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Fusion of Features and Synthesis Classifiers for Gender Classification using Fingerprints

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Abstract— the objective of this work is to study the impact of feature level fusion and synthesis of classifiers for gender classification using fingerprints. Initially, feature level fusion of Multi-Block Projection Profiles features and Segmentation based Fractal Texture Analysis (SFTA) features are extracted for a single instance of fingerprints. Further, along with the feature level fusion and synthesis of classifiers on fingerprint have been piloted and the experiments are conducted accordingly on four different Homologous fingerprint databases. The results reveal that feature level fusion with synthesis of classifiers greatly improves the efficiency of gender classification over the non-fused and single classifier and outperforms the earlier reported techniques.

Keywords— Gender Identification, Biometrics, Fingerprint, SFTA, MBPP, KNN,SVM and Decision Tree classifier.

I. INTRODUCTION

Identifying human's gender based upon their biometric traits, such as fingerprint [14][15][18][19][20], palmprint[12], face[28], gait[6], iris[8] and voice[10] plays a vital role in forensics application[16] and has now become an important area of research in biometrics. Now-a-days e-security is in acute need of finding accurate, secure and cost effective alternative to password and personal identification. Undoubtedly fingerprint biometrics is one of the most reliable and viable solution for all these problems. A person's fingerprint data is distinctive [1] and cannot be relocated. An advantage of using the fingerprint is that it cannot be lost or elapsed. A fingerprint is one of the decisive biometric traits [23], which has gained a lot of popularity because of their high authentication capabilities and gender identification. But a very few amount of work has been carried out with regard to finding gender information using it. Subsequently, gender classification problem [17] using fingerprint as a trait is matured to some extent, but there is still scope for development with more generic and generalized algorithm.

Fusion is generally a good practice for all the applications for improving the efficiency, robustness and applicability of the system. From the literature, it is witnessed that there are four different levels of fusion [11] they are; match score level, sensor level, feature level and classifier level fusions. Among four levels of fusion our aim is to use the feature level fusion and the synthesis of classifiers to address the issues of gender identification using fingerprints. In general, there are two types of classifier fusion possible: Fusion of multiple relative weak classifiers and building a single sophisticated classifier. Another approach is combining the multiple classifier decision outputs. This alternative is simple yet a powerful approach that helps increasing the performance rate. Likewise, Feature level fusion is generally computed by concatenation rule where feature vectors are concatenated, which yields a new feature vector.

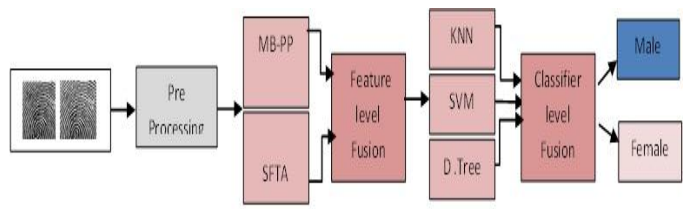
Currently, many application areas have adopted the fusion of features and fusion of classifiers, such as image recognition [25], radar emitter recognition [26], medical diagnostics [27] and face recognition [28]. In this work, a feature level fusion of Multi-block Projection Profile features and Segmentation based Fractal Texture Analysis features are computed. Further involved in the fusion of binary classifiers, are K-Nearest Neighbor, Support Vector Machine and Decision Tree classifiers. The result demonstrates that our approach outperforms the earlier reported techniques. The rest of the paper is organized as follows: section 2 contains earlier work; section 3 is focused on the proposed work. Section 4 explains the classification and in section 5 experimental results are discussed and finally the conclusion is drawn in section 6.

II. RELATED WORK

In this section we have compared the proposed work with similar works found in literature. Gnanasivam .P et al.[2] have performed fusion of Fast Fourier Transformation, Discrete Cosine Transformation features on 400 fingerprint database out of which 200 are male and 200 are female, with threshold based Singular value decomposition and an accuracy of 94.8% is obtained. Pragya Bharti et al.[7] have recognized and implemented 5 level of Haar decomposition over smaller dataset of 300 fingerprint images which have been classified using neural network and an accuracy of 91.3 % is yielded. Akanchha Gour et al. [3] have implemented fusion of features like Discrete Wavelet and Discrete Cosine Transformation technique over a very few images based on the dataset of 100 fingerprints and by utilizing KNN classifier an accuracy of 90% is obtained. Similarly R Jackson et al.[12] have performed Discrete Wavelet transformation based principal component analysis technique over smaller database of 400 fingerprint images ,over which they managed to obtain an result of 70%. A. S. Falohun et al. [5] developed a system which is implemented on 280 fingerprint images using discrete wavelet transformation which are trained by back-propagation neural network and attained a classification accuracy of 80%. Similarly Prabha et al.[21] have used multi-resolutional statistical features on 740 fingerprint database images by using back-propagation neural network and an accuracy of 96.6% is noted. Manish Verma et al. [9] employed ridge based density feature for experimentation on database of 400 fingerprints using SVM classifier and 89% accuracy is attained. Pallavi C et al.[13] have implemented fusion of FDA and 2D DWT features on a smaller dataset of 100 fingerprint images, further by KNN classifier classification rate an accuracy of 80% is obtained. S. F. Abdullah et al [4] implemented a methodology to extract ridge density, ridge thickness to valley thickness ratio and white lines count features from relatively larger dataset of 1430 male fingerprints and 1570 female fingerprints which have further been trained and fed to Multilayer Perceptron Neural Network classifier and an overall accuracy of 96.25% is obtained. S.S Gornale et al. [15] have utilized Haralick texture descriptor on a dataset consisting 740 fingerprint images and the performance of the system is noted to be 94%. S.S Gornale et al. [20] utilized Local binary pattern features on dataset consisting 740 fingerprint images and further by using KNN classifier obtained an accuracy of 95.8%. S.S Gornale et al. [19] have performed feature level fusion of discrete wavelet transformation along with Gabor Wavelets on a dataset consisting of 740 fingerprint images and by Quadratic discriminant analysis classifier obtain an accuracy of 97%. S.S Gornale et al.[30] have performed feature level fusion of local binary pattern along with local phase quantization on two datasets i.e. publicly available SDUMLA-Fingerprint dataset and other is self- created dataset. Further by using support vector machine classifier they obtained an accuracy of 84.13% and 97.0% respectively. From the literature it is observed that there are certain limitations reported in the prior work because they have implemented their experimental setup on very compact and a limited database.

III. PROPOSED METHODOLOGY

Gender classification using fingerprint biometrics generally involves three steps namely pre-processing, feature-extraction and classification. The initial task is to perform pre-processing which is application dependent. Feature computation step, which deals with the extraction of textural information using fusion of multiblock Projection profile and SFTA. Then the method is evaluated with different binary classifier and further, synthesis of classifiers is carried out. The flow chart of proposed methodology is represented below in figure 1.



A. *Pre-processing*

In this step, each fingerprint image of the above-mentioned datasets is normalized for better feature extraction. The images are de-noised and resized to 240 x 240 size and finally contrast limited adaptive histogram equalization (CLAHE) is applied to enhance the quality of the images.

Fig. 3**.** (a)Input Fingerprint (b) Binarized Image (c)Scaled Image

B. *Feature-Extraction*

In this work, two local textural feature-extraction methods namely Multi-Block Projection Profile features and SFTA features are computed.

1) *Multi-Block Projection Profile(MB-PP)*

Projection Profile is used to store the number of non-background pixel, when it is projected over the normal X-Y plain of a I image which may be represented as

$$X , Y = I(x, y) \tag{1}$$

Here each cell of the projection vector is associated with a number of pixels of the background. A Projection Profile is a histogram of number of black pixel values gathered parallel in an image which may be denoted by:

$$PP(I) = \sum_{1 \le y \le n} F(x, y) \quad (2)$$

Where x and y are rows and columns for any image. The fingerprint image is successively, split into r x r non-overlapping sub-blocks that are individually equivalent in self-representing, blocks like: Sblock1, Sblock2….Sblockn(r x r). Likewise, we have obtained non overlapping r x r sub-blocks for each fingerprint image here S is the size of a fingerprint image. Further, on each sub-block horizontal projection profile feature extraction is performed by using the equation-2. Features are calculated by alternative runs of either black or white pixels, added by all column-wise white pixels skipping all alternative black pixels. Finally, resulting features from each sub-block are integrated and stored in the form of feature vector for a fingerprint image. The computed feature vector contains 9 features from each male and female fingerprint images.

2) Segmentation based Fractal Texture Analysis (SFTA)

In this work, the applicability of the fractal dimension on fingerprint image is explored. The fractal dimension theory was originally developed by Mandelbrot [29] for identifying the objects with irregular, broken or fragmented shapes. Generally fractal dimension (FD) is determined by the following equation

$$FD = \lim_{\varepsilon \to 0} \frac{\log(N(\varepsilon))}{\log\left(1/\varepsilon\right)} \quad (3)$$

Where N (∊) is the number of specimen of the initial objects, (1/∊) is the scale factor and FD is obtained by a least square regression method. SFTA feature extraction is split into two parts. Firstly, input image is decomposed into the set of binary images by Two Threshold Binary decomposition (TTBD). The TTBD takes an input image and yields a set of binary images. By computing the T threshold values that minimizes image intra class variances.

$$IB_{(x,y)} = \begin{cases} 1, if\ .T_L < (x,y) \le T_U \\ 0, Otherwise \end{cases} \quad (4)$$

Where IB is a binary image, I(x, y) is input image, T_L and T_U are lower and upper limit threshold values. Secondly, SFTA feature vector is created by calculating binary image size (pixel count) and mean grey level and the limits by computing fractal domain (FD) given by equation-3 and 4. The Mean grey level value and size (pixel count) are complementary information calculate and extracted without increasing the computational time. The SFTA operator computes 45 features from each male and female from fingerprint images. Further, these features are used to train and test the method using basic classifiers with 10 folds cross-validation.

3) Feature Fusion

In the feature level fusion technique given a fingerprint image di of size m*n, with a suitable set of feature using say k feature extraction technique are extracted say{f1,f2…..fk} where internally fi={fi1.fi2…..fij}.j being the number of features obtained. The features extracted using k feature extraction techniques are fused together using concatenation rule and then fused features are fed to appropriate classifiers for classification.

In this work, we have employed two feature extraction techniques i.e. MB-Projection Profile and SFTA descriptors. The combined feature vector is computed features from MB-Projection Profile operations i.e.9 features which are fused with 45 features of SFTA and final feature vector is generated by concatenation rule. Thus, the final feature vector contains 54 features obtained from each male and female fingerprint image. Further, these features are stored and are used to train and test the system to classify male and female based on the subject's fingerprints. For the evaluation, the system is trained with different parametric and non-parametric classifiers individually and the classifiers are synthesized to check robustness of the algorithm

IV. CLASSIFIER

K-Nearest Neighbour classifier will classify the class label based on measuring the distance between testing and training data. KNN [22] will classify by suitable K value and interns which finds the nearest neighbour and provides a class label to un-labelled. Depending on the types of problem, a variety of different distance measures can be implemented. In this work, City-block distance is considered with K=3 which is empirically fixed throughout the experiment. Basically, K-NN is non-parametric which finds the minimum d distance between training sample M and testing pattern N using the following equation:

$$D_{CityBlock}(M,N) = \sum_{J=0}^{n} \left| M_J - N_J \right| \quad (5)$$

Support Vector Machine It attempts to search for an optimal hyperplane which separates the classes from a set of n data vectors say Yi .In the particular instance, a discriminant function: F (X) = WT .Y − b split up each data item into 2 classes. In our experiment Yi yields the results of male (+1) or female (0).

$$f(x) = WT.Y_i - b \ge 1. \quad (6)$$

Decision tree Classifier: In a decision tree the attributes are examined by non-leaf nodes on account of which multiple branches are framed. While constructing the decision tree the main step is to determine which attribute is to be examined and which of many possible tests based on attribute values should be performed. A partition of the n distinct values of the attribute induces a partition of the examples. The class impurity of the examples in each branch is computed, weighted, summed and assigned to the given partition. An n by k contingency matrix can be used to compute the impurity measure for each partition that is considered. The Gini diversity index impurity is measured using the following equation

$$gdi = 1 - \sum_i p^2(i) \quad (7)$$

Where i is number of classes at the node, p (i) is the observed fraction of classes with class i that reach the node.

a) *Synthesis OF Classifiers*

A single classifier is always used in a traditional pattern recognition problem, but it is quite obvious, when the members of classifier are diverse and uncorrelated, the multiple classifiers potentially offer better results than single classifiers. The synthesis mechanism can be implemented generally by two types: building a single sophisticated classifier by fusing multiple relative weak classifiers another way is fusing the classifier outputs of different classifiers.

Voting Strategy is implemented for several classifier systems assuming that each of the classifier gives a single class label as an output. There are a number of approaches to synthesize the classifiers which lead to a generalization of voting criteria. The output of the classifiers which form a decision vector d, is defined as d= [d1,d2,...dn]T where d1,d2…dn belongs to c1,c2,…cn and which denotes the label of ith class and is defined as

$$B_j(c_1) = \begin{cases} 1, if\ ..d_j = c_1 \\ 0, if\ ..d_j \neq c_1 \end{cases} \quad (8)$$

The voting Strategy can be defined as:

$$E(d) = \begin{cases} 1, \\ 0, \end{cases} if \forall_{t \in \{1...m\}} \sum_{j=1}^{n} B_j(c_i) \leq \sum_{j=1}^{n} B_j(c_i) \geq \alpha.m + K(d) \quad (9)$$

The K (d) is interpreted as a level of adjunction to the most often selected class and refers mainly to the score of the selected class. The voting can be derived from the majority rule E with a threshold denoted by

$$E = \begin{cases} c_1, if\ ..MAX.(\sum_{i}^{K} e_i) \geq \alpha.K \\ rejected \end{cases} \quad (10)$$

Where K is the number of classifiers to be fused and for α=1, the final class is assigned to the class label of the most represented among the classifiers outputs else the final decision is rejected, this process is known as Majority Voting Concept. If the classifier produces the same output for α=1 then the voting process will be conservative decision. This rule can be liberalized even by lowering the parameter α=0 this produces the simple majority voting.

V. EXPERIMENTAL ANALYSIS

In this experiment, independent performance of MB-Projection Profile (MB-PP) and Segmentation based Fractal Texture Analysis (SFTA), are separately computed and further fusion of features on the different fingerprint databases are tested. Likewise, to check the effectiveness of the proposed algorithm, we have separately classified gender information from the fingerprint using three different binary classifiers namely KNN, SVM and Decision Tree classifiers and further synthesized these classifiers for classification.

A. *Dataset and Evaluation Protocol*

In this work 4 different datasets were considered for experimentation out of which, first one is publicly available SDUMLA-HMT standard dataset which is collected by machine learning and application lab of Shandong University[24]. This dataset includes real multimodal data from 106 individuals with FT-2BU sensor out of which 59 are male subjects and 47 are female subjects acquired. For each subject samples of both hands thumb; index and middle fingerprint images were collected by giving prerequisite directions.

Second dataset is KVK Multimodal dataset which is collected and maintained by KVK multimodal Biometric Lab Researchers Aurangabad, Maharashtra [31]. This dataset includes real multimodal database from 48 individuals of which 39 are male subjects and 9 are female subjects. It contains images which are acquired with Futronic fingerprint sensor; from each such subject all finger images were collected from both hands.

Third Database created by us contains fingerprint captured by Fingkey Hamster Fingerprint sensor from 348 individuals of different age groups and these were chosen from southern rural part of Karnataka. These individuals belong to the age ranging between 15-60 years, out of which 183 are male and 165 are female subjects. From each such subject 10 images each from right and left hand thumb were collected. This dataset can be made available for the further comparisons.

Fourth Dataset which is collected from 427 individuals of different age groups from northern part of Karnataka. These individuals belong to the age ranging between 18-60 years, out of which 157 are male and 270 are female subjects. From each such subject 10 images each from right and left hand fingers were collected by giving prerequisite directions from Secugen Hamster Pro Fingerprint sensor. This dataset can be made available for further comparisons if required. The samples fingerprints of the above mentioned datasets are shown in figure 2(a) – 2(d) respectively.

Fig. 2(a) SDUMLA-Fingerprint Database

Fig. 2(b)KVK-Fingerprint Database

Fig. 2(c) Self-created database by Fingkey Hamster

Fig. 2(d) Self-created database by Secugen Hamster

From the experimental analysis, it is observed that the overall result is found to be optimal by fusing Multi Block-Projection Profile and SFTA along with the synthesis of classifiers as it provides higher accuracy rather than using them alone. The results obtained by applying SFTA, MB-PP and Fusion of SFTA with MBPP with different classifiers predicted as the confusion matrix are shown in table-1 to table-4.

For the SDUMLA-Fingerprint database, from table-1 it is observed that independent analysis of SFTA features yields the highest accuracy of 94.25 using the decision tree classifier. Likewise, by independent analysis of MB-PP the highest accuracy of 93.30 is obtained by using decision tree classifier. Further, by fusing the SFTA with MB-PP features the highest accuracy of 93.77% is achieved by using decision tree classifier.

For self-created Fingerprint database generated, by Fingkey-Hamster, from table-2 it is observed by independent analysis of SFTA features that the highest accuracy of 52.5 is obtained using the decision tree classifier. Likewise, by independent analysis of MB-PP the highest accuracy of 92.9 is obtained by using decision tree classifier. Further, by fusion of SFTA with MBPP features the highest accuracy of 95.48% is achieved by using decision tree classifier.

For KVK Fingerprint database, from table-3 it is observed by independent analysis of SFTA features that the highest accuracy of 96.4% is obtained using the decision tree classifier. Likewise, by independent analysis of MB-PP features the highest accuracy of 95.2 is obtained by using decision tree classifier. Further, by fusion of SFTA with MB-PP features the highest accuracy of 96.6% is achieved by using decision tree classifier.

For the self-created Fingerprint database by Secugen Hamster, from table-4 it is observed that by independent analysis of SFTA features the highest accuracy of 94.9% is obtained using the decision tree classifier. Likewise, by independent analysis of MB-PP features the highest accuracy of 92.7 is obtained by using decision tree classifier. Further, by fusing of SFTA with MB-PP features the highest accuracy of 95.12% is achieved by using decision tree classifier.

From the above experiments it is observed that for different features and classifiers varying results are obtained. Thus, for achieving robustness in the classification accuracy the synthesis of classifier is performed. Synthesis of classifiers approach usually fusses the output of different classifier decision and generates new classification result. In this experiment for synthesis of classifiers voting strategy is implemented and fusion of classifier based upon the results obtained from the feature level fusion of individual classifiers is performed. The results are predicted in the form of confusion matrix shown in the table-5.

Table 5 Result of different databases by synthesis of classifiers

Dataset	Female	Male	Accuracy
SDUMLA-fingerprint dataset	470	0	98.96
	11	579	
Self-created database captured with Fingkey Hamster sensor	1650	0	98.64
	47	1783	
KVK-Fingerprint dataset	90	0	100
	0	390	
Self-created database captured with Secugen Hamster sensor	2710	0	95.14
	208	1362	

From the table-5, it is observed that by synthesis of classifiers accuracy is increased by 5-10 % for all the above underlying experiments. An experimental result demonstrates that feature level fusion along with synthesis of classifiers shows improvement over the non-fused and single classifier reported in the literature.

VI. CONCLUSION

The objective of this work is to develop a generic system that can differentiate between a male and a female subject efficiently based on the fingerprints. In this experiment, the independent evaluation of Feature-level fusion and Synthesis of classifiers are performed. But the overall result is observed to be optimal by the fusion of Feature-level and synthesis of classifiers which provides higher accuracy rather than using them alone. In this proposed work, we explore the performance of gender identification over the 4 different state-of-the-art fingerprint databases. However, by empirical testing it is witnessed that fusion scheme significantly improves the performances of gender classification which provides better results than feature level fusion and by using individual classifiers.

Conflict of Interest: The authors have no conflicts of interest for the publication of this work.

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Table 1 Result of SDUMLA-Fingerprint Database

	SFTA				MBPP				Fusion of SFTA+MBPP		
Classifier	Female	Male	Accuracy		Female	Male	Accuracy		Female	Male	Accuracy
KNN	388	82	86.60		332	138	80.75		392	78	87.26
Cityblock	60	530			66	524			57	533	
SVM	387	83	89.90		390	80	91.03		391	79	91.03
RBF	24	566			15	575			16	574	
Decision	450	20	94.25		434	36	93.30		440	30	**93.77**
Tree	41	549			35	555			36	554	

Table 2 Result of Self-created Fingerprint Database captured by Fingkey-Hamster

	SFTA				MBPP				Fusion of SFTA+MBPP		
Classifier	Female	Male	Accuracy		Female	Male	Accuracy		Female	Male	Accuracy
KNN	1650	0	47.41		1410	240	86.7		1524	126	91.81
Cityblock	1830	0			220	1610			159	1671	
SVM	0	1650	52.5		1485	192	91.4		1539	111	94.54
RBF	0	1830			106	1724			79	1751	
Decision	0	1650	52.5		1528	122	92.9		1572	78	**95.48**
Tree	0	1830			122	1708			79	1751	

Table 3 Result of KVK-Fingerprint Database

	SFTA				MBPP				Fusion of SFTA+MBPP		
Classifier	Female	Male	Accuracy		Female	Male	Accuracy		Female	Male	Accuracy
KNN	54	36	87.5		59	31	91.04		55	35	88.1
Cityblock	24	366			12	378			22	368	
SVM	46	44	90.8		46	44	90.41		46	44	90.6
RBF	0	390			2	388			1	389	
Decision	80	10	96.4		78	12	95.2		76	14	**96.6**
Tree	6	384			11	379			5	385	

Table 4 Result of Self-created Fingerprint Database captured by Secugen Hamster

	SFTA				MBPP				Fusion of SFTA+MBPP		
Classifier	Female	Male	Accuracy		Female	Male	Accuracy		Female	Male	Accuracy
KNN	2448	262	84.7		2421	289	82.0		2466	244	84.6
Cityblock	390	1180			480	1090			415	1155	
SVM	2544	166	86.8		2596	114	86.3		2567	143	88.4
RBF	395	1175			469	1101			353	1217	
Decision	2615	95	94.9		2565	145	92.7		2606	104	**95.12**
Tree	120	1450			164	1406			102	1468	

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