

Developing a Novel Approach for Content Based Image Retrieval Using Modified Local Binary Patterns and Morphological Transform

Farshad Tajeripour, Mohammad Saberi, and Shervan Fekri-Ershad

Department of Computer Science, Engineering and IT, Shiraz University, Iran

Abstract: *Digital image retrieval is one of the major concepts in image processing. In this paper, a novel approach is proposed to retrieve digital images from huge databases which using texture analysis techniques to extract discriminant features together with color and shape features. The proposed approach consist three steps. In the first one, shape detection is done based on top-hat transform to detect and crop main object parts of the image, especially complex ones. Second step is included a texture feature representation algorithm which used Color Local Binary Patterns (CLBP) and local variance as discriminant operators. Finally, to retrieve mostly closing matching images to the query, log likelihood ratio is used. In order to, decrease the computational complexity, a novel algorithm is prepared disregarding not similar categories to the query image. It is done using log-likelihood ratio as non-similarity measure and threshold tuning technique. The performance of the proposed approach is evaluated applying on corel and simplicity image sets and it compared by some of other well-known approaches in terms of precision and recall which shows the superiority of the proposed approach. Low noise sensitivity, rotation invariant, shift invariant, gray scale invariant and low computational complexity are some of other advantages.*

Keywords: *Image retrieval, texture analysis, local binary pattern, top-hat transform, log likelihood.*

Received August 16, 2013; accepted July 28, 2014; published online December 3, 2014

1. Introduction

The requirement to find the relevant images from huge databases created due to recent technological developments in diversity of domains is an important field of research which calls image retrieval. The need to find a desired image from a collection is shared by many professional groups, including journalists, forensic experts, design engineers, forensic experts and art historiographers.

Content Based Image Retrieval (CBIR) is a technique to retrieve images on the basis of image specific features such as color, texture and shape. In CBIR, initially, features are computed for both stored and query images and used to declare images most closely matching the query.

Color-based retrieval first evolved from simple statistical measures such as average color to color histograms and spatial color descriptors [15]. Unfortunately, color histograms have limited discriminative power with respect to the spatial organization of colors. The other popular color features in CBIR applications include color correlograms [14] and color descriptors [5]. Partly due to the imprecise understanding and definition of what exactly visual texture actually is texture features have an even larger variety than color features. As for the texture feature extractors, many approaches have been proposed based on Gabor filtering [12] Micro-Structure [8], GLCM [9] and histogram properties in discrete cosine transform [11].

A comparative study on texture analysis from mostly transform-based properties can be found in [17]. Shape is a key attribute of segmented image regions, and its efficient and robust representation plays an important role in retrieval. Synonymous with shape representation is the way in which such representations are matched with each other. Some researchers are used shape features to retrieve similar images. In this respect, many techniques are used for shape detection such as morphological operations [10], edge detection [3] and primitive shape filters [2].

In this paper, we proposed an approach using combination of color, texture and shape features together. It is included two main steps. First one is prepared to crop the main object part of the query and database images based on top-hat transform as a shape detector. Second step is included an algorithm for extracting features from object part image. Color Local Binary Patterns (CLBP) and local variance are used as feature extractors in this step. According to the size of huge image databases, we proposed a novel extra algorithm to reduce computational complexity. It is done as a preprocess step before retrieving. The proposed preprocess algorithm compares non-similarity amount between query image and each category to disregard nowhere near categories. The performance of the proposed approach is evaluated by applying on image sets in terms of precision and recall and it is compared by some other state of the art CBIR algorithms. Low noise sensitivity, rotation invariant,

gray scale invariant, shift invariant and Low computational complexity are some other advantages of proposed approach which are demonstrated in the result section.

2. Object Cropping

According to the image sets which are used in image retrieval problems, there are just one or some objects in the images and all of other regions are not relevant. The irrelevant regions may disturb the values in extracted feature vectors. Shape detection techniques detect objects in the images. In this paper an algorithms is proposed to crop object parts in images based on top-hat transform.

2.1. Top-Hat Transform

The groups of image operations which process the image based on shapes are referred as morphological operations. In morphological operations the output image is created with help of applying structuring element to the input image. In case, the value of each pixel in the output is based on a comparison of the corresponding pixel in the input with its neighbors [4].

Dilation and erosion are the most basic morphological operations. Dilation creates the swelling effect of shapes of the objects by adding pixels to the boundaries of objects in an image, while erosion forms the object shape shrinking effect by removing pixels on object boundaries [4]. The size and shape of structuring element decide number of pixels added or removed from the objects in an image.

Dilation of a grey-scale image $I(x, y)$ by a grey-scale structuring element $B(s, t)$ is denoted by:

$$I \oplus B(x, y) = \text{Max} \{I(x-s, y-t) + b(s, t)\} \quad (1)$$

The domain of $I \oplus B$ is the dilation of the domain of I by the domain of B . Erosion of a grey-scale image $I(x, y)$ by a grey-scale structuring element $B(s, t)$ is denoted by:

$$I \ominus B(x, y) = \text{min} \{I(x+s, y+t) - b(s, t)\} \quad (2)$$

The domain of $I \ominus B$ is the erosion of the domain of I by the domain of B .

Opening operator is erosion followed by dilation and closing operator is dilation followed by erosion. Opening smoothes the contour of an image, breaks narrow gaps. As opposed to opening, closing tends to fuse narrow breaks, eliminates small holes and fills gaps in the contours.

Top-hat transform is an operation that extracts small elements and details from given images. There exist two types of top-hat transform: The white top-hat transform is defined as the difference between the input image and its opening by some structuring element Equation 3. The black top-hat transform is

defined dually as the difference between the closing and the input image Equation 4.

$$T_1 = I - (I \circ S) \quad (3)$$

$$T_2 = (I \bullet S) - I \quad (4)$$

Where I means the input image and S is the structure element. T_1 shows the white top-hat transform output and T_2 shows the black top-hat transform output. Also, \circ denotes the opening operation and \bullet denotes closing operation.

2.2. Proposed Object Cropping Algorithm

In the previous section, black (white) top-hat transform is described as a robust shape detection technique. In order to crop object parts, an algorithm is proposed in this section which consists 3 sub-steps as follows:

1. Apply black (white) top-hat transform on input image to detect edge pixels of the input image. The output result is called Shape Detected Image (SDI) to referee in this paper.
2. In order to crop the object parts of the original input image, it's enough to detect zone of the object region. The zone is limited between four bands (up, down, left and right). The second step is detecting each of bands individually in SDI.
3. Cropping each pixel in the original image which is limited in the object zone using computed bands. Some results of applying the top-hat transform on simplicity set images to detect and crop object parts are shown in Figure 1.

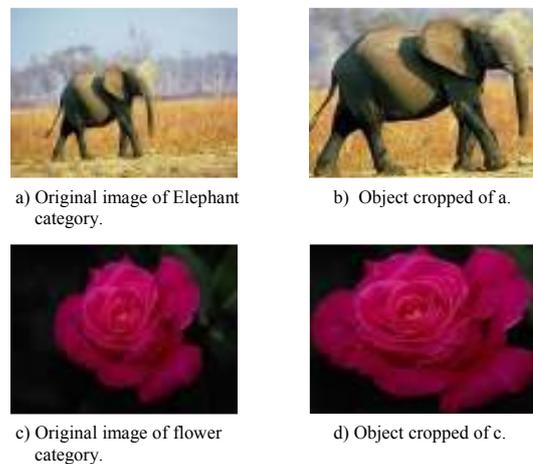


Figure 1. Some examples of object cropping using corel dataset images.

3. Texture Feature Extraction

3.1. Local Binary Patterns

The Local Binary Patterns (LBP) is a non-parametric operator which describes the local contrast and local spatial structure of an image. First time, Pietikäinen *et al.* [16] introduced this operator and showed its high severability and discriminative power for texture analyzing and classification.

In order to evaluate the LBP, at a given pixel position (x_c, y_c) , LBP is defined as an ordered set of binary comparisons of pixel intensities between the center pixel and its surrounding pixels. Usually to achieve the rotation invariant, neighborhoods would be assumed circular. Points which the coordination's are not exactly located at the center of pixel would be found by interpolation. Some of the circular neighborhoods by different radius R and P number of neighborhoods pixels are shown in Figure 2.

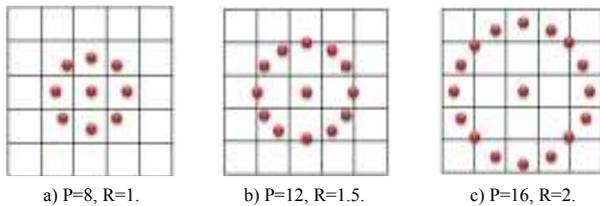


Figure 2. Some examples of circular neighborhoods.

Now, the LBP are defined at a neighborhood of image by Equation 5.

$$LBP_{P,R} = \sum_{k=1}^P \varphi(g_k - g_c) 2^{k-1} \quad (5)$$

Where g_c corresponds to the grey value of the centered pixel and g_k to the grey values of the neighborhood pixels. So, P will be the number of neighborhoods of center pixel, and function $\varphi(x)$ is defined as:

$$\varphi(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{else} \end{cases} \quad (6)$$

The $LBP_{P,R}$ operator produces 2^P different output values, corresponding to the 2^P different binary patterns that can be formed by the P pixels in the neighbor set.

3.1.1. Modified Local Binary Patterns

Practical experience of the Pietikäinen *et al.* [16] however, has shown that LBPROT as such does not provide very good discrimination and the computation complexity of basic LBP is high. To solve these problems, [13] defined a uniformity measure U , which corresponds to the number of spatial transitions (bitwise 0/1 changes) in the “pattern”. It is shown in Equation 7. For example, patterns 00000000 and 11111111 have U value of 0, while 11001001 have U value of 3.

$$U(LBP_{P,R}) = \varphi(g_1 - g_c) - \varphi(g_p - g_c) + \sum_{k=2}^P |\varphi(g_k - g_c) - \varphi(g_{k-1} - g_c)| \quad (7)$$

In this LBP, the patterns which have uniformity amount less than U_T are grouped as uniform patterns and the patterns with uniformity amount more than U_T grouped as non-uniform patterns. Finally, the LBP is computed by using Equation 8.

$$LBP_{P,R}^{riu_T} = \begin{cases} \sum_{k=1}^P (g_k - g_c) & \text{if } U(LBP_{P,R}) \leq U_T \\ P+1 & \text{elsewhere} \end{cases} \quad (8)$$

Superscript riu_T reflects the use of rotation invariant “uniform” patterns that have U value of at most U_T . According to Equation 8, applying $LBP_{P,R}$ will assign a label from 0 to P to uniform patterns and label “ $P+1$ ” to non-uniform patterns. Because, $LBP_{P,R}$ just one label ($P+1$) is assigned to all of the non-uniform patterns, so uniform labels should cover mostly patterns in the image. In [6, 18] show that if in the value of U_T is selected equal to $(P/4)$, only a negligible portion of the patterns in the texture takes label $P+1$.

As it was described in previous, a label is assigned to each neighborhood. Regarding the Equation 8, if the number of neighbors is considered “ P ” pixels, applying $LBP_{P,R}$ will assign a label from zero to “ P ” to uniform segments and label “ $P+1$ ” to non-uniform segments. So, for every image, one “ $P+2$ ” dimensional feature vector can be extracted.

To extract the feature vector, first the $LBP_{P,R}$ is applied on the image and the labels are assigned to neighbors. Then, the occurrence probability of each label in the image is regarded as one of the dimensions of the feature vector. The occurrence probability of a specific label in the image can be approximated by the ratio of the number of that label to the number of all labels Equation 9.

$$P_k = \frac{N_{P_k}}{N_{total}} \quad 0 \leq k \leq P+1 \quad (9)$$

Where N_{P_k} is the number of neighbors that labeled as P_k and N_{total} is the number of all neighbors. The extracted feature vector is shown in Equation 10.

$$F = \langle P_0, P_1, \dots, P_{P+1} \rangle \quad (10)$$

Where F is the feature vector extracted for neighbors and P_i is the occurrence probability of label i in neighbors.

3.2. Local Variance

The $LBP_{P,R}$ operator is a gray-scale invariant measure, i.e., its output is not affected by any monotonic transformation of the gray scale. It is an excellent measure of the spatial pattern, but it by definition, discards contrast [13]. If gray-scale invariance is not required and it is wanted to incorporate the contrast of local image texture as well, we can measure it with a rotation invariant measure of local variance Equation 11:

$$VAR_{P,R} = \frac{1}{P} \sum_{k=1}^P (g_k - \mu)^2 \quad (11)$$

$$\text{Where } \mu = \frac{1}{P} \sum_{k=1}^P g_k$$

$VAR_{P,R}$ is by definition invariant against shifts in gray scale. Since, $LBP_{P,R}$ and $VAR_{P,R}$ are complementary, their joint distribution $LBP_{P,R} / VAR_{P,R}$ is expected to be a very powerful rotation invariant measure of local image texture.

A vector showing the variance of all points in the range is calculated by applying variance operator

$VAR_{P,R}$ on a neighbor in size of P and R , for all points. After sorting this vector, it is divided into K bins and the number of variances falling in each bin is calculated. The final vector shows the number of similar variances in all K bins. This vector is represented as $VAR_{P,R}^K$.

4. Proposed Image Retrieval Approach

CBIR is a technique to retrieve images on the specific features. In CBIR, initially, features are computed for both all of the stored and query images, and used to declare images most closely matching the query. The general block diagram of CBIR algorithms is shown in Figure 3.

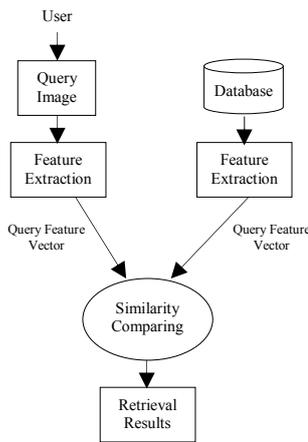


Figure 3. CBIR general block diagram.

The main step of the CBIR algorithms is feature extraction. In the proposed approach, the feature extraction step is included 3 sub-steps which is described ones by ones as follows:

1. Cropping the object parts of the query and database images using the algorithm which is proposed in the section 2.2. The object cropped image is called Object Cropped Image (OCI).
2. The OCIs are in RGB color space or may transform to the RGB space. The second step is applying the $LBP_{P,R}$ on each color channels of the OCIs individually and extracting features based on the proposed approach in section 3.1.2 from each color channels.

After considering color features, to provide a main discriminated feature vector for each OCI, the Equation 12 should be used which is described as follows:

$$F_{CLBP}^i = (F_{red}^i + F_{green}^i + F_{blue}^i) / 3 \tag{12}$$

Where F_{CLBP} is the output vector and F_d is shown the extracted vector for color channel d . Also, I is the dimension number of the feature vectors.

3. Applying the $VAR_{P,R}$ on OCIs and extracting features based on the proposed approach in section 3.2.1. The extracted feature vector is called F_{VAR} .

As it was mentioned in this section, the image analysis and feature extraction technique is done considering color, texture and shape features together. Using the proposed feature extraction algorithm, two feature vectors are provided for each input images either query or database images. The total block-diagram of the proposed feature extraction algorithm is shown in the Figure 4.

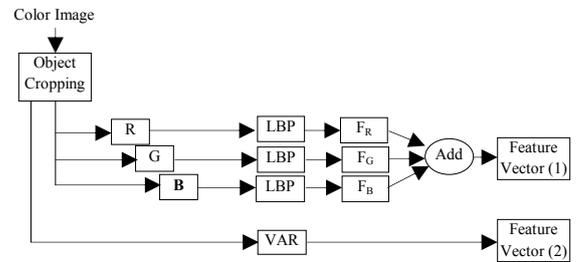


Figure 4. The block-diagram of the proposed feature extraction algorithm.

According to the Figure 3, after feature extraction another important step is similarity comparing, to retrieve database images which are closer to the query. The extracted feature vectors are probabilistic and sum of all dimension values are one. Tajeripour and Fekri-Ershad [6, 18] are used log-Likelihood to evaluate non-similarity amount between extracted local binary patterns feature vectors. In this respect, after researching about distance and similarity criteria, the log-likelihood ratio is selected as distance measure for similarity comparing step [13]. Log-likelihood ratio between two probabilistic feature vector (A, B) is computed as described in the Equation 13.

$$L(A, B) = \sum_{k=1}^K A_k \text{Log} \left(\frac{A_k}{B_k} \right) \tag{13}$$

Where L is the log-likelihood ratio and K is number of dimensions of the A and B vectors.

To declare database images most closely matching the query, the log-likelihood ratio is computed between query and each database image extracted feature vectors. Finally, the total similarity amount is considered sum of two computed ratios. It is shown in the Equation 14.

$$L(Q, I) = L(F_{Q,CLBP}, F_{I,CLBP}) + L(F_{Q,VAR}, F_{I,VAR}) \tag{14}$$

Where $L(Q, I)$ is shown the similarity amount between query image Q and database image I . F_{CLBP} and F_{VAR} are two extracted feature vectors which are evaluated based on $LBP_{P,R}$ and $VAR_{P,R}$.

4.1. Proposed Computational Complexity Reduction Algorithm

In order to, declare images most closely matching the query, all of the stored images must be processed. It imposes high complexity to the CBIR system. According to each query, some of categories are absolutely not close to it. In retrieving step, it is not

necessary to compute distance between query and the images which were grouped in absolutely not close categories.

In order to, recognize not close categories, a preprocess step is proposed in this section. After computing the feature vectors (F_{CLBP} and F_{VAR}) for all of the images, where grouped in a specific category, the mean feature vector will be a good identifier of that category. The mean vector can be computed as following:

$$F_C^k = \sum_{i=1}^C F_i^k / C \text{ for } k=1,2,\dots,N \quad (15)$$

Where F_C is the mean vector for the specific category C and F_i is shown the extracted feature vector for i_{th} sample (image) of that category. Also, C is the total number of category's images and N is the total number of vector dimensions.

In order to, disregard absolutely not close enough categories to the query, each category which is farther than a threshold is recognized as a not close category, so it is not necessary to compute similarity measure between its samples (images) and the query. The non-similarity amount between each category and the query is calculated as follows Equation 16:

$$L(C, Q) = \sum_{k=1}^K F_{C.VAR} \log\left(\frac{F_{C.VAR}}{F_{Q.VAR}}\right) + \sum_{P=1}^{P+2} F_{C.CLBP} \log\left(\frac{F_{C.CLBP}}{F_{Q.CLBP}}\right) \quad (16)$$

Where $F_{Q.VAR}$ and $F_{Q.CLBP}$ are two feature vectors that are extracted from the query using $VAR_{P,R}$ and $LBP_{P,R}$ operators. $F_{C.VAR}$ and $F_{C.CLBP}$ are the mean feature vectors from the category C based on Equation 15. Finally $L(C, Q)$ is show the non-similarity amount between Query image (Q) and the Category (C).

According to our research, the not close threshold is described as follows:

$$Not\text{-}Close\ Threshold = \frac{Max.D + min.D}{2} \quad (17)$$

Where $Max.D$ is the maximum not-similarity amount, where computed between categories and the query. Also, $Min.D$ is shown the minimum not-similarity, where is computed between category and the query. Using the proposed computational complexity reduction algorithm can be decrease the number of required operations in retrieving step.

5. Results

The performance of the image retrieval approach was tested upon the following two popular databases: simplicity images and corel 5,000 miscellaneous database which are downloaded from [19]. The corel contains 50 categories. There are 5000 images from diverse contents such as fireworks, bark, microscopic, tile, food and etc. Each category contains 100 images of size 192×128 in JPEG format. The simplicity database includes 10 different categories. These categories are titled: Beach, africa, elephants, buildings, buses, dinosaurs and etc., each category has

absolutely 100 images, along with some images undergoing changes due to rotation, scaling, noise injection, illumination, etc., in order to evaluate the effectiveness of the proposed approach, the Precision and Recall curves are adopted, which are the most common criteria used for evaluating image retrieval performance. *Precision* and *Recall* are defined as follows:

$$\begin{aligned} Precision &= I_N / N \\ Recall &= I_N / M \end{aligned} \quad (18)$$

Where I_N is the number of images retrieved in the top N positions that are similar to the query image, M is the total number of images in the database similar to the query (each category size) and N is the total number of images retrieved.

In order to evaluate the performance, N is considered 10, 20, 30 and 40 for both of test datasets. Also, for feature extraction, different sizes was tested for CLBP and VAR, $P=8$ and $K=16$ provided maximum accuracy.

In corel and simplicity categories, M is 100. The average retrieval precision and recall for corel and simplicity dataset are shown in the Tables 1 and 2.

Table 1. The average precision and recall of proposed approach on corel (5000s) dataset.

| Retrieved Images \ Dataset | Precision | Recall |
|----------------------------|-----------|--------|
| N = 10 | 53.62 | 5.36 |
| N = 20 | 51.64 | 10.32 |
| N = 30 | 50.24 | 15.07 |
| N = 40 | 46.12 | 18.44 |

Table 2. The average precision and recall of proposed approach on simplicity dataset.

| Retrieved Images \ Dataset | Precision | Recall |
|----------------------------|-----------|--------|
| N = 10 | 81.33 | 8.13 |
| N = 20 | 76.22 | 15.24 |
| N = 30 | 74.86 | 22.45 |
| N = 40 | 67.22 | 26.88 |

Some of the query results of the simplicity and corel data set are shown in Figures 5 and 6.



Figure 5. Retrieved images for horse query (First image) from simplicity database.



Figure 6. Retrieved images for dinosaur query (first image) from simplicity database.

The query which is shown in the top left position of the Figure 5 is of a two horses, which is able to identify similar images that have undergone background and illumination changes. The image in the top left position of the Figure 6 is from the dinosaur category. The precision obtained is very high in this case. In order to compare our approach, some of other previous well-know approaches [1, 7] were survived.

Banerjeea *et al.* [1] proposed an approach for CBIR using visually significant point features and evaluated their approach performance using simplicity dataset considering $N=10, 20$ and 40 . The precision% is computed for each category separately. The average precision of their approach [1] is shown in the Table 3 and it was compared by our proposed approach.

Table 3. The average precision% of proposed and [1] on Simplicity.

| Approach | [1] | | | Proposed | | |
|-----------|--------------|--------------|--------------|--------------|--------------|--------------|
| | N=10 | N=20 | N=40 | N=10 | N=20 | N=40 |
| Africa | 70.50 | 61 | 58 | 67.34 | 61.04 | 56.76 |
| Beach | 71.48 | 56.23 | 52.58 | 73.10 | 59.11 | 53.87 |
| Building | 72.40 | 63.67 | 56 | 76.48 | 68.72 | 60.64 |
| Bus | 81.45 | 72.77 | 62.67 | 93.23 | 91.47 | 71.83 |
| Dinosaur | 100 | 95 | 92 | 100 | 98.87 | 95.48 |
| Elephant | 85 | 77 | 66 | 80 | 75.92 | 61.5 |
| Flower | 92 | 83 | 71.2 | 94.58 | 89.44 | 73.5 |
| Horses | 100 | 95 | 83 | 92.28 | 89.76 | 79.62 |
| Mountains | 72 | 68 | 62 | 72.4 | 68.38 | 63.24 |
| Food | 62 | 57 | 55.2 | 63.96 | 59.49 | 55.78 |
| Average | 80.68 | 72.86 | 65.86 | 81.33 | 76.22 | 67.22 |

Guang *et al.* [7] are prepared an algorithm based on multi-texton histograms. They evaluated their CBIR system performance using corel dataset and considering $N=12$. The average precision and recall based on [7] are shown in the Table 4. It is compared by proposed approach in a same situation ($M= 5000, N=12$). It can be seen from the Tables 3 and 4, that our method achieves much better results than [1, 7] methods.

Table 4. The average precision% and Recall% of proposed and [7] on Corel, $N=12$.

| Approach | Measure | Precision | Recall |
|----------|---------|-----------|--------|
| [7] | | 49.98 | 6.00 |
| Proposed | | 53.04 | 6.36 |

5.1. Computational Complexity

If the number of all database images is considered N , the total number of required operations in retrieving step of a classic CBIR system are $N \times [K+P+2]$ divisions, $N \times [K+P+2]$ multiplications and $N \times [K+P+1]$ additions.

After using the complexity reduction algorithm, instead of each category which is labeled as absolutely not close to the query, the number of required additions is decrease to:

$$NK+NP+N-WK-WP-W$$

Also, the number of required multiplications and divisions are decrease to:

$$NK+NP+2N-WK-WP-2W$$

Where W is the number of samples of the disregard category. P is the number of neighbors in $CLBP_{P, R}$ operator and K is the number of bins using $VAR_{P, R}$.

6. Conclusions

The aim of this paper was to propose a robust approach for CBIR. The performance of the proposed approach is evaluated using corel and simplicity image sets and it was compared some of other well-known approaches in terms of Precision and Recall. The results are shown the high performance of the proposed approach to retrieve certainly same category images by the query. Some of other advantages of the proposed approach are as follows:

1. According to the description of local binary pattern and local variance [13], the proposed feature extraction is rotation invariant.
2. The proposed computational complexity reduction algorithm reduces the noise sensitivity of the CBIR System. In order to, disregard not close categories to the query, the noise samples of the disregarded categories are eliminated.
3. In this paper, a novel feature extraction is described using combination of top-hat transforms and local binary patterns that can be used for other image processing cases to analyze the color images.

References

[1] Banerjeea M., Malay K., and Maji P., "Content-based Image Retrieval using Visually Significant Point Features," *Fuzzy Sets and Systems*, vol. 160, no. 23, pp. 3323-3341, 2009.

[2] Belongie S., Malik J., and Puzicha J., "Shape Matching and Object Recognition using Shape Contexts," *IEEE Transactions on Pattern*

- Analysis and Machine Intelligence*, vol. 24, no. 4, pp. 509-522, 2002.
- [3] Berman P. and Shapiro G., "A Flexible Image Database System for Content-Based Retrieval," *Computer Vision and Image Understanding*, vol. 75, no. 1, pp. 175-195, 1998.
- [4] Chen T., Wu H., Rahmani R., and Hughes J., "A Pseudo Top-Hat Mathematical Morphological Approach to Edge Detection in Dark Regions," *Pattern Recognition*, vol. 35, no. 1, pp. 199-210, 2002.
- [5] Eidenberger H., "Statistical Analysis of MPEG-7 Image Descriptions," *Multimedia Systems*, vol. 10, no. 2, pp. 84-97, 2004.
- [6] Fekri-Ershad S. and Tajeripour F., "A Robust Approach for Surface Defect Detection based on One Dimensional Local Binary Patterns," *Indian Journal of Science and Technology*, vol. 5, no. 8, pp. 3197-3203, 2012.
- [7] Guang L., Lei Z., Ying H., Zuo-Yong Li., and Jing-Yu Y., "Image Retrieval Based on Multi-Texture Histogram," *Pattern Recognition*, vol. 43, no. 7, pp. 2380-2389, 2010.
- [8] Guang L., Zuo L., Lei Z., and Yong X., "Image Retrieval based on Micro-Structure Descriptor," *Pattern Recognition*, vol. 44, no. 9, pp. 2123-2133, 2011.
- [9] Jhanwar N., Chaudhuri S., and Zavidovique B., "Content based Image Retrieval using Motif Co-Occurrence Matrix," *Image and Vision Computing*, vol. 22, no. 14, pp. 1211-1220, 2004.
- [10] Kekre B., Mukherje P., and Wadwa S., "Image Retrieval with Shape Features Extracted using Morphological Operators with BTC," *the International Journal of Computer Applications*, vol. 12, no. 3, pp. 1-5, 2010.
- [11] Malik F. and Baharudin B., "Effective Image Retrieval Based on Experimental Combination of Texture Features and Comparison of Different Histogram Quantization in the DCT Domain," *the International Arab Journal of Information Technology*, vol. 11, no. 3, pp. 258-267, 2014.
- [12] Manjunath S. and Ma Y., "Texture Features for Browsing and Retrieval of Image Data," *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 18, no. 8, pp. 837-842, 1996.
- [13] Ojala T., Pietikainen M., and Maenpaa T., "Multi Resolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971-987, 2002.
- [14] Ojala T., Rautiainen M., Matinmiko E., and Aittola M., "Semantic Image Retrieval with HSV Correlograms," available at: <http://www.medioteam oulu.fi/publications/pdf/68.p>, last visited 2013.
- [15] Pass G. and Zabih R., "Comparing Images using Joint Histograms," *Journal of Multimedia Systems*, vol. 7, no. 3, pp. 234-240, 1999.
- [16] Pietikäinen M., Ojala T., and Xu Z., "Rotation-Invariant Texture Classification using Feature Distributions," *Pattern Recognition*, vol. 33, no. 1, pp. 43-52, 2000.
- [17] Randen T. and Husoy H., "Filtering for Texture Classification: A Comparative Study," *IEEE Transaction Pattern Analysis and Machine Intelligence*, vol. 21, no. 4, pp. 291-310, 1999.
- [18] Tajeripour F. and Fekri-Ershad S., "Developing a Novel Approach for Stone Porosity Computing using Modified Local Binary Patterns and Single Scale Retinex," *the Arabian Journal for Science and Engineering*, vol. 39, no. 2, pp. 875-889, 2014.
- [19] Stanford Vision Lab., available at: <http://vision.stanford.edu/>, last visited 2014.



Farshad Tajeripour received his BSc and MSc degrees in electrical engineering from Shiraz University, in 1994 and 1997, respectively and the PhD degree in electrical engineering from the Tarbiat Modarres University of Tehran, in 2007. In 2007, he joined the Department of Electrical and Computer Engineering at Shiraz University, Shiraz, as an Assistant Professor. His research interests include digital image processing, machine vision, medical image processing, signal processing, and the design and implementation of vision based inspection systems. He has published several papers in the fields of pattern recognition, signal and image processing.



Mohammad Saberi received his BSc degree in computer software engineering from Islamic Azad University of Najaf-Abad, Iran in 2008 and his MSc degree from Shiraz University, Iran in 2013, majored in artificial intelligence. He joined the Isfahan Municipality Information and Communication Organization in 2013. His research interests are skin detection, texture analysis and image retrieval and etc.



Shervan Fekri-Ershad received his BSc degree in computer hardware engineering from Islamic Azad University of Najaf-Abad, Iran in 2009 and his MSc degree from Shiraz University, Iran in 2012, majored in artificial intelligence.

Currently, he is a PhD student in the School of electrical and computer engineering, Shiraz University, Iran. He joined the department of Computer Engineering at Amin University, Isfahan, as a lecturer in 2012. His research interests are image processing applications includes visual inspection systems, visual classification, texture analysis, surface defect detection and etc.