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Gender Classification Based on Selecting Features LBP, Intensity, and Shape

[1.] Pavithra A, [2.] Saravanan P, [3.] Venkataraman N L
[1.] II-M.E(communication systems), Jayaram College Of Engineering & Technology, Tamil Nadu, India,
[2.] Assistant professor, (ECE), Sri Ranganathar Institute of Engineering and Technology, Tamil Nadu, India
[3.] Assistant Professor, (ECE), Jayaram College Of Engineering & Technology, Tamil Nadu, India,

***Abstract*— The gender will be classified by selecting a feature using mutual information of an image through Spatial Scales, Histogram, LBP, Intensity and Shape. There are three groups of features, three spatial scales, and four different mutual information measures. To select features we compare the results of those types and fused all those results together. The result of fusion LBP features with different radii and spatial scales, and the selection of features using mutual information will also improve. The mutual information measures have four different types, minimum Redundancy and Maximal Relevance (mRMR), Normalized Mutual Information Feature Selection (NMIFS), Conditional Mutual Information Feature Selection (CMIFS), and Conditional Mutual Information Maximization (CMIM). We use four databases: FERET and UND, under controlled conditions, the LFW database under unconstrained scenarios, and AR for occlusions for testing the results. The accuracy in gender classification significantly improved by the selection of features together with fusion of LBP features while compared to previously published results. By the feature selection the processing time significantly gets reduced, which makes real-time applications of gender classification feasible.**

***Index Terms*—Feature fusion, feature selection, gender classification, local binary patterns, mutual information.**

I. INTRODUCTION

The gender, age, and ethnicity are used to identify the human faces and that are crucial information of an image. Gender classification have been used in different applications, such as biometric information collection, marketing research, criminology. In an image analysis research Gender Classification is one of the most challenging problem. In a raw image data has very high dimensionality and the number of samples are very limited. Here, the accuracy efficiency and scalability are improved by using a feature selection method.

The two most popular methods are used, and they are used to reduce the dimensionality in gender classification. The two methods are (LDA) Linear discriminate analysis and (PCA) Principal component analysis. The Bing Li et al, proposed that he utilizes 6 facial components: forehead, eyes, nose, mouth, hair and clothing. The overall accuracy reached to 88.5% and 91.5% on 682 and 2183 images on 2 databases using a five-fold cross validation. We are focusing on fusion and feature selection methods based on mutual information (MI).The MI as a measure of relevance and redundancy among features. There are two approaches: exp 1and exp 2. And by comparing the information fusion from different spatial scales, with information fusion from different features types on a single scale and the accuracy also determined. Here, the use of three different types of face features to classify gender in Exp.1 based on histograms of uniform LBP features using different radii, spatial scales.

II. INFORMATION THEORY FEATURE SELECTION

In information theory we used 4 feature selection methods and to measure the uncertainly of random variables and the information theory provides intuitive tool entropy and MI are 2 critical concepts.

A. Mutual Information (MI)

The measure of uncertainly of random variables by the entropyH. Let X be a discrete random variable.
The entropy of X is:

$$H(X) = -\sum_{x\in X} p(x)\log\big(p(x)\big) \qquad (1)$$

The mutual information (MI) between two variables, x and y, is defined by joint probabilistic distribution p(x, y) and the respective marginal probabilities p(x) and p(y) as:

$$MI(x,y) = \sum_{i,j} p(x_i, y_j)\log\frac{p(x_i,y_j)}{p(x_i)p(y_j)} \quad (2)$$

(MI) Mutual information is to measure the level of "similarity" between pixels. The minimal redundancy concept is the selection of pixel pairs that are maximally dissimilar. When 2 features are highly dependent on each other the class-discriminating power would not change much, one of them were to be removed. Minimum redundancy (min WI) condition added for selecting mutually exclusive features.

$$minW_I, W_I = \frac{1}{|s|^2}\sum_{f_i, f_s\in S} MI(f_i; f_s) \qquad (3)$$

Where, s-denotes the feature subset, $|S|$-number of features in S, and is used to represent the mutual information (MI) between f_i and f_j. $MI(C; f_i)$- mutual information between features f_i and class C. The maximum relevance condition maximizes the total relevance of all features in S, $maxVI$ is used to search features that approximate the mean value of all mutual information (MI) values between individual features fi and class C .

$$maxV_I, V_I = \frac{1}{|S|}\sum_{f_i \in S} MI(C; f_i) \quad (4)$$

1) Minimum Redundancy and Maximal Relevance (mRMR):

The mRMR feature set is obtained by simultaneously optimizing the MID and MIQ. MID –Mutual information difference MIQ-Mutual information quotient. Optimizing both conditions, combining them into a single criterion function,

$$f^{mRMR}(X_i) = MI(C; f_i) - \frac{1}{|s|} MI(f_i; f_s) \quad (5)$$

where, $MI(C; fi)$ is measures the relevance of feature to be added for the output class and the term $(\frac{1}{|S|})\sum_{f_i \in S} MI(f_i; f_s)$ which estimates the redundancy of the feature f_{ith} with respect to the subset of previously selected features S.

2) Normalized Mutual Information Feature Selection (NMIFS):

It's an improved version of mRMR based on the normalized feature of mutual information (MI); and the mutual information between 2 random variables is bounded above by minimum of their entropies. The entropy feature could vary greatly, before applying this measure to the global set of feature it is normalized. The global set of feature as,

$$f^{NMIFS}(X_i) = MI(C; f_i)\frac{1}{|S|}\sum_{f_i \in S} MI_N(f_i; f_s) \quad (6)$$

where, $MI_N(fi; fs)$-normalized minimum entropy of both features,

$$MI_N(f_i; f_s) = \frac{MI(f_i; f_s)}{\min(H(f_i), H(f_s))} \quad (7)$$

3) Conditional Mutual Information Feature Selection (CMIFS):

Adding one feature at a time into a feature S subset and it built up step by step. CMIFS determines the feature redundancy. Then it decrease the probability of mistaking important features as redundant features in searching process. Let S be the set of already-selected features, and Ω the set of candidate features, $S \cap \Omega = \emptyset$ and C is the class. The next feature in Ω to be selected is the one that makes $MI(C; fi, XS)$ maximum, where

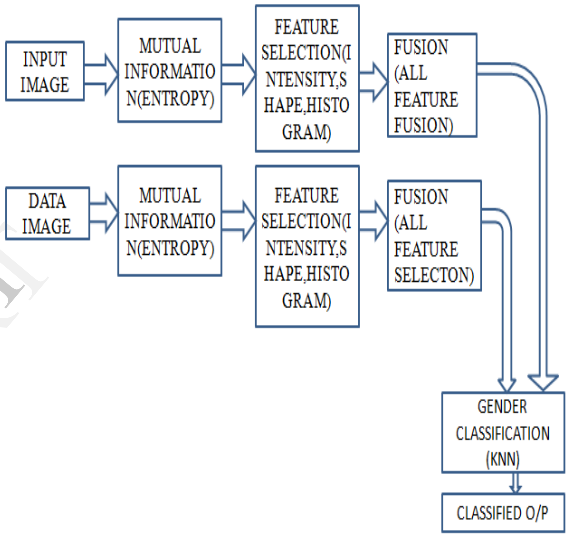
$$MI(C; f_i, X_s) = MI(C; f_i) - [MI(f_i; X_s) - MI(f_i; X_s|C)] \quad (8)$$

4) Conditional Mutual Information Maximization (CMIM):

The CMIM by considering the MI between the candidate feature variable f_i and the class C, it approximates the relevance criterion. CMIM considers only the relevant feature and it should provide large amount of information about class C and that information is not contained in any of the variables already selected. One strategy to find an optimal subset $S \subset F$, is to evaluate all possible subsets in F of cardinality d. However, this process generates a combinatorial explosion of possible solution. A greedy selection begins with the empty set of selected features and features successively adds one by one because to avoid an exhaustive search. For the first feature selection, set F represents the initial set of m features for S empty set ($S = \emptyset$). After the first iteration the set will not be empty set ($S \neq \emptyset$).

$$CMIM = \begin{cases} argmaxf_i \in F\{MI(f_i; C)\} & forS = \emptyset \\ argmaxf_{j \in f/s}\left\{min_{f_j \in S} MI(f_i; C/f_j)\right\} & forS \neq \emptyset \end{cases} \quad (9)$$

B. BLOCK DIAGRAM



III. DATABASES, FEATURE EXTRACTION AND FUSION

A. Dataset Experiment 1:

1. FERET database contains the gray scale images of 1199 individuals with different poses, with uniform illumination. From the FERET database, 199 female ad 212 male images were used.

2. UND database, the UND images was composed. Here there are set of images. The image filenames used for training and testing, the window crop around the faces, and that are available as text files. So, the images of 487 frontal face images with 186 female and 301 male images and which contains gray scale image. There are three image sizes were used (20x20, 36x36, 128x128) to compare our results.

1) Feature Extraction and Fusion for Experiment 1:

To classify gender we used 3 different types of face features. By using 3 different types of spatial scales extracted intensity, shape and texture.

Fig1. Examples of face images under unconstrained scenarios from the LFW database (top rows). Face images under controlled scenarios from the UND database (bottom row).

The gray level of each pixel which is an intensity feature. From the edges histogram the shape feature is extracted. Using the masks [-1,0,1] and $[-1,0,1]^t$ the horizontal and vertical edge values at any pixel, were obtained by convolution of the edge mask with an original image. By using $\theta = tan^{-1}((v/h))$ the edge map is found and $m = \sqrt{v^2 + h^2}$ is the edge magnitude. At 18 degree intervals the edge map is discretized. Every pixels adds the magnitude m to the binary and that corresponds to the edge direction θ. There are six possible variants for the shape and texture features at 128x128 and 36x36 and three possible variants at 20x20 and given different types of windows. For each image we choose only the best case. For all the cases we chose to use the variants with 50% overlay. For 128x128 image, the window size will be 16x16; for 36x36 image, the image size is 6x6, and for 20x20 image, the window size is 10x10. Here, we used the local binary patterns (LBP) transformation for the texture feature. LBP is gray scale texture operator. LBP operator which characterizes the spatial structure of the local image the texture. The central pixel in an image, a binary pattern number is computed and compares the value of its neighbors. So, the original LBP operator used a 3x3 window size containing 9 values and the other LBP operators were generated by changing the window size. The LBP features computed from pixel intensities in a neighborhood.

$$LBP_{P,R}(x,y) \quad = \bigcup_{(x',y')\in N(x,y)} h(I(x,y), I(x',y')) \quad (10)$$

Where, $N(x,y)$ –vicinity around (x,y), $\cup$ is the concatenation operator and P is the number of neighbors, R is the radius of the neighborhood. LBP was widely used in the face analysis, to distinguish texture features, the LBP showing the high discriminating power.

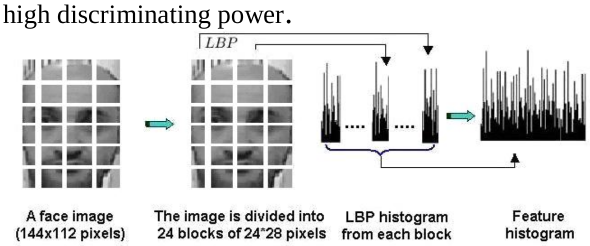


Fig. 2. Face image, divided into sub regions with the corresponding concatenated LBP histogram.

Fig2: shows the face image, divided into subregions with the corresponding concatenated LBP histogram. The LBP is uniform, it contains atmost 2 transitions from 0 to 1 (or) 1 to 0, which considered to be circular code. To obtain a reduced set of LBP features, we propose an effective feature selection method, by using the (MI) mutual information between class labels and features. From all training and testing images the LBP features are extracted. The features of LBP are organized in a matrix of DXN size, $F_{LBP} = \{f_1, f_2, \dots f_N\}$ Where, f_i- D dimensional LBP feature vector at the i_{th} pixel position. $MI(C_i, f_i)$ Mutual information - computed between the feature vector f_i for i=1, 2,….N and class C . By this it obtain the selected feature index set $S_{LBP} = \{p_1, p_2, \dots p_M\}$ by applying different feature selection methods they are (mRMR, NMIFS, CMIFS, CMIM). The LBP feature with radii from 1.8 may represent redundant patterns and the feature selection by mutual information (MI) which allows the selection of most relevant features.

Experiment 1:

The face images divided into N overlapping blocks, and for each block the LBP operator was applied by using 8-connected neighbors and radius one. For an each block, a histogram with 59 bins was created. The features selected by using mRmR, NMIFS, CMIFS, CMIM in the ranges of 50-400 for image size 20x20, 50-16,384 for size 128x128 and 50-1,296 for size 36x36. We fused the feature extraction information at the feature level by concatenating feature vectors from the different sources into a single feature vector. And that becomes the input to the feature selection methods becomes input to the classifier, and the classifiers train with selected features for each feature extraction method, and fused selected features. Fig:3. Shows there are 7 combinations of features and spatial scales. Here, L1, L2, and L3 were obtained from vertical fusion of features at different spatial scales, L4, L5, L6 are the horizontal fusion of features for different feature types, with same spatial scale. Combination of L7 includes all scales and features and the features were selected with (MI) mutual information methods, we chose windows with 50% overlap for each case. The accuracy in the FERET database 96.26% and in the UND database 86.78%, based on the shape features in the best gender classification. Intensity, Shape and texture are three features that are fused together and the three sizes of images they are 20x20, 36x36, 128x128 and the best score on the FERET database was 99.07% and 9.19% for UND database. The total number of inputs was increased nearly nine-fold by using the scales and three types of features. So, all the results were obtained by five-cross validation, simulation using an gender classifier.

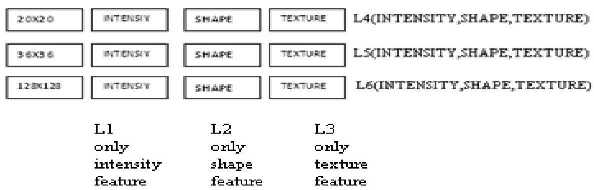


Fig. 3. Representation of the possible combinations of the three feature types (intensities, shape, and texture) and the three different spatial scales (20x20, 36x36, and 128 x128) for Experiment 1.

B. Dataset Experiment 2

LFW (Labelled Faces, in the Wild), is composed of real life faces with varying facial expressions, illumination changes, head pose variations, occlusions and use of make-up, and including poor image quality. The FERET and UND database images are of good quality and under controlled conditions, in LFW the quality significantly varies.

1) Feature Extraction and Fusion For Experiment 2:

Each face image can be composition of the micro-patterns which described by LBP. From the local regions only the LBP histograms are extracted. LBPH fusion and feature selection methods for different subwindows shifted and scaled separately in steps of 12 pixels vertically and 10 pixels horizontally i.e., (12x10) and 24x20 for last scale. So, the fusion was done among the best results of each feature selection method for 3 scales. To compare different methods, we computed the time and the computational time that depends directly on the number of inputs to the classifier. It is an important factor in real-time applications in the face processing.

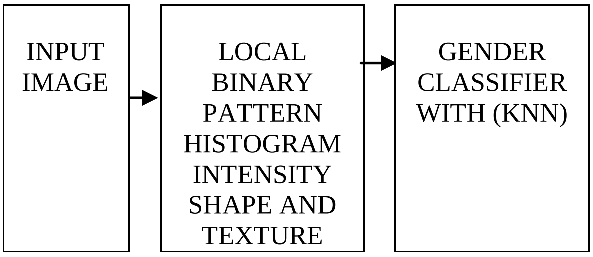


Fig:4. Diagram showing the fusion of selected LBPH features selection in Experiment 2.

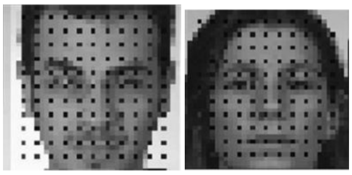


Fig:5. Two images, male and female, from the FERET database. The squares represent 1,200 selected features from L3 using mRMR which reached the best results for Experiment 1.

The fusion considers three scales for image sizes: 20x20, 36x36, and 128x128.

The squares intensities moving towards black represent an increasing number of bins selected in that area. If no square is shown the area will not select.

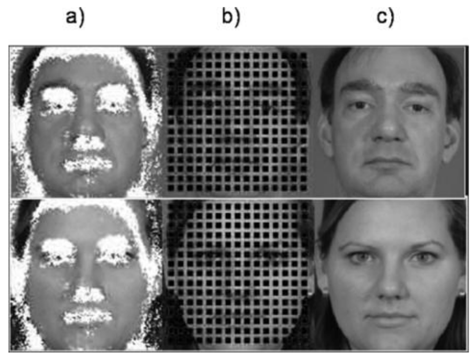


Fig 6: The selected features for best results obtained with feature selection method CMIFS.

Two images from the UND database for the L6 feature fusion with the 7,900 selected features. This method were fused the selected features from the intensity, histogram, shape and texture. The LBP in the three images of size is 128 x 128. Here, in this diagram the white pixels from a). represent the selected pixels from the intensity features, b). the squares represent the selected areas from shape features where the darker squares indicate a higher number of selected binary. C). the best result of feature fusion for the UND database with the CMIFS method.

The feature selection is performed by using the detected face, within a rectangle in sizes 20x20, 36x36 and 128x128. Here, comparing the faces with long hair and short hair, these features were contributed to differentiate between male and female.

Fig:7. Two original images, male and female, from the LFW database. The selected pixels for 300, 500, 1,000, 1,400, and 1,900 pixels are shown in white using: (a) mRMR, (b) NMIFS, (c) CMIFS, and (d) CMIM for Experiment 2.

The selected features obtained with feature selection methods a) mRMR, b) NMIFS, c) CMIFS, d) CMIM. Two images, one male and female from LFW database with 300, 500, 1,000 and 1,900 selected features on the size of 64x64 images. Here, in an image the square shows the selected area, and the black intensity increases and the number of bins selected in that area. If no area was selected, the square is white.

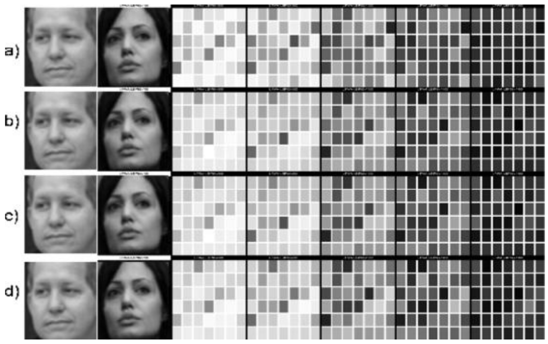


Fig. 8. Two original images, male and female, from the LFW database. Selected features from the LBPH (8, 2) histogram with 300, 500, 1,000, 1,400, and 1,900 features are shown for (a) mRMR, (b) NMIFS, (c) CMIFS, and (d) CMIM for Experiment 2. The darker the square, the larger the number of bins selected or the histogram.

After analyzing the result, it was concluded that feature selection and the fusion significantly improved the performance of the gender classification in the three databases FERET, UND and LFW the FERET databases provide good face quality.

IV. Experimental Results

NO.OF FEA.	ACCURACY	TIME
FERET	72 %	6.71%
UND	95 %	4.79%
LFW	73.5 %	8.2%

V. Conclusion

In this paper we used feature selection methods and it act as a filters which eliminates the most of the low relevance features or it eliminates the high redundancy features which provide an efficient approach and the computational time required for gender classification. The gender classification significantly improved by the feature selection by using the different spatial scales, by fusion of selected intensity, shape, texture features. The feature selection method based on (MI) mutual information, and the total number of features gets reduced depending on the image size. The FERET database get reduced at 72%, UND database get 73.5%, and 95% on the LFW database and significantly the computational time gets reduced while comparing to the previous published papers, in our paper the accuracy gets increased which makes real time gender classification gender feasible.

REFERENCE

[1] Gender Classification Based on Fusion of Different Spatial Scale Features Selected by Mutual Information From Histogram of LBP, Intensity, and Shape Juan E. Tapia, and Claudio A. Perez., IEEE transactions on information forensics and security, vol. 8, no. 3, march 2013.

[1]. Gender Classification Using Support Vector Machines Ashwin Swaminathan

[2]. Real-time Gender Classification Bo WU, Haizhou AI, Chang HUANG

[3]. Feature Selection for Efficient Gender Classification M. Nazir, Muhammad Ishtiaq, Anab Batool, M. Arfan Jaffar, Anwar M. Mirza.

[4] .Axelrod andG. Yovel, "External facial featuresmodify the representationof internal facial features in the fusiform face area," NeuroImage,vol. 52, no. 2, pp. 720–725, 2010.

[5]. C. A. Perez, C. M. Aravena, J. I. Vallejos, P. A. Estevez, and C. M.Held, "Face and iris localization using templates designed by particleswarm optimization," Pattern Recognit. Lett., vol. 31, no. 9, pp.857–868, 2010

[6]. P. A. Estevez, M. Tesmer, C. A. Perez, and J. M. Zurada, "Normalized mutual information feature selection," *IEEE Trans. Neural Netw.*, vol. 20, no. 2, pp. 189–201, Feb. 2009.

[7]. F. Fleuret and I. Guyon, "Fast binary feature selection with conditional mutual information," *J. Mach. Learning Res.*, vol.5,pp.1531–1555,2004. [8] Gender Classification of Faces Using Adaboost Rodrigo Verschae1,2,3, Javier Ruiz-del-Solar1,2, and Mauricio Correa1,2

[9] Gender Classification of Human Faces Arnulf B.A. Grafand Felix A. Wichmann[11] H. Liu, J. Sun, L. Liu, and H. Zhang, "Feature selection with dynamic mutual information," *Pattern Recognit.*, vol. 42, no. 7, pp. 1330–1339, 2009.

[10] H. Peng, F. Long, and C. Ding, "Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 8, pp. 1226–1238, Aug. 2005.

[11]. B. Jun, T. Kim, and D. Kim, "A compact local binary pattern using maximization of mutual information for face analysis," *Pattern Recognit.*, vol. 44, no. 3, pp. 532–543, 2011.

[12]. Local Binary Patterns and Its Application to Facial Image Analysis: A Survey Di Huang, *Student Member, IEEE*, Caifeng Shan, *Member, IEEE*, Mohsen Ardabilian.

[13] Z. Zhang, E. Hancock, and J. Wu, "An information theoretic approach to gender feature selection," in *Proc. IEEE Int. Conf. Computer Vision Workshops (ICCV Workshops)*, Nov. 2011, pp. 1425–1431. [22]

[14] S.-I. Choi, C.-H. Choi, and G.-M. Jeong, "Pixel selection in a face image based on discriminant features for face recognition," in *Proc. IEEE Int. Conf. Automatic Face and Gesture Recognition*, 2008, pp. 1–6.

[15] B. Li, X.-C. Lian, and B.-L. Lu, "Gender classification by combining clothing, hair and facial component classifiers," *Neurocomputing*, vol. 76, no. 1, pp. 18–27, 2012, Seventh International Symposium on Neural Networks Advances in Web Intelligence.

[16] Z. Xu, L. Lu, and P. Shi, "A hybrid approach to gender classification from face images," in *Proc. 19th Int. Conf. Pattern Recognition, 2008 (ICPR 2008)*, Dec. 2008, pp. 1–4.

[17] C. Perez, J. Tapia, P. Estévez, and C. Held, "Gender classification from face images using mutual information and feature fusion," *Int. J. Optomechatronics*, vol. 6, no. 1, pp. 92–119, 2012.

[18] E. Makinen and R. Raisamo, "An experimental comparison of gender classifications methods," *Pattern Recognit. Lett.*, vol. 29, pp. 1544–1556, 2008b.

[19] E. Makinen and R. Raisamo, "Evaluation of gender classification methods with automatically detected and aligned faces," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 3, pp. 541–547, Mar. 2008.

[20] V. Axelrod andG. Yovel, "External facial featuresmodify the representation of internal facial features in the fusiform face area," *NeuroImage*, vol. 52, no. 2, pp. 720–725, 2010.