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Content Based Image Retrieval using Improved Local Tetra Pattern and Neural Network

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ABSTRACT

Because of the exponential increase in digital images, image databases have grown to a much large volume that retrieval of required images from these databases is a very difficult task. Image retrieval can also be practiced via human annotation but it cannot be trusted. So, now a days, a more relied and effective method to retrieve relevant images from a large databse is Content Based Image Retrieval (CBIR). These days, main focus is to achieve a more accurate CBIR algorithm so that retrieval efficiency can be increased. In this paper, we have proposed a CBIR algorithm which retrieves images from database with increased precision. For feature extraction, we have used Improved Local Tetra Patterns which is a texture descriptor and based on the direction of pixel. Direction of all the pixels in an image is calculated; based on direction of each pixel, an 8-bit pattern is achieved which is further divided into 7 binary patterns and 1 magnitude pattern. For experimental purposes, we have used Corel database which has been used by most researchers. After performing experiment on the said dataset, improved precision rates were observed when proposed technique was compared with some previous approaches. Average precision observed in our experiment was 82%.

1. Introduction

Image retrieval through human annotation is tedious task because of growing volumes of digital databases. We see millions and billions of images daily on different websites. These images are much unorganized and if we want to retrieve required images, retrieval is very difficult. So, we are in need of an algorithm which can help us in efficient retrieval of relevant images from large databases. Commonly used retrieval methods add metadata (e.g keywords, captions, descriptions) to images. These annotated words are then used to retrieve relevant images. Technique based on this method is known as annotation based image retrieval (ABIR). Time complexity is the main drawback of this technique. Adding metadata to each image in a huge volume of image database is done by humans, which is very time consuming task. A single word cannot represent a whole image. This is the 2nd drawback of ABIR. As we know, an image speaks 1000 words. So, representing image by single word is injustice. A single word would only reflect a single viewpoint of image. Thus, a more trustworthy approach is needed to mitigate these deficiencies. Content based image retrieval (CBIR) works more effectively in this respect.

Visual contents of an image are dealt in CBIR. Content means texture, color, shape or any other visual information relevant to image. CBIR plays a vital role in my applications like medical, video searching, surveillance etc. It has been always tried to enhance the retrieval accuracy in CBIR approaches. The problem still persists, as image understanding is tough for both computers and humans. An example of this confusion is shown in Fig. 1. For example, if Fig. 1(a) is searched as a query image; system will retrieve both images Fig. 1(b) and Fig. 1(c) as a result. But for some persons, Fig. 1(b) would be their relevant result while for others Fig. 1(c) would be required result; depending upon their interests (i.e park or boy) respectively. So, designing a comprehensive system that works exactly according to one's needs is a difficult task.

(a) (b) (c)

Fig. 1: CBIR based retrieval; (a) query (b) & (c) retrieved images

The basic principle of CBIR system is to convert all the images in a database into feature vectors. When the feature vector of a query image is fetched to system; it calculates distance with other feature vectors of the images in the database. Relative images are retrieved which have minimum distance to query image. Distance can be measured using any distance formula like Euclidian or Manhattan. We also can't get 100% result using images' visual contents because images of different classes may have same visual contents. Fig. 2 shows two images of same visual contents. System can retrieve dog image when girl image is searched and vice versa because of their similar visual contents.

Fig. 2: Girl and Dog images having same visual features but are from different classes

Considering the above mentioned flaws in retrieval systems, we have proposed an algorithm that mitigates these flaws and increases retrieval precision. A texture based approach, Improved Local Tetra Patterns ($LTrP_i$), has been implied in our algorithm for feature extraction. Rest of the paper has been organized as below: related work has been provided in section 2, local tetra patterns have been dealt in section 3, and proposed algorithm has been discussed in section 4, experiments results have been provided in section 5 while the discussion has been concluded in section 6.

2. Related Work

The first and foremost step in CBIR is the feature extraction of the images. Most commonly used texture techniques are co-occurrence matrices [1], Wavelet Transform [2, 3] and Gabor Filter [4, 5]. Texture features can be divided into two main components spectral method and spatial method. Spatial domain includes Tamura features, Markov field, co-occurrence matrix, fractal technique etc. while spectral domain includes Fourier Transform, Wavelet Transform, Gabor Filter, Curvelet Transform etc.

Tamura features contain 6 components which are contrast, likeliness, roughness, coarseness, directionality and regularity [6, 7]. Another texture descriptor is Markov Random Field (MRF). MRF is a probabilistic process [8]. Many researchers have used fractal technique for feature extraction [9, 10].

On the other hand, spectral domain methods have the advantage of being insensitive to noise. That's why these techniques are widely used for texture description. Fourier transforms (FT) measures the frequency components of the signal. Its purpose is to convert a time domain signal into frequency domain signal [11, 12].

Unlike texture, color is also used for feature extraction. Color is an image visual feature. To represent colors in digital form, color spaces are used. A three dimensional color coordinate system is represented by color space where colors are represented by points. Most commonly used color space is red, green and blue (RGB) color space where colors are represented by red, green and blue colors [13]. Other than RGB, hue, saturation and value (HSV) and hue min max difference (HMMD) color spaces are also used. Commonly used techniques for color feature extraction are color histogram, color coherence vector, HMMD and HSV color descriptor.

A simple color feature descriptor is color histogram in which color space is converted into bins and each bin has its own frequency. Color Coherence Vector (CCV) is different from color histogram in a sense that it captures spatial information in an image [14]. RGB color space considers image as a collection of red, green and blue colors while humans do not perceive an image as exactly the combination of red, green and blue colors so HSV color space resolves this issue by representing an image color in a way similar to what humans perceive [15].

In this paper we have proposed Improved Local Tetra Pattern ($LTrP_i$). Local Binary Patterns (LBP) has been proposed in [16]. In LBP each pixel gray value is compared with its eight neighbors' gray values and a final equivalent LBP value is calculated. Local Ternary Pattern (LTP) is another technique for image texture extraction which is an extended version of LBP [17]. Local Derivative Patterns (LDP) has been proposed in [18] which is also the extension of LBP. A new pattern known as Local Tetra Pattern was introduced in [19] which propose a four directional code to enhance the performance. Horizontal and vertical derivatives were used to calculate directions. In our proposed $LTrP_i$, we have also used diagonal derivative along with horizontal and vertical to produce eight directional codes in order to further enhance the method performance.

3. Local Tetra Patterns

Texture of image can be described via Local Tetra Patterns using direction of center pixel. If g_{hor}, g_c, and g_{ver} are the gray pixel values of horizontal, center and vertical pixels respectively and I_θ represents derivative then by using Eq. (1) first order derivative can be calculated around center pixel.

$$I_{hor}(g_c) = I(g_{hor}) - I(g_c)$$
$$I_{ver}(g_c) = I(g_{ver}) - I(g_c) \quad (1)$$

while Eq. (2) can be used to calculate direction of center gray pixel.

$$I_d(g_c) = \begin{cases} 1, & I_{hor}(g_c) \geq 0 \text{ and } I_{ver}(g_c) \geq 0 \\ 2, & I_{hor}(g_c) < 0 \text{ and } I_{ver}(g_c) \geq 0 \\ 3, & I_{hor}(g_c) < 0 \text{ and } I_{ver}(g_c) < 0 \\ 4, & I_{hor}(g_c) \geq 0 \text{ and } I_{ver}(g_c) < 0 \end{cases} \quad (2)$$

Using the direction calculated in Eq. (2), LTrP are calculated. While 2nd order LTrP can be obtained using Eq. (3).

$$LTrP^2(g_c) = \left\{ f_4(I_d(g_c), I_d(g_1)), f_4(I_d(g_c), I_d(g_2)), \ldots f_4(I_d(g_c), I_d(g_N)) \right\}_{N=8} \quad (3)$$
$$f_4(I_d(g_c), I_d(g_N)) = \begin{cases} 0, & I_d(g_c) = I_d(g_n) \\ I_d(g_n), & else \end{cases}$$

LTrP can be further divided into three binary patterns. Eq. (4) depicts division when direction of center gray pixel is 1.

$$LTrP^2\big|_{dir=\Delta} = \sum_{n=1}^{N} 2^{(n-1)} * f_5(LTrP^2(g_c))\big|_{dir=\Delta}$$
$$f_5(LTrP^2(g_c))\big|_{dir=\Delta} = \begin{cases} 1, & LTrP^2(g_c) = \Delta \\ 0, & otherwise \end{cases} \quad (4)$$

where $\Delta = 2, 3, 4$

Magnitude of vertical and horizontal derivates is used to calculate fourth binary pattern using Eq. (5).

$$M_{I(g_n)} = \sqrt{(I_{hor}(g_n))^2 + (I_{ver}(g_n))^2}$$
$$MP = \sum_{n=1}^{N} 2^{n-1} * f_6(M_{I(g_n)} - M_{I(g_c)})\big|_{N=8} \quad (5)$$
$$f_6(x) = \begin{cases} 1, & x \geq 0 \\ 0, & else \end{cases}$$

LTrP is defined using these four binary patterns. Equations used in this section have been taken from [19] and detailed analysis can be seen from there. Figure 3 shows the explanation that how LTrPs are calculated from an image window. Calculations are based upon the equations given above.a

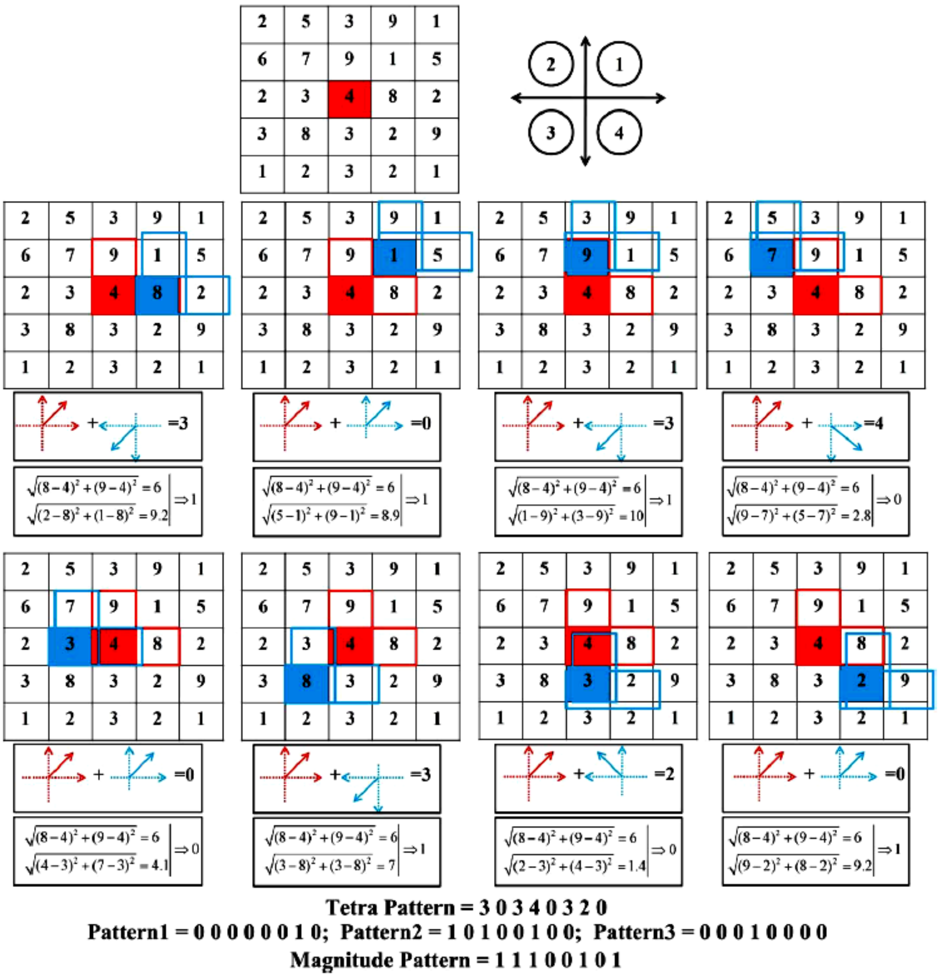

Fig. 3: Calculation of LTrP for a center pixel in an image window [19]

4. Proposed Approach

4.1 $LTrP_i$

To enhance retrieval accuracy, we have proposed an improved pattern known as Improved Local Tetra Pattern ($LTrP_i$) which is an extension of LTrP. Similar to LTrP, $LTrP_i$ is also based upon direction of center pixel for feature extraction. As in LTrP, only vertical and horizontal derivatives are considered for direction calculation. In $LTrP_i$, diagonal derivatives have also been considered along with horizontal and vertical derivatives. Contrary to LTrP, image is converted into 8 directions based on the eight possible directions of center pixel. After calculating the direction of center pixel, improved pattern can be calculated using Eq. (6)

$$LTrP_i^2(g_c) = \left\{ \begin{array}{l} f_7(I_d(g_c), I_d(g_1)), f_7(I_d(g_c), I_d(g_2)), \\ \ldots\ldots f_7(I_d(g_c), I_d(g_N)) \end{array} \right\}_{N=8} \qquad (6)$$

$$f_7(I_d(g_c), I_d(g_N)) = \left\{ \begin{array}{ll} 0, & I_d(g_c) = I_d(g_n) \\ I_d(g_n), & else \end{array} \right\}$$

8 bit $LTrP_i$ is achieved using Eq. (6). This pattern can be further divided into 7 binary patterns. This distribution is performed using the direction of center pixel. Eq. (7) given below is used to convert 8 bit pattern into 7 binary patterns. The equation is specific for the case when direction of center pixel achieved is '1'.

$$LTrP_i^2{}_{dir=\Delta} = \sum_{n=1}^{N} 2^{(n-1)} * f_8(LTrP_i^2(g_c))_{dir=\Delta} \qquad (7)$$

$$f_8(LTrP_i^2(g_c))_{dir=\Delta} = \left\{ \begin{array}{ll} 1, & LTrP_i^2(g_c) = \Delta \\ 0, & otherwise \end{array} \right\}$$

where Δ=2,3,4,5,6,7,8.

Pattern for other directions can be calculated similarly. An eighth binary pattern known as magnitude pattern can be calculated using Eq. (8) below.

$$M_{I(g_n)} = \sqrt{(I_{hor}(g_n))^2 + (I_{ver}(g_n))^2 + (I_{dig}(g_n))^2}$$

$$MP = \sum_{n=1}^{N} 2^{n-1} * f_9(M_{I(g_n)} - M_{I(g_c)})_{N=8} \qquad (8)$$

$$f_9(x) = \left\{ \begin{array}{ll} 1, & x \geq 0 \\ 0, & else \end{array} \right\}$$

Fig. 4 depicts the whole procedure. An image window has been chosen and $LTrP_i$ for center pixel has been calculated. Green being neighbor while red is center pixel. M(c), D(c), M(1), D(1), M(2), D(2) are the magnitudes and directions of center, first neighbor and 2nd neighbor respectively. Whenever directions of center and neighbor pixels are same, $LTrP_i$ bit is 0 otherwise it is same as the direction of neighboring pixel. In our example $LTrP_i$ code is 41383183. This can be further divided into 7 binary patterns. 1st binary pattern can be achieved by replacing

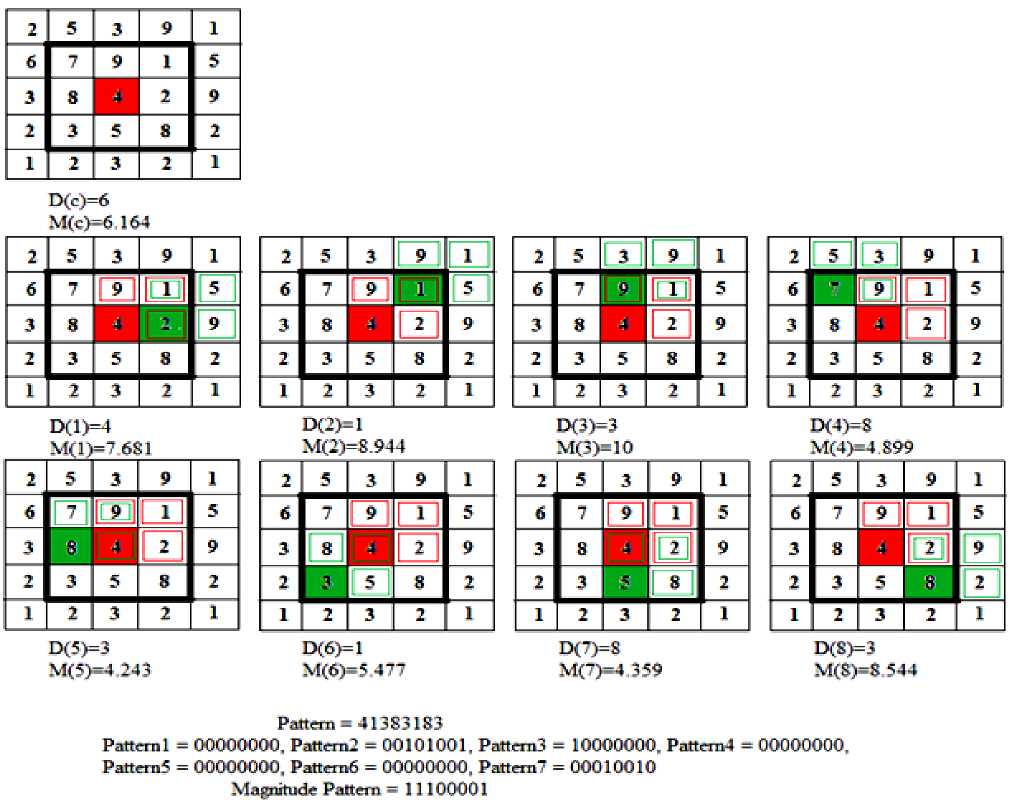

Fig. 4: Calculation of proposed improved local tetra patterns ($LTrP_i$) [M & D are magnitude and direction respectively]

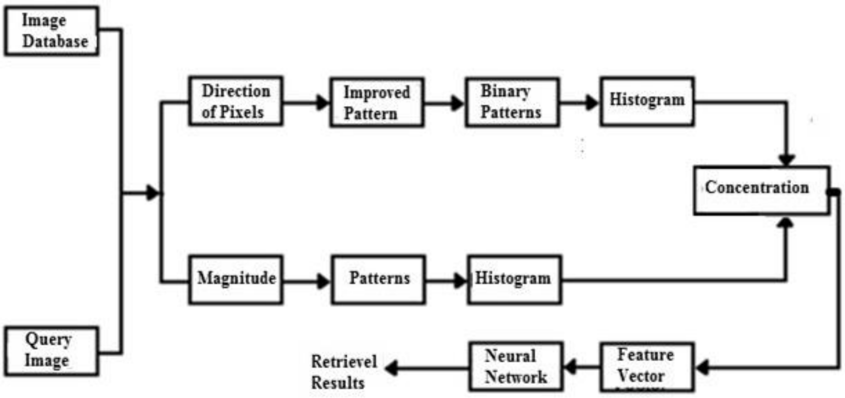

Fig. 5: Block diagram of proposed algorithm

2's with 1's and other values with 0's in $LTrP_i$ code. Other binary patterns can be achieved in the same fashion. Comparing magnitudes of neighbors and center pixel, an eighth binary pattern known as magnitude pattern is achieved and in this case it is 11100001. Image texture can be defined using these eight binary patterns. For other center pixel directions, $LTrP_i$ can be achieved similarly. Fig. 5 shows the block diagram of proposed approach. Implementing proposed algorithm, initially image is converted into gray scale and derivatives are calculated. Afterwards, based on the direction of center pixel $LTrP_i$ is computed and then divided into eight binary patterns. Feature vector of image is made by concatenating the histograms achieved from binary and magnitude patterns.

4.2 Classification and Matching

After obtaining feature vectors from whole database, Neural Network has been applied for classification. By applying neural network, the goal is to find weights between different neurons in a network. At first random weights are applied say between 1 and -1 then inputs are applied and output is obtained. This output is obviously very different from the desired output. The obtained output is represented by "target" and desired output by "actual output". Then an error function is obtained by taking difference between these two outputs. Now, the goal is to minimize this error function. As the error is minimized, weights are updated such that output is near to the desired. The procedure is continued until the error is minimized and output is nearest to the desired one. In our experiment we have taken 40 images from each category to make 10 clusters of 40 samples each on which we trained neural network. Testing results are obtained through neural network classification when test samples are taken as query image.

5. Results and Discussions

Database used, performed experiments and precision of proposed algorithm have been discussed in this section. The algorithm can be divided into three steps: feature extraction, feature matching and classification.

5.1 Database Used

In order to perform experiments, first step is to choose a suitable database. Although there is no specific standard of image database but we have used Corel database for our experiments because most researchers have used it. Database contains a large set of images. Total of 1000 images have been divided into 10 categories. Each category has 100 images in it and images are either of 384 x 256 or 256 x 384 resolution. Database can be easily obtained from [23].

5.2 Precision Rate

In order to test our algorithm, precision rate is measured; that is, we have to check how many relevant results are achieved when query image is given to system. Retrieval performance is measured using precision rate which can be defined using (9)

$$P = \frac{R_{ret}}{T_{ret}} \tag{9}$$

where T_{ret} can be defined as total number of retrieved images, R_{ret} can be defined as number of relevant retrieved images and P is precision.

5.3 Retrieval Results

Retrieval results of proposed technique have been stated in this section. Fig. 6 shows retrieved images for each of the query image passed to the system. In each row, 1st image is query while rest are retrieved images. In our experiment, for each query, 20 images were retrieved but here only 10 for each category have been shown.

Proposed algorithm was compared with other approaches and improved precision rates were observed. Comparison has been tabulated in Table 1 and shown graphically in Fig. 7.

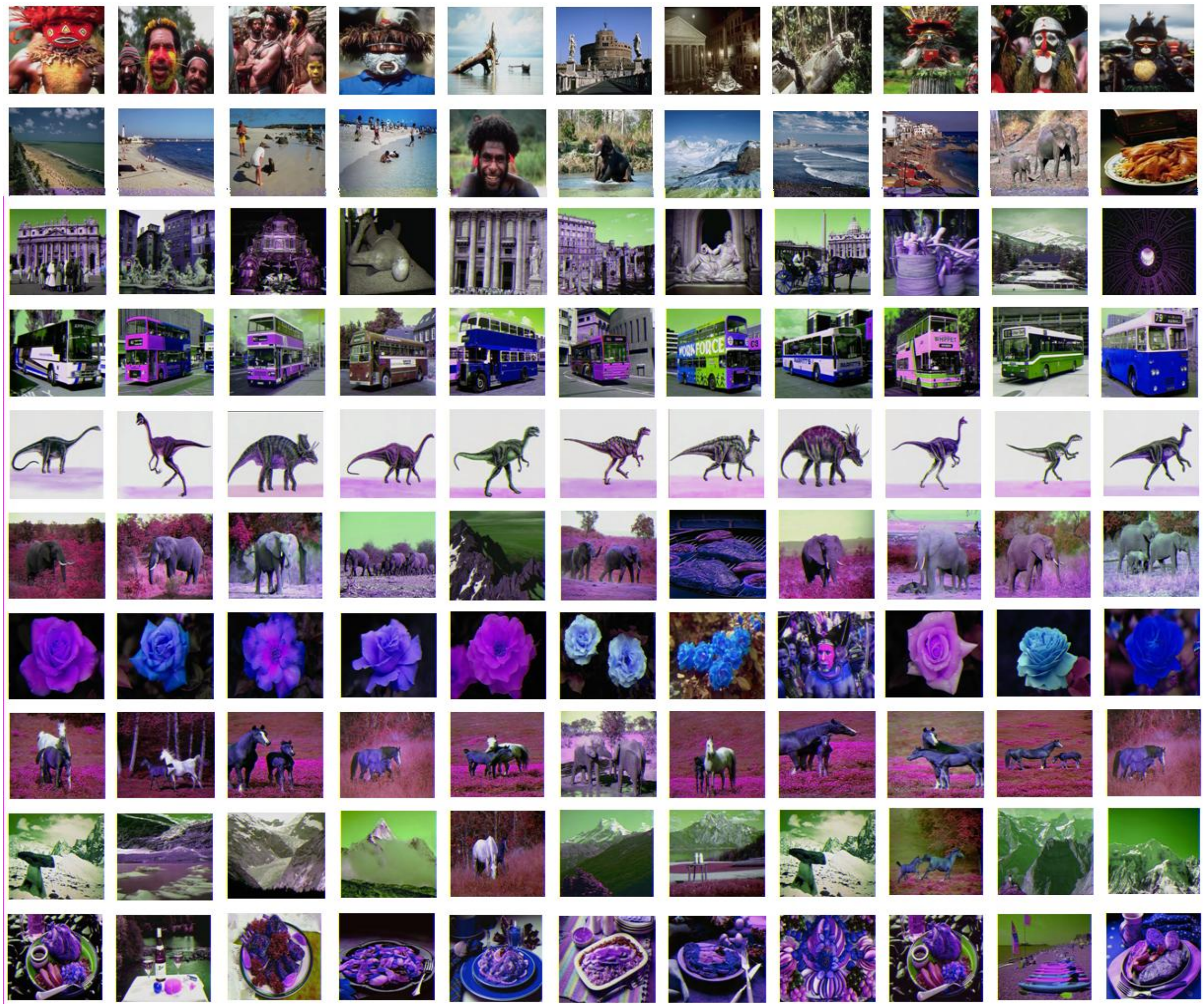

Fig. 6: Visual results of proposed algorithm for image retrieval (1st image in each row is query while rest are retrieved images) [23]

Table 1: Comparison of proposed algorithm with other image retrieval techniques

Category	[19]	[20]	[21]	[22]	Proposed
African people	0.66	0.72	0.50	0.63	0.82
Beach	0.63	0.59	0.70	0.64	0.49
Building	0.72	0.59	0.20	0.69	0.72
Buses	0.96	0.89	0.80	0.91	0.95
Dinosaurs	0.96	0.77	0.90	0.99	0.96
Elephants	0.60	0.99	0.60	0.78	0.80
Flowers	0.90	0.70	0.10	0.94	0.91
Horses	0.81	0.93	0.80	0.95	0.91
Mountains	0.42	0.86	0.50	0.73	0.79
Food	0.89	0.56	0.20	0.80	0.83
Average Precision	0.75	0.76	0.62	0.81	0.82

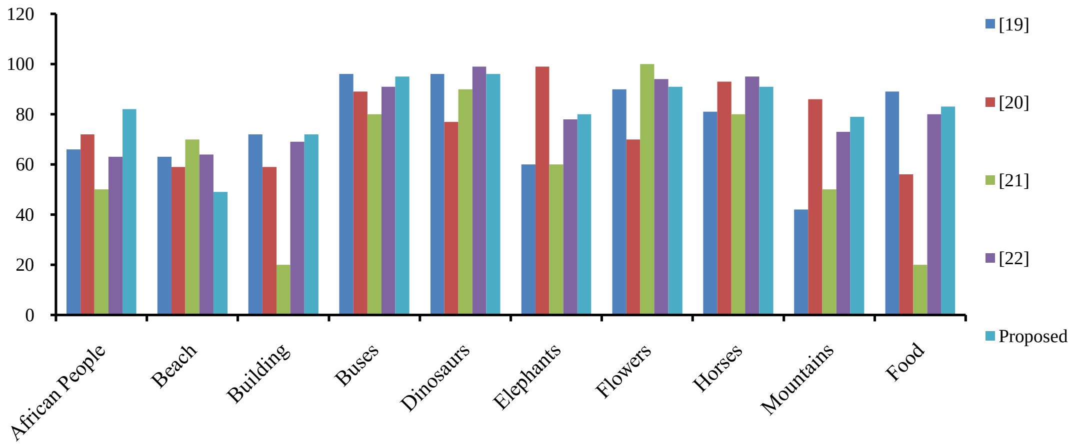

Fig. 7: Comparison of different Image retrieval techniques

7. Conclusion

In this paper improved tetra patters ($LTrP_i$) have been proposed. Diagonal derivative has also been considered for direction calculation. $LTrP_i$ was used with neural networks for experiments. Corel image database was used for experimental purposes. When our proposed algorithm was compared with previous techniques, improved precision rates were observed. Average precision observed in our proposed approach was 82%.

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