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ROBUST GENDER CLASSIFICATION USING LMnP - LOCAL MINIMA PATTERN

Mohammad Shahidul Islam

Abstract— Gender classification is an important matter for Human Computer Interaction devices. A new methodology for gender classification is examined in this study where the facial feature is extracted from local region of a face using gray color intensity. The facial area is divided into eighty-one equal sized square sub-regions and Local Minima Pattern (LMnP) method is applied to each pixel. LMnP histograms extracted from those regions are concatenated into a single vector to represent that particular face. The classification accuracy obtained using Local Minima Pattern (LMnP) along with support vector machine as a classifier has outperformed all traditional feature descriptors for gender classification. It is evaluated on the images collected from popular FERET database

Index Terms— Gender Classification, Facial Feature Extraction, Local Minima Pattern, Texture Analysis, Pattern Recognition, Computer Vision, FERET

1. Introduction

IN social interactions, it is very important to know the gender. Face has some unique symptoms for gender recognition. Body movement also helps to identify the gender. Computer vision and pattern recognition is playing an important role in manmade machines for the last few years. Human Computer Interaction devices can be more user-friendly and behave like human if it can extract gender information from human face [1]. Gender recognition is very important in human-robot interaction; vision based human monitoring, passive demographic data collection, and human retrieval from video databases.

Due to the inherent variability of human-face caused by age, ethnicity and image quality [2,3], image-based gender classification is difficult. Appearance-based method and geometric-feature based method are the two ways to derive features from human faces[1]. Appearance-based methods consider the facial screen color, color difference, texture or color gradient direction to derive feature pattern from the image. It can be local region based e.g. local binary pattern [4], Local Minima[5] or holistic e.g. Gabor Filter [6]. Geometric-based methods use location and distance between facial components like eyes, nose or mouth. Therefore, it needs extra computation before feature extraction to localize facial components. Any error during the component localization may lead to substantial accuracy drop.

Appearance-based methods get popularity due to its robustness in environmental change. Moreover local region-based feature extraction is independent to the location information of facial components, which makes it more favorite for the researchers. Local binary pattern is an example of local region-based feature descriptor, which is adopted by many researchers in the field of texture analysis for both object and human face. It was propose by Ojala et al. [4] for texture description, later used by Ahonen et al. [7] on human face for face recognition. An example of obtaining local binary pattern is shown in Figure 1.

Local binary pattern was also used for gender classification [8,9] and achieved very competitive results. LBP is gray-scale invariant as it uses the color difference to compute the binary pattern. Therefore, it is robust in illumination changes and performs better in an uncontrolled environment. However, its noise tolerance is very poor as little changes in some pixels intensity caused by noise changes the binary pattern. In addition, the LBP histogram length is too high, which is time and cost effective.

S_1(56)	S_2(89)	S_3(45)
S_8(54)	C(56)	S_4(25)
S_7(48)	S_6(89)	S_5(26)

→

1	1	0
0	LBP(56)	0
0	1	0

→ 11000100

$$\mathrm{LBP(C)} = \sum_{k=1}^{8} f(\mathrm{S_k} - \mathrm{C})2^{8-k}\text{; Where, } f(X) = \begin{cases} 0, & X < 0 \\ 1, & X \geq 0 \end{cases}$$

And $S_{1\text{-}8}$ and C represents the gray value of that pixel

$$\mathrm{LBP}(56) = 1*2^7+1*2^6+0*2^5+0*2^4+0*2^3+1*2^2+0*2^1+0*2^0=196$$

Figure 1: Example of Local Binary Pattern formulation

A new methodology Local Minima Pattern is proposed in this study for gender recognition which was already proved to be cost and time effective as a facial feature descriptor for facial expression recognition [5]. In this study, LMnP is combined with Kirsch edge response mask [10] to make it more stable in the noise. Experiments were performed on FERET dataset [11] using LBP and LMnP in matlab. Gaussian white noise was added to prove LMnPs stability in the noisy environment.

• *Dr. Mohammad Shahidul Islam is currently working as an Assistant Professor in the Faculty of Science and Technology at Atish Dipankar University of Science and Technology, Dhaka, Bangladesh*
• *E-mail: suva93@gmail.com*

2. Feature Extraction

For each pixel in the gray-scale image, nine pixels from 3x3 pixels region are used to extract local feature. Firstly, that 3x3 pixels region is multiplied with Kirsch edge response mask in eight directions (Figure 2) to get eight-mask value.

NW

5	5	-3
5	0	-3
-3	-3	-3

N

5	5	5
-3	0	-3
-3	-3	-3

NE

-3	5	5
-3	0	5
-3	-3	-3

E

-3	-3	5
-3	0	5
-3	-3	5

5	-3	-3
5	0	-3
5	-3	-3

W

-3	-3	-3
5	0	-3
5	5	-3

SW

-3	-3	-3
-3	0	-3
5	5	5

S

-3	-3	-3
-3	0	5
-3	5	5

SE

Figure 2: Kirsch edge response mask in eight directions.

20	52	63
59	78	45
25	48	71

(a) local region from the gray scale image

$$\begin{bmatrix} 20 & 52 & 63 \\ 59 & 78 & 45 \\ 25 & 48 & 71 \end{bmatrix} * \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} = \begin{bmatrix} -101 & & \\ & & \\ & & \end{bmatrix}$$

(b) Mask value for the pixel '20' using NW directional mask

$$\begin{bmatrix} 20 & 52 & 63 \\ 59 & 78 & 45 \\ 25 & 48 & 71 \end{bmatrix} * \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} = \begin{bmatrix} & -69 & \\ & & \\ & & \end{bmatrix}$$

(c) Mask value for the pixel '52' using N directional mask

Similarway other directional masks are also computed.

Direction	NW	N	NE	E	SE	S	SW	W
Pixel value	20	52	63	45	71	48	25	56
Mask value	-101	-69	131	283	163	3	-93	-317

(d) Corresponding Mask value in eight directions.

-101	-69	131
-317		283
-93	3	163

(e) New representation of (a) using mask value

Figure 3: Obtaining mask value for a 3x3 region

After applying the directional masks, the pixels original color value is replaced by the corresponding mask value (Figure 3-e) and LMnP is applied on that region to obtain LMnP code (Figure 4 and Figure 5) which is more stable in the noisy environment than LMnP code without applying masking. In 3x3 pixels local region, the center pixel of the pattern is surrounded by 8 neighboring pixels in 8 possible directions. The directions are denoted by 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315° (Figure 4). The direction of the neighboring pixel with the minimum, the second minimum and so on for the gray scale values can be considered as the local feature for the given pixel. The direction would represent the changing direction of the gray scale color values at the particular center pixel. Thus, eight possible bins are needed to build the histogram on the numbers of pixels in a block for the possible 8 directions as shown in Figure 4.

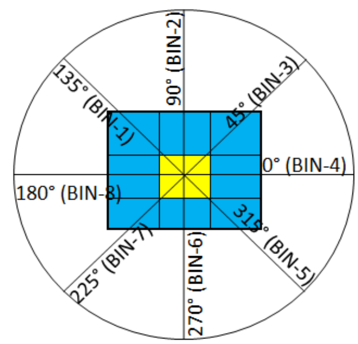

Figure 4: 8 possible BINS denoted as 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315°

The histograms for all blocks for an image can then be concatenated to form the feature vector for the whole image. Notice that the direction is insensitive to light changes since the light changes would change the gray scale color values of all the pixels by nearly same amount but not the direction of the minima for each of the pixels.

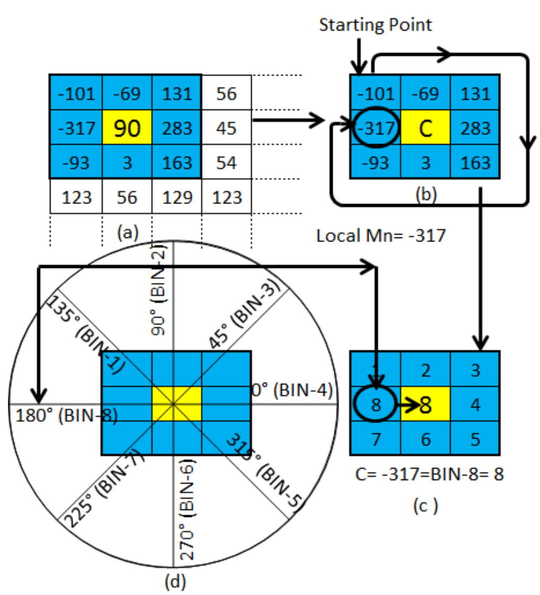

Figure 5: Obtaining LMnP code from a 3x3 pixels region

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2.1 Feature Vector

The gray scale image is divided into 81 equal sized blocks and histogram of LMnP codes from each block is concatenated to form the feature vector (Figure 6Figure). LMnP considered at most single transition patterns only. Therefore, histogram length for each block was eight and the feature vector length for the whole image was 81*8= 648.

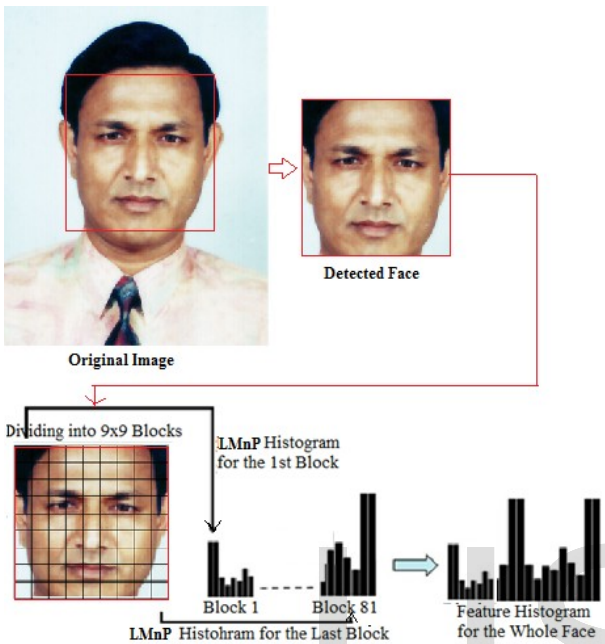

Figure 6: Building feature vector for a image

0.2 Classification Using Support Vector Machine

Support vector machine, a well known linear classier is successfully used in many research work for classification [12]. It maps the feature data in to high dimensional feature space and draws a clear separation line between them. Let the set of training examples D be $\{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_r, y_n)\}$, where $\mathbf{x}_i = (x_1, x_2, \ldots, x_r)$ is an input vector in a real-valued space $X \subseteq R^r$ and y_i is its class label (output value), $y_i \in \{1, -1\}$. 1: positive class and -1: negative class. SVM finds a linear function of the form (w: weight vector)

$$f(x) = \langle \mathbf{w} \cdot \mathbf{x} \rangle + b \quad (1)$$

So that an input vector $\mathbf{x}_i$ is assigned to a positive class if $f(\mathrm{x}_i) \geq 0$, and to the negative class if $f(\mathrm{x}_i) < 0$.

$$y_i = \begin{cases} 1 & if \langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b \geq 0 \\ -1 & if \langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b < 0 \end{cases} \quad (2)$$

For linear data, it is easy to separate them but for non-linear data, SVM uses some sort of kernel function to create non-linear separation line. Some popular kernel functions are polynomial, RBF (radial basis function) etc. Support vector machine is a binary classifier.

3. Experimental Results

The performance of gender classification using proposed LMnP feature is experimented on FERET [11] database. The FERET database has a total 14,051 gray-scale images from 1,199 subjects. The images have variations in lighting, facial expressions, pose angle, aging effects etc. For this study, 2000 mug-shot face images are collected out of which 1100 faces are male and rest 900 faces are female. Fdlibmex, a free face detecting tool for matlab is used to detect the facial area. After that each face is divided into 9x9 sub-blocks to generate spatially combined LMnP histogram feature vector as discussed earlier. Experiments show that increasing the number of blocks can enhance the performance but it increases the length of the feature vector and requires extra bit of processing both time and space. The classification performance in respect to different number of blocks is shown with Table I. Performance of the proposed method in comparison other state of the art methods including LBP method is shown in Table II, which demonstrate superiority of proposed LMnP feature over LBP and other feature in gender classification domain. Stability of LMnP in noisy environment is shown in Table III.

Table I: Classification Accuracy with Different Block.

Number	Feature	Classification Accuracy		
of Block	**Length**	**Overall**	**Male**	**Female**
3-by-3	200	91.15%	91.30%	90.00%
5-by-5	200	95.15%	95.31%	94.99%
7-by-7	392	94.94%	94.65%	95.23%
9-by-9	*648*	*95.91%*	*95.94%*	*95.98%*
11-by-11	968	95.91%	95.91%	96.01%
13-by-13	1352	95.73%	95.35%	96.11%
15-by-15	1352	94.94%	94.65%	95.23%

Table II: Classification Accuracy with Other Method

Methods	Classification Accuracy		
(Feature + Classifier)	**Overall**	**Male**	**Female**
LMnP + SVM	*95.91%*	*95.94%*	*95.98%*
LBP + Chi-square [13]	81.90%	82.27%	81.44%
LBP + Adaboost [13]	92.25%	92.00%	92.55%
LDP + SVM [14]	95.05%	94.81%	95.33%

Table III: Results of LMnP+SVM and other popular methods in noisy environment

Method	Classification Accuracy(Overall)	
	No noise	**With white noise***
LMnP	*95.91%*	*95.05%*
LBP	91.68%	87.41%
$\mathbf{LBP_{U2}}$	91.51%	85.36%
$\mathbf{LBP_{RI}}$	84.51%	75.36%
$\mathbf{LBP_{RIU2}}$	87.51%	76.36%

*Gaussian White noise of 0 mean and 0.001 variance is applied.

4. Conclusion

A novel facial feature extraction method for gender classification is proposed in this study named LMnP (Local Minima Pattern). The LMnP codes are less sensitive to noise because they use edge response value instead of the pixels gray color value to compute features. It has very tiny feature vector length. Therefore, LMnP codes provide less cost and time effective robust features to represent facial landmarks. The classification accuracy achieved using powerful classifier SVM is very competitive. Future plan is to work with real time video and more complex images.

References

[1] Kim, H., Kim, D., Ghahramani, Z. & Bang, S. Appearance-based gender classification with Gaussian processes. *Pattern Recognition Letters* **27**, 618–626 (2006).

[2] Zhao, W., Chellappa, R., Phillips, P. J. & Rosenfeld, A. Face recognition: A literature survey. *Acm Computing Surveys (CSUR)* **35**, 399–458 (2003).

[3] Fasel, B. & Luettin, J. Automatic facial expression analysis: a survey. *Pattern Recognition* **36**, 259–275 (2003).

[4] Ojala, T., Pietikäinen, M. & Harwood, D. A comparative study of texture measures with classification based on featured distributions. *Pattern recognition* **29**, (1996).

[5] Islam, M. S., & Auwatanamongkol, S. (2013). A Novel Feature Extraction Technique for Facial Expression Recognition., *International Journal of Computer Science Issues*, *10(1), pp- 9-14*

[6] Zhang, Z. & Lyons, M. Comparison between geometry-based and gabor-wavelets-based facial expression recognition using multi-layer perceptron. *In Automatic Face and Gesture Recognition, 1998. Proceedings. Third IEEE International Conference on (pp. 454-459). IEEE* (1998).

[7] Ahonen, T., Hadid, A. & Pietikäinen, M. Face description with local binary patterns: application to face recognition. *IEEE transactions on pattern analysis and machine intelligence* **28**, 2037–41 (2006).

[8] Lian, H.-C. & Lu, B.-L. Multi-view gender classification using local binary patterns and support vector machines. *Advances in Neural Networks-ISNN 2006* 202–209 (2006).

[9] Fang, Y. & Wang, Z. Improving LBP features for gender classification. *Wavelet Analysis and Pattern Recognition, 2008. ICWAPR'08. International Conference on* **1**, 373–377 (2008).

[10] Kirsch, R. A. Computer determination of the constituent structure of biological images. *Computers and Biomedical Research* **4**, 315–328 (1971).

[11] Phillips, P. J., Wechsler, H., Huang, J. & Rauss, P. J. The FERET database and evaluation procedure for face-recognition algorithms. *Image and vision computing* **16**, 295–306 (1998).

[12] Cortes, C. & Vapnik, V. Support-vector networks. *Machine learning* **20**, 273–297 (1995).

[13] Sun, N., Zheng, W., Sun, C., Zou, C. & Zhao, L. Gender classification based on boosting local binary pattern. *Advances in Neural Networks-ISNN 2006* 194–201 (2006).

[14] Jabid, T., Hasanul Kabir, M. & Chae, O. Gender classification using local directional pattern (LDP). *Pattern Recognition (ICPR), 2010 20th International Conference on* 2162–2165 (2010).