CIRCULAR SHIFT RIGHT LINEAR NETWORK CODING (CSR-LNC) WITH LOCAL PATTERNS FOR CONTENT-BASED IMAGE RETRIEVAL

Dr. M. NESTER JEYAKUMAR[1],
Assistant Professor, Dept. of Computer Science
Loyola College, Chennai-34, India.

Dr. JASMINE SAMRAJ[2]
Associate Professor, PG & Research Dept. of Computer Science,
Quaid-E-Millath Government College for Women (A), Chennai-2, India.

ABSTRACT: Content Based Image Retrieval (CBIR) is associated with the recovery of identical images from image repositories, employing the feature vectors obtained from images. These feature vectors provide the global definition for the visual content that exists in an image, for instance, texture, colour, shape, and spatial associations between the vectors. In our recent work the Complete Local Spatial Distribution Pattern (CLSDP) was proposed to successfully represent the spatial distribution image feature. In this paper, defining the feature vectors employing the Local Binary Pattern (LBP) operator is proposed. In order to improve the retrieval performance, we will also take into account a feature coding method based on Circular Shift Right (CSR) to make CLSDP with rotation invariance and scale invariance. Circular Shift Right Linear Network Coding (CSR-LNC) is proposed to CLSDP based on circular shift right with rotation invariance and scale invariance. CSR-LNC was performed in order to determine the optimum CLSDP and here circular shift right is proposed for the general definition of image feature vectors with rotation invariance and scale invariance. CLSDP with CSR-LNC is proposed for CBIR applications which capture the directions in a local region. To compare its performance, this proposed CLSDP with CSR-LNC technique is applied to a Corel 1K Database and is compared with the CLSDP, and LBP. Result shows that the proposed technique achieves good retrieval rate. The outcomes reveal that CLSDP with CSR-LNC technique offers outstanding performance in comparison with the available algorithms in terms of both mean precision and recall.

INDEX TERMS: Feature extraction or construction, Content Based Image Retrieval (CBIR), Feature representation, Complete Local Spatial Distribution Pattern (CLSDP), Circular Shift Right Linear Network Coding (CSR-LNC).

I. INTRODUCTION

In recent days the availability of internet and mobile phones provide the facility to take photos everywhere and upload them through social media services. This leads to the explosive growth in the volume of digital images, and makes it an extremely hard task to manually annotate and search images. In order to handle the huge volume of images, image retrieval techniques are used to automatically extract the features of images and provide effective image search services.

For effective services in the field of government, academics, hospital, crime prevention, engineering, architecture, journalism, fashion and graphic design, these images has to be put to use efficiently [1]. As the demand for these digital images has increased, it led to a huge database where the searching and acquiring of necessary images became a tedious and a time consuming process [2]. So, a conventional text-based retrieval system helped to rectify these issues. In this text-based system the user gives the query to the system with search terms as keywords and the system will return images similar to the query image [3]-[6].

In order to overcome the issues associated with the text-based image retrieval [7], the Content-Based Image Retrieval (CBIR) system was brought-in. CBIR makes use of the image contents to search and acquire the desired digital images. The search examines the contents of the image and not the metadata such as keywords or tags incorporated with the image. The Content of the image points to the colour, shape, texture or any other information that is extracted from the image. The CBIR system follows a technique as follows: it considers an image as an input and retrieves images according to the image attributes that matches with the most similar ones from the huge collection of database[8]-[10]. A Complete Local Spatial Distribution Pattern (CLSDP) descriptor is utilized by this system to extract the entire texture image feature. CLSDP is performed based on the circular shift right with rotation invariance and scale invariance with Circular Shift Right Linear Network Coding (CSR-LNC) [11].

II. RELATED WORK

Pattanaiket.al. [1] introduced a novel automated indexing and image retrieval for CBIR, and in this the images depend on the image contents referred to as features. The features could be either of low or high level. One individual feature can denote just a portion of the image characteristic. Therefore, the extraction of a number of features are done and employed for enhancing the process of image retrieval. In addition, it makes use of a color histogram, color mean, color structure descriptor and texture for the extraction of features. The feature matching process relies on their Euclidean distance for achieving the retrieval for CBIR.

Fan et al., [6] demonstrated a model using Local Patterns Constrained Image Histograms (LPCIH) for retrieving the image with efficiency. The extraction of information was done by aggregating the local texture patterns and the global image histogram. LPCIH becomes an efficient image feature representation technique along with a convenient image segmentation process. LPCIH is valuable for many real-world applications of image retrieval.

Meenakshi Madugunki et.al. [12], explained about an elaborate classification method of CBIR Systems. The Global color histogram, Local Color histogram and the HSV techniques were used for the extraction of the color feature and the results were compared employing Euclidean Distance, Canberra Distance and City Block Distance. Also Discrete Wavelet Transform (DWT) was used for the extraction of texture Feature and a comparison analysis was carried out with the outcome acquired utilizing multiple features.

Wan et al. [13] proposed a Complete Local Spatial Distribution Pattern (CLSDP) descriptor to describe the texture image feature, which confirms the retrieval performance. Beside three directions, *i.e.*, horizontal, vertical, and diagonal, they suggested system groups of the gray level variations. In order to indicate the spatial distribution image feature, every group will be joined with a Local Spatial Distribution Pattern (LSDP). It also constructs the LSDP patterns for gradient and filtered images, and finally forms the Complete Local Spatial Distribution Pattern (CLSDP) descriptor to completely describe the texture image feature. The performance of the algorithm is superior in terms of both mean precision and recall.

Tang et al. [14], suggested a Circular-Shift Linear Network Coding (LNC) to be a specialized kind of vector LNC, having local encoding kernels of an L-dimensional circular-shift linear code of degree 'δ''. It encounters severe overhead due to random coding, and therefore circular-shift LNC is highlighted in this research work.

III. PROPOSED METHODOLOGY

Associating the spatial distribution image feature with the conventional local patterns is the main objective of this work and it provides a new spatial-distribution-enhanced local pattern for texture features, which is termed as the Completed Local Spatial Distribution Pattern (CLSDP) with Circular Shift Right-Linear Network Coding (CSR-LNC).

3.1. Local Spatial Distribution Pattern (LSDP)

Given an image *I*, assuming that p refers to the pixel referenced in the image *I*, the system uses the symbol $\mathrm{GVP_r}$ to denote the gray-level change pattern in the horizontal and vertical orientations, and $\mathrm{GVP_d}$ to specify the pattern diagonally. Then, we define $\mathrm{GVP_r}$ and $\mathrm{GVP_d}$ w.r.t. Eq. (3).

$$\mathrm{GVP_r(p)} = \sum_{i=1}^{R} 2^{i-1} \times f_{GVP}(\mathrm{p}, p_i) \quad (1)$$

$$\mathrm{GVP_d(p)} = \sum_{i=1}^{D} 2^{i-1} \times f_{GVP}(\mathrm{p}, p_i) \quad (2)$$

$$f_{GVP}(\mathrm{x,y}) = \begin{cases} 1, & if\, x \geq y \\ 0 & if\, x < y \end{cases} \quad (3)$$

Where R refers to the number of the neighbours enclosing p in the horizontal and vertical orientations, D refers to the number of the neighbours enclosing p diagonally. The definition of LSDP works according to $\mathrm{GVP_r}$ and $\mathrm{GVP_d}$. LSDP of p is determined by integrating the horizontal, vertical or diagonal patterns of these pixels together, as determined in Eq.(4).

$$LSDP_r(\mathrm{p}) = \{GVP_r(p_i), GVP_r(p)\}$$

$$LSDP_d(\mathrm{p}) = \{GVP_d(p_i), GVP_d(p)\} \quad (4)$$

Eq. (3) and Eq. (4), also links two 4-bit patterns into 8-bit pattern LSDP value for every referenced pixel. Here, we will assume a window size of 3×3, and also select, right, right-up, up and left-up as four neighbour pixels. Also acquire every four LSDP patterns of the referenced pixel and its neighbour pixel individually on horizontal, vertical and diagonal directions. The entire image is indicated by constructing a histogram ranged from 0 to 255, after recognizing the local spatial distribution pattern.

$$\text{Histogram (x)} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{H} f_{HIS}(LSDP(p), x)$$

$$f_{HIS}(x,y) = \begin{cases} 1, & if\, x = y \\ 0, & else \end{cases} \quad (5)$$

3.2. Completed local spatial distribution pattern

Through three components, the entire Local Spatial Distribution Pattern is composed, they are: LSDP O, LSDP G and LSDP F. LSDP O is the local spatial distribution pattern of original gray image, whereas LSDP G and LSDP F are the LSDP of gradient image and filtered image respectively. The magnitude component associated with the local difference operator is used by Guo et al. [15] to suggest the magnitude LBP, along with the conventional LBP for texture classification. Likewise, the gradient component can draw-out more edge information, so this idea has stimulated us to suggest the LSDP G with the help of the gradient image g_I converted image I by the matrix in Eq.(6).

$$G= \begin{bmatrix} -1 & -1 & -1^{1} \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \quad (6)$$

We can also draw-out the LSDP feature from the gradient image such as the LSDP G, after computing the gradient image from the original gray image. The pattern value can be entirely modified through an individual noise pixel, because LBP is very sensitive to the noise in image. In order to minimize the noise's effect, we have suggested the LSDP F with the help of the filtered image f_I, which is computed through Eq.(7), where g_c is a referenced pixel in the filtered image, P is the number of neighbours of g_c and g_i is the i^{th} neighbour pixel of g_c. The noise pixels can be filtered by their neighbour pixels, also it can draw-out the LSDP feature from the filtered image, like LSDP F.

$$g_c^F = \frac{1}{P} \times \sum_{i=1}^{P} |g_i| \quad (7)$$

The system links LSDP O, LSDP G and LSDP F together into the CLSDP with the help of CLSDP as the input feature of the retrieval system. To segment the gray-level values of the LSDP feature image, the threshold T in every LSDP result image is utilized. If the LSDP values of pixels were less when compared with T, they will be observed as background points; else, they are identified as feature points. The CLSDP has the ability to draw-out the elaborated details individually on horizontal, vertical and diagonal directions, as distinguished with the conventional LBP.

3.3. Circular Shift Right Linear network coding (CSR-LNC)

A circular shift defines the operation of reorganizing the entries present in a tuple, either through the shifting of the last entry to the initial first position, when moving all other entries to the next subsequent position, or by carrying out the reverse operation. A circular shift is a certain type of cyclic permutation that is a particular sort of permutation. Mathematically, a circular shift involves a permutation σ over the *n* entries in the tuple so that either

- $\sigma(i) \equiv (i+1)$ modulo n, for all the entries i = *1, ..., n*
- Or$\sigma(i) \equiv (i-1)$ modulo n, for all the entries i = *1, ..., n*.

The outcome of recursive application of circular shifts on a provided tuple is also known as the circular shifts on the tuple. For instance, recursively using circular shifts on the four-tuple (a, b, c, d) consecutively yields

- (*d*, *a*, *b*, *c*),
- (*c*, *d*, *a*, *b*),
- (*b*, *c*, *d*, *a*),
- (*a*, *b*, *c*, *d*) (the actual four-tuple),

And then the series is repeated; therefore, this four-tuple exhibits four different circular shifts. But, not every *n*-tuple have *n* unique circular shifts. For example, the 4-tuple (*a*, *b*, *a*, *b*) just exhibits 2 unique circular shifts. Generally, the number of circular shifts of an *n*-tuple can be any divisor of *n*, based on the entries present in the tuple.

Consider length-N sequences specified for $0 \le n \le N - 1$. These sequences possess sample values equivalent to zero for $n < 0$ and $n \ge N$. For a random integer n_0, the shifted sequence$x_1[n] = x[n - n_0]$, may no more be specified over the range $0 \le n \le N - 1$. This necessitates the use of another kind of shift, which will maintain the shifted sequence in the range $0 \le n \le N - 1$ always.

In addition, another shift called as the "circular shift" is also introduced here.

$$x_c[n] = x[\langle n - n_0 \rangle_N] \quad (8)$$

Where,$\langle m \rangle_N = m modulo N$. for n_0>0 (right circular shift) the below mentioned equations are applicable:

$$x_c[n] = \begin{cases} x[n - n_0] \\ x[N - n + n_0] \end{cases} n_0 \le n \le N - 1,$$

$$0 \le n \le n_0 (9)$$

Linear Network Coding (LNC) is called as circular-shift LNC, whose operations of encoding at the intermediate nodes are carried out on the basis of the circular-shifts and bit-wise addition (XOR). Using this framework, an inherent connection between scalar LNC and circular-shift LNC is created. Specifically, on a typical network, for few block lengths L, each scalar linear solution over $GF(2^{L-1})$ can initiate an (L−1,L)-fractional circular-shift linear solution of degree (L−1)/2. Especially for multicast networks, an (L−1,L)-fractional circular-shift linear solution of random degree δ can be constructed with efficacy.

Suppose that each edge present in a network sends a binary sequence with length L. Various Linear Network Coding (LNC) approaches operate on the binary sequences by various techniques. With traditional scalar LNC and vector LNC the binary sequence transmitted at each edge is modelled, correspondingly, to be an element of $GF(2^L)$ and an L-dimensional vector over GF(2). The coding operations carried out at each intermediate node using scalar LNC and vector LNC are the linear functions over $GF(2^L)$ and over the ring of L×L binary matrices, correspondingly.

One more technique for reducing the complexity involved in the encoding of LNC is to cautiously create the coding operations conducted at the intermediate nodes. A specialized kind of vector LNC dependent on permutation operations, form an arbitrary coding technique. In the case of permutation-based vector LNC, at an intermediate node, each binary sequence coming inward gets permuted first, and after that, a binary sequence that is going outward is created through the bit-wise addition of the permutated binary sequences that are in the inwards directly. On the same notes, local encoding kernels at intermediate nodes are selected from L × L binary permutation matrices, instead of the random L × L binary matrices. Even though permutation can be implemented with more efficiency compared to the usual matrix multiplication over a binary sequence.

Concepts similar to LNC based on circular-shifts and bit-wise addition are taken into consideration in [16] and [17]. Their technique is based on the cyclic codes in coding theory, and associates the binary sequences which are sent along the edges and the local encoding kernels to polynomials and also in addition, in place of model circular-shift LNC in the form of a subclass of vector LNC. The benefit of such kind of expression is that more open matrix manipulations can be carried out on the local encoding kernels. An intrinsic connection between circular-shift LNC and scalar LNC can be easily unravelled on a typical network. For a positive integer L, the below L × L cyclic permutation matrix is represented by C_L

$$C_L = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \ddots & 0 \\ 0 & \ddots & \ddots & \ddots & 0 \\ 0 & \ddots & \ddots & 0 & 1 \\ 1 & 0 & \dots & 0 & 0 \end{bmatrix} \qquad (10)$$

and I_L refers to the identity matrix of size L. Both C_L and I_L are described over GF(2). Moreover, for $1 \le \delta \le L$, let C_δ represent the below set of matrices:

$$C_\delta = \{\textstyle\sum_{j=0}^{L-1} a_j C_L^j : a_j \epsilon \{0,1\}, \sum_{j=0}^{L-1} a_j \le \delta\}, \qquad (11)$$

that is, C_δ has the matrices, which is the sum of at most δ cyclic permutation matrices with size L.

IV. EXPERIMENTAL RESULTS

To calculate the effectiveness of the suggested system and the current system like Completed Local Spatial Distribution Patterns (CLSDP) with Circular shift Right-Linear Network Coding (CSR-LNC), three benchmark databases were utilized and the experiments were implemented on Corel 1K Database. The performance of the proposed image retrieval algorithm is computed with respect to Average precision (AP), Average recall (AR), and Average Accuracy (AA).

$$Precision(I_{q,n}) = \frac{1}{n}\sum_{i=1}^{|DB|} |f(I_i = I_q)| Rank(I_i = I_q) \le n| \qquad (12)$$

$$Recall(I_{q,n}) = \frac{1}{N_C}\sum_{i=1}^{|DB|} |f(I_i = I_q)| Rank(I_i = I_q) \le n| \qquad (13)$$

$$AP(n) = \frac{1}{N_C}\sum_{i=1}^{N_C} Precision\ (I_i = n) \qquad (14)$$

$$AR(n) = \frac{1}{N_C}\sum_{i=1}^{N_C} recall\ (I_i = n) \qquad (15)$$

$$f(I_i, I_q) = \begin{cases} 1, I_i = I_q \\ 0, otherwise \end{cases} \qquad (16)$$

Here, n denotes the number of retrieved images, and $|DB|$ is the size of the image database. $f(x, y)$ returns 1 if the category of x and y are the same, $Rank\ (I_i, I_q)$ returns the rank of image I_i (for the query image I_q) among all images of $|DB|$, NC is the size of every image category in database while the T utilized in Local Tera Pattern (LTP) is set as 10.

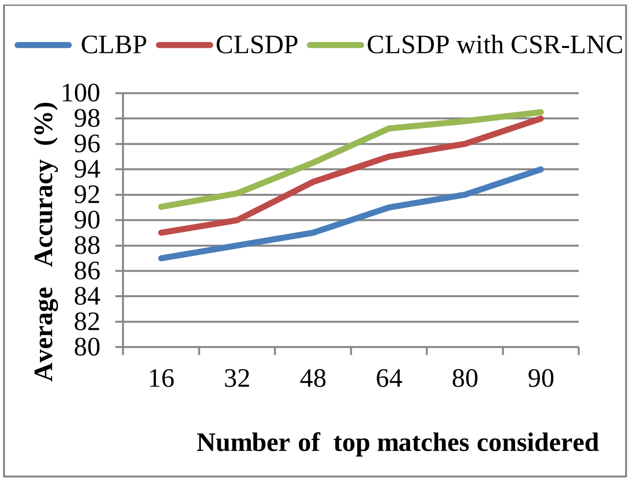

Figure 1. Average Accuracy comparison

Figure 1 indicates the evaluation chart of accuracy performance for the Complete Local Binary Patterns (CLBP), Complete Local Spatial Distribution Pattern (CLSDP) descriptor and the proposed Complete Local Spatial Distribution Pattern (CLSDP) with CSR-LNC. The number of top matches is plotted as x-axis and the average accuracy is plotted as y-axis. From the results it concludes that the proposed CLSDP with CSR-LNC produces higher average accuracy results of 95.19% , whereas other methods such as CLBP and CLSDP provides accuracy results of 90.16% and 93.5% respectively.

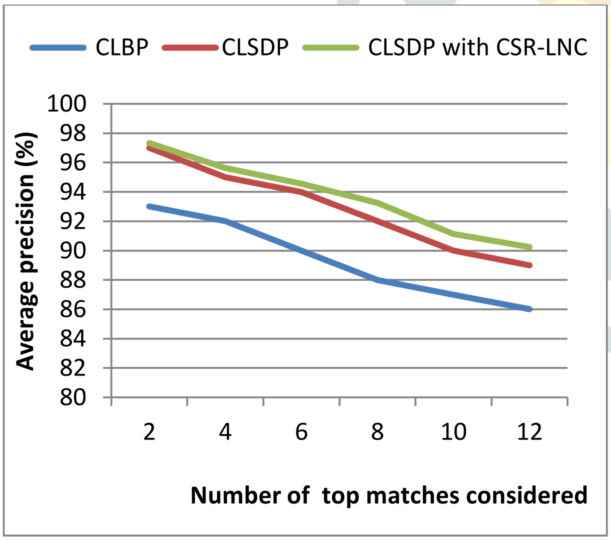

Figure 2. Average precision comparison

Figure 2 indicates the suggested Complete Local Spatial Distribution Pattern (CLSDP) with CSR-LNC descriptor is distinguished with the existing Completed Local Binary Patterns (CLBP) and Complete Local Spatial Distribution Pattern (CLSDP) descriptor with respect to precision. The number of top matches is plotted as x-axis and the average precision is plotted as y-axis. From the results it concludes that the proposed CLSDP with CSR-LNC produces higher average precision results of 93.69%, whereas other methods such as CLBP and CLSDP provides average precision results of 89.33% and 92.83% respectively.

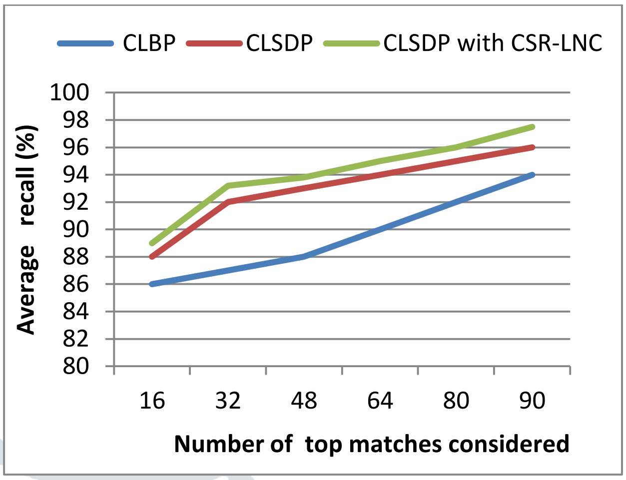

Figure 3. Average Recall comparison

Figure 3 indicates the proposed Complete Local Spatial Distribution Pattern (CLSDP) with CSR-LNC descriptor is distinguished with the existing Completed Local Binary Patterns (CLBP) and Complete Local Spatial Distribution Pattern (CLSDP) descriptor with respect to average recall. From the results it concludes that the proposed CLSDP with CSR-LNC produces higher average recall results of 94.08% , whereas other methods such as CLBP and CLSDP provides average recall results of 89.5% and 93% respectively.

V. CONCLUSION AND FUTURE WORK

This paper aims at incorporating the spatial distribution image feature with the traditional local patterns, and present a spatial-distribution-enhanced local pattern for texture features. Circular Shift Right Linear Network Coding (CSR-LNC) is integrated to Complete Local Spatial Distribution Pattern (CLSDP) known as CLSDP with CSR-LNC. This research work has influenced to introduce the computation of circulation based right variation patterns on various directions and the spatial distribution pattern is constructed. In order to perform the texture feature extraction more elaborately, the spatial distribution patterns of the actual, gradient and filtered images is separately extracted for the Content Based Image Retrieval (CBIR). It is found that the newly introduced CLSDP with CSR-LNC considerably enhances the retrieval performance over every database and performs better than the other techniques in terms of the average retrieval precision and mean retrieval rate. Nevertheless, currently CLSDP with CSR-LNC only focuses on the texture information of gray image. In the future work, we will concentrate on the color information of natural scene images.

REFERENCES

1. Pattanaik, S. and Bhalke, D.G., 2012. Beginners to content based image retrieval. International Journal of Scientific Research Engineering and Technology, 1(2), pp.040-044.

2. Agrawal, S., Verma, N.K., Tamrakar, P. and Sircar, P., 2011, Content based color image classification using SVM. Eighth International Conference on Information Technology: New Generations (ITNG), pp. 1090-1094.

3. Banerjee, M. and Kundu, M.K., 2003, Content based image retrieval with fuzzy geometrical features. The IEEE International Conference on Fuzzy Systems, 2003. (FUZZ'03), Vol. 2, pp. 932-937.

4. Kim, D.H. and Chung, C.W., 2003, Qcluster: relevance feedback using adaptive clustering for content-based image retrieval. In Proceedings of the 2003 ACM SIGMOD international conference on Management of data , pp. 599-610.

5. Deb, S. and Zhang, Y., 2004. An overview of content-based image retrieval techniques. International Conference on Advanced Information Networking and Applications, 2004 (AINA 2004), Vol. 1, pp. 59-64.

6. Fan, Z.G., Li, J., Wu, B. and Wu, Y., 2008, Local patterns constrained image histograms for image retrieval. IEEE International Conference on Image Processing, 2008 (ICIP 2008), pp. 941-944.

7. Zhao, L. and Tang, J., 2010, Content-based image retrieval using optimal feature combination and relevance feedback. International Conference on Computer Application and System Modeling (ICCASM), Vol. 4, pp. V4-436.

8. Bovolo, F., Bruzzone, L. and Carlin, L., 2010. A novel technique for subpixel image classification based on support vector machine. IEEE Transactions on Image Processing, 19(11), pp.2983-2999.

9. Xu, B., Yin, Q. and Lv, G., 2009, Using SVM to Organize the Image Database. International Conference on Computational Intelligence and Security, 2009 (CIS'09), Vol. 1, pp. 184-187.

10. Muneesawang, P. and Guan, L., 2004. An interactive approach for CBIR using a network of radial basis functions. IEEE Transactions on multimedia, 6(5), pp.703-716.

11. Jaggi, S., Cassuto, Y. and Effros, M., 2006, Low complexity encoding for network codes. IEEE International Symposium on Information Theory, pp. 40-44.

12. Madugunki, M., Bormane, D.S., Bhadoria, S. and Dethe, C.G., 2011, Comparison of different CBIR techniques. International Conference on Electronics Computer Technology (ICECT), Vol. 4, pp. 372-375.

13. Wan, S., Jin, P., Xia, Y., & Yue, L. (2016). Incorporating spatial distribution feature with local patterns for content-based image retrieval. Chinese Journal of Electronics, 25(5), 873-879.

14. Tang, H., Sun, Q. T., Li, Z., Yang, X., & Long, K. (2017). Circular-shift Linear Network Coding. arXiv preprint arXiv:1707.02163.

15. Z. Guo and D. Zhang, “A completed modeling of local binary pattern operator for texture classification”, IEEE Transactions on Image Processing, Vol.19, No.6, pp.1657–1663, 2010.

16. A. Keshavarz-Haddad and M. A. Khojastepour, “Rotate-and-add coding: A novel algebraic network coding scheme,” IEEE ITW, Ireland, 2010.

17. Hou, H., Shum, K.W., Chen, M. and Li, H., 2016. BASIC codes: Low-complexity regenerating codes for distributed storage systems. IEEE Transactions on Information Theory, 62(6), pp.3053-3069.