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A novel approach for Face Recognition using Local Binary Pattern

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***Abstract*—This paper presents Local Binary pattern (LBP) as an approach for face recognition with the use of some global features also. Face recognition has received quite a lot of attention from researchers in biometrics, pattern recognition, and computer vision communities. The idea behind using the LBP features is that the face images can be seen as composition of micro-patterns which are invariant with respect to monotonic grey scale transformations and robust to factors like ageing. Combining these micro-patterns, a global description of the face image is obtained. Efficiency and the simplicity of the proposed method allows for very fast feature extraction giving better accuracy than the other algorithms. The proposed method is tested and evaluated on ORL datasets combined with other university dataset to give a good recognition rate and 89% classification accuracy using LBP only and 98% when global features are combined with LBP. The method is also tested for real images to give good accuracy and recognition rate. The experimental results show that the method is valid and feasible.**

***Keywords*— Classification Accuracy, Face recognition, Global Features, Local Binary Pattern, Recognition Rate**

I. INTRODUCTION

A face recognition system would allow user to be identified by simply walking past a surveillance camera. Human beings often recognize one another by unique facial characteristics. One of the latest biometric technologies, automatic facial recognition, is based on this phenomenon. Facial recognition is the most successful form of human surveillance. Facial recognition technology, is being used to improve human efficiency when recognizing faces, is one of the fastest growing fields in the biometric industry. Interest in facial recognition is being fueled by the availability and low cost of video hardware, the ever-increasing number of video cameras being placed in the workspace, and the noninvasive aspect of facial recognition systems. In this area, the variations of light, gesture, expression, age or the imaging conditions in the face image have become a key challenge. For this extracting local structure based on texture and structural characteristics is important.

In Local Binary Pattern (LBP) which is frequently used for texture classification, for each pixel, a binary code is produced by thresholding its value with the value of the centre pixel. A histogram is created to collect the occurrences of different binary patterns.

For face recognition, the face area is first divided into small regions from which Local Binary Pattern (LBP) histograms are extracted and concatenated into a single, spatially enhanced feature histogram efficiently representing the face image. Efficiency & the simplicity of the proposed method allows for very fast feature extraction. The textures of the facial regions are locally encoded by the LBP patterns while the whole shape of the face is recovered by the construction of the face feature histogram.

The idea behind using the LBP features in face recognition is that the face images can be seen as composition of micro-patterns which are invariant with respect to monotonic grey scale transformations. Combining these micro-patterns, a global description of the face image is obtained.

II. RELATED WORK

Visually it is easy to detect face and identify it. For a computer to recognize faces the face area should be detected and recognition comes next. Hence, for a computer to recognize faces the photographs should be taken in a controlled environment; a uniform background and identical poses makes the problem easy to solve. These face images are called mug shots. From these mug shots, canonical face images can be manually or automatically produced by some preprocessing techniques like cropping, rotating, histogram equalization and masking. Much work has been done on face recognition using geometrical local feature based methods, and holistic template matching based systems and combinations of these two methods, namely hybrid methods.

LBP features have performed very well in various applications, including texture classification and segmentation,

Image retrieval and surface inspection. Rotation invariant LBP have also been used. Work has been done on Local Binary Patterns, for person-independent facial expression recognition where experiments illustrate that LBP features are effective and efficient for facial expression recognition. LBP technique and Nearest Feature Space (NFS) classifier has the good generalization ability and are combined to construct a new way for satisfying the real-time and robustness decision performance. Combining the local features by LBP with global features as the total features of the image is more power discriminating. This is illustrated in this paper.

III. PRELIMINARIES

i. LBP

LBP is advantageous because its local texture character can be described efficiently. The most important property of LBP operator is its tolerance against illumination changes. Also it is computationally simple to use it in real-time applications. Designers of LBP operators must face three fundamental issues. The first issue is how to describe different local patterns of textures and then how to extract these local patterns. Since not all of local patterns are with the same importance to texture analysis, the second issue is how to select the essential subset of these local patterns to represent textures. The third issue is how to use these selected local patterns to form an effective texture descriptor. The original LBP algorithm is a grayscale irrelevant texture analysis algorithm with powerful discrimination. LBP provides a unified description including both statistical and structural characteristics of a texture patch, so that it is more powerful for texture analysis.

LBP is a gray-scale texture operator which characterizes the spatial structure of the local image texture. Given a central pixel in the image, a pattern number is computed by comparing its value with those of its neighborhoods. With the neighborhood set P and a circle of radius R, and the difference between the central pixel "g_c" and its neighborhood $\{g_0, g_1, \ldots\ldots g_{p-1}\}$, we can get the value of LBP operator :

$$LBP_{P,R} = \sum_{i=0}^{p-1} s(g_i - g_c)2^p \quad \text{---------------------- (1)}$$

$$s = \begin{cases} 1, g_i - g_c > 0 \\ 0, g_i - g_c \le 0 \end{cases} \quad \text{----------------------------- (2)}$$

The original LBP labels the pixels of an image by thresholding the local area, neighborhood of each pixel with the center value and considering the result as a binary number. Function (2) means pixels greater than the central pixel are mapped to 1, otherwise 0. The functions (1) and (2) give the computation of $LBP_{P,R}$. $LBP_{8,1}$ is a basic operator in LBP algorithm. Fig. 1 gives an example of computing $LBP_{8,1}$.

The functions (1) and (2) give the computation of $LBP_{P,R}$. The algorithm considers the weight of central pixel in local area. Take $LBP_{8,1}$ as an example, $2^8 = 256$ different values can be obtained in the 3x3 area. In fact we can get $2^9 - 1 = 511$ patterns (all zeros and all ones are the same) including the central pixel.

Generally the maximum value divided by 2 is considered to be the threshold. Suppose the texture image is NxM. After identifying the LBP pattern of each pixel (i, j), the whole texture image is represented by building a histogram which is used as a texture descriptor.

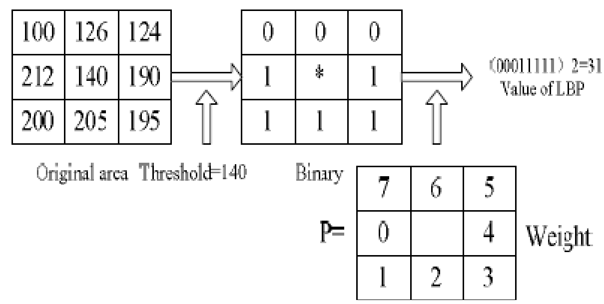


Fig. 1. An example of computing $LBP_{8,1}$

The LBP histogram contains information about the distribution of the local micro-patterns, such as edges, spots and flat areas, over the whole image, so can be used to statistically describe image characteristics.

An example of LBP computation is given in Fig. 2 as –

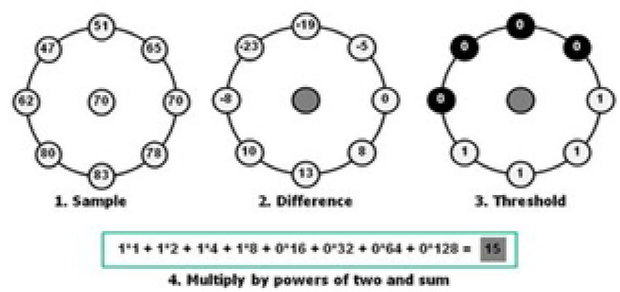


Fig. 2. An example of LBP computation

Another extension to the original operator is the definition of so called uniform patterns, which can be used to reduce the length of the feature vector and implement a simple rotation-invariant descriptor. This extension was inspired by the fact that some binary patterns occur more commonly in texture images than others. A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is traversed circularly. For example, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) and 01010010 (6 transitions) are not.

In the computation of the LBP labels, uniform patterns are used so that there is a separate label for each uniform pattern.

ii. FACE RECOGNITION

Face recognition has received quite a lot of attention from researchers in biometrics, pattern recognition, and computer vision communities. This common interest among researchers is because human activity is a primary concern both in everyday life. There are a large number of commercial, securities, and forensic applications requiring the use of face recognition technologies. These applications include automated crowd surveillance, access control, mugshot identification (e.g., for issuing driver licenses), face reconstruction etc.

Face recognition scenarios can be classified into two types: (i) face verification (or authentication) and (ii) face identification (or recognition).

(i)Face verification is a one-to-one match that compares a query face image against a template face image whose identity is being claimed.(ii) Face identification is a one-to-many matching process that compares a query face image against all the template images in a face database to determine the identity of the query face. The identification of the test image is done by locating the image in the database that has the highest similarity with the test image.

Face recognition algorithms should take into consideration many factors like 3D head pose, illumination, facial expression, occlusion due to other objects or accessories (e.g., sunglasses, scarf, etc.), facial hair, aging etc.

Recognition algorithms can be divided into two main approaches, geometric, which looks at distinguishing features or photometric, which is a statistical approach that distill an image into values and comparing the values with templates to eliminate variances uses the visual details of the skin, as captured in standard digital images. Some algorithms use skin texture analysis. It turns the unique lines, patterns, and spots apparent in a person's skin into a mathematical space. Tests have shown that with the addition of skin texture analysis, performance in recognizing faces can increase 20 to 25 percent.

IV. METHODOLOGY

Fig. 3 gives the block diagram of the steps to be followed for face recognition using LBP.

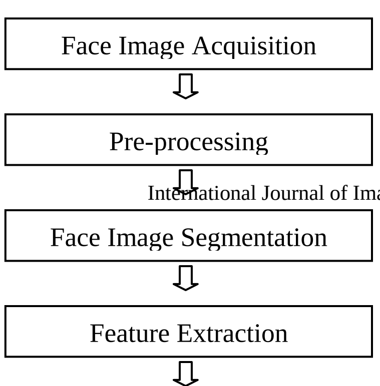


Fig. 3. Block diagram for face recognition using LBP

Initially a database of images is prepared. The histogram of all those reference images is found out for further use.

Face Image Accquisition:

The subject image is taken from either the reference database or from the camera for the further processing.

Pre-processing:

Initially the image taken from camera is de-noised. The image taken might contain some noise due to some dust etc. It can be a blurred image also.

Face Image Segmentation:

Face image is not a texture image. But the cheeks, eyes, forehead in it can be considered as a texture image. So the face image should be segmented to obtain small parts to obtain texture images.

Feature Extraction:

Now on each of the segmented images LBP is applied and features are extracted to obtain histograms.

Building Histogram:

Now the histograms obtained from these segmented images are concatenated to obtain a single histogram.

Histogram Matching:

Now this obtained histogram of the entire subject image is matched with the histograms of the reference images algorithm in the database, with the help of distance matching to obtain the match of the subject image.

And then the decision is given.

V. FACE RECOGNITION USING LBP

The LBP operator can be extended to use different size or different shape. In addition to the regular 8 pixels shown in Fig 1, circular neighbourhoods can also be used in neighbourhood selection. Ojala also extended the concept of the basic LBP operator, which was called uniform patterns. In this case, there are at most two different conversions from

0=>1 or 1=>0. Ojala noticed that uniform patterns account for about 90% and 70% of all patterns when using the (8, 1) and (16, 2) neighbourhood respectively. By using uniform patterns can greatly reduce the bin numbers of LBP histogram. We notate this LBP operator by $LBP_{P,R.}$ where P is number of neighbourhood pixels and R is the radius of circular neighbourhoods. The formation process of a LBP histogram is shown in Fig. 4.

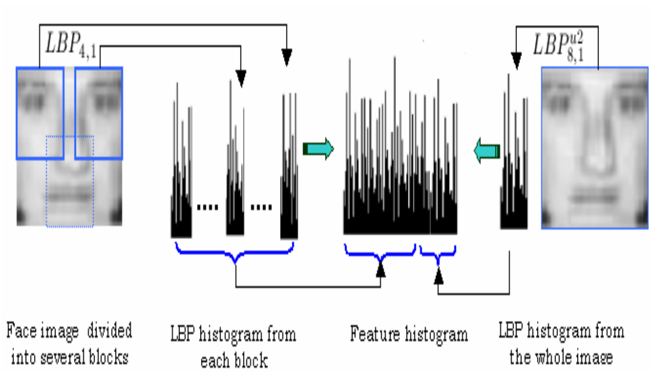


Fig. 4. Formation of LBP Histogram

As shown in Fig 4, the process of formatting LBP the process of formatting LBP histogram has three stages. Firstly, the face is divided into sub-regions. Then LBP spectrums of each region are calculated. And finally feature histogram of image is formed by linking the statistical histograms of each region. This strategy effectively indicate face features with different scales: LBP value contains the information of pixels in regions, and the LBP histogram of one region represent local feature; arraying the sub-regional histogram represent global characteristics of the image.

VI. RESULTS

In order to express the facial features well, we consider partitioning the image to independently non-overlapping blocks, such as 3x3. First get the histograms of every block and define as l1,l2…ln , n is the number of blocks; then calculate the histogram of image which doesn't partition, define as g; last connected l1,l2…ln, g together to be one histogram h. This histogram contains information about the distribution of the LBP and TLBP features over the whole image, and is able to represent the facial image. An illustration of combining is shown in Fig. 5 -

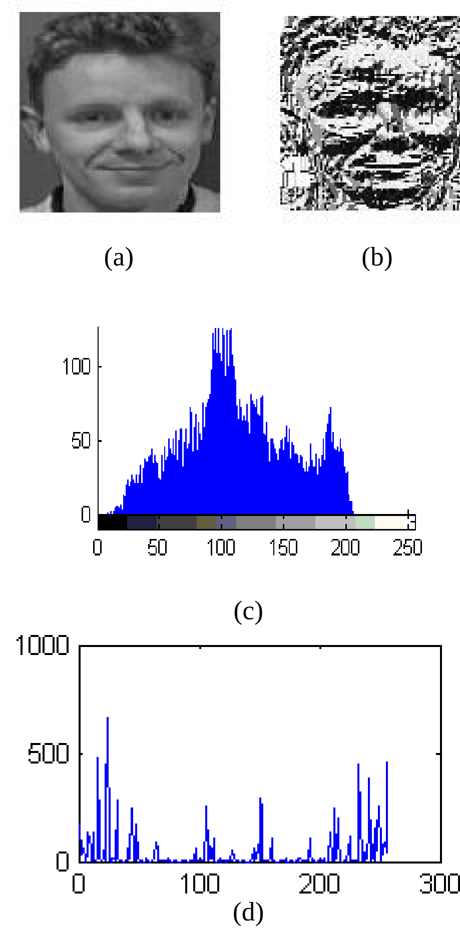


Fig. 5 (a) Original Image (b) LBP Image
(c) Histogram of Original Image
(d) Histogram of LBP Image

Experiments are performed on ORL images of 5 different individuals. A training set of 2, 4, 7 and 8 images of an individual and the same number of images of the same individual are taken for testing and their success rates are found out. Fig. 6 gives the plot of the same.

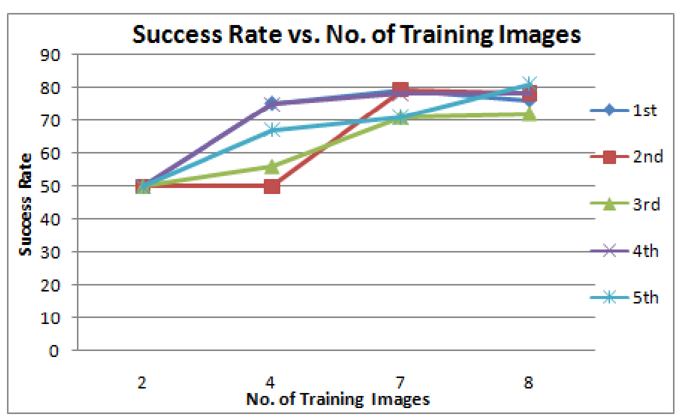
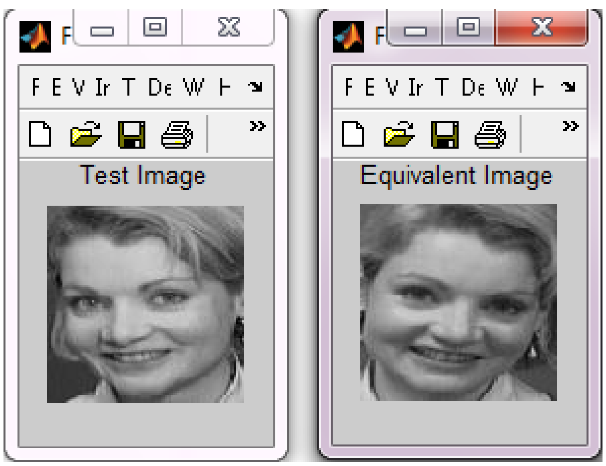


Fig. 6 Success Rate of 5 images in ORL database

From Tab. 1 it can be seen that the average classification accuracy using LBP only for (8,1) neighbourhood is 94% and for (16,2) neighbourhood is 89%. When these local features are combined with global features the accuracy for (8,1) neighbourhood increases to 99% and for (16,2) neighbourhood increases to 98%.

TABLE I
AVERAGE CLASSIFICATION ACCURACY OF LBP

Images	**Neighbourhood**	**CA using LBP**	**CA using LBP + global features**
200	8,1	94%	99%
200	16,2	89%	98%



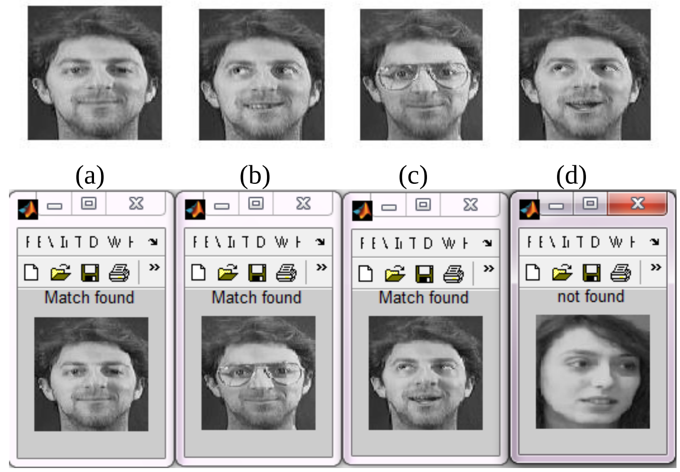
(a) (b)

Fig. 7 (a) Test Image
(b) Equivalent Training Image

When global features are combined with local features, although the classification accuracy increases, but the number of incorrect matches between the training and testing datasets also have increased from 5% to 11% for (8,1) neighbourhood and 8% to 11% for (16,2) neighbourhood. This means the recognition rate reduces to a small extent when global features are also used. Fig. 7 shows that a query or a test image is given as an input and its equivalent match in the training set has been found out.

Fig. 8 shows the training images in the upper row and the test images in the lower row. Below each test image its Euclidean distance (EU) w.r.t. to the training image above it is mentioned. It shows that for EU values below the threshold for fig. 8 (e), (f) and (g) the image match is found. For fig. 8 (h) which is an unknown image, its Euclidean distance is above the threshold. So it is not found in the training database.

Experiments are carried out for rotated images. 40 images from the ORL dataset are used. The accuracy for that is 91% but the incorrect matches between training and testing datasets is poor. It is 70%. These results for rotated images are to be further improved upon and work is still going on.



EU=0 EU=167.6 EU=213.5 EU=912.1
(e) (f) (g) (h)

Fig. 8 (a)(b)(c)(d) Training Images (ORL database)
(e)(f)(g)(h) Test Images (ORL database)

Experiments are carried for real images taken from camera. The following Tab.2 gives the average classification accuracy for real images taken from the camera.

TABLE III
AVERAGE CLASSIFICATION ACCURACY OF LBP FOR REAL IMAGES TAKEN FROM CAMERA

Images	**Neighbourhood**	**CA using LBP**	**CA using LBP + global features**
50	8,1	98%	99%
50	16,2	87%	98%

The total number of real images taken from camera are of 50 different individuals and experiments are carried to give the above mentioned classification accuracy.

(a) (b)

Fig. 9 (a) Test Image (Real)
(b) Equivalent Training Image (Real)

Fig. 9 shows the real test image and its equivalent training image. Unlike the recognition rate for standard database mentioned above, the recognition rate for real images remains the same when only LBP is used and when global features are coupled with it. The recognition rate for (8,1) neighbourhood is 74% and for (16,2) neighbourhood is 90%.
Experiments are also performed to check how robust the algorithm is against ageing. A database of 3 different age-groups has been made. The first group is for kids, second group for young people and third group of old people. The performance of LBP for the same is as given in Tab.3.

TABLE IIIII
AVERAGE CLASSIFICATION ACCURACY OF LBP FOR 3 DIFFERENT AGE GROUPS

Age Group	**No. of Images**	**CA for (8,1) neighbourhood**	**CA for (16,2) neighbourhood**
Kids	15	94%	95%
Young	20	99%	92%
Old	15	98%	90%

The recognition rate for age group of young people is 75% and 70% respectively for (8, 1) and (16, 2) neighbourhood and that for the age group of old people is 100% for both the neighbourhoods. These images are from the standard database. The classification accuracy for the kids group is 94% and 95% for (8, 1) and (16, 2) neighbourhood respectively. The images for children are real and not from any standard database. The recognition rate for them is lower as 69% and 75% respectively for the two types of neighbourhoods. All the above results for classification accuracy are performed considering one image of the same individual in training and testing dataset. These results show that LBP is quite robust to the factor-ageing.
These results of LBP have to be further compared with some other algorithm.

VII. CONCLUSION AND FUTURE WORK

The current status of LBP is that it has simple theory with computational simplicity. It is invariant with respect to any monotonic transformation of gray scale. It has powerful rotation-invariant analysis with uniform patterns. It discriminates excellently between various kinds of textures. LBP incorporates both structural and statistical texture analysis. LBP is used in many tasks which have not been earlier considered as texture analysis problems. The important application which we described is face recognition which has received quite a lot of attention from researchers in biometrics, pattern recognition, and computer vision communities.

This paper has concentrated on face recognition using LBP in isolation and LBP combined with global features. Expected results are obtained for the same using (8,1)and (16,2) neighbourhood. However the results for rotated images still have to be improved and work is going on in that direction. The algorithm is tested for real images to give good classification accuracy and recognition rate. It has been proved that LBP is robust against the factor-ageing.

Although LBP gives good results, most practical system would use LBP with some other algorithms for expression-robust face recognition or automatic facial expression recognition and several other factors.

LBP promises to be a suitable technique for face recognition with several advances in near future giving better results as compared to other algorithms.

A limitation of the current work is that we have not considered head pose variations and occlusions, which will be addressed in the future work. Possible future work includes incorporating other face information into the descriptors and investigating their effectiveness in the results.

REFERENCES

[1] Yu Wang, Xueye Wei, Shuo Xiao, "LBP texture analysis Based on the Local Adaptive Niblack Algorithm," *2008 Congress on Image and Signal Processing*, DOI 10.1109/CISP.2008.403
[2] Zhenhua Guo,LeiZhang, DavidZhang, "Rotation invariant texture classification using LBP variance(LBPV) with global matching," *Pattern Recognition*, 43 (2010) pp.706–719

[3] Hui Zhou , Runsheng Wang, Cheng Wang, "A novel extended local-binary-pattern operator for texture analysis," *Information Sciences 178 (2008)*, pp.4314–4325

[4] Guoying Zhao and Matti Pietik¨ainen, "Dynamic Texture Recognition Using Local Binary Patterns with an Application to Facial Expressions," *IEEE transactions on Pattern Analysis and machine intelligence, 2007*

[5] Matti Pietikanen, "Image analysis with Local binary Patterns," *Lecture notes in Computer Science, 2005*, volume 3540/2005.

[6] Jun Meng, Yumao Gao, Xiukun Wang, Tsauyoung Lin, Jianying Zhang, "Face Recognition based on Local Binary Patterns with Threshold," *2010 IEEE International Conference on Granular Computing,* DOI 10.1109/GrC.2010.72

[7] Xiaoshan Liu, Minghui Du, Lianwen Jin, "Face Features Extraction Based on multi-scale LBP," *2010 2nd International Conference on Signal Processing Systems (ICSPS)*

[8] Hengliang Tang, Yanfeng Sun, Baocai Yin, Yun Ge, "Expression-Robust 3d Face Recognition Using LBP Representation," *2010 IEEE*

[9] Wencheng Wang, Faliang Chang , Jianguo Zhao, Zhenxue Chen, "Automatic Facial Expression Recognition Using Local Binary Pattern," *Proceedings of the 8th World Congress on Intelligent Control and Automation July 6-9 2010*

[10] Jae Young Choi, Plataniotis, K.N, Yong Man Ro, "Using colour Local Binary Pattern for Face Recognition," *Image Processing(ICIP), 2010 17th International Conference on Digital Object Identifier, pp.4541–4544*

[11] Mihran Tuceryan, Anil K. Jain, "Texture Analysis, The Handbook of Pattern Recognition and Computer Vision (2nd Edition)", *Chapter 2*