Uniform Extended Local Ternary Pattern for Content Based Image Retrieval

Faiq Baji[1] and Mihai Mocanu[2]
Computer Science and Information Technology,
Faculty of Automation, Comp. and Electronics, Univ. of Craiova,
Craiova, Romania
faiq.baji2015@gmail.com[1],mmocanu@software.ucv.ro[2]

Abstract— **The retrieval of images depending on content is a recurrent research topic in medical imaging. Most CBIR systems are designed to help physicians in the diagnostic of the pathologies. Image retrieval according to the content of the texture features can be performed through various methods developed so far. Local texture features are very beneficial for the analysis of the texture, thus, they are extensively used in image retrieval. The original LBP is improved in this paper with a new addition for CBIR called uniform extended local ternary pattern (UELTP). The method decomposes the image into objects; local texture features are extracted and stored into n-dimensional texture feature vectors. Then, the images are frequently obtained from a huge database dedicated for images using these vectors. In this paper, the performance of LBP descriptor, LTP and ELTP are evaluated for CBIR. According to the results, uniform extended local ternary pattern more accurate than other descriptors in terms of image retrieval.**

Keywords— CBIR, Feature Extraction, LBP, LTP, uniform patterns

I. INTRODUCTION

To browse, search and retrieve images from a huge image database, a Content Based Image Retrieval (CBIR) method is used according to the contents of the image, such as color, texture, and shape [1]. The retrieved images are then indexed through matching the input query image and the stored images based on a resemblance ratio of their features [2]. The image searching and retrieving based on content of texture characteristic can be achieved through various methods developed. These techniques are constructed according to the comparison of the values obtained from query and target images, also known as second-order statistics. These methods are used for computing the measurements of image texture such as coarseness, directionality, moments and GLCM [3]. This paper proposes new methods of texture analysis for image retrieval, implying the use of local texture features. These techniques can be implemented in various applications, such as medical diagnosis [4]. Ojala et al. [5] first presented the Local Binary Pattern (LBP) descriptor, which is robust tool to characterize the local feature of a texture. Numerous of the applications of LPB include face recognition, analysis of facial expressions, texture classification, and background modeling [6].

In the field of medicine, Devrim Unay *et al.* [7] tried to process different intensity problems in MR images by applying Kanade-Lucas-Tomasi feature points and local binary patterns. These are invariant features based on complementary intensity. Oana Vatamanu et al. [8] tried to compare several CBIR mechanisms, namely, LBP, Intensity Histogram and Color Coherence Vector. Color Coherence Vector is used to increase accuracy of Intensity Histogram. G.MALYADRI [9] proposed an automatic technique for brain tumor detection that consists of multiple steps: the first phase of the process includes the preprocessing of the MRI image for correction and removing the noise; in another step, the segmentation process is used for separating the interest region from the background of the image. Finally, the computation of LBP by using LBP-TOP and bar chart of HOG-TOP. However, LBP is sensitivity to various noises especially in smooth image regions and to the high dimensionality of the histogram. Tan and Triggs recommended another variant of LBP [10] to overcome these problems. This method, which known as the local ternary patterns method (LTP), three value codes are used: 1, 0 or −1 whereas the coding in LBP method is based on 2-valued codes (0,1) that includes fixed a threshold defined by user. Liao [11] proposed a different and more noise-resistant operator derived from the original operator of the LTP. This operator, called Extended Local ternary Pattern (ELTP) is similar to the LTP method but the threshold (t) is not used when the codes is creating. Liao and Young [12] attempted to perform the uniform patterns in ELTP; this work is based on the partition of the input images into sub images without application of the image segmentation process. The authors used the constant (t) as a threshold value in calculating the codes of ELTP, and the Hamming distance method to decrease the size of the pattern histogram. Comparing our work with Liao and Young method [12], in our work we used the variable thresholds computed automatically based on local features neighboring pixels of the current pixel that are statistically computed. To cut down the dimension of the pattern histogram, the ternary pattern is converted from 3^n into 2^n by partition each ternary pattern into two LBP channels, high and low. Finally, we used the active contours model for segmenting the input image into objects; local texture features (LBP, LTP, and UELTP) are extracted and stored into n-dimensional texture feature vectors.

This work is structured into the following sections: the section 2 includes the presentation of Materials and method, which are pre-processing, segmentation, feature extraction and

retrieval. The feature extraction includes LBP, LTP and ELT P. Section 3 describes the experiments and results of image retrieval based on local texture features. Section 4 presents the conclusions of the paper.

II. MATERIALS AND METHODS

The method suggested follows three phases: first, pre-processing, by using sharpening filter and median filter to, image enhancement and removing the noise respectively. Second, segmentation, by applying snakes method and third, feature extraction. Fig. 1 illustrates the method system through a block diagram.

On-line   Off-line

```
Query Image          Images D.B
     ↓                   ↓
Pre-processing      Pre-processing
     ↓                   ↓
Image Segmentation  Image Segmentation
     ↓                   ↓
Local Texture       Local Texture
Feature Extraction  Feature Extraction
     ↓                   ↓
Texture Vector      Texture Vector
     ↓                   ↓
Results ← Matching ← Image vectors feature D.B
```
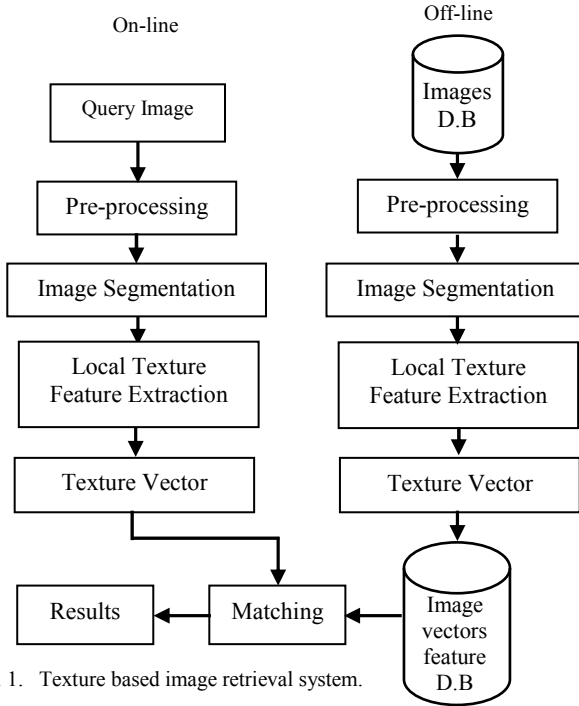
Fig. 1. Texture based image retrieval system.

A. Preprocessing

For numerous applications, the preprocessing of the input image before extracting the features is very beneficial. The aim of the preprocessing approach is minimizing the influence of pixels lighting alteration prior to classification. Hence, it is necessary to apply image enhancement before performing any image segmented and texture analysis [13]. In this paper, sharpening and median filters are employed for the preprocessing of the input image after its conversion into gray-scale image. The median filter, which is a nonlinear digital filtering technique, is useful in preserving edges of objects shape intact whilst reducing impulsive or salt-and-pepper noise from images. The sharpening process is one of the applications of a high frequency filter to an image; this process is used to eliminate low frequency component in an image or to enhance details that have been blurred. We need to sharpen the edges because this will help us to detect the boundary of the segmented object [14].

B. Segmentation

In image processing techniques, it is necessary to apply image segmentation in order to separate the image into segments for simplification of the original image used for deeper analysis [15]. In this paper, we use the active contours model, also called snakes, which was introduced by Kass et al [16]. Snakes' is generally applied in various applications, such as object motion tracking, shape recognition, edge detection and stereo matching. The active contours method is used for the segmentation into two parts (object, or foreground and background) of the 2D grayscale image. Fig. 2 illustrates this segmentation. This technique requires initial contour as a starting contour for image segmentation. The shape of contour changes and moves towards the boundaries of the desired object for the image, the moving contour technique is based on the equation usually derived from numerical method and finally, it completely shrinks and wraps around the object [17].

The snake can be represented as a curve $v(s) = [x(s), (y(s))]$, $s \in [0,1]$, which can move based on two force; internal and external. The internal is responsible for maintaining the smoothness of the object when deformation process occurs. The external forces, is responsible for moving the snake model toward an object boundary or edges of specific body structures within the image [18].The internal and external forces functions are shown below:

$$E_{\text{int}} = \int_0^1 \left[\frac{1}{2} \left(\alpha \left| v'(s) \right|^2 + \beta \left| v'''(s) \right|^2 \right) \right] ds \qquad (1)$$

Where the parameters α and β are represent the controlling contour elasticity and solidity respectively, while v' and v'' represent the first derivative and the second derivative order of the moving contour.

$$E_{ext} = -\left| \nabla (G_\sigma(x,y) * I(x,y)) \right|^2 \qquad (2)$$

Where $G_\sigma(x,y)$ is represented the Gaussian filter function, σ is the standard deviation and ∇ is the gradient operator. The edge map of the image is smoothened through the implementation of the Gaussian filter. It also reduces the noise in the image.
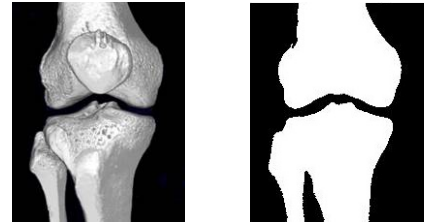

Fig. 2. An example of segment the 2-D grayscale knee image into foreground (white) and background (black) regions by using active contour model.

C. Feature Extraction

1) Local Binary Pattern (LBP)

The basic LBP method was firstly applied by Ojala et al. [5] it is used to provide a robust way for describing texture analysis. A standard LBP of a pixel is generated depending on the value of the central pixel for each 3x3 neighboring pixel. In each 3x3 window, the neighboring pixels intensity values (g_p) are compared to the central pixel gray value (g_c). The pixel binary result is established at 0 is the neighboring pixels intensity values are lower than the central pixel gray value ($g_p<g_c$). When the value is higher, the result is set to 1. Afterwards represented the weights to the all the digits of the binary result number. Finally, it is transformed into a decimal number for convenience [7]. Fig. 3 illustrates the basic LBP operations.

$$LBP_{p,r} = \sum_{p=0}^{p-1} S(g_p - g_c)2^p \qquad (3)$$

Where p represent the count of the neighbor points ($p \geq 8$), on a rounded area of a radius r that is greater than 0.
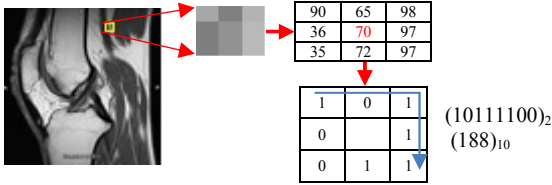

Fig. 3. An example of LBP Operation

The texture image corresponding to an input image is produced after the pixel-by-pixel processing of the image through the application of the LBP code operator (3). For image retrieval, the resulting image histogram is used. Fig.4 depicts the texture histogram of the example in Fig.3.
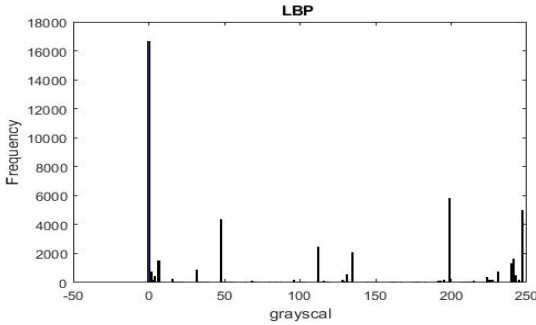

Fig. 4. Texture histogram.

2) uniform patterns

The existence of features invariable to rotations of the input image is recommended in numerous applications of texture analysis. Ojala et al. [5] proposed a new concept called uniform patterns (ULBP). The number of bit wise varying from 0 to 1 or from 1 to 0 in each circular pattern of the LBP code gives the uniformity measure U. The uniform and rotation invariant operator is given as [1]:

$$LBP_{p,r}^{riu2} = \begin{cases} \sum_{p=0}^{p-1} S(g_p - g_c) & \text{if } U(LBP_{p,r}) <= 2 \\ P+1 \end{cases} \qquad (4)$$

Where *riu2* is the rotation invariant, U is uniform patterns gauge that value ($U \leq 2$). A LBP is called uniform if the value of U is less than or equal 2. For example, the patterns 11111111 (0 transforms), 11110001 and 01110000 (two transforms), represent a uniform patterns, whereas the patterns 11001010 (six transforms) and 01110010 (4 transforms) do not. In uniform LBP mapping, there are two separate output labels: first, uniform pattern that represent different output labels and the total number of these patterns can be calculated by used $P(P-1) + 3$, where P is the neighbors points . In the second is performed the assignment to a single label of all the non-uniform patterns. For example, the neighborhoods of 8 sampling points generate 59 output labels after mapping.

3) Local Ternary Pattern

In the uniform or near-uniform areas of the images, LBP displays high sensitivity to noisy images or on flat image. To overcome this issue, Tan and Triggs [10] recommended another variant of LBP, which known Local Ternary Patterns (LTP). For ternary encoding, three values are used: 1, 0 or −1. To improve the resistance to the noise, binary patterns contain a constant value ±t as a threshold. The LTP code can be expressed as follows:

$$LTP_{p,r} = \begin{cases} 1 & g_p \geq (g_c + t) \\ 0 & |g_p - g_c| < t \\ -1 & g_p \leq (g_c - t) \end{cases} \qquad (5)$$

Where g_p represents the intensities of the grey levels of the pixels that are in neighborhood, while g_c represents the origin pixel. p represent the count of the neighbor points, ($p \geq 8$), on a rounded area of a radius r that is greater than 0, t is a threshold defined by the user. The length of the local ternary pattern histogram is very high (3^8). The pattern histogram dimension is reduced by dividing the ternary pattern into positive (up) LTPU and negative (low) parts LTPL and is treated as two separate binary patterns. The positive part is called as high-LTP, which represents the values +1, replacing other values (-1,0) by zeros. Low-LTP is the negative part, which represents the values −1, replacing by zero other values (1,0). Fig.5 depicts an example of LTP encoding procedure using t=5 and the range of width is ±5 [25,35] and their Positive and Negative code [14].
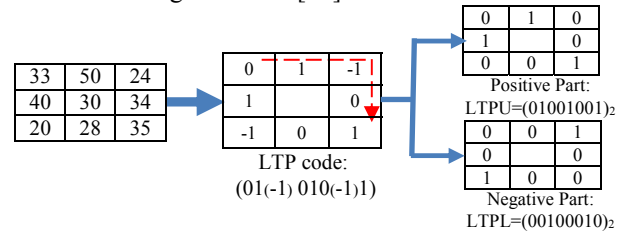

Fig. 5. Calculation of the LTP where p=8, r=1 and t=5.

To calculate the rotation-invariant $LTP_{p,r}$ features $LTPU_{p,r}^{riu2}$ and $LTPL_{p,r}^{riu2}$, we use the same operations that usually used to transform $LBP_{p,r}$ to $LBP_{p,r}^{riu2}$:

$$LTPU_{p,r}^{riu2} = \begin{cases} \sum_{p=0}^{p-1} S(g_p - g_c) & \text{if } U(LTPU_{p,r}) <=2 \\ P+1 \end{cases} \quad (6)$$

$$LTPL_{p,r}^{riu2} = \begin{cases} \sum_{p=0}^{p-1} S(g_p - g_c) & \text{if } U(LTPL_{p,r}) <=2 \\ P+1 \end{cases} \quad (7)$$

4) Extended Local Ternary Patterns (ELTP)

As a constant value for the threshold is applied to all the database images and all neighborhoods, the LTP codes become more sensitive to gray-level transformations, although they are generally more noise-resistant [1]. Instead of employing a fixed threshold, liao [11] proposed a different and more noise-resistant operator derived from the original operator of the LTP). This operator, called Extended Local ternary Pattern (ELTP), is dislike the mentioned operator due to its independency on unchanged (t). Whereas the local pattern threshold (*t*) is computed automatically based on local features neighboring pixels of the current pixel that are statistically computed [19].

$$ELTP_{p,r} = \begin{cases} 1 & g_p - g_c \geq (\sigma \times \alpha) \\ 0 & |g_p - g_c| < (\sigma \times \alpha) \\ -1 & g_p - g_c \leq -(\sigma \times \alpha) \end{cases} \quad (8)$$

where σ represents the standard deviation of the pixels that are neighboring the current pixel and α represents the used scaling factor, its value ranged from 0 to 1. To reduce the size of the feature dimensionality of the pattern histogram, the *ELTP* pattern is divided into two LBP channels by applying the same operations that are used in LTP. Fig. 6 illustrates an example that explains and compares between LTP and ELTP methods with threshold value *t*=5, the width is ranged from -5 to +5 [29,39] and let the value of α is 0.7
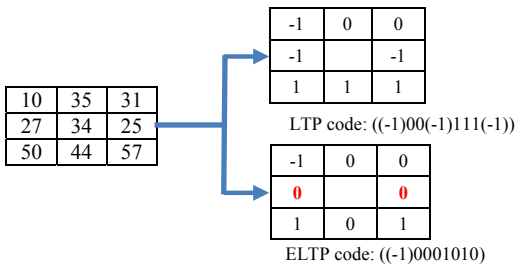

Fig. 6. An example illustrate Comparison between LTP and ELTP methods

The calculate the rotation-invariant. The calculation of the $ELTP_{p,r}$ features $ELTPU_{p,r}^{riu2}$ and $ELTPL_{p,r}^{riu2}$ is done by using the same operations that usually used to transform $LBP_{p,r}$ to $LBP_{p,r}^{riu2}$:

$$ELTPU_{p,r}^{riu2} = \begin{cases} \sum_{p=0}^{p-1} S(g_p - g_c) & \text{if } U(ELTPU_{p,r}) <=2 \\ P+1 \end{cases} \quad (9)$$

$$ELTPL_{p,r}^{riu2} = \begin{cases} \sum_{p=0}^{p-1} S(g_p - g_c) & \text{if } U(ELTPL_{p,r}) <=2 \\ P+1 \end{cases} \quad (10)$$
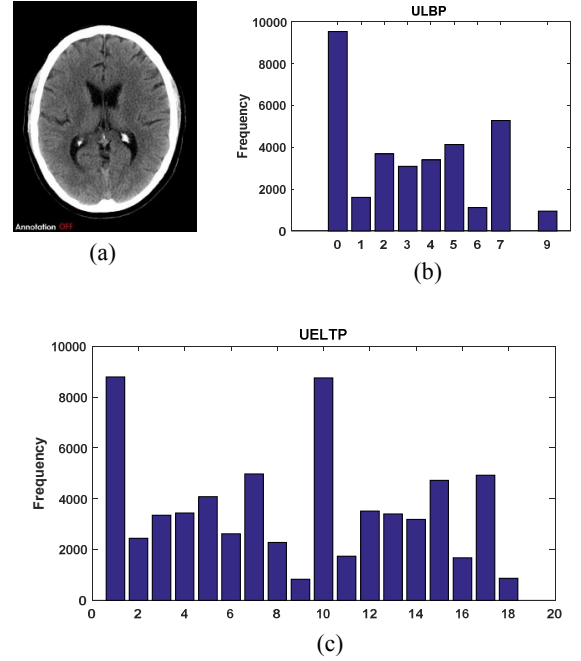

Fig. 7. Calculation of the ULBP and UELTP histogram, (a) original image, (b) ULBP feature, (c) bar charts 1–9 represent UELTP-up feature and bar charts 10–18 represent UELTP-low feature.

5) Images Retrieval

In CBIR systems, image features extractions are in general stored into n-dimensional feature vectors. Thus the comparison of the query image and the target can be achieved by calculating the distance among the corresponding feature vectors. In this paper, the local texture features are extracting and representing by using the histogram. A similarity score of 1 indicates two equivalent histograms. When the similarity score is near 0, the similarity level of the histograms decreases [20]. The similarity score of the input image and the database images is calculated as:

$$S(h_1, h_2) = 1 - \sqrt{\sum_{\forall i}(h_1(i) - h_2(i))^2} \quad (11)$$

Where h_1 and h_2 are the corresponding histograms features

III. Experiments and Results

The implementation of the all the phases of the proposed retrieval system, in this work, is performed, is performed using MATLAB R2016A and 400 MRI JPEG images database of different sizes. The database contains three different categories that include knees, brains slices and hand. Six images are chosen from each category in order to execute the system. By using the histogram, the extraction and representation of local texture features is achieved. Therefore, these histograms are used to calculate the similarity scores among the current image and the images stored in the database.

The experimental results of the proposed retrieval system performance are shown. At first, we calculate the of average precision parameter and recall parameters, without applying the segmentation process and using classical methods LBP and LTP, as depicted in Table I. Secondly, Table II represents the results of the suggested system without segmentation objects. Finally, Table III shows results related to the proposed system based on segmentation objects for various image categories. While Table IV illustrates the proposed retrieval system performance by using different dimensionality of radius r. In this experiment, the comparison between the proposed methods ULBP and UELTP are given in Table III. It is demonstrated that the ULBP[riu2] and UELTP[riu2] reach an average of precision with higher performance than classical LBP and LTP as shown in Table I. The precision is 13% and 18% higher for the improved methods, ULBP[riu2] and UELTP[riu2], compared to the original versions. The proposed user interface of the system is shown in Figs. 8, 9 and 10.

TABLE I. CLASSICAL LBP AND LTP BASED PRECISION AND RECALL ANALYSIS WITHOUT USING SEGMENTATION OBJECT.

Category	LBP		LTP	
	Precision	*Recall*	*Precision*	*Recall*
Knee	0.60	0.35	0.67	0.30
Brain slice	0.70	0.28	0.71	0.26
Hand	0.65	0.33	0.69	0.28
Average	0.65	0.32	0.69	0.28

TABLE II. ULBP AND UELTP BASED PRECISION AND RECALL ANALYSIS WITHOUT USING SEGMENTATION OBJECT

Category	$ULBP_{8,1}^{riu2}$		$UELTP_{8,1}^{riu2}$	
	Precision	*Recall*	*Precision*	*Recall*
Knee	0.72	0.28	0.78	0.25
Brain slice	0.70	0.30	0.74	0.23
Hand	0.75	0.23	0.79	0.25
Average	0.72	0.27	0.77	0,24

TABLE III. ULBP AND UELTP BASED PRECISION AND RECALL ANALYSIS BASED ON SEGMENTATION OBJECT

Category	$ULBP_{8,1}^{riu2}$		$UELTP_{8,1}^{riu2}$	
	Precision	*Recall*	*Precision*	*Recall*
Knee	0.80	0.24	0.91	0.18
Brain slice	0.75	0.28	0.88	0.21
Hand	0.79	0.24	0.83	0.25
Average	0.78	0.25	0.87	0.21

TABLE IV. ULBP AND UELTP BASED PRECISION ANALYSIS BASED ON DIFFERENT DIMENSIONALITY

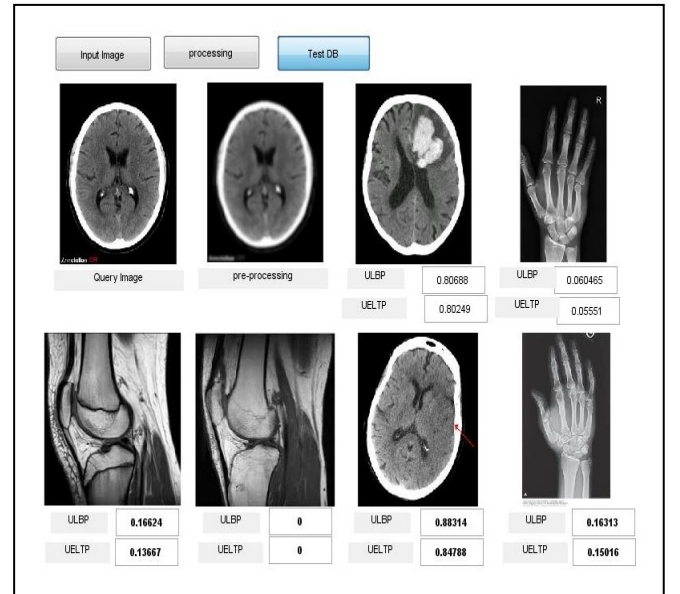| Category	$ULBP_{p,r}^{riu2}$			$UELTP_{p,r}^{riu2}$		
	(p,r)			*(p,r)*		
	8,1	8,2	8,3	8,1	8,2	8,3
Knee	0.80	0.79	0.77	0.91	0.88	0.90
Brain slice	0.75	0.75	0.73	0.88	0.85	0.86
Hand	0.79	0.77	0.73	0.83	0.83	0.80
Average	0.78	0.77	0.74	0.87	0.85	0.85

Fig. 8. ULBP and UELTP results GUI to find the similarity level between brain and different hand wrist, knee and brain images.
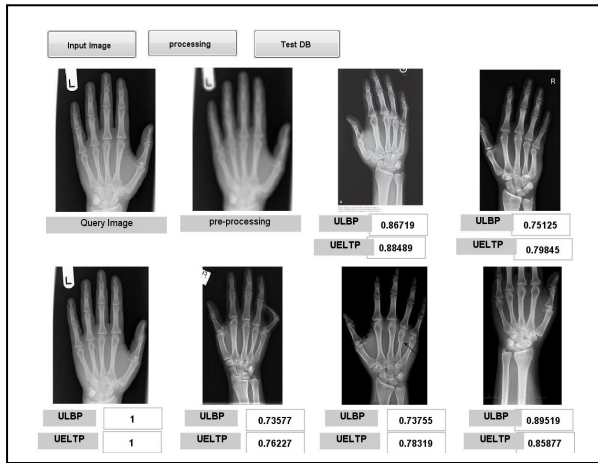
Fig. 9. ULBP and UELTP results GUI to find the similarity level between different hand wrist images.
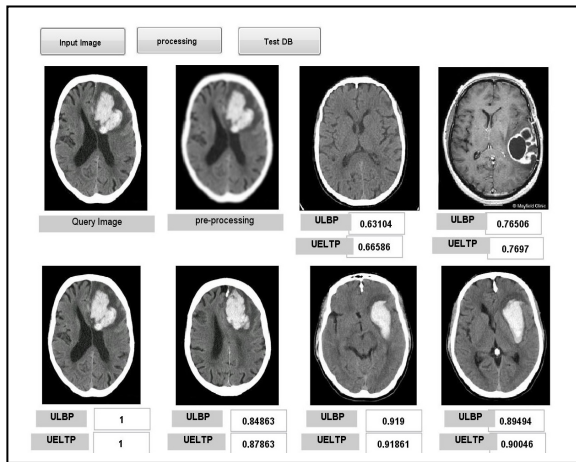

Fig. 10. ULBP and UELTP results GUI to find the similarity level between different brain slice images.

IV. CONCLUSION

The present study presents the Uniform Extended LTP (UELTP) method for the CBIR system. The new method is based on the original LTP operator. The main principle of the new method is based on automatically computing of the variable thresholds of local statistics of a center pixel neighborhood. Consequently, the histogram feature vectors are generated in order to assess the query image and the database images similarity levels. Many conclusions can be extracted; First conclusion, texture features histogram is a good method to retrieval of the matching images from the database. Another conclusion, the experimental results show that the $UELTP_{8,1}^{riu2}$ achieves an average of precision higher in performance than classical LBP and LTP as shown in Table I and Table III. The experiments show that the performance of $UELTP_{8,1}^{riu2}$ by using segmentation method is powerful for increasing retrieval precision as shown in Table III and Table IV.

REFERENCES

[1] P. Pawar and P.P.Belagali, " Image Retrieval Technique Using Local Binary Pattern (LBP)," *International Journal of Science and Research*, vol.4(10) , pp.1440-1443, 2015.

[2] E. R. Vimina, and K. P. Jacob, " Content Based Image Retrieval Using Low Level Features of Automatically Extracted Regions of Interest," *Journal of Image and Graphics,*vol. 1(1), pp. 7-11, Mar. 2013.

[3] N. Bagri and P. K. Johari," A Comparative Study on Feature Extraction using Texture and Shape for Content Based Image Retrieval," *International Journal of Advanced Science and Technology*, vol.(80), pp. 41-52, 2015.

[4] A. Suruliandi and G. Murugeswari," Empirical Evaluation of LBP and its Derivates For Abnormality Detection In Mammogram Images," *Ictact Journal on Image and Video Proc.*, Vol. 4(4). pp. 824-830, 2014.

[5] T. Ojala, M. Piettikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24(7), pp. 971-987, July, 2002.

[6] X. Sun, H. Xu, C. Zhao, and J. Yang, "Facial Expression Recognition Based on Histogram Sequence of Local Gabor Binary Patterns," *2008 IEEE Conference on Cybernetics and Intelligent Systems,* Chengdu, China, pp. 158-163 , Sept. 2008.

[7] D. Unay, A. Ekin and R. Jasinschi," Medical Image Search and Retrieval Using Local Binary Patterns and Klt Feature Points," *15th IEEE International Conference on Image Processing*, San Diego, CA, USA, pp. 997-1000, Oct. 2008.

[8] O. A. Vatamanu, M. Ionescu, M. Frandes, And S. Apostol "Content-Based Image Retrieval using Local Binary Pattern, Intensity Histogram and Color Coherence Vector," *The 4th IEEE Int. Conference on E-Health and Bioengineering - EHB 2013, Iaşi, Romania,* Nov., 2013.

[9] G.Malyadri, J. Kavati and K.L.Sravani, "Brain Tumor Detection System For Health Monitoring," *International Journal of Pure and Applied Mathematics*, vol. 114(10), 2017, pp. 291-300.

[10] X. Tan, B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," IEEE Trans. Image Process. 2010, pp. 1635–1650.

[11] W. H. Liao, "Region Description Using Extended Local Ternary Patterns," *proc. IEEE, International Conference on Pattern Recognition*, Istanbul, Turkey, pp. 1003-1006, 2010

[12] W. H. Liao T. J. Young, "Texture Classification Using Uniform Extended Local Ternary Patterns," *proc. IEEE International Symposium on Multimedia*, Taichung, Taiwan, pp. 191-195, 2010.

[13] U. Maya, and K. Meenakshy," Brain Tumor Segmentation Using Asymmetry Based Histogram Thresholding nd K-Means Clustering", *Int. Journal of Research in Eng. and Tech.*, vol. 3(15), pp. 62-65, 2014.

[14] Z. Guo, L. Zhang and D. Zhang, "Rotation invariant texture classification using LBP variance (LBPV) with global matching," *Pattern Recognition*, vol. 43, pp. 706-719, 2010.

[15] S. Chack and P. Sharma, " An Improved Region Based Active Contour Model for Medical Image Segmentation," *Int. Journal of Signal Processing, I.P and Pattern Recognition*, Vol. 8(1), pp.115-124, 2015.

[16] M. Kass, A. Witkin, and T. Terzopoulous," Snakes: Active Contour Models," lnt. Journal of Computer Vision, pp.321-331, 1988.

[17] T. Boonnuk, S. Srisuk, and T. Sripramong," Texture Segmentation Using Active Contour Model with Edge Flow Vector," *Int. Journal of Information and Electronics Engineering,* Vol. 5(2), pp.107-111, 2015.

[18] A. Chopra , B.R. Dandu, "Image Segmentation Using Active Contour Model," *International Journal Of Computational Engineering Research*, vol. 2(3), pp. 819-822, june 2012.

[19] A. A. Mohamed, and R. V. Yampolskiy," Adaptive Extended Local Ternary Pattern (AELTP) for Recognizing Avatar Faces," *2012 11th International Conference on Machine Learning and Applications,* Boca Raton, FL, USA,pp. 57-62, Dec. 2012.

[20] R. K. Lingadalli, and N. Ramesh, "Content Based Image Retrieval using Color, Shape and Texture," *International Advanced Research Journal in Science, Engineering and Technology*, vol. 2(6), pp.40-45, Jun. 2015.