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Gender Identification using Combination of Face and Fingerprint

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Abstract Gender Identification plays very important role in many computer applications such human robot interaction, forensic investigation, supporting soft biometric and targeted advertisement etc. Sometimes alone fingerprint cannot reveal the needed information; in such case fusion of face information with fingerprint enhances the performance of gender identification. In this paper, we have presented an approach for gender recognition using face and fingerprint. In our algorithm we have applied Uniform Local Binary Patterns (ULBP) for feature extraction and three classifiers were tested separately for classification. We have noted encouraging results during the experimentation.

Keywords — Biometric Fusion, Gender Identification, Fingerprint, Face, Uniform Local Binary Patterns, Soft Biometric

I. INTRODUCTION

Gender identification plays important role in day to day life, as many interactions in real life are gender based. Gender identification has several applications like Human Computer Interaction, focused advertising & marketing, demographic studies & forensic investigation. In addition to this, gender also considered as one of the most promising soft biometric. IT is useful in enhancement of personal identification performance in biometric system. It also helps in reducing the search space to, a particular gender only. Many attempts are made in identification of gender based on various traits such as palmprint, face, fingerprint, clothing style, gait etc. But alone unmoral system can't give confirm decision is few cases, therefore to enhance system of gender identification we proposed a methods based on combination of face & fingerprints.

Finger prints are most widely and accepted biometric trait, which becomes easily available. During fingerprint based gender estimation, if confusion occurs, then addition facial information boosts the performance & provides promising confirm result.

In this paper, we have proposed a method to identify the gender based on face & finger print biometric. This bimodal method more promising & confirmative as compared to unimodal methods reported in literature.

II. LITERATURE REVIEW

Gender identification is one of the popular problems in biometric research community, lot of works being reported in literature, few of them we have presented in below paragraphs.

Authors in [14] cross verified the advantages and limitation of the automated classification of soft biometric traits. They have created the dual datasets One is near infrared(NIR band) at night time face images and another one is face images at different distances such as 30,60 ,90 and 120 meters long, to classify the gender. They classified the gender ethnicity by using deep convolution neural network after conducting experiment they achieved significant improvement rank _ I recognition rate, compared to other system.

Authors in [15] have used Local Phase Quantization (LPQ) operators, which are nothing but taken from the intensity of the image and monogenic images to classify the gender. Total four components considered one is intensity and other three are from the monogenic images, used SVM as a classifier and compared two datasets, which are, one is LFW another one is Group dataset and achieved an higher accuracy for LFW as 97% whereas, on group dataset they got an 91.58% accuracy.

Authors in [16] classified the gender by combining clothing, hair, and facial components to recognize the gender. Authors considered mainly five components of the face. Such as forehead, chin, eyes mouth and nose. and also

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they have considered external information's such as hair of the gender and clothing of the gender, to classify the gender. SVM used as a classifier .They realized that higher accuracy or higher robustness was obtained for facial components instead of hole face image as input.

Authors in [17] proposed a method, which is nothing but combination of facial, hairstyle and clothing of the image or gender to classify the gender. In this they separated facial, hairstyle and clothing of the input images they had considered each region PCAs and GMMs values and applied Bay's rule to classify the gender and got low error rate compared input is facial only.

Authors in [18] presented periocular biometric for gender classification in the wild. They analyzed that to classify the gender periocular validity area is difficult when the input image is not face or it is blurred one or it is changed .Authors worked on group dataset. Achieved an higher accuracy of 92.46% and 20% error reduction when compared with best face based gender classification.

Author in [19] proposed MCCT as a features to classify the gender. MCCT is nothing but multichannel complementary census transform. which is texture pattern feature ,which will hold the information of the image in the sign and magnitude form of the image .these sign and magnitudes information's will be combined and used as a features to extract the image or classify the gender.

Authors in[20] presented one of the iris image to classify the gender. They have also used uniform LBP as a feature to classify THE gender. They concatenated the histogram with LBP OF the image to improve the accuracy and achieved an accuracy of 91%.

Authors in [6]proposed a multimodal estimation to classify the gender ,first they have used finger print as one modal and face information as another model .with Bayesian hierarchical model. They have used local features used to extract the gender from the input image they worked on their own dataset and achieved good results.

Authors in [7] presented a method to recognition of the gender on the basis of images from the visible and captured from the thermal camera. They conducted experiments by applying different feature extraction and fusion methods to reach highest accuracy.

Authors in [8] have proposed a combination of fuse gait and face as input to classify the gender. They have used one of the canonical correlations as a tool to correlate the two sets of measurements. And achieved an higher accuracy of 97.2%on large dataset

Authors in [9] investigated gender classification by using audio and visual cues. They have designed SVM classifier by considering visual signal as a data by taking different three types of the data one is raw data second one is PCA and third one is non-negative matrix information, and for audio pitch melcepstral coefficients are used as input data. they achieved higher accuracy for speech data as100%.whereas 95.31 accuracy for visual data.

Authors also compared the SVM with other two classifiers which are neural network and KNN . Authors in [10] worked on real word face images they have used facial local images and LBP as a features extract the gender. And these features also combined with clothing features to get increased in the accuracy rate. Authors have combined particle swarm optimization (pso) and Genetic algorithm as a one of the important features to extract the image thy achieved an accuracy of 98.3% by using SVM classifier.

Authors in [11] classified the gender by using the combination of appearance and motion of the image. They considered publically available video dataset and taken LBP as features they have also used spatiotemporal representation for describing and analyzing the image.

Authors in [12] mainly three layers to classify the gender the stages are preprocessing and alignment of the face image second one is constructed pyramid level multilevel face representation from which local features are extracted and third one is extracted features to feed to hierarchical estimator.

Authors in [13] classified the gender on the basis of multi scale local descriptors as features. And also they have used facial patch and holistic and combination of features to extract the gender they reached an 94% accuracy as compared with deep learning approach.

III. PROPOSED METHOD

Gender identification using fingerprint and face combination is main aim of this paper, to do this, our method comprises several steps such as preprocessing, Feature Extraction, Feature level fusion and Classification. Local Binary Patterns are used to encode the image information in fixed size feature vector , further in sequential manner , we have applied the feature level fusion and to determine the gender three classifiers were tested separately those are k-nearest neighbor, support vector machine and Linear Discriminant Analysis.

A. Pre-Processing

Facial images in our dataset were captured using Smartphone and therefore, before experiments we cropped facial regions manually and resized to 200* 164. Later in preprocessing we have simply attempted image enhancement operation, to balance the varying lighting conditions. To utilize contextual information like clothes, ears and hair style, the whole images are used during experimentation, instead of cropping the only facial region. First input image is converted from RGB to Grayscale, where pixels are represented in two dimensional space ranging from 0 -255 gray levels. For fingerprint we have

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resized it 164*164 and then converted to grayscale. To enhance the grayscale images Contrast limited adaptive histogram equalization (CLAHE) is applied. The advantage of this method over traditional histogram equalization is, it provides enhancement of contrast of part of the image wherever necessary. More details on CLAHE are given [4].

B. *Feature Extraction*

Feature extraction is one of the very significant processes in any computer vision applications. In our case, we have biometric traits such as faces and fingerprint. We have applied Local Binary Patterns [1], to extract the meaningful information from gray levels and encode it in single feature vector.

Local Binary Pattern (LBP) is one of the very efficient texture descriptor, it labels the pixel of an image based on thresholding operation, later post thresholding sequence of 0 and 1 considered as binary number further which is represented by its equivalent decimal. The same process is repeated for whole image. The histogram of these labels $2^8 = 256$ is used as texture descriptor. Further it can be optimized by considering only limited intervals as given in which gives only 59 descriptors.[1] Once the labeled image IL(x,y) is obtained , we can define the histogram of LBP as :

$$H_i \sum_{x,y} IL\{(x,y) = i\}, i = 0, \ldots\ldots, n-1.$$

Where n is number of labels. And IL{A} is 1 if true or 0 if false.

Feature Level Combination : In this work, we have proposed a bimodal gender identification system which identifies gender based on combination of fingerprint and face biometric. To combine the information from both the biometric traits, we have applied the feature level fusion. First Features were extracted from each image finger print and face and then later feature vector of fingerprint and face is combined in the sequential manner. After applying LBP we got 59 features from each fingerprint and face, after sequential combination it becomes i.e.59x2 = 118 dimension feature vector. The details process can be depicted from the figure give below:

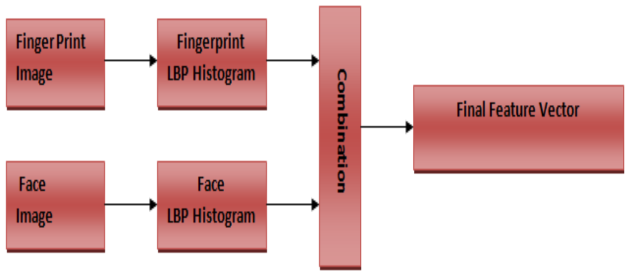

Fig 1: Feature Level combination of Face and Fingerprint Biometric

C. *Classification*

K-Nearest Neighbor is simplest classifier; it stores all training data & based on suitable distance measure, it classifies the unknown sample. The Labeling of unknown sample is done by majority of its neighbors. It assigns the label based on the class most among its nearest neighbor's.

In our case we have given Euclidian Distance to find nearest neighbor & values of k=1. Let [(c1,c2,c3……cn)] be the training samples and D[(d1,d2,d3,….dn)] be the testing samples. The Euclidian distance between A & B can be define as

$$: dist(D,C) = \sqrt{(c_i - d_i)^2}$$

Support vector Machine: In machine learning, support vector machines are supersized learning algorithm which is used popularly for classification & Regression analysis. It is developed by vapnik [ref] based on statistical learning theory SVM .The idea of separating hyper plane is used by SVM to find out separation in given 'n'data. Vector x_i.To separate data points a discriminate function is given $.g(x) = W^T \cdot X - b$; two separate each data point in one of given two classes.

$$g(x) = W^T . X_i \geq 1$$

Where y_i is the classes either +1 (male) or -1 (female) .

Linear Discriminate Analysis:

LDA is one the simplest classifier, which having ability of generalization. The class discrimination is achieved in LDA by maximizing the ratio between & within class variance.

Let consider the data set X=[x1,.xn] of 'n' samples in M dimensional space where each sample. Belongs to the either Male or Female class denoted by 'C'. The computation of Decision is given as:

$$g(x) = W^T X$$

Where W is linear projection vector which minimizes the between scatter matrix S_b

$$S_{b=\sum_{i=1}^{c} n_i}(m_i - m)(m_i - m)^T$$

And maximizes the within class scatter matrix:

$$S_{w=\sum_{i=1}^{c}\sum_{x\epsilon X} n_i}(X - m_i)(X - m_i)^T$$

Where m denotes the means, m_i is the mean over class & n_i is the number of samples in class. The optional projection based on fishers analysis is given by:

$$W_{opt} = arg_W^{max} \frac{|W^T S_b W|}{|W^T S_b W|}$$

This optimization problem can be solved by generalized eigen-problem

$$S_b = A S_W W$$

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Based on the Euclidian distance measure in LDA space in new sample x is classified to class label W € C, given:

$$w = \operatorname{argmin} d(g(x)_1, v_i) 1 \leq 1 \leq i \leq C$$

In depth discussion is given in [3].

IV. EXPERIMENTS

Dataset : In this chapter, we have prepared our own dataset, as there is no public dataset is available for bimodal gender identification. From each individual we have collected 5 faces and five fingerprints. Total 420 Faces and 420 Finger are collected from 42 males and 42 females belonging to different age groups. Face images are captured using different smart phones to make data base more challenging and fingerprints are captured using fingkey hamster device. Informed consent is taken from the volunteers while collecting the dataset.

Evaluation Protocol: Evaluation of proposed method carried out using k-fold cross validation method instead of using the traditional classification. We have divided our data in 10 sub parts and each sub part used for training - testing in such a way that, when one part serves for testing then another 9 parts are used for training. The same procedure is repeated for all 10 parts average results of 10 trials are considered as final accuracy. Addition to this, we have also computed the confusion matrices and ROC curves to exhibit the effectiveness of our method. The accuracy is defined as follows:

$$\text{Accuracy} = \frac{\textit{Correctly Classified Images}}{\textit{Total Images in Class}}$$

Results: In order to evaluate our method for gender identification using fingerprint and face biometric, we have used the large dataset of 420 images for male and 420 image for female which includes face and fingerprints. We have performed exhaustive experiments and computed different evaluation metrics such as Accuracy. Our experimental tests go as follows:

1. First we have performed experiments only with fingerprints with LBP features and recorded performance of all three classifiers for gender identification.
2. Second, combination of face and fingerprint is considered for the gender identification and feature level fusion is done in sequential manner.

In table 4.1, we have shown the results of gender identification using only fingerprints, we have evaluated three classifiers namely k-NN, Linear Discriminant Analysis, Support Vector Machine. The highest accuracy of 89.60% is recorded with k-NN classifier. LDA has given an accuracy of 77.10%, whereas 76.00% of accuracy is given by SVM while considered only fingerprints for gender identification.

In table 2. we have shown the results with combination of fingerprint and face biometric. In this experiment also, we have evaluated the performance of three different classifiers such as k-NN, SVM and LDA. It is noted that the accuracy increased considerably when facial information is added to fingerprints. Support Vector Machine and Linear Discriminant Analysis performed effectively and yield the accuracy of 100%. On the other hand k-NN has given 99 % accuracy with Euclidian distance and K=3. Finally comparison between accuracies for fingerprint and alone in combination with Facial information is given in figure. From the investigations during our experiments, it is proved that the combination of facial information given superior performance than alone fingerprint.

Table 1 : Gender Identification Accuracy using only fingerprints

Sr No.	Classifier	Accuracy in %
1	k-NN Classifier	89.60
2	Linear Discriminant Analysis	77.10
3	Support Vector Machines	76.00

Table 2 : Gender Identification Accuracy using both face and fingerprint biometric

Sr No.	Classifier	Accuracy in %
1	k-NN Classifier	99
2	Linear Discriminant Analysis	100
3	Support Vector Machines	100

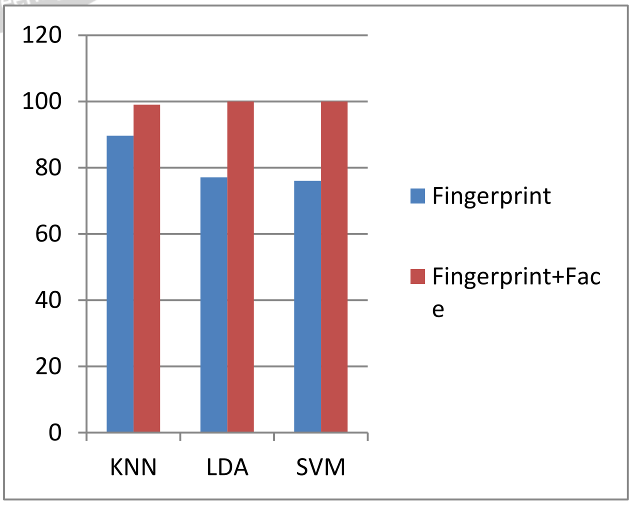

Figure 1: Performance of fingerprint alone and fingerprint + face for gender identification

V. CONCLUSION

In this paper, combination of biometrics for gender identification is investigated with feature level fusion

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approach. We have presented a gender identification system based on fusion of face and fingerprint biometric. During our experiments, we have noted that alone fingerprint cannot reveals the gender information; in such case addition of facial information would be the best choice, this results in enhancement of system. This proposed system is tested on considerably large dataset of 420 faces and fingerprints and we have achieved promising results with the accuracy of 100%. In future, we will focus on improvement of the system by considering the rotation, translation and scaling transformations. Further we will also study the cross database performance of our method for gender identification.

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