ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645
Indian Journal of Science and Technology, *Vol 8(7), 614–621, April 2015*
DOI: 10.17485/ijst/2015/v8i7/62845

Global Neighbour Preserving Local Ternary Co-occurrence Pattern (GNPLTCoP) for Ultrasound Kidney Images Retrieval

Callins Christiyana Chelladurai[1*] and Rajamani Vayanaperumal[2]

[1]Department of Computer Science and Engineering, Sethu Institute of Technology, Madurai, Tamilnadu, India; callinschristiyana_c@yahoo.co.in

[2]Department of Electronics and Communication Engineering, Veltech Multitech Dr. Rangarajan Dr. Sakunthaladevi Engineering College, Chennai, Tamilnadu, India; rajavmani@gmail.com

Abstract

Objectives: This work proposes a feature extraction procedure named as Global Neighbour Preserving Local Ternary Co-occurrence Pattern (GNPLTCoP) in the Content Based Image Retrieval (CBIR) Task for ultrasound kidney images retrieval. Methods/Analysis: The proposed GNPLTCoP feature finds the local pattern based on the co-occurrence of first order derivatives in ternary fashion from radius 1 and radius 2 neighbourhoods of the center pixel in a small 3X3 square region. Then the pattern is classified into two in order to integrate the global information. The classification is based on the correlation between the global and local region mean intensities. Findings: The Performance of GNPLTCoP is compared with the Ternary co-occurrence Pattern (LTCoP) as it computes the co-occurrence of first order derivatives. The LTCoP considers the co-occurrence of 8 pixels in the radius 1 neighbourhood with the 8 pixel candidates in the radius 2 neighbourhood. Among the 16 pixels in the radius 2 neighbourhood, 8 pixels are used and 8 pixels information are left in the LTCoP computation. This problem is addressed in the computation of GNPLTCoP. The proposed GNPLTCoP feature is different from the LTCoP by means of considering the pixel candidates of radius 2 neighbourhood and adding in the global information. The pixel candidates of radius 2 neighbourhood are replaced by the mean value of itself and its two neighbours to preserve the neighbour pixels information. This work employs GNPLTCoP feature as a feature extraction procedure in image retrieval system consists of database of ultrasound kidney images. The performance of GNPLTCoP is compared with LTP and LTCoP. The discriminative power of GNPLTCoP is substantiated through Precision and Recall measures. Conclusion/Application: The proposed GNPLTCoP can be applied as the feature extraction procedure for other types of medical images and pattern recognition applications.

Keywords: CBIR, GNPLTCoP, Local Patterns, LTCoP, Texture, Ultrasound Kidney Images

1. Introduction

Million amounts of medical images are generated and stored in the database all over the world day by day. These images should be properly indexed for make use of them into various medical applications such as assisting diagnosis and medical citation etc. The above said applications are facilitated by the technique called as Content Based Image Retrieval (CBIR)[1]. Callins Christiyana et al[2] have narrated the processes involved in CBIR for medical applications. The important process in CBIR is feature extraction. The feature extraction process derives the content of an image by means of visual features. The features such as color, texture, shape and the combinations of these are used to represent the image content. Among the visual features, texture feature[3] is very much desirable in medical images since it has characteristics to reflect other features and so brings semantic information.

There are many methods which are widely used in texture representations such as Grey Level Co-occurrence

*Author for correspondence

Matrix (GLCM)[4], Gabor filtering[5], wavelet transform[6,7], wavelet frames[8] and Local Binary Pattern (LBP)[9]. Even though many number of texture features are used in CBIR, the local texture descriptors gain more attention nowadays. The local descriptors have the property of being distinctive and invariant to many transformations, and so they show promising performance[10]. The computation of local descriptor falls under two categories such as sparse and dense. The local sparse descriptor identifies the interest points in an image, models the local patch from them and expresses its invariant features[11,12]. The local dense descriptor derives the local features from an image pixel by pixel[13]. The most popular local dense descriptor is LBP.

The LBP has the property of computational simplicity and discriminates the texture features in a good manner. In spite of its better performance, the LBP has some limitations and problems[14]. To take up this issue, the different LBP variants are proposed for various applications[15,16]. Among the range of local patterns such as Local Binary Pattern (LBP), Center Symmetric Local Binary Pattern (CSLBP)[17], Local Ternary Patterns (LTP)[18], Local Derivative Pattern (LDP)[19] and Local Quinary Pattern (LQP)[15], Antonio Fernandez. et al[20] proved that the LTP operator performed better. Despite the superiority of LTP, there is the thirst for new local pattern for medical application.

The authors Subrahmanyam Murala et al[21] have devised Local ternary co-occurrence pattern for the retrieval of MRI and CT images. The LTCoP outshines the LTP feature as, it combines the notion of LTP, LDP and co-occurrence matrix. The LTCoP encodes the co-occurrence of local ternary edges in a small square region. The local ternary edges are computed based on the grey values of center pixel and its surrounding neighbours in radius 1 and radius 2 neighbourhoods. The radius 1 neighbourhood has 8 pixels and radius 2 neighbourhood has 16 pixels. The co-occurrence between all the 8 pixels of radius 1 and the corresponding 8 pixels of radius 2 neighbourhoods are taken into consideration. Thus the computation of LTCoP involves the 8 pixel information in radius 2 neighbourhood and leaves the other 8 pixel information. Figure 1 shows the involvement of pixels in LTCoP computation.

From Figure 1, it is clear that the radius 2 neighbourhood information is not fully utilized in the computation of LTCoP. In order to apply the intended feature in medical applications, it should use every pixel value in an image. The new feature is proposed with the aim of using

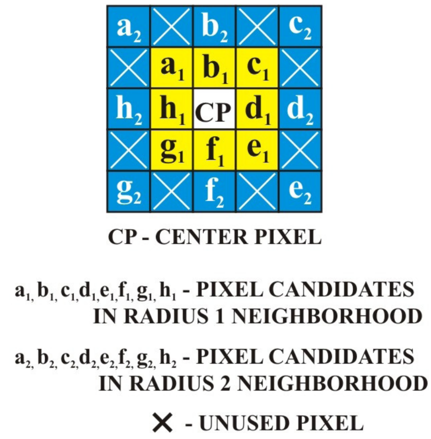


Figure 1. Pixels involvement in LTCoP computation.

all the pixel information in radius 2 neighbourhood. In our proposed work, the pixel candidates in radius 2 neighbourhood are replaced by the mean value of itself and its two neighbours in that neighbourhood. The mean is the standard and basic technique in statistical inference theory. The mean value is considered as most robust and less affected by the presence of outliers because each data in the data set has an influence on its (mean) value. The pixel candidate values in radius 2 neighbourhood are modified in order to use all the pixel information. The revision of pixel candidates in radius 2 neighbourhood is shown in Figure 2.

It is inferred from Figure 2 that every pixel candidate in the radius 2 neighbourhood preserves the information of its neighbours. Then the local pattern is computed based on the co-occurrence of pixel candidates of radius 1 neighbourhood and revised pixel candidates of radius 2 neighbourhood. In addition to that, the local patterns are classified into two categories in order to incorporate global information[22] since the two different local regions sometimes yield the same local pattern. The classification is

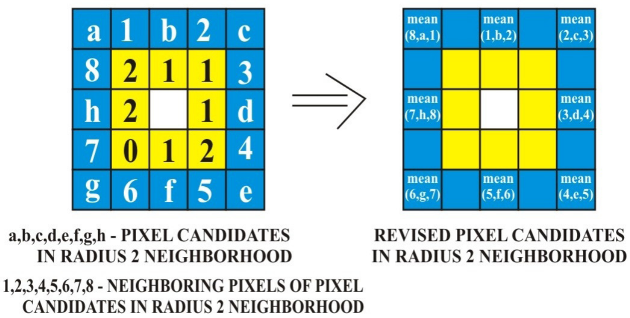


Figure 2. Revision of pixel candidates in radius 2 neighbourhood.

based on the comparison of local mean intensity with global mean intensity since the superiority of mean in statistical analysis. The resulting pattern is called Global Neighbour Preserving Local Ternary Co-occurrence Pattern (GNPLTCoP). This work applies this GNPLTCoP feature for the retrieval of ultrasound kidney images. The performance of this feature is compared with the local patterns such as LTCoP and LTP. The main contributions of this new pattern are involving all the pixel values in the local neighbourhoods during the computation of LTCoP and fitting in the global information to enhance the discrimination power of local pattern.

The rest of the paper is organized as follows. Section 2 describes the related works. Section 3 illustrates the computation of the proposed GNPLTCoP feature and the algorithm of image retrieval system using the proposed GNPLTCoP feature. Section 4 furnishes the details about the similarity matching. The significant experimental results which prove the proficiency of the proposed method are reported in Section 5 and followed by the concluding remarks in Section 6.

2. Related Works

Many Researchers have contributed suitable texture feature extraction procedures for medical images analysis. Landeweerd et al[23] have extracted first order and second order statistics information to distinguish different kinds of white blood cells. Chen et al[24] have used fractal texture features to classify ultrasound images of livers. Stavroula et al[25] have applied first order statistics, spatial grey level dependence matrix, grey level difference method, Laws texture energy measures for liver tissue classification. Kehong yaun et al[26] have applied Non-negative tensor factorization to build the brain CT image database.

Yu-Ying Liu et al[27] have framed global descriptors by means of Multi-scale spatial pyramid and local descriptors through dimension reduced local binary pattern histograms for the analysis of Optical Coherence Tomography (OCT) images. Rodrigo Pereira Ramos et al[28] have designed the CAD system for digitized mammograms using GLCM, wavelet and ridgelet transforms. Muthu Rama Krishnan et al[29] have employed Higher Order Spectra (HOS), LBP and Laws Texture energy features to detect the benign/malignant oral lesions from histopathological images. Callins Christiyana et al[30,2] have devised statistical texture features from grey level difference histogram and CSLBPGLCM for the retrieval of ultrasound kidney images. Subrahmanyam et al[31] have formulated Directional Binary Wavelet Patterns (DBWP) for Biomedical image retrieval. Kumar et al[32] have derived the statistics from GLCM, wavelet and contourlet for identifying both benign and malignant liver tumors on CT images. These literature works gave the motivation to us to propose the new texture feature. Sasikumar et al[33] have applied discrete sine transform for the retrieval of medical images.

3. Image Retrieval System with the Proposed GNPLTCOP

This section illustrates the computation of the proposed GNPLTCoP and gives the retrieval process of images using GNPLTCoP feature.

3.1 The Proposed Global Neighbour Preserving Local Ternary Co-occurrence Pattern (GNPLTCoP)

The intention of proposing the GNPLTCoP is to make use of all the pixels in the radius 2 neighbourhood of the center pixel for co-occurrence pattern computation and to include global information. The GNPLTCoP computation starts with finding the First Order Derivative (FOD) of the pixels in radius1 and radius 2 neighbourhoods. The FOD of pixel candidates in radius 1 neighbourhood is computed with respect to the center pixel and is calculated as follows.

$$\mathrm{FOD}(g_{ir}) = g_{ir} - g_c \,|\, i = 1, 2, \ldots 8 \,\&\, r = 1 \tag{1}$$

The term g_{ir} in Equation 1 denotes the grey value of pixel candidates in radius 1 neighbourhood and the term g_c is the grey value of the center pixel.

The FOD of pixel candidates in radius 2 neighbourhood is calculated in connection with the corresponding pixel candidates in radius1 neighbourhood. Initially, the pixel candidates of radius 2 neighbourhood are replaced as the mean of its own and its two neighbours as said in Section 1. The FOD determination is done with this new value and it is given in the Equation 2.

$$\mathrm{FOD}(g_{jr+1}) = \mathrm{mean}(g_{jr+1},\ g_{jpr+1},\ g_{jsr+1}) - g_{ir} \,|\, i = 1, 2, \ldots 8,\ j = 1, 3, \ldots 15 \,\&\, r+1 = 2 \tag{2}$$

In Equation 2, the term g_{jpr+1} and g_{jsr+1} are the predecessor and successor neighbours of the candidate pixel g_{jr+1} in radius 2 neighbourhood. The ternary encoding of FOD's of pixel candidates in radius 1 and radius 2 neighbourhoods are done using Equation 3.

$$T_1(x) = \begin{pmatrix} 0 \text{ if } FOD(x) = 0 \\ 1 \text{ if } FOD(x) > 0 \\ 2 \text{ if } FOD(x) < 0 \end{pmatrix} \quad (3)$$

The function $T_1(x)$ in Equation 3 is a ternary threshold function. The co-occurrence between the corresponding pixel candidates of radius 1 and radius 2 neighbourhoods are computed using Equation 4.

$$\text{NPLTCoP}(i) = T_2(T_1(i), T_1(j)) \,|\, i = 1, 2, \ldots 8 \,\&\, j = 1, 3, \ldots 15 \quad (4)$$

The term $T_1(x)$ is the FOD of radius 1 neighbourhood pixel candidates in ternary form and $T_1(j)$ is the FOD of radius 2 neighbourhood pixel candidates in ternary form. The definition of the function $T_2(x, y)$ is given in Equation 5.

$$T_2(x, y) = \begin{pmatrix} 1 \text{ if } x = y = 1 \\ 2 \text{ if } x = y = 2 \\ 0 \text{ otherwise} \end{pmatrix} \quad (5)$$

The NPLTCoP is further divided into two binary patterns such as NPLTCoPU and NPLTCoPL for the encoding purpose. The encoding of NPLTCoPU and NPLTCoPL is based on the Equations 6 and 7 respectively.

$$T_3(x) = \begin{pmatrix} 1 \text{ if } x = 1 \\ 0 \text{ otherwise} \end{pmatrix} \quad (6)$$

$$T_4(x) = \begin{pmatrix} 1 \text{ if } x = 2 \\ 0 \text{ otherwise} \end{pmatrix} \quad (7)$$

The terms $T_3(x)$ and $T_4(x)$ in Equations 6 and 7 are binary threshold function of NPLTCoPU and NPLTCoPL respectively. The computation of NPLTCoPU and NPLTCoPL for the center pixel is described in Equations 8 and 9 respectively.

$$\text{NPLTCoPU}(CP) = \sum_{i=1}^{8} T_3(i) \times 2^{i-1} \quad (8)$$

$$\text{NPLTCoPL}(CP) = \sum_{i=1}^{8} T_4(i) \times 2^{i-1} \quad (9)$$

In Equations 8 and 9, the term CP represents the center pixel. The patterns NPLTCoPU and NPLTCoPL of small square region are further divided into 2 classes with respect to the global mean value of an image. Totally four patterns are used to encode the center pixel of the small square region. The computational illustration of GNPLTCoP is given in Figure 3.

3.2 Image Retrieval Process using the Proposed GNPLTCoP

The image retrieval process with the proposed GNPLTCoP is given in the following algorithmic steps. The algorithm gets the query image as the input and retrieves similar images from the database in connection with the query image as the output. The algorithm considers that the feature vector formation of database images is done in offline and assumes there are N images in the database. The steps are as follows.

1. Get the query image.
2. Considering every pixel of a query image as a center pixel, form two classes of GNPLTCoPU and GNPLTCoPL patterns using radius 1 and radius 2 neighbourhood pixels.
3. Construct the histograms of two classes of GNPLTCoPU and GNPLTCoPL for a query image. Then finally four histograms are concatenated to form a feature vector (of length 1024) of a query image.
4. Set the threshold value.
5. Compare the feature vector of the query image with the feature vector of every image in the database. If the feature vectors comply with the threshold value then retrieve the database image as similar to the query image.

The feature vector formation using two classes of GNPLTCoPU and GNPLTCoPL histograms for an ultrasound kidney image is depicted in Figure 4.

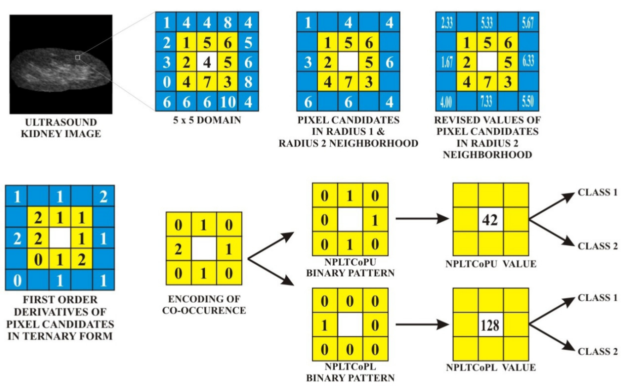
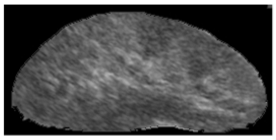
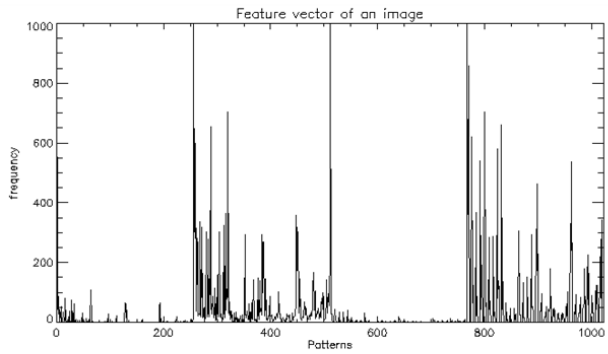


Figure 3. Computation of GNPLTCoP.



a. Ultrasound Kidney Image



b. Feature vector formation of an image 'a' using GNPLTCoP patterns

Figure 4. Feature Vector Formation of a Ultrasound Kidney Image using GNPLTCoP.

4. Similarity Matching

Similarity matching is the important task in an image retrieval system. The results of an image retrieval system depend on two aspects. They are: feature extraction algorithm and similarity measure[34]. In this work, the GNPLTCoP feature is extracted from the images for content representation. The feature vector F = (f1 to fn | n=1024) is framed from the histograms of two classes of GNPLTCoPU and GNPLTCoPL. Since the histogram contains many zeros, the chi square distance metric is more appropriate for similarity matching process[35]. The chi-square distance measure is given in Equation 10.

$$\chi^2(x, y) = \sum_i \frac{(x_i - y_i)^2}{x_i^2 + y_i^2} \tag{10}$$

The term $\chi^2(x, y)$ in the Equation 10 is the distance between the feature vectors of the query image and the database image.

5. Experimental Results and Discussions

This work designs the GNPLTCoP based image retrieval system for ultrasound kidney images to examine the performance of the proposed GNPLTCoP feature extraction algorithm in medical applications. The database of different categories of ultrasound kidney images like Normal, Cortical Cysts (CC), Medical Renal Diseases (MRD)[36] are considered in the performance evaluation of GNPLTCoP based CBMIR. The ultrasound kidney images which are used in this analysis are acquired by using scanning systems ATL HDI 5000 curvilinear probe with transducer frequency 5-240 MHz and Wipro GE LOGIQ 400 curvilinear probe with transducer frequency 3-5 MHz. Transducer frequency at 4 MHz is fixed for taking the longitudinal cross section of the kidney. The image retrieval is done by passing a query image to the system and gathers similar images from the database. Every image in the database is taken as a query image.

The efficiency of the CBIR system is measured with two familiar measures such as precision and recall[7] which are defined in Equations from 11 to 14. The values of both precision and recall are rated in the scale of 0 to 1.

The precision value of the query image q is denoted as P(q), and it is computed as follows.

$$\text{Precision}: P(q) = \frac{\text{Number\_of\_Relevant\_images\_Retrived}}{\text{Total\_Number\_of\_images\_Retrived}} \tag{11}$$

The Average Precision (AP) value with respect to the number of images in the database (n) is estimated as follows.

$$AP = \frac{1}{n}\sum_{i=1}^{n} P(q_i) \tag{12}$$

The recall value of the query image q is denoted as R(q), and it is computed as follows.

$$\text{Recall}: R(q) = \frac{\text{Number\_of\_Relevant\_images\_Retrived}}{\text{Total\_Number\_of\_Relevant\_images\_in\_Database}} \tag{13}$$

The Average Recall (AR) value with respect to the number of images in the database (n) is estimated using the following equation.

$$AR = \frac{1}{n}\sum_{i=1}^{n} R(q_i) \tag{14}$$

In order to prove the proficiency of the proposed image retrieval system using GNPLTCoP, the comparison is done with the well performed local patterns such as LTP and LTCoP. The number of top images retrieved is the threshold in our analysis. The average precision comparison of each category of ultrasound kidney images database is shown from the Figures 5 to 7. The average recall comparison of overall database is given in the Figure 8.

The average top 10 images precision values and the average top 100 images recall values of ultrasound kidney images retrieval system using GNPLTCoP are given in the Table 1. From the Table 1, it is noticed that the GNPLTCoP based ultrasound kidney images retrieval system has better retrieval efficiency as compared to LTP and LTCoP. The feature vector length comparison of LTP, LTCoP and GNPLTCoP is given in the Table 2. Though the length of the feature vector of GNPLTCoP is more, its discriminative power outshines the LTP and LTCoP features. So, the GNPLTCoP feature is best suited for representing the content of the medical images. The sample results of

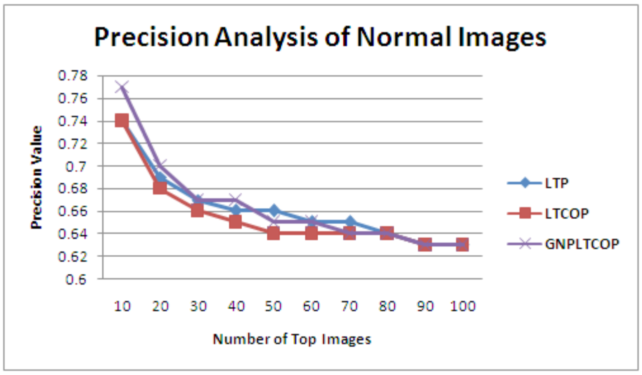


Figure 5. Average Precision Comparison of Normal Ultrasound Kidney Images.

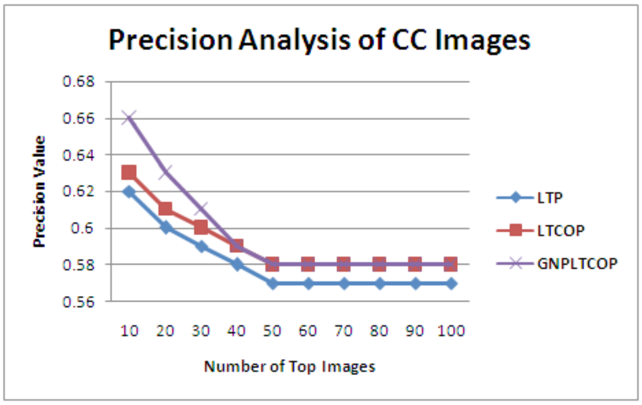


Figure 6. Average Precision Comparison of CC Ultrasound Kidney Images.

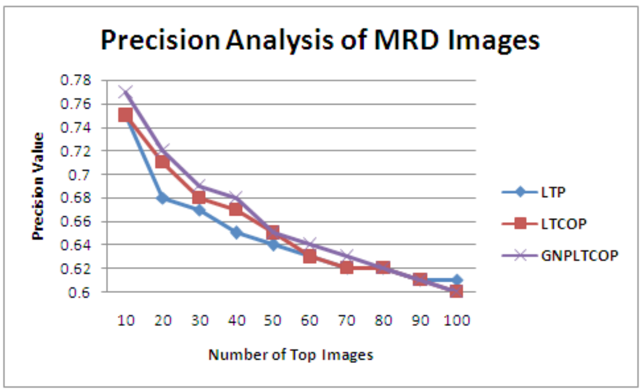


Figure 7. Average Precision Comparison of MRD Ultrasound Kidney Images.

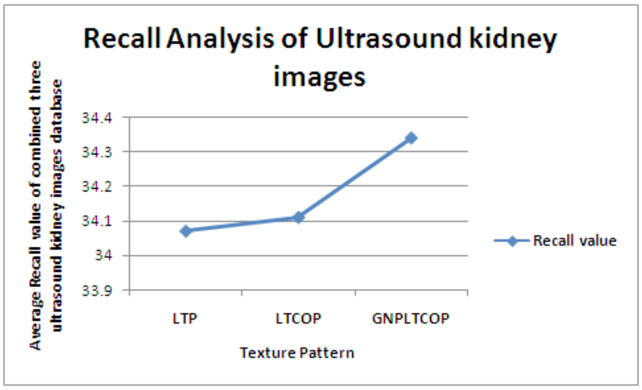


Figure 8. Average Recall Comparison of Ultrasound Kidney Images.

Table 1. The Retrieval Efficiency Comparison of GNPLTCoP, LTCoP and LTP based Ultrasound Kidney Images Retrieval System

Method	Average Precision for Top 10 Images			Combined Average Recall values in Top 100 Images(%)
	Normal	CC	MRD	
GNPLTCoP	0.77	0.66	0.77	34.34
LTCoP	0.74	0.63	0.75	34.11
LTP	0.74	0.62	0.75	34.07

Table 2. The Feature Vector Length Comparison of GNPLTCoP, LTCoP and LTP

Method	Number of bits in the Encoded Pattern	Length of the feature vector
GNPLTCoP	2*2*8	1024
LTCoP	2*8	512
LTP	2*8	512

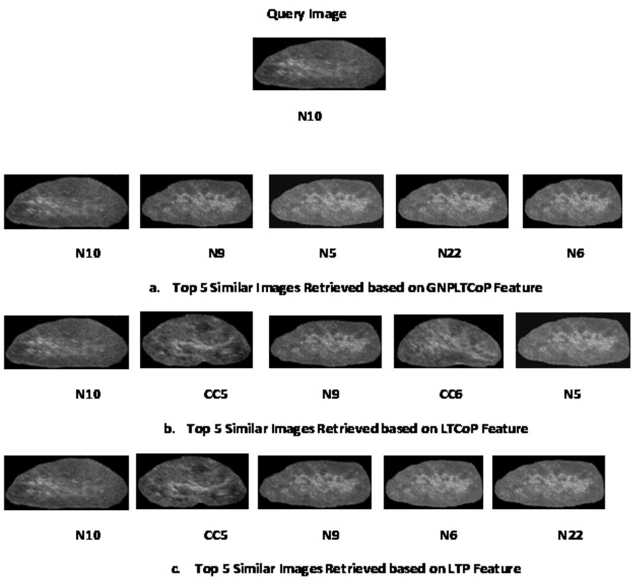


Figure 9. Top 5 Retrieval Results of Ultrasound Kidney Image Retrieval System with GNPLTCoP, LTCoP and LTP features.

the ultrasound kidney images retrieval system which are experimented in this work are given in the Figure 9.

6. Conclusion

The GNPLTCoP feature based ultrasound kidney images retrieval system is proposed in this work. The GNPLTCoP feature finds the co-occurrence of ternary pattern between the corresponding pixel candidates in the radius 1 and radius 2 neighbourhoods of the center pixel to compute the local pattern. To embed the global information into the local pattern, the pattern is classified according to the relation between the local mean and the mean of the entire image. Unlike the LTCoP, all the pixel values in the radius 1 and radius 2 neighbourhoods of center pixel are involved in the local pattern computation of GNPLTCoP. No one pixel information is missing in this computation. Because of this characteristic, the proposed GNPLTCoP feature has more application value in medical field. The performance of the ultrasound kidney images retrieval system using GNPLTCoP is compared with other features such as LTP and LTCoP. From the experimental results, it is concluded that the GNPLTCoP feature outruns LTCoP and LTP features in terms of retrieval efficiency. Due to its success, it is recommended to use this GNPLTCoP feature in various medical applications and pattern recognition applications.

7. Acknowledgement

The authors wish to thank Dr. K. G. Srinivasagan, Professor and Head, CSE-PG, National Engineering College, Kovilpatti, Tamilnadu, India, for bringing the shape of the paper. The authors extend their thanks to Dr. S. Arul Kishnamoorthy, English Professor (Retired), Kovilpatti, Tamilnadu, India for his linguistic support.

8. References

1. Muller H, Michoux N, Bandon D, Geissbuhler A. A review of content based image retrieval systems in medical applications-clinical benefits and future directions. Int J Med Informa. 2004; 73(1):1–23.
2. Christiyana CC, Rajamani V. Second order statistical texture features from a new CSLBPGLCM for ultrasound kidney images retrieval. Appl Med Inform. 2013; 33(4): 32–9.
3. Guo Y, Zhao G, Pietikainen M. Discriminative features for texture description. Pattern Recogn. 2012; 45:3834–43.
4. Haralik RM, Shanmugam K, Dinstein I. Texture features for image classification. IEEE Transactions on Systems, Man and Cybernetics. 1973; 3(6):610–21.
5. Manjunath BS, Ma WY. Texture features for browsing and retrieval of image data. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1996; 18(8):837–42.
6. Chang T, Kuo CCJ. Texture analysis and classification with tree-structured wavelet transform. IEEE Transactions on Image Processing. 1993; 2(4):429–41.
7. Laine A, Fan J. Texture classification by wavelet packet signatures. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1993; 15(11):1186–91.
8. Unser M. Texture classification and segmentation using wavelet frames. IEEE Transactions on Image Processing. 1995; 4(11):1549–60.
9. Ojala T, Pietikainen M, Maenpaa TT. Multi resolution gray-scale and rotation in variant texture classification with local binary pattern. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2002; 24(7):971–87.
10. Jing Li, Nigel M, Allinson A. Comprehensive review of current local features for computer vision. Neuro Computing. 2008; 71:1771–87.
11. Mikolajczyk K, Schmid C. A performance evaluation of local descriptors. IEEE Transaction on Pattern Analysis Machine Intelligence. 2005; 27(10):1615–30.
12. Moreels P, Porena P. Evaluation of features detectors and descriptors based on 3D objects. Int J Comput Vis. 2007; 73(3):263–84.
13. Chen J, Sha S, He C, Zhao G, Pietikainen M, Chen X, Gao W. WLD: a robust local image descriptor. IEEE

Transaction Pattern Analysis Machine Intelligence. 2010; 32(9):1705–20.

14. Liu L, Zhao L, Long Y, Kuang G, Fieguth P. Extended local binary patterns for texture classification. Image and Vision Computing. 2012; 30:86–99.
15. Nanni L, Lumini A, Brahnam S. Local binary patterns variants as texture descriptors for medical image analysis. Artif Intell Med. 2010; 49(2):117–25.
16. Nanni L, Brahnam S, Lumini A. Survey on LBP based texture descriptors for image classification. Expert Syst Appl. 2012; 39(3):3634–41.
17. Heikkila M, Pietikainen M, Schmid C. Description of interest regions with center-symmetric local binary patterns. In: Kalra PK, Peleg S, editor. Proceedings of the 5th Indian Conference on Computer Vision, Graphics and Image Processing (ICVGIP 2006), Lecture notes in Computer Science. 2006; 4338:58–69.
18. Tan X, Triggs B. Enhanced local texture feature sets for face recognition under difficult lighting conditions. IEEE Transaction Image Process. 2010;19(6):1635–50.
19. Zhang B, Gao Y, Zhao S, Liu J. Local derivative pattern versus local binary pattern: face recognition with higher-order local pattern descriptor. IEEE Transactions on Image Process. 2010; 19(2):533–44.
20. Fernandez A, Alvarez MX, Bianconi F. Texture description through histograms of equivalent patterns. J Math Imag Vis. 2013; 45:76–102.
21. Murala S, Wu JQM. Local ternary co-occurrence patterns: a new feature descriptor for MRI and CT image retrieval. Neurocomputing. 2013; 119:399–412.
22. Sun J, Fan G, Yu L, Wu X. Concave-convex local binary features for automatic target recognition in infrared imaginary. Eurosip Journal on Image and Video Processing. 2014; 23:1–13.
23. Landeweerd GH, Gelsema ES. The use of nuclear texture parameters in the auto-matic analysis of leukocytes. Pattern Recogn. 1978; 10:57–61.
24. Chen CC, Daponte JS, Fox MD. fractal feature analysis and classification in medical imaging. IEEE Transactions on Medical Imaging. 1989; 8:133–42.
25. Stavroula G, Mougiakakou, Ioannis K, Valavanis, Nikita A, Nikita KS. Differential diagnosis of CT focal liver lesions using texture features, feature selection and ensemble driven classifiers. Artif Intell Med. 2007; 41(1):25–37.
26. Yuan K, Tian Z, Zou J, Bai Y, You Q. Brain CT image database building for computer-aided diagnosis using content-based image retrieval. Inform Process Manag. 2011; 47(2):176–85.
27. Liu Y-Y, Chen M, Ishikawa H, Wollstein G, Schuman JS, Rehg JM. Automated macular pathology diagnosis in retinal OCT images using multi-scale spatial pyramid and local binary patterns in texture and shape encoding. Med Image Anal. 2011; 15(5):748–59.
28. Ramos RP, do Nascimento MZ, Pereira DC. Texture extraction: an evaluation of ridgelet, wavelet and co-occurrence based methods applied to mammograms. Expert Syst Appl. 2012; 39(12):11036–47.
29. Krishnan MRM, Venkatraghavan V, Acharya RU, Pal M, Paul RR, Min LC, Ray AK, Chatterjee J, Chakraborty C. Automated oral cancer identification using histopathological images: a hybrid feature extraction paradigm. Micron. 2012; 43(2–3):352–64.
30. Christiyana CC, Rajamani V. Performance analysis of grey level co-occurrence matrix and co-occurrence of sum and difference histogram Probabilities for ultra sound kidney images retrieval. Eur J Sci Res. 2012; 88(3):451–9.
31. Murala S, Maheshwari RP, Balasubramanian R. Directional binary wavelet patterns for biomedical image indexing and retrieval. J Med Syst. 2012; 36(5):2865–79.
32. Kumar SS, Moni RS, Rajeesh J. An automatic computer-aided diagnosis system for liver tumours on computed tomography images. Comput Electr Eng. 2013; 39(5):1516–26.
33. Kumar SM, Kumaraswamy YS. A boosting framework for improved content based image retrieval. Indian Journal of Science and Technology. 2013; 6(4):4312–6.
34. Lakshmi RD, Damodaram A, Rao SM, Lal CJA. Content based image retrieval using signature based similarity search. Indian Journal of Science and Technology. 2008; 1(5):1–6.
35. Ahonen T, Hadid A, Pietikainen M. Face recognition with local binary patterns. In: Proceedings of European Conference on Computer Vision. Berlin: Springer; 2004. p. 469–81.
36. Nerli RB, Metgud T, Hiremath MB, Guntaka A, Patil S, Prabha V. Prevalence of renal disorders among the residents of Canacona in India: analysis of the data from a free urological medical camp. Indian Journal of Science and Technology. 2010; 3(3):296–8.