

Label Free Fruit and Pulses Image Retrieval

M. Naga Chandana¹, K. Divya Rani², S.M. Vineela³, M. Sai Triveka⁴

¹Department of Electronics and Communication Engineering, Vasireddy Venkatadri Institute of Technology, India

²Department of Electronics and Communication Engineering, Vasireddy Venkatadri Institute of Technology, India

³Department of Electronics and Communication Engineering, Vasireddy Venkatadri Institute of Technology, India

⁴Department of Electronics and Communication Engineering, Vasireddy Venkatadri Institute of Technology, India

Corresponding Author: M. Naga Chandana

Abstract: International competition of agricultural products is increasing fierce with the deepening of economic globalization. This rises the need for an automatic food understanding from images which is an interesting challenge for computer vision experts. In this project, we address the study of fruit and pulses image processing from the perspective of computer vision. The proposed local smart grid motif XoR pattern (LSMXoRP) exploits the relation between center pixel with its neighbors using 1×3 grid structure to extract local information structure. Further, it considers relation among neighboring pixels by using a clockwise scan unlike LBP which exploits the relation between center pixel and neighbor pixels only for better feature extraction. The experimental results indicate that performance of proposed LSMXoRP surpasses the existing LBP and LTP methods in terms of recognition rate.

Keywords – Automatic food understanding, Clockwise scan, LBP, Local smart grid motif XoR pattern, Recognition rate.

Date of Submission: 24-02-2018

Date of acceptance: 12-03-2018

I. Introduction

Digital media is the most important tool for human communication and it gives content based information to the world. So digital media has attained wide range of usage in various fields like medical, scientific, educational, entertainment and many others which raises the importance of automatic image retrieval system. The image retrieval is an efficient system for searching and retrieving images from a large volume of databases. Some automatic search mechanism called content based image retrieval (CBIR) is used for handling of these databases which gives appropriate annotation more than the human annotation. The search will estimate the actual contents of the image rather than the metadata such as key words, tags and descriptions associated with the image. CBIR is required because most web image search images hinge purely on metadata and this leads to a lot of undesirable material in the results. The manually entering keywords to explore image in a large data base are incapable, expensive and may not trap every keyword that describes the image. Thus a system that can filter images based on their content would provide indexing and retrieve more reliable results. The efficiency of CBIR system depends on the feature extraction as it is used to represent the essence of an image. The visual content of an image such as Color, shape and texture, or any other information that can be derived from the image itself is used to describe an image. The efficiency of feature descriptor depends mainly on the image acquisition. The acquired image may undergo different illumination changes, view angle changes etc. The literature points to the fact that no single best representation which accounts for all perceptual subjectivity is available. This motivates the current proposed algorithm. A brief review of various existing CBIR systems is presented in [1-4].

Now a day, people are more focused on maintaining healthy life style. As food intake monitoring is becoming more and more important because of the key role that it plays in health and market economies. Fruits and pulses are the main dietary supplements in food pyramid. There is a need for automated retrieval of fruits and pulses in food related industries. Many fruits and pulses may vary in shape, color and texture, as a human being it is simple task to identify them but for a machine it is a complex problem. The main goal of this paper is to represent fruit and pulses images in an efficient way for content based image retrieval.

Most important characteristic of an image is texture. Due to its potential value, texture analysis has been boundlessly used in computer vision, gesture recognition and other image processing applications. Textural

features contain information about the spatial distribution of tonal variations within a band. Texture can be evaluated as being fine, coarse, or smooth; rippled, irregular, or lineated. Texture is a built-in property of virtually all surfaces. It contains essential information about the structural arrangement of surfaces and their relationship to the surrounding environment. Although it is quite easy for human observers to recognize and describe in actual terms, texture has been resistant to exact definition and to analysis by digital computers. Since the textural properties of images rise to carry useful information for intolerance purposes, it is important to develop features for texture.

The main contributions of this paper are given below:

1. The proposed technique is a 1×3 grid structure called smart grid for exploiting the relation between center pixel and its neighbors.
2. LBP takes the sign of gray level between center pixel and neighbor pixel whereas our proposed method scans the boundary pixels of 3×3 grid in clockwise direction to exploit mutual relation among neighboring pixels for better feature extraction.

The methodology of this paper is as follows: Section 2 represents the literature survey for the proposed method. Section 3 presents the proposed feature extraction method. Section 4 illustrates the results and discussion. Finally, section 5 reveals the conclusion of the proposed descriptor.

II. Literature survey

In recent years, local image feature extraction has become more important in the field of CBIR. The image is described by local feature descriptor which uses the visual features of regions or objects. It can either be local or global. Visual features of the whole image are used in global descriptor whereas visual features of regions or objects are used in local descriptor to describe the image. Texture is one of the significant characteristic of an image. Texture analysis has been extensively used in many industrial applications such as medical, amusement, computer vision, gesture recognition and other image processing applications due to its vital role in image description. Many local descriptors are reported in the literature such as; Local binary pattern (LBP) that can show a better performance and less computational complexity for textural classification which was proposed by Ojala et al., [5]. In many research areas, it was proved that LBP is succeeded in terms of performance and speed. The local feature descriptors finds application in the area of textural classification [5], [6], image retrieval [7-12], face recognition [13] etc.,

Smith et al[14] developed a texture feature descriptor based on the mean and variance of the wavelet coefficients. A multi scale texture classification using the magnitude and phase features for complex wavelet responses was presented in Turgay et al [15]. Subrahmanyam et al [16] have introduced the wavelet and colour vocabulary tress for texture retrieval. Viparathi et al [17] presented a method called expert image retrieval system using directional local motif XoR patterns for texture databases. From above discussion it is clear that local feature descriptors are cable of capturing most of the image features. Motivated by the local feature descriptors, the proposed work also focus on local feature description for fruit and pulses image retrieval.

III. Feature Extraction Methods

Extraction of texture features from an image plays a vital role in automatic image retrieval systems. In this section, the proposed feature extraction methodology is explained in detail. The proposed method incorporates LBP in feature extraction. The LBP is briefly explained below.

3.1 Local Binary Pattern (LBP)

LBP was derived from the general definition of texture in a local neighborhood. It uses the relation between center pixel and its neighbor pixel for feature extraction. This method can show a better performance and less computational complexity for textural classification which was proposed by Ojala et al., [5]. In many research areas, it was proved that LBP is succeeded in terms of performance and speed.

For a given center pixel in 3×3 pattern, LBP value is computed by comparing its gray scale value with its surrounding neighbors as follows:

$$LBP = \sum_{n=0}^{N-1} 2^n \times f(h_n - h_c) \tag{1}$$

$$f(p) = \begin{cases} 0, & p < 0 \\ 1, & p \geq 0 \end{cases} \tag{2}$$

Where N is the number of neighbors, h_c denotes the gray value of the center pixel and h_n is the gray value of its neighbors.

3.2 Proposed feature extraction method

The proposed feature extraction method is divided into two steps. First step is to extract dual directional information from the four 1×3 smart grids and the second step is to extract the local information from the boundary pixels in a unique way.

3.2.1 Smart grid

The given image is sub divided into overlapped 3×3 grids and from each 3×3 grids four motif patterns are extracted. The fig.1 shows the consideration of 3×3 grid with ‘e’ as center pixel or focused pixel and remaining pixels are neighbors. Each 3×3 grid is sub divided into four 1×3 sub grids called smart grids. Each smart grid exploits structural information in dual direction. For example, smart grid 4 as shown in fig.1(e) exploits the relation between center pixel with its neighboring pixels in the direction (270°,0°). Similarly, other three smart grids patterns as shown in fig.1 (b), (c) and (d) obtain the structural information along (0°,90°), (90°,180°), (180°,270°) respectively.

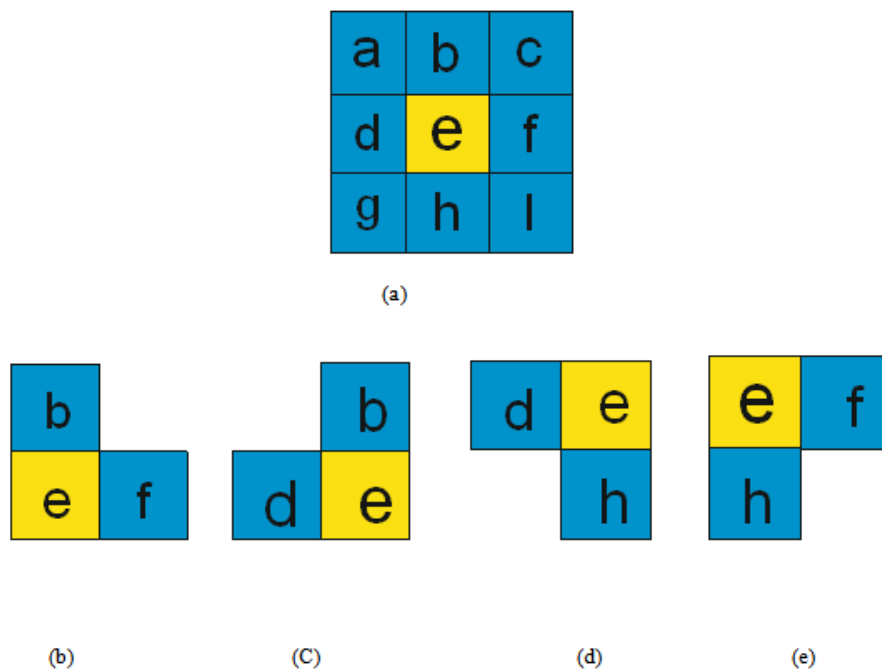


Figure 1: (a)3×3 smart grid. 1×3 smart sub-grids along (b) 0° and 90° (c) 90° and 180° (d) 180° and 270° (e) 270° and 0°

The computation of motif patterns from sub grid 4 as shown in fig.1(e) is as given below.

Let f and h are the directional neighbors along 0° and 270° for the focused pixel ‘e’. The seven motifs for this smart grid are defined as:

When any neighbor pixel is larger than the center pixel ‘e’ and the other neighbor pixel then that pixel will be represented in capitalized form as shown in fig.2(a) and (b). If any neighbor pixel in 1×3 smart grid is larger than other pixel and focused pixel then that pixel will be highlighted with a stroke as shown in fig.2(b) and (c).

1. **For motif “1”:** If it satisfies the condition of ‘ $e \geq f$ ’ and ‘ $e \leq h$ ’ then the center pixel of 3×3 grid is replaced by a new motif value ‘1’. Similarly, motif “2” is coded when ‘ $e \leq f$ ’ and ‘ $e \geq h$ ’. When $e=4$, $f=3$ and $h=5$, the center pixel ‘e’ is replaced with new motif value ‘1’.
2. **For motif “3”:** If the center pixel value is smaller than the neighbors and ‘ $f \leq h$ ’ then the new motif value “3” is coded. Similarly, motif “4” is coded when ‘ $f \geq h$ ’. When $e=3$, $f=6$ and $h=8$, the motif value ‘3’ is coded.
3. **For motif “5”:** If the center pixel value is larger than the neighbors and ‘ $f \leq h$ ’ then the new motif value “5” is coded. Similarly, motif “6” is coded when ‘ $f \geq h$ ’. When $e=9$, $f=6$ and $h=8$, the motif value ‘5’ is coded.
4. **For motif “7”:** If all the three pixels in the 1×3 sub grid are same then the new motif value “7” is coded.

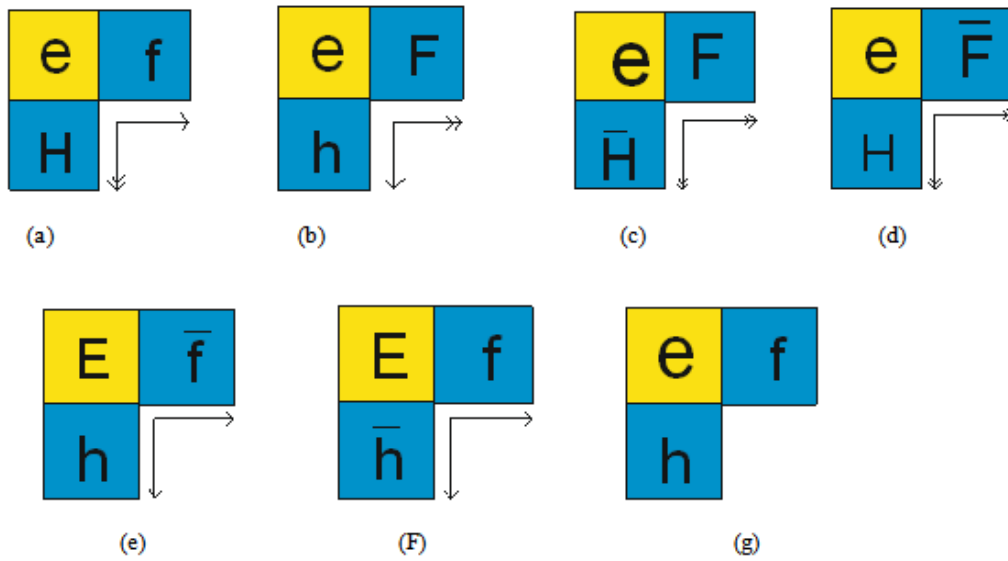


Figure 2: motif calculation along 0° and 270°

Mathematically, the motif image can be calculated using below equations:

$$LSM^{\theta_1, \theta_2}(f, e, h) = \begin{cases} 1, & ((e \geq f) \& (e \leq h)) \\ 2, & ((e \leq f) \& (e \geq h)) \\ 3, & ((e \leq f) \& (e \leq h) \& (f \leq h)) \\ 4, & ((e \leq f) \& (e \leq h) \& (f \geq h)) \\ 5, & ((e \geq f) \& (e \geq h) \& (f \leq h)) \\ 6, & ((e \geq f) \& (e \geq h) \& (f \geq h)) \\ 7, & ((e = f) \& (e = h) \& (f = h)) \end{cases} \quad (3)$$

Here $\theta_1, \theta_2 = 0^\circ, 270^\circ$

$$LSM^{\theta_1, \theta_2}(d, e, b) = \begin{cases} 1, & ((e \geq d) \& (e \leq b)) \\ 2, & ((e \leq d) \& (e \geq b)) \\ 3, & ((e \leq d) \& (e \leq b) \& (d \leq b)) \\ 4, & ((e \leq d) \& (e \leq b) \& (d \geq b)) \\ 5, & ((e \geq d) \& (e \geq b) \& (d \leq b)) \\ 6, & ((e \geq d) \& (e \geq b) \& (d \geq b)) \\ 7, & ((e = d) \& (e = b) \& (d = b)) \end{cases} \quad (4)$$

Here $\theta_1, \theta_2 = 90^\circ, 180^\circ$

$$LSM^{\theta_1, \theta_2}(b, e, f) = \begin{cases} 1, & ((e \geq b) \& (e \leq f)) \\ 2, & ((e \leq b) \& (e \geq f)) \\ 3, & ((e \leq b) \& (e \leq f) \& (b \leq f)) \\ 4, & ((e \leq b) \& (e \leq f) \& (b \geq f)) \\ 5, & ((e \geq b) \& (e \geq f) \& (b \leq f)) \\ 6, & ((e \geq b) \& (e \geq f) \& (b \geq f)) \\ 7, & ((e = b) \& (e = f) \& (d = f)) \end{cases} \quad (5)$$

Here $\theta_1, \theta_2 = 0^\circ, 90^\circ$

$$LSM^{\theta_1, \theta_2}(d, e, h) = \begin{cases} 1, & ((e \geq d) \& (e \leq h)) \\ 2, & ((e \leq d) \& (e \geq h)) \\ 3, & ((e \leq d) \& (e \leq h) \& (d \leq h)) \\ 4, & ((e \leq d) \& (e \leq h) \& (d \geq h)) \\ 5, & ((e \geq d) \& (e \geq h) \& (d \leq h)) \\ 6, & ((e \geq d) \& (e \geq h) \& (d \geq h)) \\ 7, & ((e = d) \& (e = h) \& (d = h)) \end{cases} \quad (6)$$

Here $\theta_1, \theta_2 = 180^\circ, 270^\circ$

Further, XoR operation is performed on all the four individual transformed motif images. XoR value is determined by comparing its center motif value with its surrounding motif values using the below equation.

$$LSMXoR = \sum_{i=0}^{N-1} M(P_j - P_c) \times 2^i \quad (7)$$

$$M(P_j, P_c) = \begin{cases} 0, & P_j = P_c \\ 1, & P_j \neq P_c \end{cases} \quad (8)$$

Where N is number of neighbors, P_j is the neighborhood motif value, P_c is the center pixel motif value. The feature descriptor for the given image is constructed by building a histogram after computing the motif XoR pattern for each pixel on four directions as follows:

$$H_{LSMXoR}(m) = \sum_{x=0}^{N_1} \sum_{y=0}^{N_2} f(LSMXoR(x, y), D); \quad m \in [0, (2^n - 1)] \quad (9)$$

$$f(p, q) = \begin{cases} 1, & p = q \\ 0, & else \end{cases} \quad (10)$$

Where size of the input image is $N_1 \times N_2$

3.2.2 Hoop pattern

Hoop pattern is used to exploit the mutual relation between the neighbor pixels. The hoop pattern mapped image can be computed as follows.

The whole image is converted into several overlapped 3×3 grids. It considers boundary pixels rather than the center pixel from the overlapped 3×3 grid as shown in fig.3. Further, each boundary pixel is compared with its neighbor pixel in a clockwise direction. After the completion of comparison, the boundary pixel is replaced with the value 0 or 1 based on the gray level difference. For example the boundary pixels are scanned in a clock wise fashion from ‘a’ to ‘d’ as shown in fig.3. Now from the binary mapped image, pattern values are computed as in the case of LBP. The XoR operation is performed on the transformed image.

For example, a=32, b=145 and c=95 in 3×3 grid. The boundary pixel ‘a’ is replaced with the value 0 because it doesn’t satisfy the condition $a > b$ and the boundary pixel ‘b’ is replaced with the value 1.

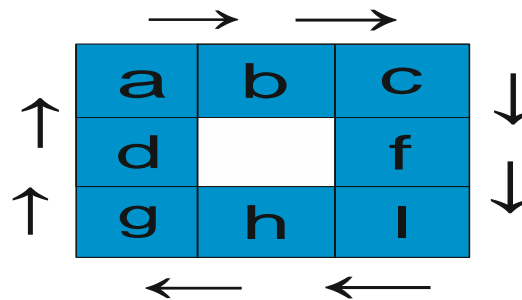


Figure 3: Hoop pattern

XoR value is determined by comparing its center motif value with its surrounding motif values using the below

equation.

$$LSMXoR = \sum_{i=0}^{N-1} M(P_j - P_c) \times 2^i \tag{11}$$

$$M(P_j, P_c) = \begin{cases} 0, & P_j = P_c \\ 1, & P_j \neq P_c \end{cases} \tag{12}$$

Where N is number of neighbors, P_j is the neighborhood motif value, P_c is the center pixel motif value.

The histogram is constructed after computing the motif XoR pattern for each pixel on four directions as follows:

$$H_{LSMXoR}(m) = \sum_{x=0}^{N_1} \sum_{y=0}^{N_2} f(LSMXoR(x, y), l); \quad m \in [0, (2^n - 1)] \tag{13}$$

$$f(p, q) = \begin{cases} 1, & p = q \\ 0, & else \end{cases} \tag{14}$$

Where size of the input image is $N_1 \times N_2$

The histogram of all five LSMXoRs is concatenated to form the proposed descriptor of the input image

$$H_{MXoR} = [H_{1MXoR}; H_{2MXoR}; H_{3MXoR}; H_{4MXoR}; H_{5MXoR}] \tag{15}$$

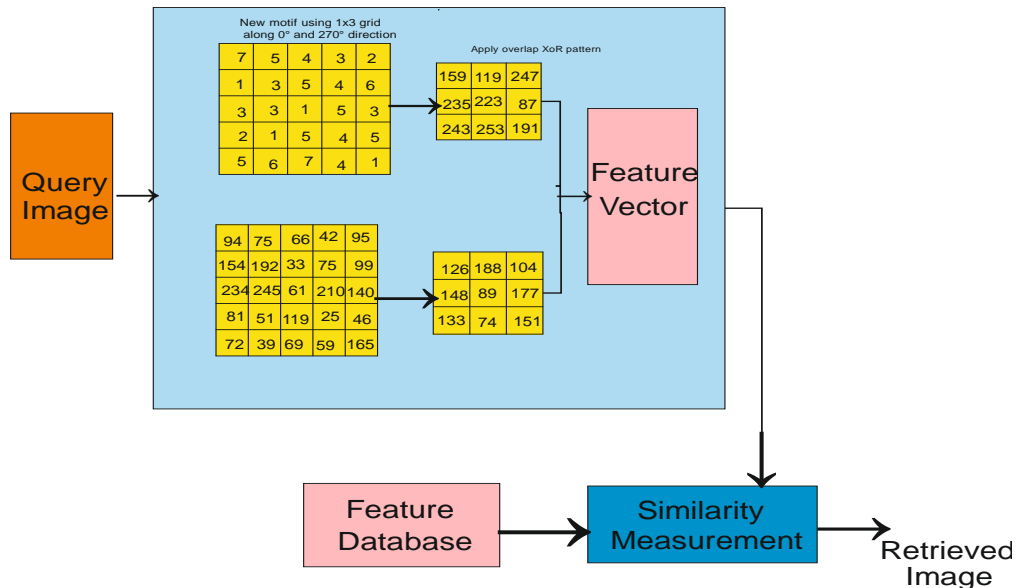


Figure 4: Proposed image retrieval system.

The proposed method (LSMXoRP) transforms all the overlapped 3x3 grid of query image into new motif using four 1x3 grids to collect dual directional information and hoop pattern to extract local information. Further, the XoR operation is applied on individual motif images. After performing XoR operation, histogram is constructed for transformed motif images. Feature vector is created by concatenating all the histograms. Then the similarity measurement is conducted on feature vector of the query image and feature database for image retrieval.

3.3 Algorithm for proposed method

Input: color image (RGB)

Output: Retrieval results

1. Load the color RGB image and converted into an HSV color image.
2. Divide the whole image into several overlapped 3x3 grids and extract four 1x3 smart grids along (0°,90°),(90°,180°),(180°,270°) and (270°,0°) from it.
3. Calculate the motif values using four 1 x 3 smart grids and also scan the boundary pixels of 3x3 grid in clockwise direction.
4. Apply XoR operation on all five motif images to form LSMXoRs.
5. Build histogram for individual transformed motif images.
6. Construct the overall histogram by concatenating all the five histograms.

7. Compare the features of query image with features in the database.

IV. Results and Discussion

In this section, the performance of the proposed LSMXoR feature descriptor is evaluated in comparison with other existing LBP variants. The SVM classifier with one-verse-the-rest strategy is used to compute the classification efficiency of all the methods using Vfeat [18] implementation. The performance of proposed and other existing methods are evaluated on two databases namely pulses and fruit image databases. The consideration of various parameters for performance evaluation is tabulated in Table1.

Experiment#1: Pulses image database

The pulses image database for image retrieval is acquired using a standard digital camera with resolution of 3456×5184 and focal length of 50mm. Total 10 categories of pulses image are captured at various illuminations and different grouping statistics as shown in the fig.5. Each category has 30 images. For performance evaluation 12 samples per category are considered for training the classifier. The results are tabulated in Table2.

Table 1: About pulse and fruit databases

Database	Pulses	Fruit
Classes	10	12
Total Samples	300	2633
Train Samples	12	16

We evaluate the performance of LSMXoRP and the different existing techniques LBP, LTP in terms of recognition rate. We also computed the retrieval performance of four dual directional motif patterns ((0°,90°), (90°,180°), (180°,270°), (270°,0°)). The proposed descriptor shows the better recognition rate of 99.62% compared to the existing techniques like LBP(98.95%), LTP (99.49%) and smart grids(98.76%) on pulses database.



Figure 5: Images of pulses

Experiment#2: Fruit database

Fruit database is acquired (<http://www.liv.ic.unicamp.br/~undersun/pub/communications.html>) with resolution of 1024×768. Total 12 categories of fruit images are collected with different view angles and 16 samples are considered for performance evaluation. The 12 categories that are mentioned in fruit database are Plum, Cashew, Kiwi, Fuji apple, Melon, Nectarine, Pear, Peach, Watermelon, Agata potato, Orange, Taiti lime as shown in fig.6. The recognition rate of the proposed descriptor and the existing techniques are mentioned in the Table.2.

Table 2: Recognition rate of fruit and pulse databases

Databases/Method	Pulses	Fruit
LBP	98.95%	68.2%
LTP	99.49%	69.51%
Smart grid	98.76%	68.27%
Proposed Descriptor	99.62%	72.39%

The proposed descriptor have shown the better recognition rate of 72.39% as compared to LBP of 68.2%, LTP of 69.51%, smart grids of 68.27% on fruit database. We can conclude from the information given in Table.2 that

the proposed technique (LSMXoRP) is the best feature extraction technique as compared to the LBP, LTP and smart grids.



Figure 6: Images of fruits.

V. Conclusion

In this paper, we developed a feature extraction technique named as local smart grid motif XoR pattern (LSMXoRP). The proposed method LSMXoRP extracted the local information structure using 1×3 grid structure and the boundary pixels of overlapped 3×3 grid in clockwise direction. Further, XoR operation is performed on the all the motif images. The performance of LSMXoR is evaluated in terms of recognition rate by testing the proposed descriptor on fruit and pulses databases. The performance of proposed descriptor is 99.62% and 72.39%, LBP is 98.95% and 68.2%, LTP is 99.49% and 69.51%, smart grid is 98.76% and 68.27% on fruit and pulses databases respectively. The recognition rates of LSMXoR have shown improvement as compared to existing techniques on pulses and fruit databases.

References

- [1] L. Liu, J.-X. Li, Integrating color into the local features based on the stable color invariant regions for image retrieval, *Optik* 124 (2013) 2577–2582.
- [2] y. Rui, T.S. Huang, Image retrieval, current techniques, promising directions and open issues, *J. Vis. Commun. Image Represent.* 10 (1999) 39–62.
- [3] Y. Liu, D. Zhang, G. Lu, W.-Y. Ma, A survey of content-based image retrieval with high-level semantics, *Int. J. Pattern Recognit.* 40 (2007) 262–282.
- [4] A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta, R. Jain, Content-based image retrieval at the end of the early years, *IEEE Trans. Pattern Anal. Mach. Intell.* 22 (2000) 1349–1380.
- [5] Ojala, T., Matti, P., & Harwood, D. (1996). A comparative study of texture measures with classification based on feature distributions. *Pattern Recognition*, 29(1), 51–59.
- [6] Guo, Z., Zhang, L., & Zhang, D. (2010). Rotation invariant texture classification using LBP variance with global matching. *Pattern Recognition*, 43(3), 706–719.
- [7] [7] Cheng-Hao, Y., & Shu-Yuan, C. (2003). Retrieval of translated, rotated and scaled color textures. *Pattern Recognition*, 36, 913–929.
- [8] Chuen-Horng, L., Chun-Chieh, C., Hsin-Lun & Jan-Ray, L. (2014). Fast K-means algorithm based on a level histogram for image retrieval. *Expert Systems with Applications*, 41, 3276–3283.
- [9] Fatahiyah, M. A., Rossitza, S., & Yu-kun, L. (2013). Trademark image retrieval using an integrated shape descriptor. *Expert Systems with Applications*, 40, 105–121.
- [10] Subrahmanyam, M., Maheshwari, R. P., & Balasubramanian, R. (2012c). Local tetra patterns: A new feature descriptor for content based image retrieval. *IEEE Transactions on Image Processing*, 21(5), 2874–2886.
- [11] Subrahmanyam, M., Maheshwari, R. P., & Balasubramanian, R. (2012d). Local maximum edge binary patterns: A new descriptor for image retrieval and object tracking. *Signal Processing*, 92, 1467–1479.
- [12] Subrahmanyam, M., Maheshwari, R. P., & Balasubramanian, R. (2012e). Directional binary wavelet patterns for biomedical image indexing and retrieval. *Journal of Medical Systems*, 36(5), 2865–2879.
- [13] Ahonen, T., Hadid, A., & Pietikainen, M. (2006). Face description with local binary patterns: Applications to face recognition. *IEEE Transactions on Pattern Analysis*, 28(12), 2037–2041.
- [14] Smith, J. R., & Chang, S. F. (1996). Automated binary texture feature sets for image retrieval. *IEEE int. conf. acoustics, speech and signal processing*, Columbia Univ., New York (pp. 2239–2242).
- [15] Turgay, Ç., & Tardi, T. (2011). Multiscale texture classification and retrieval based on magnitude and phase features of complex

- wavelet sub bands. Computers and Electrical Engineering, 37, 729–743.
- [16] Subrahmanyam, M., Maheshwari, R. P., & Balasubramanian, R. (2012a). Expert system design using wavelet and color vocabulary trees for image retrieval. International Journal of Expert systems with applications, 39, 5104–5114.
- [17] Santosh Kumar Vipparthi ,S.K. Nagar ,Expert image retrieval system using directional local motif XoR patterns, Journal of expert systems with applications,2014,pp 8016-8026.
- [18] SVM classifier, http://www.vlfeat.org/matlab/v1_svmtrain.html
- [19] Fruit database, <http://www.liv.ic.unicamp.br/~undersun/pub/communications.html>

IOSR Journal of Computer Engineering (IOSR-JCE) is UGC approved Journal with Sl. No. 5019, Journal no. 49102.

M. Naga Chandana " Label Free Fruit and Pulses Image Retrieval." IOSR Journal of Computer Engineering (IOSR-JCE) 20.2 (2018): 15-23.