24	64	12	15	21	74	71	6	8	4	2	0	1	93	
18	1380	116	119	28	77	8	23	12	114	48	9	10	10	4	2	1	177	
19	9593	4	2	0	1	1	0	0	1	3	0	0	0	0	0	0	1	
20	532	113	119	45	93	9	34	13	120	66	5	21	15	12	0	2	176	
21	665	112	85	57	93	13	42	16	130	74	8	21	9	2	5	5	199	
22	603	144	111	70	111	8	47	17	166	75	7	14	6	5	4	4	198	
23	1188	101	68	32	73	10	38	18	76	59	6	6	7	1	2	5	102	
24	1876	117	103	37	105	15	21	18	89	79	6	11	7	1	2	1	97	
25	1853	78	63	14	55	8	13	15	74	43	3	10	6	6	6	3	70	
26	1311	90	87	22	72	6	23	11	84	40	6	8	5	3	0	1	111	
27																		
28																		
29																		

Figure.8 The Feature Vector Database

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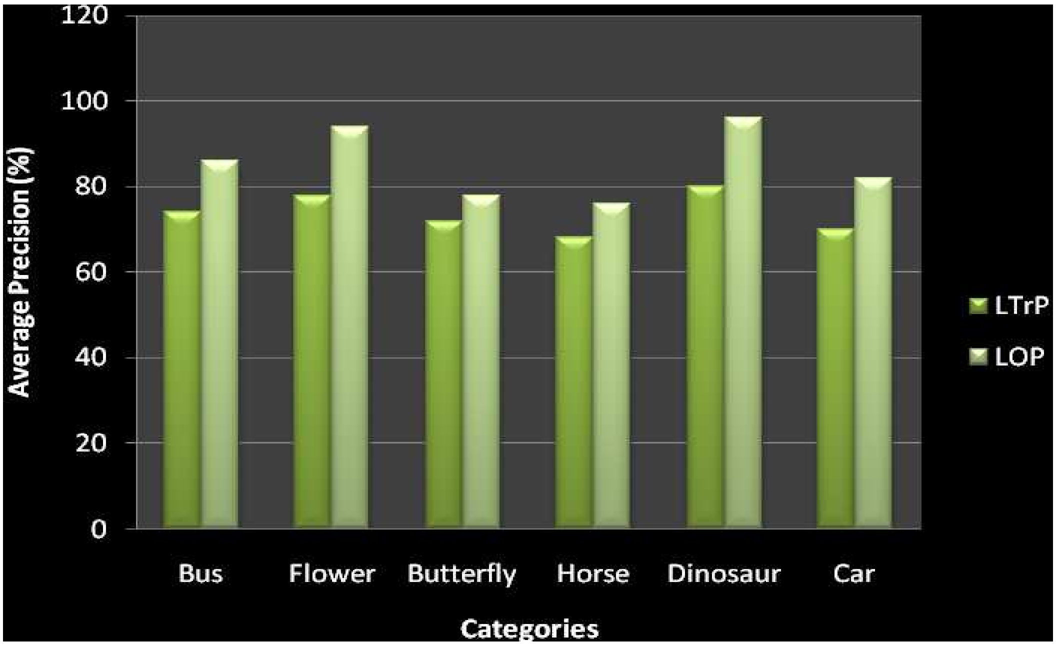

Fig .10 Performances Analysis of Local Octa Pattern Vs Local Tetra Pattern

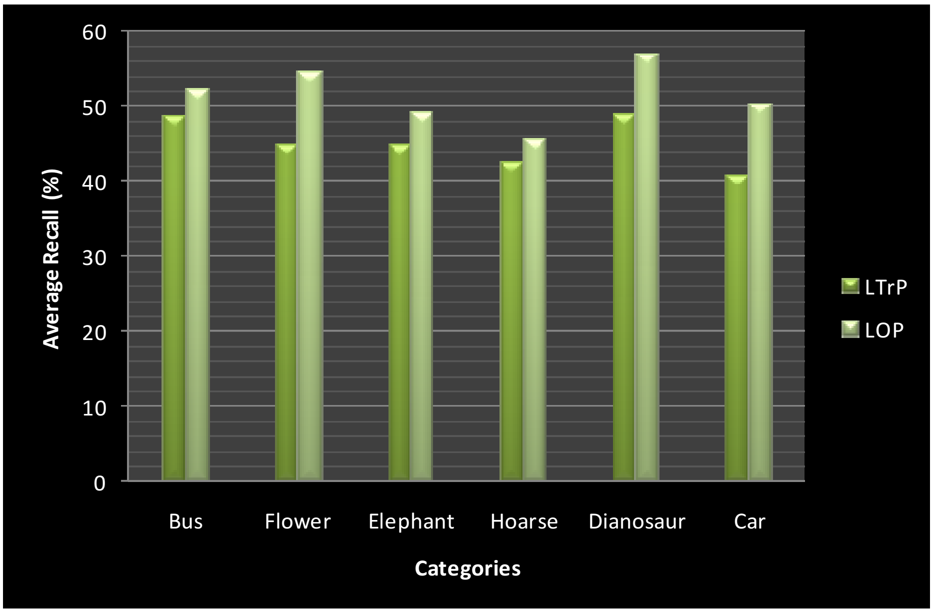

Fig.11 Average Recall using LTrP and LOP

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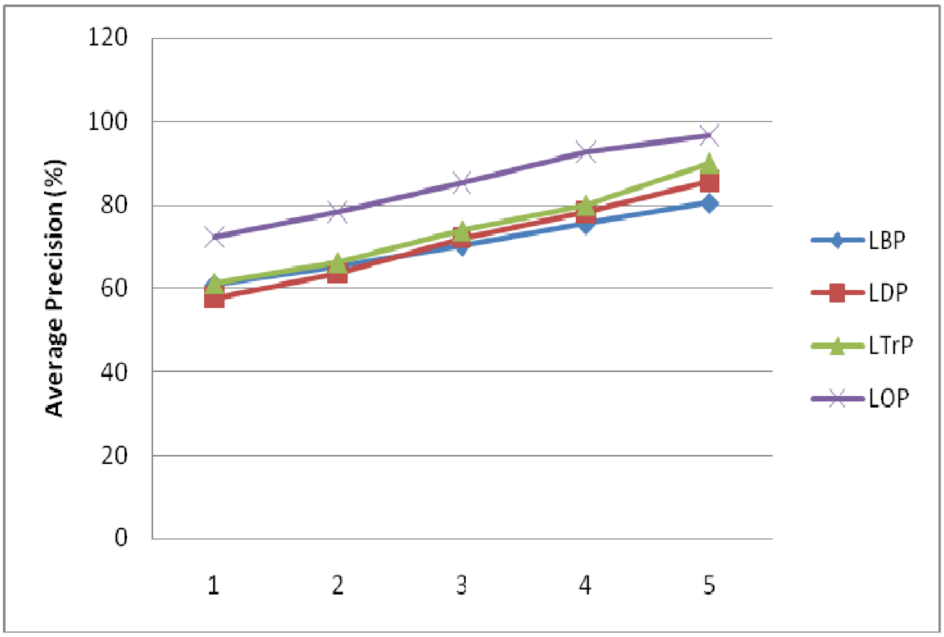

Fig .12 Comparison of the Proposed System with other Existing Methods.