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Decision Level Fusion Based Multimodal Biometric System

V.SIREESHA, K.SANDHYARANI

Research Scholar, Professor: Dept of Computer Science S.P.M.V.V, Tirupati, Andhra Pradesh

***Abstract*—Systems that use unimodal biometrics tend to have less accuracy, variations that are due to intra class, restricted degree of freedom, non-universality, error rates that are not acceptable, etc. Based on these reasons, in the near past, most of the researchers have been concentrating on multimodal biometrics. Multimodal biometrics integrates various types of biometrics which outperform unimodal biometric systems. In this paper, it is proposed to combine Iris and Fingerprint biometric systems and try to exploit the use of such combination. Different features viz., texture, local binary pattern, are extracted from Iris and Fingerprint images of each class and combined to form the final feature vector. Various fusion techniques exist and in this work we concentrate on fusing the classifier results and then make an efficient decision out of that fusion. Results show that the proposed technique is outperformed existing techniques and an accuracy of 99% is achieved.**

***Keywords*: Multimodal Biometrics, Iris, Fingerprint, Texture, Local Binary Pattern**

I. INTRODUCTION

In the recent years, providing security is of major concern. Conventional methods like password based systems can be easily hacked by clicking on "Forgot password" option that is available. Hence, a hack proof technique is needed. For this biometric have been introduced in the security. Various biometric traits exist, viz., Iris, Fingerprint, Voice, Signature etc. Recognition of a person using biometrics can be done in two modes. The two modes are identification and verification. Identification is comparing the query sample with enrolled database samples. It is one- many comparison. Verification is one- one comparison and it is to verify individual's identity. Iris and Fingerprint are the two biometric traits which have high FRR when compared to other biometric traits. Hence, in this work we consider only these two biometric traits. Considering the case of unimodal biometrics, which takes into account, only one type of biometric for training as well as testing, resulting in a less efficient system. Hence, combination of biometric traits is proposed here to improve the efficiency of the system. Iris is found to be the best biometric trait. Earlier techniques that use Iris as biometric, makes a template from the trained database and stores these templates in the database for testing purpose. In the testing phase, again template is formed for the test case and compared with that of the stored templates in the database for best match result and identifies the class. But it is observed that such a template based technique tend to decrease the performance of the system

. Hence, various features need to be extracted to improve the accuracy of the system. Still the false match rate does not decrease when it comes to a large database. Hence, it is proposed to use or combine another biometric along with Iris. Fingerprint is found to have next priority after Iris. Hence, fingerprint is considered here in this work which is combined with Iris for authentication purpose.

Figure 1 shows the block diagram of such multimodal biometric system. Features are extracted from various biometric traits, in this case various features, as the number of features increases, the accuracy also increases. These features are stored in the database for further use. This is called training phase which shown as solid line in figure 1. Next is the testing phase which is shown as dotted line, where, a test case is taken, different features are extracted similar to that of the training phase and are compared with that of the features pertaining to each class in the database to identify the test case to which class it belong to. It is observed that such a single classifier based system tend to have less accuracy when compared to multi classifier based systems. Hence, the existing system requires a modification such that better performance can be achieved over the existing system.

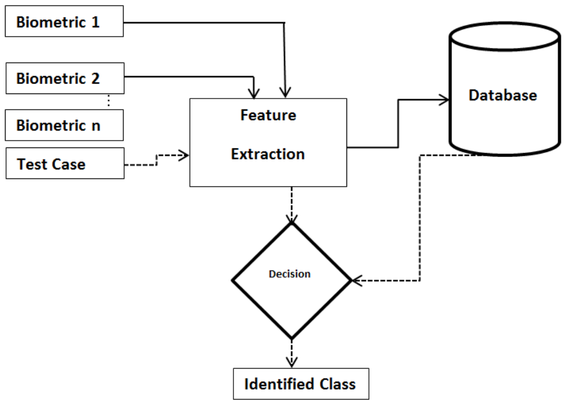


Figure 1 Block diagram of a multimodal biometric system

This paper is organized into seven sections. Section 1 introduces the need for biometrics and their pros and cons. Section 2 details the past wok in this direction. Section 3 discusses problem definition. Section 4 details the proposed solution. Section 5 explains how the proposed solution is implemented in the current context. Section 6 shows the results of the proposed system and compares the existing system with the proposed system. Section 7 gives the conclusion.

II. Literature Survey

In representing human identity IRIS is considered to be one of the best biometric. An efficient recognition technique is proposed to reduce the space complexity; further increasing the recognition accuracy of the system within a limited number of classes is proposed and achieved an accuracy of 99.73% within 1500 classes in 3.6 seconds. [1]. The existing Iris recognition techniques concentrate only on ideal iris sets. A non-ideal iris recognition is proposed which extracts half of the Iris part. Such a segmentation has resulted in 90% recognition accuracy apart from segmenting the iris within 1.8 seconds[2]. The performance of Iris recognition system depends on the inter dependability and separability of the features that are extracted from various classes in a feature plane. If such a dependency is taken into consideration and exploited, then an optimal solution to the Iris recognition technique which is fast enough can be designed[3].
Another biometric modality which is highly accurate after Iris is Fingerprint. In the recent past several research works concentrate on this biometric and try to improve the efficiency of the system. Still there are many lapses in the system that is designed using fingerprint as biometric. To overcome the side effects that is caused due to shift and rotation of the fingerprint while matching is an unsolved problem. The orientation field around the fingerprint core has a certain specific regularity. Hence, a novel technique is proposed to extract the reference point and reference direction based on the orientation field of the image. Such a technique is observed to have an advantage over the existing system having a problem in the matching phase[4].
In order to improve the recognition accuracy of a biometric system, the number of features that are extracted from the biometrics must be increased, which increases the processing time. Hence, an optimal feature vector needs to be considered for classification. Adjacent Feature Vector is used for fingerprint matching which contain four adjacent features of the fingerprint. These include features like minutiae and the number of ridges between the minutiae. Such a technique is observed to achieve high accuracy with less number of features[5]. Haar wavelet is used for decomposing the image into sub bands. It can be applied directly over the fingerprint image without any need of preprocessing[6]. Then the statistical features are extracted from the decomposed sub bands and are stored in the database which can be verified with a test case using a simple distance vector formula[7].
Combining classifiers increases the accuracy of the biometric system. Such a scheme is designed in a way such that it would select sufficient data available to obtain reasonable estimates of the join densities of classifier outputs[8]. Multimodal biometrics can be used to strengthen the security in the client-server network architecture. Fusion of two modalities based on score level fusion is proposed and classification is performed using decision tree classifier[9]. Use of clustering algorithms is proposed for decision level data fusion. Authentication of a person is made by having the results achieved by combining various clustering algorithms such as Fuzzy Vector Quantization, Fuzzy K-Means and Median Radial Basis Function network. These are further modified and further the result is fuzzified to get the finalized output[10]. Decision level fusion is applied is different fields. Three decision level fusion methods and four schemes are applied over the input data that is extracted from the hyperspectral sensors. The application that is specified here is remote sensing. The hyperspectral images that are acquired are analyzed and decision level fusion is applied to improve the performance of the classification over the existing classification techniques[11]. Decision level fusion is suitable for non-commensurate data sampled at non-coincident points as the targets are not detected by all sensors will not obtain the complete benefits of fusion[12]. Different features are extracted from unimodal biometrics and are used for further classification against a given test case. In order to improve the accuracy of the unimodal biometrics fusion is proposed. For extraction of features contourlet transform and linear discriminant analysis is proposed and are further classified using ant colony optimization

against a given test case[13]. Various techniques are applied in order to improve the accuracy of multimodal biometric systems. Z-Score based normalization is performed and fusion is applied using product rule. Such a score based fusion is observed to have better results in terms of FAR and FRR over the existing systems[14]. Detection of the states that are affective is a speech signal helps in improving the way that the users try to interact with the latest devices. Features are extracted from the speech signals and classified using Naive-Bayes and support vector machine. The performance of the system is improved using decision level fusion[15]. Majority of the existing biometric systems use information that is extracted from a unimodal biometric. When a large scale biometric systems is taken into consideration which takes into account large population, unimodal biometrics obviously are observed to have more FAR. Hence multimodal biometrics came into existence. Score level fusion is used which combines score from various score based techniques such as Min-max, Z-score, Hyperbolic Tangent etc[16]. Decision level fusion is a high level fusion service, that simulates logic reasoning and cognitive thinking of human brain. The model specified involves the approach of quantitative description and dynamic fusion of the decision level fusion, the modeling algorithm of the services resources and the modeling process based on multi-agent, the flexible and dynamic decision-level fusion mechanism[17]. Template based biometric system tend to decrease the performance of the system, hence, fusion is the only way to increase the performance[18].

III Problem Definition

Section 1 details the introduction to biometrics and their need. Existing biometric systems are based on unimodal biometrics which offers less accuracy and the false acceptance rate increases as the number of classes increase. Further, single classifier based system tend to have less recognition accuracy. Hence, a new technique or method need to developed to increase the efficiency of the system.

IV Proposed Solution

Unimodal biometrics is observed to have less efficiency when compared to multimodal biometrics. Hence, in this works it is proposed to use multimodal biometrics. In this work, Iris and Fingerprint biometrics are considered and combined to form a reliable biometric trait which is observed to increase the efficiency of the system. Further, decision level fusion is also implemented to improve the accuracy of the system.

V Methodology

Initially, each biometric trait, fingerprint and Iris of each class are trained and various features are extracted. The features that are extracted from each biometric trait include GLCM (Gray Level Co-occurrence Matrix), LBP (Local Binary Pattern), and Gabor features.

A) GLCM (Gray Level Co-Occurrence Matrix)

GLCM gives a matrix consisting of probability of a given image which is having a size N x M, which means the image is having a size of N rows and M coloumns, and is defined by

$$P_d(i;j)=\frac{\{((r,s)(t,v)):I,I(t,s)=i,I(t,v)=j\}|}{NM} \quad [19]$$

This is also called as gray level spatial dependence matrix, which is used to capture the statistical measure which characterizes the texture of an image by calculating how often pairs of pixels, with specific values and in a specified spatial relationship occur in an image and then by extracting statistical measures from this matrix. The spatial relationship is defined as the pixel of interest and the pixel to its immediate right which is horizontally adjacent. GLCM gives a square matrix of size G x G, where G is the number of gray levels in the image. Each element (i,j) in the resultant matrix is simply the sum of the number of times that the pixel with intensity I occurred in the specified spatial relationship to a pixel with value j in the input image. The $(i,j)^{th}$ element of the matrix is generated by finding the probability that if the pixel location (x, y) has gray level I_i then the pixel location (x+dx , y+dy) has a gray level intensity I_j. Different statistical features are extracted using GLCM. They are: Autocorrelation, Contrast, Correlation, Cluster Prominence, Dissimilarity, Energy, Entropy, Homogeneity, Maximum probability, Variance, Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation1, Information measure of correlation2, Inverse difference, Inverse difference normalized, Inverse difference moment normalized[20]. All these statistical measured values combine to form a feature vector.

In this work it is proposed to extract texture features from two biometric modalities, Iris and Fingerprint. Hence, GLCM is applied over Iris and fingerprint images and texture features are extracted. These texture features that are extracted from the Iris and fingerprint images are combined to form the final feature vector.

B) LBP (Local Binary Pattern)

Local binary pattern is also called as visual discriptor. Such a discriptor is used for image classification. LBP provides a texture spectrum which helps in classification. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. LBP operator forms labels for the image pixels by thresholding the 3 x 3 neighborhood of each pixel with the center value and considering the result as a binary number. The histogram of these $2^8 = 256$ different labels can then be used as a texture descriptor[2].

C) Gabor features

Gabor Features are nothing but texture based features which are obtained by convolving the image with Gabor filter, which is a linear filter used for edge detection. Gabor filters provide a response that is similar to that of the human visual system, and hence used in this case to extract the texture features from the biometrics[21].

In this work it is proposed to combine all these features to form the final feature vector. Such final feature vector will be having larger dimension and also will be strong enough such that the classification accuracy increases. The next step is classification.

Different classifiers are considered in this work to enhance the performance of the system. The test case is given to the system and features are extracted using the above discussed techniques, are compared with the stored features in the database. Each classifier provides its own decision. Further these decisions are fused to provide one final decision.

The classifiers that are used in this work are Support Vector Machine, Simple Distance based classifier, Decision Tree Classifier.

D) Distance Based Classifier

In this work we have proposed a simple distance based classifier which performs classification of the test vector within the existing feature vectors that are saved in the database by calculating the Euclidean distance between them. Minimum distance classifier finds the distances between an unknown pattern X and different known classes. The pattern is assigned to the class with the smallest distance.It is designed in such a way that if this classifier fails to provide the result then the entire classification process stops, thus providing a message that the test vector is not trained and does not exist in the database.[1]

E) Support Vector Machine

SVM (Support Vector Machine) is basically a binary classifier which classifies the given test case based on a separating hyperplane. It is a supervised model. It discriminates the test case based on the trained data. The algorithm outputs an optimal hyperplane such that it can categorize the new case as one of the trained one. Thus, operation of SVM algorithm is to find a hyperplane that gives the largest minimum distance to the training samples. As this distance increases in two fold, then margin increases. Hence, the optimal separating hyperplane maximizes the margin of the training data, resulting in better classification[1].

F) Decision Tree Classifier

Decision tree classifier perform repetitive partition of the given data space. It is capable of performing multiclass classification on a dataset. A decision tree consists of a rooted tree which will be directed with a node called root, which is prime and remaining nodes are leaves. Decision tree algorithm constructs a decision tree for the given dataset automatically such that the error is minimal. Decision tree classifier tries to optimize the cost function to find a decision tree T with a given set of L labeled samples. Here it tries to optimize the decision tree and find an optimal class out of the given dataset when a query image is given as a test case[2].To predict the response, follow the decisions in the tree from the root node down to a leaf node. Leaf node contains responses.

The final feature vector which is formed by combining all the features is saved in the data against each class. Now, when a test case is given to each classifier, each classifier provides its own decision. If each decision is individually considered, then FAR increases when it comes to a large dataset. Hence, in this work we propose to use a decision level fusion over the individual decisions given by all the classifiers.

Let the decision of first classifier be $a_1^1, a_1^2, ..., a_1^n$. Similarly for nth classifier be $a_n^1, a_n^2, ..., a_n^n$. Here we try to find the maximally repeated set which is given by the formula

$$fd = \arg\max\{\bigcap_n \{a_1^1, a_1^2, ..., a_1^n, ..., a_n^1, a_n^2, ..., a_n^n\}\} \quad \ldots (1)$$

and fd is the final decision provided by the decision level fusion.

The results of the decision level fusion are provided in the next section.

VI Results

Figure 2 shows the database[22-23] used in this work.

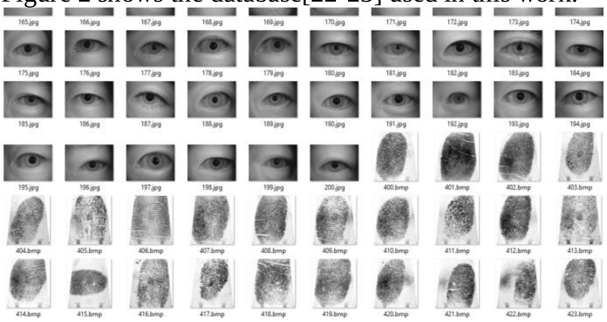
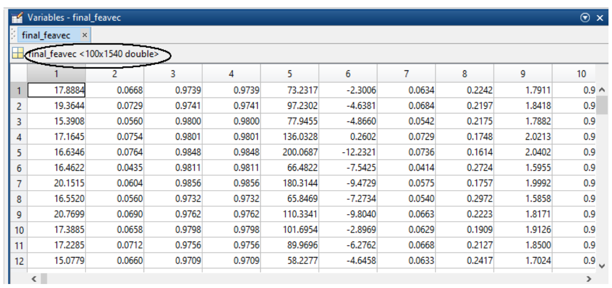


Figure 2. Database used in this work

The features that are extracted from each Iris and Fingerprint of each class are concatenated to form the final feature vector and is given in figure 3, which clearly shows the number of feature values that are extracted from each class is 1540. In this work we have considered 100 classes for training, hence, the final feature vector is of 100 x 1540. This final feature vector is saved in the database after training. Now the testing phase begins.

A test case consists of both iris as well as fingerprint images which are subjected to feature extraction. Features that are extracted are taken as test case feature vector which are used for comparison using classifiers.



Variables - final_feavec

final_feavec <100x1540 double>

	1	2	3	4	5	6	7	8	9	10
1	17.8884	0.0668	0.9739	0.9739	73.2317	-2.3006	0.0634	0.2242	1.7911	0.9
2	19.3644	0.0729	0.9741	0.9741	97.2302	-4.6381	0.0684	0.2197	1.8418	0.9
3	15.3908	0.0560	0.9800	0.9800	77.9455	-4.8660	0.0542	0.2175	1.7882	0.9
4	17.1645	0.0754	0.9801	0.9801	136.0328	0.2602	0.0729	0.1748	2.0213	0.9
5	16.6346	0.0764	0.9848	0.9848	200.0687	-12.2321	0.0736	0.1614	2.0402	0.9
6	16.4622	0.0435	0.9811	0.9811	66.4822	-7.5425	0.0414	0.2724	1.5955	0.9
7	20.1515	0.0604	0.9856	0.9856	180.3144	-9.4729	0.0575	0.1757	1.9992	0.9
8	16.5520	0.0560	0.9732	0.9732	65.8469	-7.2734	0.0540	0.2972	1.5858	0.9
9	20.7699	0.0690	0.9762	0.9762	110.3341	-9.8040	0.0663	0.2223	1.8171	0.9
10	17.3885	0.0658	0.9798	0.9798	101.6954	-2.8969	0.0629	0.1909	1.9126	0.9
11	17.2285	0.0712	0.9756	0.9756	89.9696	-6.2762	0.0668	0.2127	1.8500	0.9
12	15.0779	0.0660	0.9709	0.9709	58.2277	-4.6458	0.0633	0.2417	1.7024	0.9

Figure 3. Final feature vectors extracted from the combined biometric modality.

The classifiers that are proposed here gives an output as a decision which is the detected class. Hence, the final output from each classifier may be having a single decision or multiple decision in the case of a distance based classifier. For this case, we have proposed a final decision classifier based on equation 1, which outputs the decision based on the maximum count given by all the classifiers. The output that is generated using the designed classifier is the fusion of the decisions that is given by all the classifiers.

Figure 4 shows the decision level fusion output of the proposed classifier. Figure 4 shows the output which depicts the test class and the identified class from the database. Figure 5 shows the class number in a message box.

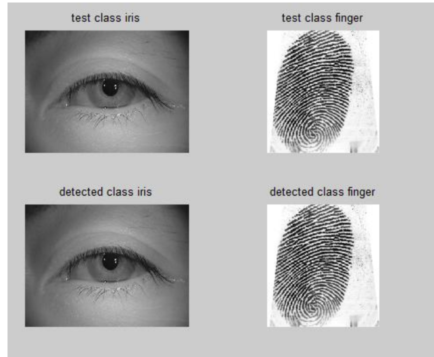


Figure 4 Test Class and Detected Class

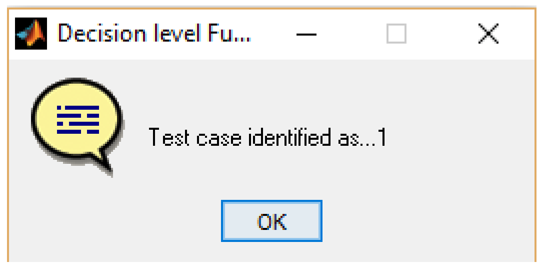


Figure 5 Identified Test Class

The advantage of the proposed technique here is that the distance based classifier fails to provide the output if the distance between the test class and the one in the database is more than the threshold prescribed, hence providing an output stating that the test case is not trained and does not exist in the database. Such a provision is observed to provide much higher efficiency when compared to the existing traditional systems. The output of such test case is shown in figure 6.

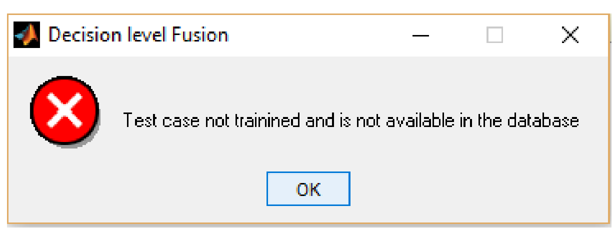


Figure 6 Untrained test case result with proposed system.

Figure 7 shows the comparative study of the proposed technique with the use of unimodal biometrics as well as individual features into consideration. It is observed that the recognition accuracy increases in the case of combined features with multimodal biometrics.

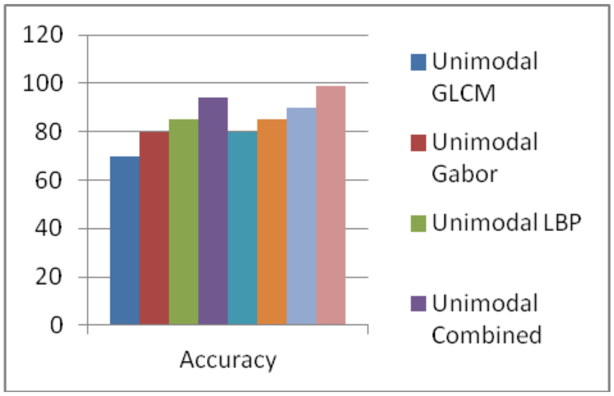


Figure 7 Comparative study of individual features combined with unimodal and multimodal biometrics.

VII Conclusion

Biometric based security systems are designed to enhance the security that is provided by the existing password based authentication systems as biometrics cannot be synthesized. In this juncture, Unimodal biometrics came into picture whose accuracy is limited as only one biometric is considered. Hence, in this work we propose multimodal biometric to improve the efficiency of the system. In this work we try to improve the accuracy of the system by combining two biometric modalities, that is, Iris and Fingerprint. Features are extracted from these biometrics and are combined to form the final feature vector and are further classified using different classifiers. The output of these classifiers is improved based on the final decision classifier proposed in this case, which makes a decision fusion based on the individual decisions provided by each classifier. Results show that an accuracy of 99% is achieved using the proposed technique while it is also observed that FAR tends to zero as the proposed technique checks the test case as a level based classification, wherein the decision at every level is further fused to give the final decision.

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