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Fingerprint Based Gender Classification Using Local Binary Pattern

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Abstract

Gender classification from a fingerprint is an crucial step in forensic anthropology which plays a vital role for criminal identification which minimizes suspects searc list. A fingerprint biometric trait is one of the important traits working with good results in gender classification and identification. In this research work, local texture features are used for detection and classification of gender knowledge using fingerprints. As an experiment 400 real fingerprints were collected from different age groups of urban and rural people. An experimental observation is 95.88 % of classification rate is succeed using features of local binary pattern. The work has been analyzed and the results reported in this are found to be satisfactory and more competitive.

Index Terms: Gender Classification, Local Binary Pattern (LBP), Local Structure Pattern (LSP), Local Texture Features.

I. INTRODUCTION

In various fields of practical application grouping of gender is composit problem for identification of a person. For example, by using demographic information for seeking worthy consumer statistics in shopping centre, a robust gender classification system can provide a base or foundation for performing passive surveillance, through which performance of biometric systems can also be improved like authentication and recognition. In biometric, majority of studies are based on face recognition since it provides important clues with visual information from human faces for gender classification. On the basis of various information obtained from the fingerprints the identity along with gender age and ethnic can be processed. By noticing deference's in match scores, image quality and texture the impact of gender in fingerprints images is checked first then automatic age and gender estimators for fingerprints is proposed. A final action is taken based on comparison of its features. Hence, a generic biometric system can be focused on four main major modules: A sensor module; a quality assessment and feature extraction module; A match matching module; Database module.

In our model three categories of features are extracted (*i*)image quality, which is captured as ridge strength and based on energy concentrated pertained to forth different frequencies is completed and estimated. *ii*) image texture, captured by the Local Binary Pattern (LBP) descriptors with optimized division of the whole image in sub-regions; *iii*) characteristics related to the extractability of features (e.g., ridge bifurcation count, contrast, etc.). Due to simple computational calculation with impressive classification on texture database representation LBP methods have gained its popularity. Effective texture operator of LBP has proved to be invariant to monotonic gray scale transformations. Hence to facilitate more precise description of local structures, in the work we have proposed different frame works at local structure pattern (LSP).Completed LSP (CLSP), Robust LSP (RLSP), Completed Noise-invariant LSP (CNLP) and Completed Noise-invariant Global-structure Pattern (CNGP). Utilizing local and global intensities and image contrast information the patterns are coded in LBP with computed threshold. To represent the texture of an image, the classical CLBP frame work is used to combine LBP histogram different patterns into a signal histogram. As the values of the centre pixel the proposed patters are more robust to noise [2,20].

In this work, local binary pattern features are used to extract the gender information for classification of male and female using fingerprints. The local binary pattern features were extracted and classified using K-NN classifier. The rest of the paper is organized as follows: the section-2 gives the outline of the related work. Section-3 gives the proposed methodology and algorithm. Section-4 will gives an analysis and discussion of the experimental work followed by the conclusion and future work in section-5

II. LITERATURE REVIEW

Acree M. [1] has presented a study whose aim is to determine if women have significantly higher ridge density, hence finer epidermal ridge detail, than men by counting ridges that occur within a well-defined space. If significant gender differences do exist then the likelihood of inferring gender from given ridge densities will be explored. Their study focused on 400 randomly picked ten - print cards representing 400 subjects. The demographic composition of this sample population represents 100 Caucasian males, 100 African American males, 100 Caucasian females and 100

African American females all within the age range of 18 - 67. Results show that women tend to have a significantly higher ridge density than men and that this trend is upheld in subjects of both Caucasian and African American descent ($F = 81.96$, $P < 0.001$). Application of Bayes' theorem suggests that a given fingerprint possessing a ridge density of 11 ridges/25 mm 2 or less is most likely to be of male origin. Likewise a fingerprint having a ridge density of 12 ridges/25 mm 2 or greater is most likely to be of female origin, regardless of race.

Ahmed Badawi, et al,[3] have proposed a Gender classification from fingerprints, which is an important step in forensic anthropology in order to identify the gender of a criminal and minimize the list of suspects search. A dataset of 10 - fingerprint images for 2200 persons of different ages and gender (1100 males and 1100 females) was analyzed. Features extracted were; ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, and ridge count asymmetry, and pattern type concordance. Fuzzy - C Means (FCM), Linear Discriminate Analysis (LDA), and Neural Network (NN) were used for the classification using the most dominant features. They obtained results of 80.39%, 86.5%, and 88.5% using FCM, LDA, and NN, respectively.

Manish Verma , et al,[5] have proposed a method for Gender classification from fingerprints. Features extracted were; ridge width, ridge thickness to valley thickness ratio (RTVTR), and ridge density.SVM is used for the classification. This method is experimented with the internal database of 400 fingerprints in which 200 were male fingerprints and 200 were female fingerprints. They found male - female can be correctly classified up to 91%.
Jen feng wang, et al,[6] have worked on gender determination using finger tip features. He obtained fingerprints from 115 normal healthy adults in which 57 were male fingerprints and 58 were female fingerprints. They have used ridge count, ridge density, and finger size features for classification. However, the ridge count and finger size features of left little fingers are used to achieve a classification. The best classification result of 86% accuracy is obtained by using ridge count and finger size feature together.

Ramanjit Kaur, Rakesh K. Gargin [7] with their study provided an aid for the fingerprint examiner in analyzing fingerprint samples as it shows that there is a significant difference in epidermal ridge density between males and females of the two populations. Their study has been carried out to examine ridge density differences in two Northern Indian populations (Sikh Jat and Bania). In their study it has been found that 92% of Sikh Jat females have a mean ridge density above 13, whereas 76% of Sikh Jat males have (a mean ridge density) below 13, while in Bania, 100% of females have mean ridge density above 14 and 80 % of males below 14. The study suggested that there are significant differences in epidermal ridge density between males and females within each of the two populations, and also significant differences between the two populations.

Dr. Prateek Rastogi, Ms. Keerthi R Pillai,[8] have presented that there is an association between distribution of fingerprint patterns, blood group and gender. This prospective study was carried out over a period of 2 months among 200 medical students (100 male & 100 female) belonging to the age group 18 - 25 of Kasturba Medical College, Mangalore, India. Results show that each finger print is unique; loops are the most commonly occurring fingerprint pattern while arches are the least common. Males have a higher incidence of whorls and females have a higher incidence of loops. Loops are predominant in blood group A, B, AB and O in both Rh positive and Rh negative individuals except in O negative where whorls are more common. Thus, they concluded that there is an association between distribution of fingerprint patterns, blood group and gender and thus prediction of gender and blood group of a person is possible based on his fingerprint pattern.

Gnanaswami P, et al., [9] have proposed a method for Gender Identification Using Fingerprint through Frequency Domain Analysis to estimate gender by analyzing fingerprints using fast Fourier transform (FFT), discrete cosine transform (DCT) and power spectral density (PSD). A dataset of 400 persons of different age and gender is collected as internal database. Frequency domain calculations are compared with predetermined threshold and gender is determined. They obtained the results of 92.88 % and 94.85 % for male and female respectively.

Gnanaswami P, et al.,[11] have proposed a method for Gender Classification from Fingerprint based on discrete wavelet transform (DWT) and singular value decomposition (SVD). The classification is achieved by extracting the energy computed from all the sub-bands of DWT combined with the spatial features of non-zero singular values obtained from the SVD of fingerprint images. K nearest neighbor (KNN) used as a classifier. This method is experimented with the internal database of 3570 fingerprints finger prints in which 1980 were male fingerprints and 1590 were female fingerprints. They obtained Finger wise gender classification which is 94.32% for the left hand little fingers of female persons and 95.46% for the left hand index finger of male persons. Gender classification for any finger of male persons tested is obtained as 91.67% and 84.69% for female persons respectively. Overall classification rate is 88.28% has been obtained.

RituKaur et.al, [12] have worked on fingerprint based gender identification using frequency domain analysis. The classification is achieved by analyzing fingerprints using Fast Fourier transform (FFT), Discrete Cosine Transform (DCT) and Power Spectral Density (PSD). A dataset of 220 persons of different age and gender is collected as internal database. Frequency domain calculations are compared with predetermined threshold and gender is determined. They obtained results of 90%, and 79.07% for female and male samples respectively.

Rijo Jackson Tom, et al, [13] have proposed a method for Fingerprint Based Gender Classification through frequency domain analysis to estimate gender by analyzing fingerprints using 2D Discrete Wavelet Transforms (DWT) and PCA.A dataset of 400 persons of different age and gender is collected as internal database. They have used minimum distance method for classification and achieve overall success rate in gender classification of around 70%.

Philominal Divya, et al, [14] have proposed an image indexing and retrieval algorithm using local tetra texture features. The four direction code called local tetra pattern (LTrPs) for CBIR method encodes the relationship between reference and neighbours pixel in vertical and horizontal directions.

Heena Agarwal et al,[15] have worked on fingerprint based gender classification using multi class SVM. Ridge thickness, ridge density to valley thickness ratio(RTVTR) and ridge measurement is used for gender detection using multi class SVM as classifier which overcome the problem of SVM(binary classifier).

Ganesh B. Dongre, et al,[16] have proposed a review and study on fingerprint based gender classification using classified frequency domain analysis and spatial domain analysis techniques using FFT,DCT and PSD features are used and extracted the results of 88% for female and 78% for male for rural and urban peoples.

Emanuela Marasco, et al.,[17] proposed method Estimate Age and Gender from fingerprints by Exploiting Quality and Texture Features. Features extracted from Frequency Demine, Local Binary Pattern and Local Phase Quantization. A dataset of 494 users with left slap, right slap and thumbs slap fingerprints were collected. The results obtained 89.1% and 88.7% for age and gender respectively.

S S Gornale et al,[18] have worked on gender classification using fingerprints based on support vector machine(SVM) with 10-cross validation techniques. An 89% and 91% classification rate is achieved for DWT using SVM(RBF sigma) and SVM(polynomial) using SVM classifier respectively.

S S Gornale et al, [19] have worked on Heralick features descriptors for gender classification using fingerprints: A machine learning approach. In this work Heralick features are extracted and obtained the result of 92% and 94% classification for male and female for linear Discriminant analysis and Quadratic Discriminant analysis classifiers respectively.

According to above literature review it is observed that many number of researchers have worked on fingerprint based gender classification using different approaches and forecasted some promising results with their dataset. But still there is a scope for developing robust algorithm using different parameter like age, characterization on rural and urban people. And also different robust features are required to get more accurate results to increase the rate of gender classification.

III. PROPOSED METHODOLOGY FOR GENDER ESTIMATION FROM FINGERPRINTS

The general steps involved in the gender estimation from the fingerprints are as shown in below figure-1.

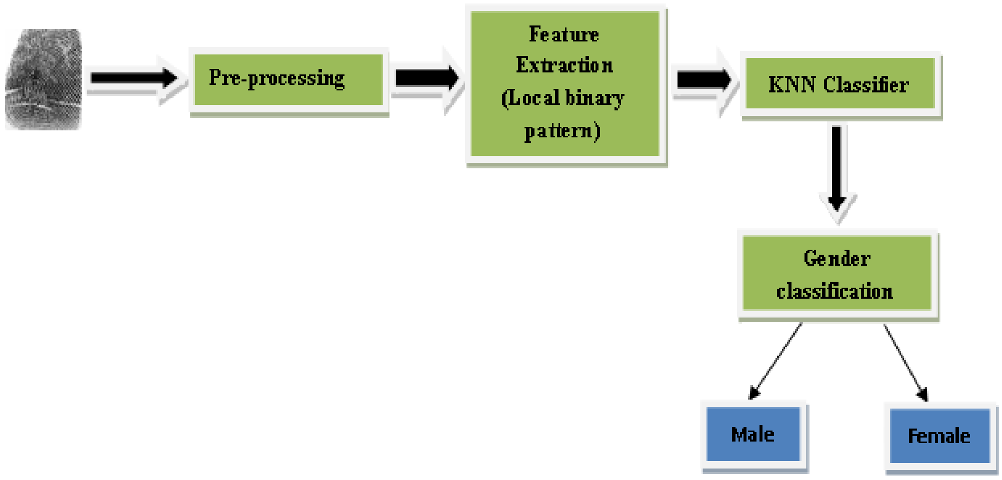

Fig-1: The general block diagram for gender classification

A. Fingerprint acquisition

By considering course of research study no separate standard fingerprints database is available for male and female. For an experiment we have collected a data set of 400 fingerprints of different age groups from different rural and urban area were collected which is acquired using "Finkey hamster 2nd" scanner manufactured by Nitgen biometric solution (30 with interface USB 2.0).A captured image is changed into 512 DPI in gray scale of 156x156 pixels for better accuracy and performance.

B. Pre-processing

After acquiring the images, the initial step is to do pre-processing, which are application dependent. Fingerprint images are preprocessed such as background elimination, cropping, converting color images into binary image etc., which increases the computer efficiency and saves the memory.

C. Feature extraction and computation

A Textured area in an image is characterized by a non-uniform spatial distribution of image intensities. A Color image also contains the textures. We limit ourselves to grey scale images. The texture descriptor models are classified into three main classes.

- Pixel based models: In this model texture is described by statistics of the distribution of grey levels of intensities in the texture.
- Local feature based model: In this model statistics are computed with respect to the distribution of local features such as edges or lines.

- Region based model: In this model the texture is segmented into the regions and then statistics on the shape and spatial arrangement of regions are used to characterize the texture.

In this work is based on local texture features four different methods.
- Rotation-Invariant Uniform Local Binary Patterns (RIU-LBP)
- Completed Local Binary Patterns (CLBP)
- Co-occurrence of Adjacent LBPs (Co ALBP)
- Rotation-Invariant Co-occurrence of Adjacent LBPs (RIC-LBP)

Mainly, in this work, rotation invariant uniform local binary patterns (CRIV-LBP) method is used extracting features using K-NN classifier for gender classification. When the bit pattern is traverse circularly, it does not contain more than two bitwise transitions form 0 to 1 or vice versa then it is called uniform binary patterns. Comparing to others texture description uniform patterns are found to be very predominant. Therefore, uniform patterns are used to produce compact rotation invariant LBP feature vectors. This work concatenates three histograms with different scales of LBP neighbourhood, for obtaining feature vector of dimension 42.

D. Local binary pattern
In local binary pattern the shape and texture of digital image features are extracted by dividing image into several regions.[2], [20]. The original LBP operator works with eight neighbour pixel, using centre pixel as threshold. If neighbour pixel has higher gray value than centre pixel then a “1” is assigned to that pixel, else it gets ‘0’. LBP code for centre pixel is produced then by concatenating light ones or zeros to binary code (Fig 3)

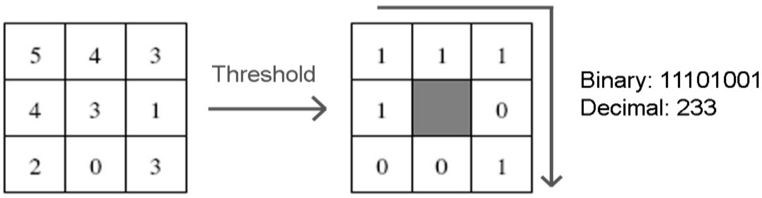

Fig 2: An example for neighbour pixel representation using Basic LBP operator

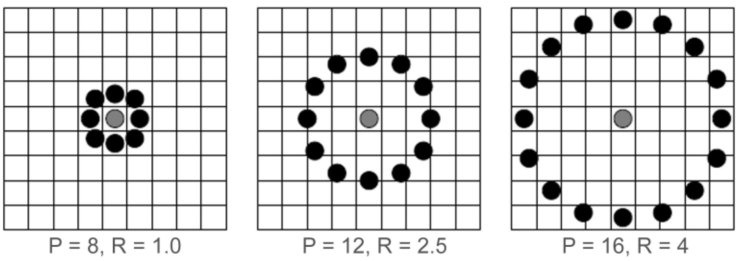

Fig 3: An example for Extended Local Binary Pattern operator with circular neighbourhoods of (8,1), (12,2.5), and (16,4).

For the different sizes LBP operator extends the use of neighbourhoods lastly. And circle is made with radius R from centre pixel on the edge of circle sampling points ‘P’ are compared with the centre pixel value. To get sampling points values of the neighbourhood for any radius and any number of pixels (bilinear) interpolation is required (P,R) notation is used for neighbourhood. For different values of P and R, three neighbour sets give the explanatory in fig. 3

If the coordinates of the centre pixel (x_c, y_c) and co-ordinates of its P neighbours (x_p, y_p) on the edge of the circle with radius R is calculated with sinus and cosines:

$$x_p = x_c + R\cos(2\pi p/P) \quad \text{--}1\text{ (a)}$$
$$y_p = y_c + R\sin(2\pi p/P) \quad \text{--}1\text{ (b)}$$

The gray value of center pixel g_c and gray values of its neighbours are g_p, with P= 0,......, p-1, then texture T in local neighbour pixel (xc, yc) can be defined as

$$T = t(g_c, g_0, \ldots, g_{p-1}) \quad \text{--}2$$

The obtained values subtracting the centre pixel from values of circle points describes the texture, which is represented as joint distribution values of centre pixel and its defences.

$$T = t(g_c, g_0 - g_c, \ldots, g_{p-i} - g_c) \quad \text{--}3$$

Overall luminance of image is described by t(gc), which is not related to local image texture, and does not necessarily useful knowledge for texture analysis. Hence much informational of textural characteristics in original join distribution (eq.3) is preserved in joint difference distribution.[2].

$$T = (g_0 - g_c, \ldots, g_{p-1} - g_c) \quad \text{--}4$$

The differences are influenced by sealing even though invariant gray scale shifts. With respect to any monotonic transformation of the gray scale to achieve invariance, only signs of difference are considered. It means point on the circle has higher gray value than centre pixel (or same value), in that case, where ‘1’ is assigned to that point, else it gets ‘0’

$$T = (s(g_0 - g_c), \ldots, s(g_{p-1} - g_c)), \quad \text{---------------------------------------}5$$

Where

$S(x)=1$ when $x \geq 0$

$S(x)=1$ when $x<0$

In the last step to produce the LBP for pixel (x_c, y_c) a binomial weight 2^p is assigned to each sign $s(g_p - g_c)$. These binomial weight are summed:

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{p=1} s(x_c - y_c)\, 2^P \text{--------------------------------------}6$$

The local image texture is characterized around (xc ,yc) by the local binary pattern. In the figure 3, the original LBP is very similar this operator with P=8 and R=1 thus LBP.

The main difference between operators is that LBP the pixels first need to be interpolated to get point values on the circle.[10], [20].

E. Feature classification

For the gender classification K-NN classification is used, K-nearest neighbour algorithm (K-N N) classifiers the objects of training samples which are closest in features space. An object is classified by vote of neighbours in majority; with the assigned objects which are most common class among its K nearest neighbours (K is positive integer which is typically small). The object is assigned to the class to its nearest neighbour when K=1, which is thought of by training set of algorithm, with no explicit training step. In the final classification phase, fused feature vector of fingerprint input is compared with feature vector in the database by using K-N N classifier.

IV. EXPERIMENTAL ANALYSIS AND DISCUSSION

In this section the performance of gender classification algorithm is verified by using internal database collected. A real 400 fingerprints were collected and conducted experiments on 240 samples, 120 male and 120 female fingerprints are trained and tested. The K-NN classifier was used for gender classification.

Proposed Algorithm:

Input - Fingerprint image

Output - Classification of male and female fingerprint images using success rate by K-NN classifier.

Step1 -The fingerprint undergoes pre-processing i.e. noise removal, cropping etc.

Step2 - The fingerprint is converted into gray scale image.

Step3 - The gray scale image is normalized to 156x156 and defines matrix co-occurrence.

Step4 - The local binary pattern statistical features were extracted.

Step5 - Apply K-NN classifier and find the class of the unknown fingerprint by using the database generated in LBP.

End of algorithm.

Table-I: LBP test run summary

Number of Trained Images	400
Number of Test Images	240
Number of correct recognition	235
Number of failed recognition	5
Classification accuracy rate	95.88%

V. CONCLUSION AND FUTURE WORK

Fingerprint evidence is undoubtedly the most reliable and acceptable evidence till date in the court of law. Due to the immense potential of fingerprints as an effective method of identification, in this work we have proposed a new method for gender classification of fingerprint images based on LBP and KNN classifier. By the proposed method, the gender classification rate achieved is 95.88% for fingerprint images of male and female. Our future work is to extend the proposed method of gender classification using the spatial parameters. Also, it is aimed to use various other techniques to increase the success rate.

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