Comparison Study Of Local Pattern Algorithms In Content-Based Image Retrieval Systems

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(Received 2 / 6 / 2021. Accepted 8 / 2 / 2022)

□ ABSTRACT □

The increasing need to retrieve images from huge databases has made image retrieval system an imperative and necessary field of research. Researchers have proposed a lot of image retrieval algorithms by extracting important and distinctive features from the visual content of the image for the importance of the extracted features in improving the accuracy of CBIR systems. In this paper, a study has been made to compare the effectiveness of six famous local pattern algorithms: LBP, LTP, LTrP, MMCM, COALTP and LMP and testing these algorithms using two different types of databases: color image databases and texture database, using four distance measures (L1, Euclidean, Cityblock and Cosine) to retrieve the images with the shortest distance. The performance of the studied algorithms was evaluated using three measures: Average Retrieval Precision (ARP), Average recall and Average Retrieval Rate (ARR). This study revealed the superiority of COALTP over other tested algorithms. In addition, the results showed that local pattern algorithms were more efficient in retrieving images from texture databases as compared to color databases.

Keywords: Content-Based Image Retrieval, Local Pattern Algorithms, Average Recall, and Distance Measures.

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دراسة مقارنة لخوارزميات الأنماط المحلية في أنظمة استرجاع الصور المعتمدة على المحتوى

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(تاريخ الإيداع 2 / 6 / 2021. قُبِل للنشر في 8/ 2 / 2022)

□ ملخّص □

إن الحاجة المتزايدة لاسترجاع الصور من قواعد البيانات الضخمة جعلت مجال استرجاع الصور بالاعتماد على المحتوى Content-Based Image Retrieval (CBIR) مجالاً ملحاً وضرورياً للبحث. اقترح الباحثون الكثير من خوارزميات استرجاع الصور من خلال استخراج السمات الهامة والمميزة من المحتوى المرئي للصورة لأهمية السمات المستخرجة في تحسين دقة أنظمة الاسترجاع. وفي هذا البحث، تم إجراء مقارنة لست خوارزميات محلية مشهورة على مدى عقد من الزمن (LBP, LTP, LTrP, MMCM, COALTP and LMP) واختبار هذه الخوارزميات باستخدام نوعين مختلفين من قواعد البيانات: قواعد بيانات الصور الملونة(Color image database) و قواعد بيانات النسجة(Texture database) وباستخدام أربعة مقاييس للمسافات (L1, Euclidean, Cityblock and Cosine) لاسترجاع الصور الأكثر مطابقة لصورة الاستعلام من خلال اختيار الصور ذات المسافة الأقصر. تم تقييم أداء الخوارزميات المدروسة باستخدام ثلاثة مقاييس: متوسط دقة الاسترجاعARP (Average Retrieval Precision) ، متوسط الاسترداد Average Recall ومتوسط معدل الاسترجاع ARR (Average Retrieval Rate)، كشفت هذه الدراسة تفوق خوارزمية COALTP على الخوارزميات الأخرى المختبرة، وبالإضافة إلى ذلك، أظهرت النتائج أن خوارزميات الأنماط المحلية أكثر كفاءة في استرجاع الصور من قواعد بيانات النسجة مقارنة مع قواعد البيانات الملونة.

الكلمات المفتاحية: استرجاع الصور بالاعتماد على المحتوى، قواعد البيانات الضخمة، خوارزميات محلية، مقاييس للمسافات.

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Introduction:

Image Retrieval (IR) is the searching of the related images in the databases, and retrieve the images with the highest similarity to the query image. IR techniques can be classified into Text-Based Image Retrieval (TBIR) and Content-Based Image Retrieval (CBIR). TBIR is a manual process by adding keywords, annotations, or descriptions to the image in the database to describe the content of images. TBIR systems are simple and very fast, but they have many disadvantages [1,2], such as: (i) Adding a description of the image is manually, (ii) The most images have more details, so the images with the similar visual contents may be given different descriptions from one person to another. (iii) Textual descriptions are language dependent. However, to overcome the disadvantages of TBIR, CBIR systems are used to retrieve the images, that are most similar to the desired(query) image[3,4,5,6,7], by extracting low-level features (color, texture, shape,…etc.) from the visual content of the images [8] and represented with the feature vectors. To compare two images [9], the features are extracted from a query image and an image from the CBIR database based on the selected algorithm, then a distance measure is applied on two feature vectors to determine the retrieval images, which have the shortest distances. CBIR is considered as an active research area because of the rapidly growing amount of multimedia data so the growing need for CBIR techniques can be seen in various fields, such as satellite images [10], medical imaging [11], pattern recognition, image processing, artificial intelligence, crime prevention, remote sensing, fingerprint scanning [12], weather forecasting, etc.

Research Goal and Importance:

The research aims to make a comparison of six local algorithms in the field of image retrieval based on the visual content of the image over a decade 2010-2020. The six studied algorithms are applied and compared on the same databases (two of the texture type and one of the Color type) and using four distance measures to accurately compare the evaluation criteria of the six studied algorithms and adopt these comparison results as a rich and useful data bank when suggesting any new content-based image retrieval algorithm.

Research Methods and Resources:

1.1 Framework Of Content-Based Image Retrieval(CBIR)

As illustrated in Figure1,a typical CBIR is divided into off-line feature extraction and on-line image retrieval [5]. In off-line stage, the system automatically extracts features of each image in the database

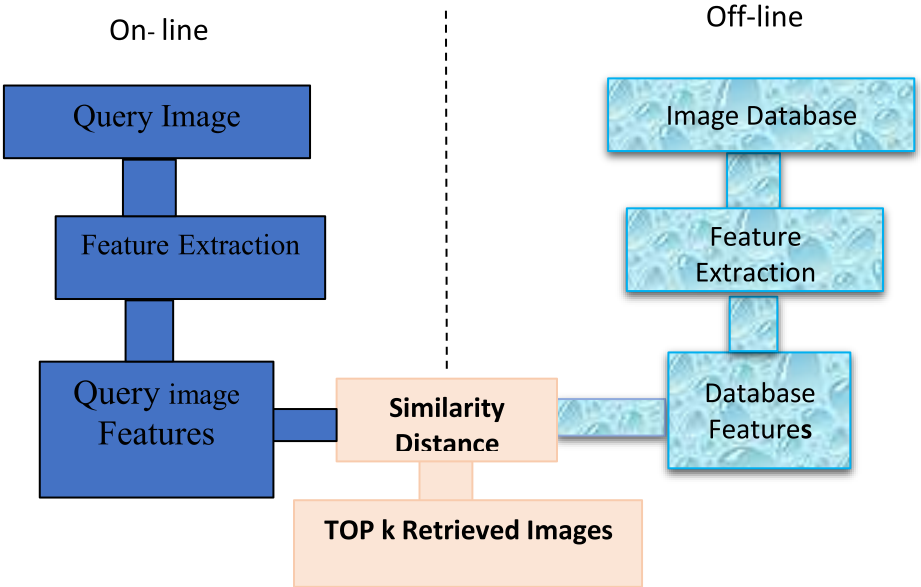


Figure 1: The framework of CBIR system

and stores them in a features database (features of the images are extracted and represented with feature vectors). In on-line stage, user input an image query to the system. The features of the query image are extracted and represented. The similarity was measured between the feature vector of the query image and the feature vectors of the images in the database. Then, the retrieval process is performed by applying an indexing scheme to provide an efficient way of searching the image database. Finally, the system retrieves the images that are most similar to the query image[1].

1.2 Local and global features

The derived features form an image can be classified as: (i) Global features that collect information from the whole image, (ii) Local features that collect information from the visual features of regions or objects in the given image [12]. In this paper, six algorithms for retrieving images based on local features for texture and color datasets are compared.

3. Local pattern algorithms

a) Local Binary Pattern (LBP)

LBP compares the gray level of center pixel with that of its neighbours. The binary value obtained is converted to its decimal value. This process is repeated for each pixel in the image [13], and all the pattern values obtained are used for measuring the histograms (Figure2). LBP value is computed by the Equations:

$$\mathrm{LBP}_{\mathrm{P,R}} = \sum_{p=0}^{p-1} f_1\left(g_p, g_c\right) \times 2^p \qquad (1)$$

$$f_1(x_1, x_2) = \begin{cases} 1 & if\ x_1 \geq x_2 \\ 0 & else \end{cases} \qquad (2)$$

$$\mathrm{Hist}_k = \sum_{i=1}^{M} \sum_{j=1}^{N} f_2(LBP(i,j), K) \qquad (3)$$

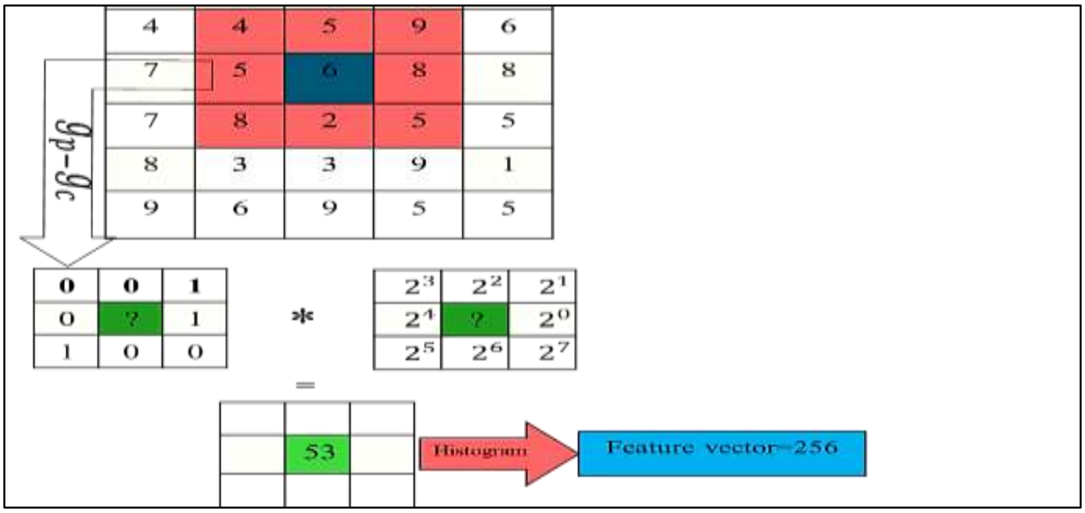


Figure2: The framework of local binary pattern (LBP)

Where g_c is the gray level of center pixel, g_p is the gray level of neighbour pixel and P is the number of neighbours, R is the neighbourhood radius.

b) **Local Ternary Pattern (LTP)**

LTP is an extension of Local binary pattern [14]. Unlike LBP, it does not threshold the pixels into 0 and 1, but thresholds the pixels into three values 0, 1, and -1. Assuming t is the constant threshold, g_c is the value of the center pixel and g_p is the value of neighboring pixel, the threshold result is given as follows:

$$\text{LTP}(g_c, g_p, t) = \begin{cases} 1 & if\ g_p > g_c + t \\ 0 & if\ g_p > g_c - t\ \ and\ \ g_p < g_c + t \\ -1 & if\ g_p < g_c - t \end{cases}$$

In this technique, after thresholding, adjacent pixels are combined to a ternary pattern that is divided into two binary patterns. Histograms are applied on the two binary patterns, and histograms obtained are concatenated to create a LTP descriptor, which has twice the size of the LBP descriptor (Figure3).

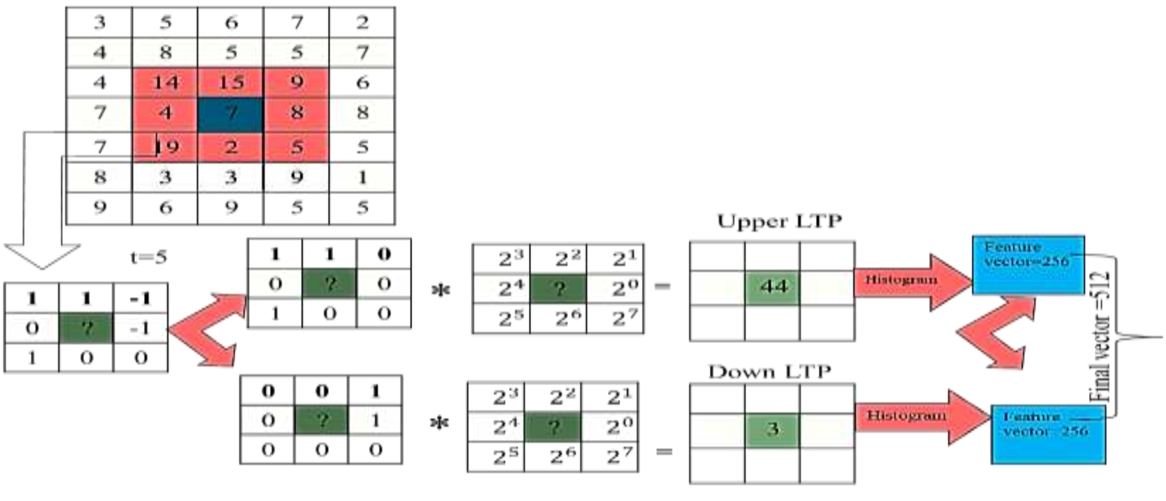


Figure 3: The framework of Local ternary pattern (LTP)

c) Local Tetra Pattern(LTrP)

Unlike the standard LBP and LTP, LTrP technique computes the gray-level difference and encodes the relationship between the specified pixel and its neighbours [15], based on the directions calculated using the vertical and horizontal first-order derivatives (Figure4).

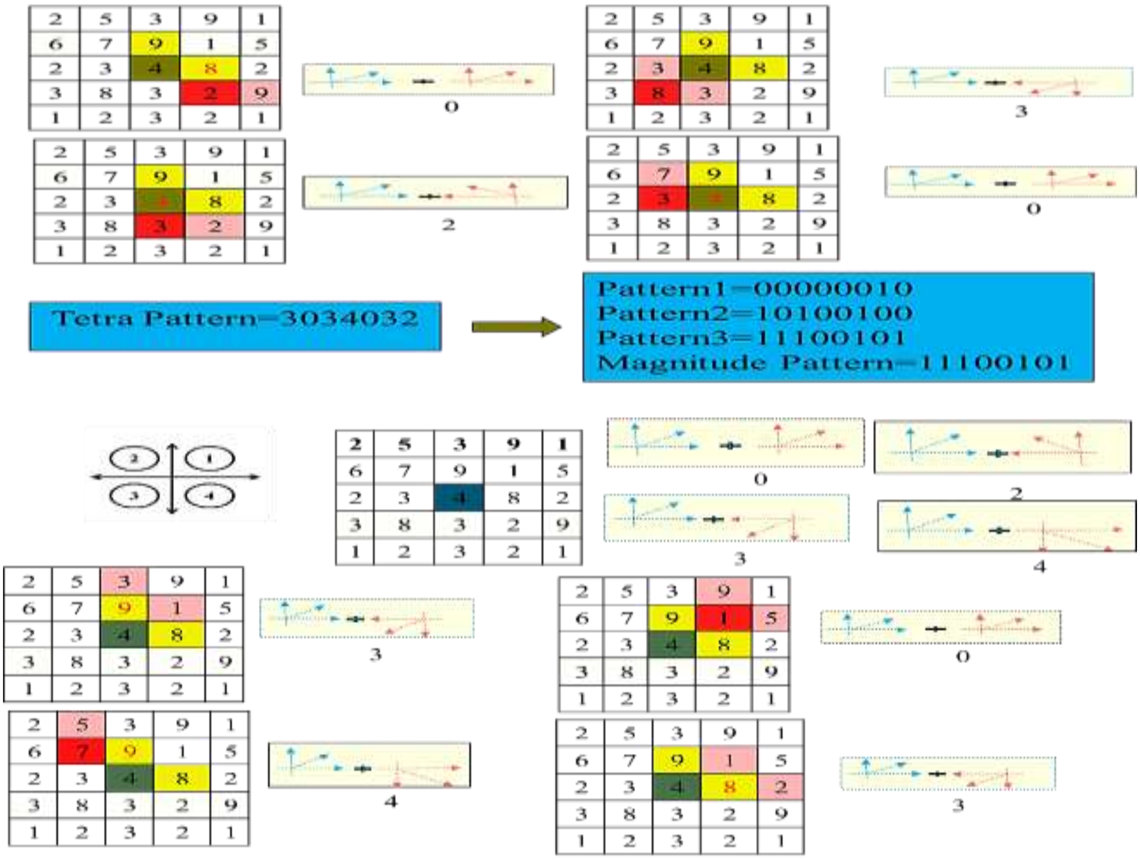


Figure 4: The framework of Local tetra pattern (LTrP) [15]

d) Co-occurrence of adjacent sparse local ternary patterns (COALTP)

COALTP proposed a combination of LTP and GLCM (which obtained with various distances and in different directions) as a method of feature extraction in CBIR framework (Figure 5). A histogram of local patterns was used in local LTP provided frequency information, so when extracting features using a histogram, there is a lack of neighbouring pixel-related spatial information, while gray-level co-occurrence matrix (GLCM) provides both frequency information and local pattern spatial relationships[16].

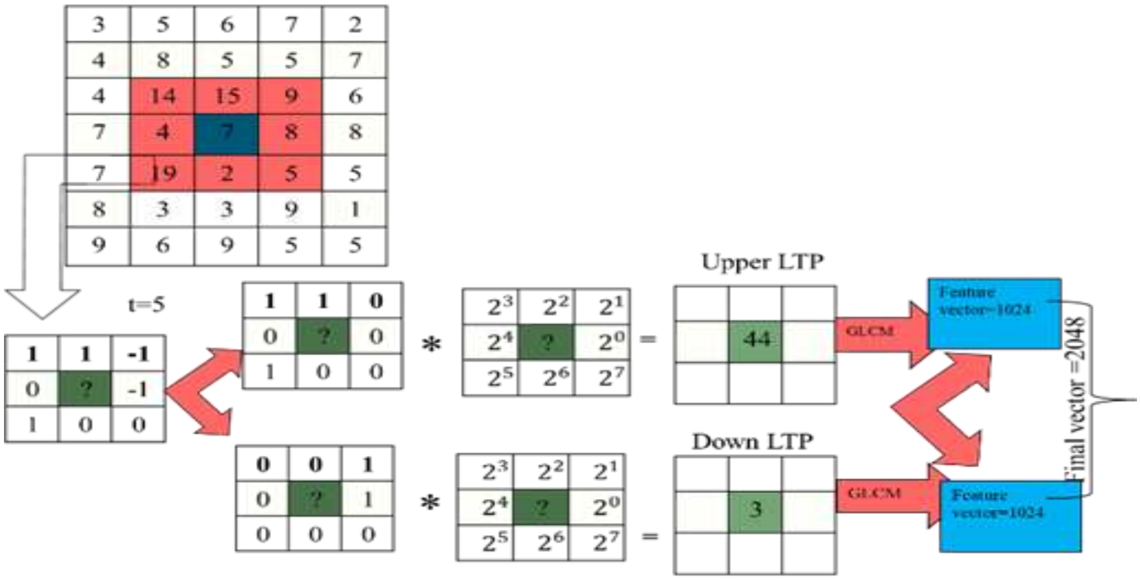


Figure 5: The framework of Co-occurrence of adjacent sparse local ternary patterns (COALTP)

e) Multi Motif Co-occurrence Matrix(MMCM)

In this method, two extended versions of motif co-occurrence matrices (MCM) are derived, and concatenated for efficient content-based image retrieval (CBIR). This algorithm divides the image into 2 x 2 grids. Each 2 x 2 grid is replaced with two different Peano scan motif (PSM) indexes, one is initiated from top left most pixel, and the other is initiated from bottom right most pixel[17,18]. This converts the whole image into two separate images, and Co-Occurrence matrices are extracted from these two transformed images: the first is called the "motif co-occurrence matrix initiated from top left most pixel (MCMTL)", and the second is named as "motif co-occurrence matrix initiated from bottom right most pixel (MCMBR)"[19,20]. This approach concatenates the MCMTL and MCMBR feature vectors and derives the co-occurrence multi-motif matrix (MMCM) features (Figure 6).

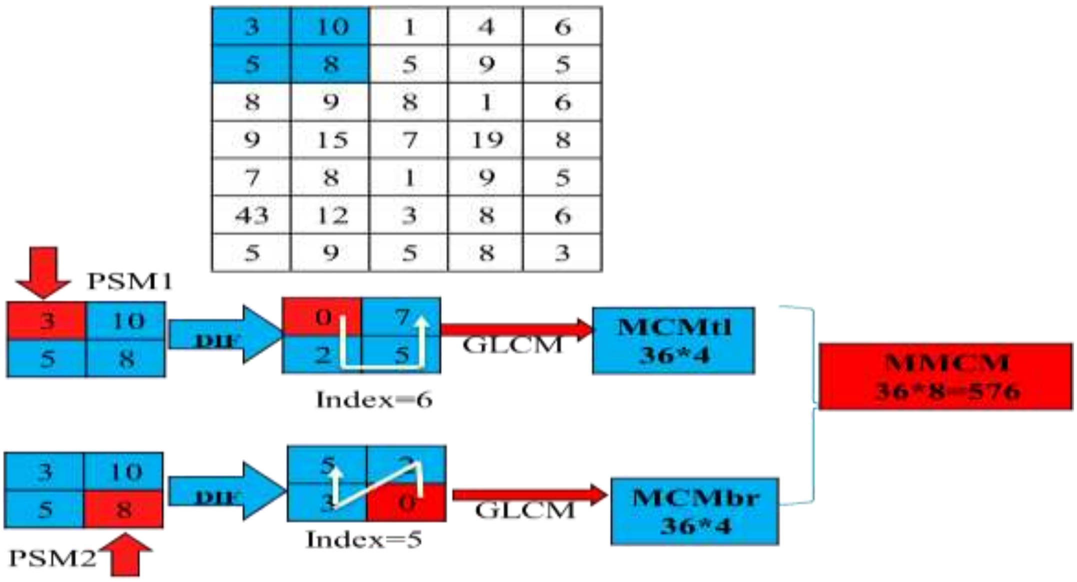


Figure 6: The framework of multi motif co-occurrence matrix

f) Local Motif Patterns (LMP)

This method is an extension of the previous MMCM approach. LMP presents a technique for content-based image retrieval by deriving a Local motif pattern (LMP) code co-occurrence matrix (LMP-CM) [21,22]. This algorithm divides the image into 2 x 2 grids. On each 2 x 2 grid, two different Peano scan motif (PSM) indexes are derived, one is initiated from top left most pixel[23], and the other is initiated from bottom right most pixel. From these two different PSM indexes, this algorithm derived a unique LMP Code for each 2 x 2 grid, which it is computed by:

$$LMP = \sum_{j=1}^{n} m_j * 6^{j-1};\ n{=}2 \qquad (5)$$

Where LMP ranges from 0 to 35(Figure7). A co-occurrence matrix is applied on LMP code, so grey level co-occurrence features are derived for efficient image retrieval [16].

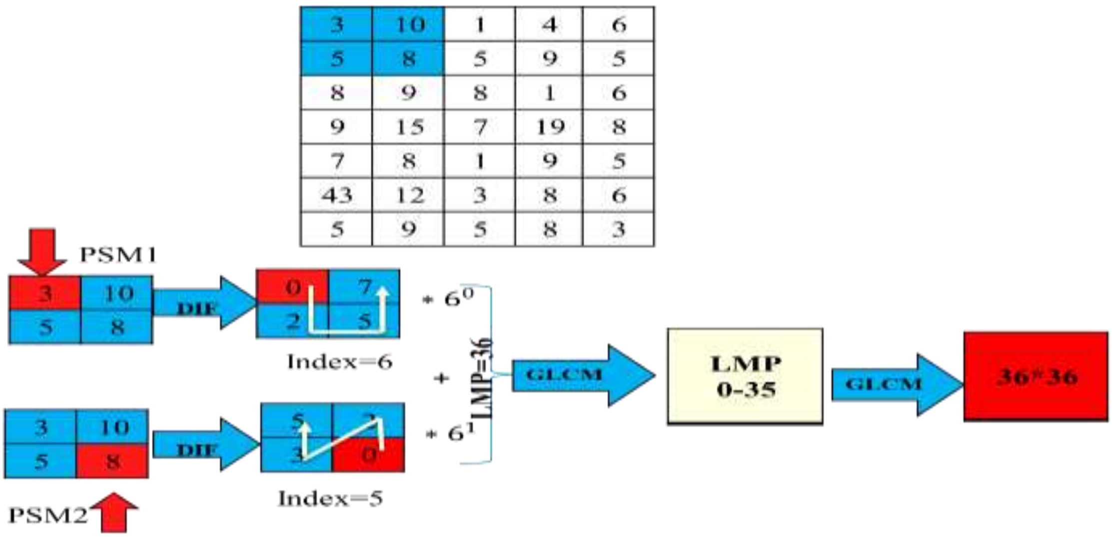


Figure 7: The framework of Local Motif Patterns (LMP).

3. Feature matching and similarity measures

After extracting features of every image in database and of the query image, feature matching is done by calculating the distance between feature vector of the query image and feature vectors of database images. The Shortest distance shows the most similarity between query image and the database images. For example, distance of 0 shows exact matching [1]. There are different measures for calculating the distance between two feature vectors. In this paper, four distance measures (L_1, Euclidean, Cityblock and Cosine) are used [16,17]:

$$\mathrm{dist}_{L1}(D,Q) = \sum_{l=1}^{L} \left| \frac{D_l - Q_l}{1 + D_l + Q_l} \right| \qquad (13)$$

$$\mathrm{dist}_{Euclidean}(D,Q) = \left(\sum_{l=1}^{L} (D_l - Q_l)^2\right)^{\frac{1}{2}} \qquad (14)$$

$$\mathrm{dist}_{cityblock}(D,Q) = \sum_{l=1}^{L} |D_l - Q_l| \qquad (15)$$

$$\mathrm{dist_{cosine}}\ (\mathrm{D},\mathrm{Q}) = \sum_{l=1}^{L} \left| \frac{(\mathrm{D_l} * \mathrm{Q_l})}{\sqrt{D_l * D_l} * \sqrt{Q_l * Q_l}} \right| \qquad (16)$$

Where D is the feature vector extracted from an image existing in database, Q is the feature vector of a query image and L is the number of features extracted. Short distance shows the similarity of query image and the image taken from database.

4. Datasets

Two texture datasets(Brodatz DB and Vistex DB) and one color database(Corel 1k DB) are selected for experiments to evaluate the performance of the six studied algorithms.

a) Color Database(Corel 1k)[25]

Corel 1k database consists of thousand color images of size 384×256 or 256×384. Corel 1k consists of 10 classes. These classes are shown in figure8 and each class consists of 100 images. Some researchers consider the Corel database satisfies all the criteria for evaluating an image retrieval system because of its large size and its heterogeneous material [1].

Figure 8.Corel1k classes

b) Brodatz Database

Brodatz database consists of 116 images of different textures. The size of each image is 512×512 which is divided into 16 non-overlapping images of size 128×128. This database consists of 116×16=1856 images [26].

a) Mit Vistex Database

Vistex database consists from 40 images. The size of each image is 512×512 which is divided into 16 non-overlapping images of size 128×128. This database consists of 40×16=640 images [27]. Figure9 illustrates Vistex database classes.

Figure 9: Vistex database classes

5. Performance Measures

After retrieving the similar images, the performance of the six algorithms is evaluated using evaluation measures. There are many evaluation criterions for CBIR from which Recall and Precision are well-known measures. Precision value is fraction of relevant images that are retrieved, while recall is the fraction of retrieved images that are relevant. Mathematically precision and recall are defined as follows:

$$\text{Precision} = \frac{\text{number of relevant images from the retrieved images}}{\text{total number of retrieved images}} \quad (6)$$

$$\text{Recall} = \frac{\text{number of relevant images from the retrieved images}}{\text{total number of relevant images in database}} \quad (7)$$

Average precision and recall can be formulated for each category as follows [16,28]:

$$\text{Precision } (\text{Cg}_\text{i}) = \frac{1}{\text{Nm}_\text{i}} \sum_{k=1}^{\text{Nm}_\text{i}} \text{Precision}\left(\text{Q}_\text{k}^\text{i}\right) \quad (8)$$

$$\text{Recall } (\text{Cg}_\text{i}) = \frac{1}{\text{n}} \sum_{k=1}^{\text{Nm}_\text{i}} \text{Recall } \left(\text{Q}_\text{k}^\text{i}\right) \quad (9)$$

Where n is the number of retrieved images, Cg_i and Nm_i are the image category i, and the number of images in category. $\text{Q}_\text{k}^\text{i}$ is the k'th image from category i, which is used as query image[29,30]. Average Retrieval precision (ARP) and Average recall are formulated as the equations [10, 11]:

$$\text{ARP} = \frac{1}{\text{DB}} \sum_{k=1}^{\text{DB}} \text{Precision } (\text{Cg}_\text{i}) \quad (10)$$

$$\text{Average Recall} = \frac{1}{\text{DB}} \sum_{k=1}^{\text{DB}} \text{Recall } (\text{Cg}_\text{i}) \quad (11)$$

Average Retrieval Rate (ARR) defined by:

$$\text{ARR} = \frac{1}{\text{DB}} \sum_{k=1}^{\text{DB}} \text{Recall } (\text{Cg}_\text{i}) \Big|_{n \le \text{Nm}_\text{i}} \quad (12)$$

Where DB is the total numbers of images in the database.

Experimental Results and Discussion:

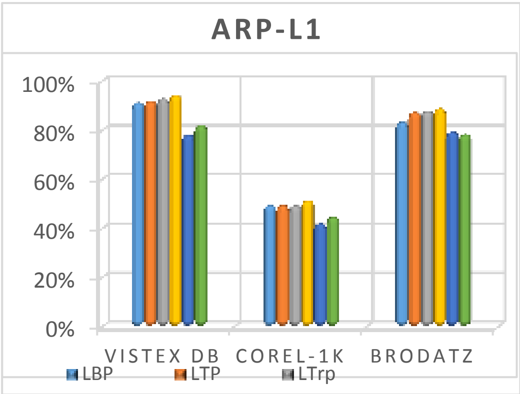
For better comparison among the six studied algorithms in the content-based image retrieval systems,performance measures(ARP,average recall,ARR) are calculated for the same standard databases(Corel1k,Brodatz DB,Vistex DB) with four similarity distances(L1, Euclidean, Cityblock and Cosine).Table1 illustrates the ARP values for Corel1k,Brodatz and Vistex databases with four similarity distances (L1, Euclidean, Cityblock and Cosine). In table 1,it is evident that the best ARP is got with COALTP algorithm for all distance measures, and for all databases, ARP=0.89(89%), 0.94(94%), 0.51(51%) for Brodatz, Vistex and corel1k respectively. The results shows:

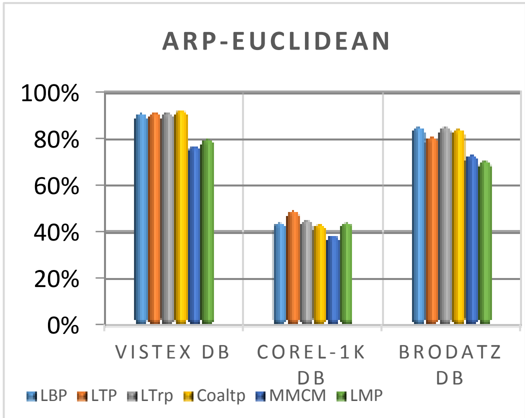
- The performance of COALTP is the best, while MMCM shows the least effectiveness as indicated by ARP values, As shown in Figure 10.
- ARP for all studied local patterns are higher for texture databases (Brodatz and MIT Vistex) compared to the color database (Corel1K) (Figure 10).
- The best ARP values are obtained with L1 distance as compared to other distance measures in all the databases (Figure 10). Therefore, the remaining performance measures are computed only with L1 distance.

Table 1: Comparison ARP of six studied algorithms for corel1k, Brodatz and Vistex DB with (L1, Euclidean, Cityblock and Cosine).

Dataset	**Performance Measures**					
Corel 1k	ARP-Average Retrieval Precision					
Method	LBP	LTP	LTrP	COALTP	MMCM	LMP
L1	0.49	0.49	0.49	0.51	0.42	0.45
Euclidean	0.44	0.49	0.45	0.44	0.37	0.40
Cityblock	0.49	0.50	0.49	0.49	0.40	0.43
Cosine	0.46	0.46	0.45	0.45	0.38	0.41
Dataset	**Performance Measures**					
Brodatz DB	**ARP**					
Method	LBP	LTP	LTrP	COALTP	MMCM	LMP
L1	0.83	0.87	0.88	0.89	0.79	0.78
Euclidean	0.85	0.81	0.85	0.85	0.74	0.71
Cityblock	0.88	0.88	0.88	0.88	0.77	0.76
Cosine	0.86	0.87	0.85	0.85	0.74	0.72
Performance Measures						
Vistex DB	**ARP**					
Method	LBP	LTP	LTrP	COALTP	MMCM	LMP
L1	0.91	0.92	0.93	0.94	0.78	0.82
Euclidean	0.91	0.92	0.92	0.93	0.77	0.80
Cityblock	0.92	0.92	0.93	0.94	0.78	0.81
Cosine	0.91	0.92	0.90	0.91	0.77	0.78

Print ISSN: 2079-3081 , Online ISSN:2663-4279





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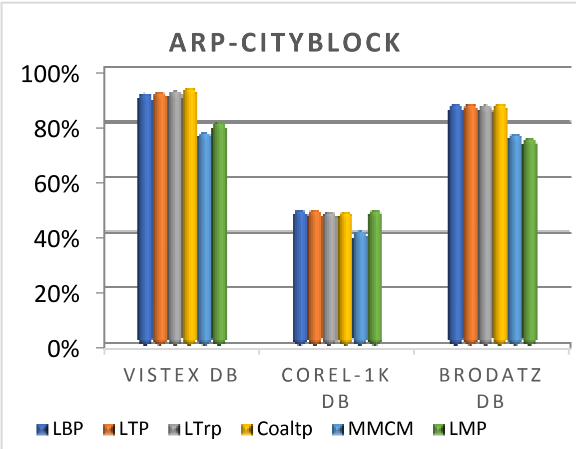
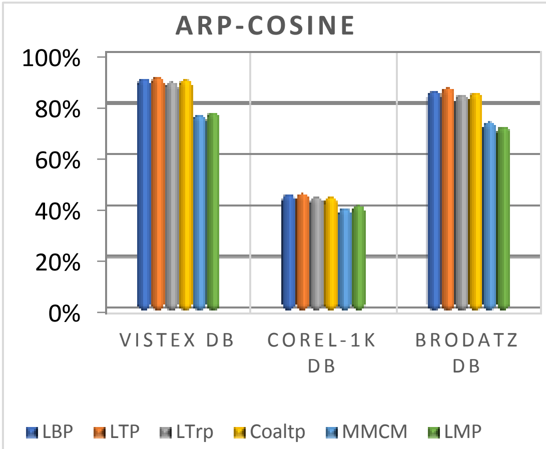




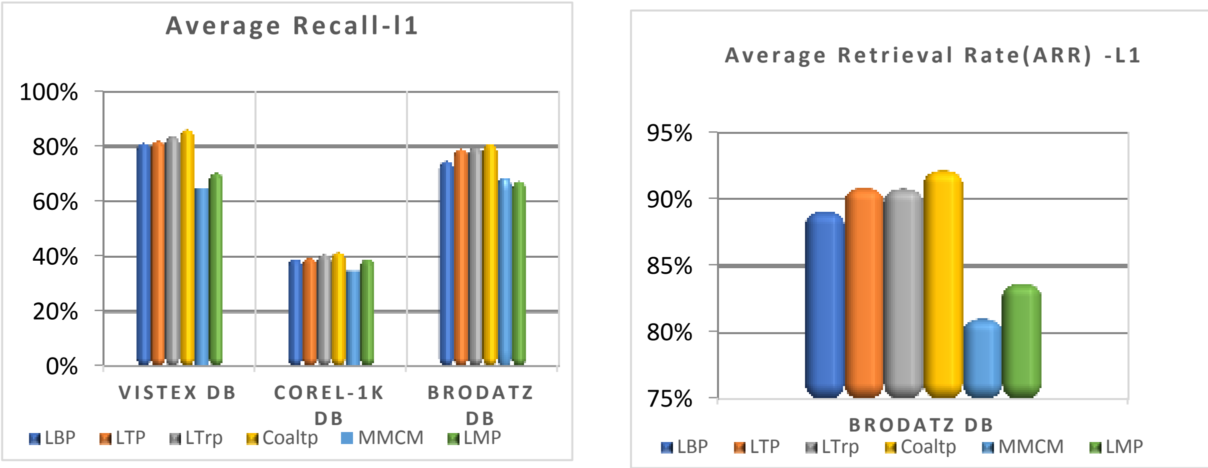
c d

Figure 10: Comparison ARP of six Local algorithms for Brodatz, corel1k and Vistex DB with distance L1 (a), Euclidean (b), Cityblock (c), Cosine (d).

In table2, it is evident that COALTP algorithm with L1 distance gives the best average recall of 0.86, 0.41 and 0.81 for Vistex, Corel1K and Brodatz DB, respectively, and the best ARR values of 0.92 for Brodatz DB, while MMCM algorithm gives the lowest Average recall and ARR values. The image retrieval system using the studied algorithms shows better performance in terms of average recall when tested on texture database compared to the color database, As shown in Figure 11(a).

Table2:comparison of Average Recall and ARR with l1 distance

Method	Average Recall			ARR
	Brodatz DB	**Corel 1k**	**Vistex DB**	**Brodatz DB**
LBP	0.75	0.39	0.81	0.89
LTP	0.79	0.40	0.82	0.91
LTrP	0.80	0.41	0.84	0.91
COALTP	0.81	0.41	0.86	0.92
MMCM	0.69	0.34	0.65	0.81
LMP	0.67	0.36	0.71	0.84



a   b

Figure 11: Comparison Average Recall and ARR of Local Pattern algorithms with L1 distance.

Feature vector length

Figure12 illustrates the length of the feature vector for all studied algorithms.

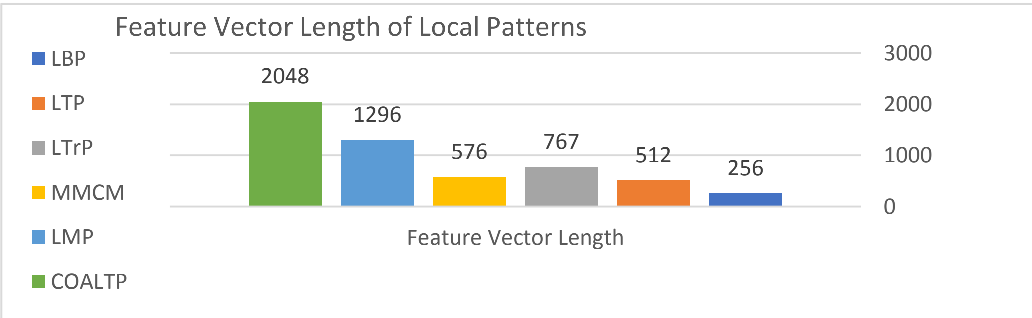


Figure 12: Feature Vector Length of Local Patterns

As shown in figure 12, the tested local patterns have different feature vector lengths. The longest feature vector (fv=2048 features) is obtained by COALTP algorithm which recorded the best performance among the tested algorithms. The shortest feature vector (fv=256 features) is obtained by LBP algorithm. Nevertheless, the effectiveness of LBP algorithm in image retrieval is better than LMP algorithm which is capable of extracting more features (fv=1296 features). This result indicated that extracting distinctive features is more important than the length of feature vector of an algorithm for improving the performance of CBIR system.

Conclusions and Recommendations:

In this paper, six well-known local image retrieval algorithms based on content are compared and several practical and experimental results are derived. In the future ,this results can be used as a bank of rich and useful information that will help to suggest more accurate and effective retrieval algorithms.

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