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Dynamic Selection of Face Recognition Algorithm in Multimodal Biometrics

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Abstract

On the basis of literature survey of face recognition algorithms, one question to be answered is: which algorithm is the best choice for a given application? This question leads the dissertation to characterize the available algorithms so that the most efficient methods can be stored out for different application.

In this thesis we have propose a dynamic approach for face recognition we have taken multiple face recognition algorithm and according to the image quality of probe image different algorithm is chosen for recognition .There are several face recognition algorithm and they all have their own advantages some of them producing good result in a condition and other may produce better result in different condition. We have proposed a dynamic algorithm which select appropriate standard algorithm from a pool of algorithm by using image quality vector .Image quality vector include pose angle , entropy and contrast of given image to select different algorithm.

***Index Terms*—Biometric, Multimodal**

1.Introduction

A biometric system operates by acquiring biometric data from a person , extracting a feature set from the acquired data, and comparing this feature set against known templates stored in the database [1].When more than one modality or algorithms are used for recognition that system is known as multimodal biometric system. Multimodal systems are robust than unimodal biometric system. Multimodal systems have many advantages over unimodal biometric systems such as they give better performance in noisy condition and malfunction, universality, and improved accuracy.There are many multimodal system which combine two or more modality or algorithm results known as fusion. The growing interest in the use of multiple modalities in biometrics is due to its potential capabilities for eradicating certain important limitations of unimodal biometrics. [2]

Multimodal biometrics based verification systems use two or more classifiers pertaining to the same biometric modality or different biometric modalities for identification. As discussed by Woodset al. [3], there are two general approaches : (1) classifier fusion and (2) dynamic classifier selection. In classifier fusion, all constituent classifiers are used and their decisions are combined using fusion rules [4], [5]. On the other hand, in dynamic selection, the most appropriate classifier or a subset of specific classifiers is selected [7], [8]

There are several algorithm which include pca lda ilda etc. which have different characteristics such as pca is most simple and used algorithm but suffer from scalability ,transformand background variance that implies if probe image is scaled or shifted or image background is changed it may leads to incorrect decision.

The Principal component analysis (PCA) [9] of the most successful techniques that have been used in image recognition and compression. PCA is a statistical method and Principal Components Analysis (PCA) find the minimum mean squared error linear subspace that maps from the original N-dimensional data space into an M-dimensional feature space. By doing this, Eigenfaces (where typically M << N) achieve dimensionality reduction by using the M eigen vectors of the covariance matrix corresponding to the largest eigenvalues. The resulting basis vectors are obtained by finding the optimal basis vectors that maximize the total variance of the projected data(The set of basis vectors that best describe the data).

It is fast, and it only needs lesser amount of memory for execution. PCA basically performs dimensionality reduction Principal component analysis (PCA) based on information theory concepts and seeks a computational model that best describes a face by extracting the most relevant information contained in that face. The simplest and easiest method is the PCA. It does have several weaknesses and problems. PCA is translational variant if the images are shifted it will not recognize the face. It is Scale variant if the images are scaled it will be difficult to recognize. It is background variant- If you want to recognize face in an image with different background it will be difficult to recognize. Beside above all, it is also lighting variant- if the light intensity changes, the face will not be recognized or recognized incorrectly. [10]

Linear Discriminant Analysis (LDA) is more suited for finding projections that best discriminate different classes. It does this by seeking the optimal projection vectors which maximize the ratio of the between-class scatter and the within-class scatter (i.e. maximizing class separation in the projected space) [11]

Among the various dimensionality reduction algorithms, linear (Fisher) discriminate analysis (LDA) is one of the popular supervised dimensionality reduction methods and many LDA-based face recognition algorithms/systems have been reported in the last decade. But the LDA-based face recognition systems suffer from the scalability Problem.[12]

To overcome this limitation, an incremental approach is a natural solution. Main difficulty in developing the incremental LDA (ILDA) is to handle the inverse of the within-class scatter matrix. Different from the existing techniques in which the new projection matrix is found in a restricted subspace, the proposed ILDA determines the projection matrix in full space.[13]

2. Related Work

2.1 Quality-Based Fusion

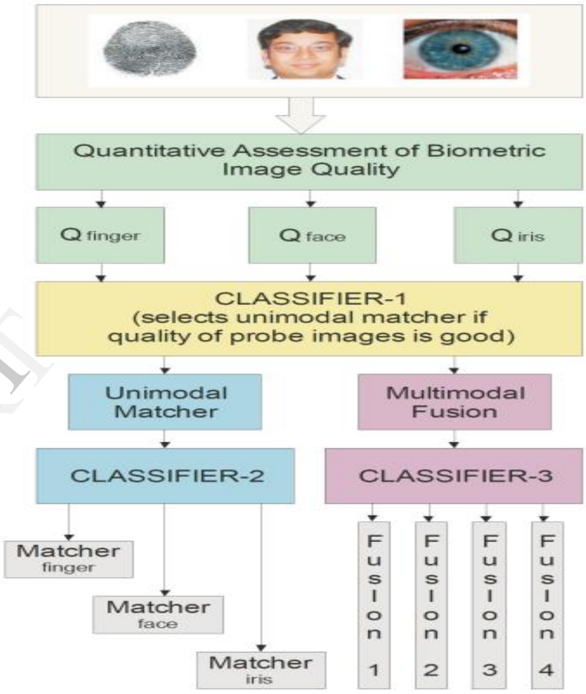
Quality measures of the input biometric signals can be used for adapting the different modules of a multimodal authentication system. Although both the score normalization and decision modules are subject to this adaptation based on quality. There is recent interest in studying the effects of signal quality on the performance of bio-metric systems [14]. As a result, it is known that the performance of an unimodal system can drop significantly under noisy conditions. Multimodal systems have been demonstrated to overcome this challenge to some extent by combining the evidences provided by a number of different traits. This idea can be extended by explicitly considering quality measures of the input biometric signals and weighting the various pieces of evidence based on this quality information. Following this idea, novel quality-based multimodal authentication schemes are proposed in this Thesis, and their benefits are demonstrated on a publicly available real multimodal biometric database.

One straightforward way to introduce the quality measures of the input biometric data into the score level fusion approach is through including weights in simple combination approaches (for instances, Weighted Sum rule, Fisher Linear Discriminate). The weights in these approaches can be calculated heuristically, by exhaustive search in order to minimize certain error criterion on a development set (e.g. Brute Force Search), or by using a trained approach based on linear classifiers.

The concept of confidence measure of matching scores was also studied by Bengioet al.[2002].In this work they demonstrated that the confidence of matching scores can help in the fusion process. In particular, they tested confidence measures based on: 1) Gaussian assumptions on the score distributions, 2) the adequacy of the trained biometric models to explain the input data, and 3) resampling techniques on the set of test scores.

2.2 Context Switching Algorithm for Selective Multibiometric

Fig. 1 illustrates the steps involved in the proposed dynamic context switching algorithm. For a biometric system with two classes (genuine, impostor) and three modalities, the algorithm uses image quality scores and three classifiers (e.g. decision tree or support vector machine (SVM)) for context switching. Classifier-1 is used to choose between the unimodal and multimodal approach based on the input evidences. If the quality of probe image is above a non-linear threshold, then unimodal approach is selected otherwise multimodal approach is selected. Next, if the unimodal approach is selected then Classifier-2 is used to select one of the three unimodal options: (1) only face, (2) only fingerprint, and (3) only iris. If Classifier-1 selects the multimodal approach, then Classifier-3 is used to select the optimal fusion rule for a given probe case. Classifier-3 selects a complex fusion algorithm only when there is uncertainty or imperfection in the image quality scores otherwise it selects a simple fusion algorithm for combining information obtained from multimodal biometric images.[15]



2.3 Dynamic Selection of Biometric Fusion Algorithms

This work proposed dynamic selection algorithm that unifies the classifiers and fusion schemes in order to optimize both verification accuracy and computational time . The case study in multiclassifier face recognition suggests that the proposed algorithm can address the issues listed belove consider the problem of designing a fusion scheme when

1) Number of training samples is limited thereby affecting the use of a purely density-based scheme and the likelihood ratio test statistic;

2) Output of multiple matchers yields conflicting results; and

3) The use of a single fusion rule may not be practical due to the diversity of scenarios encountered in the probe dataset.. Indeed, it is observed this method performs well even in the presence of confounding covariate factors thereby indicating its potential for large-scale face recognition.

3. Proposed Work

3.1 Introduction Fig 1 illustrates the working of proposed dynamic selection of face recognition algorithm. There are three face recognition algorithm PCA ,LDA ,ILDA .For selection any one of three we have calculated a quality vector that include pose angle ,entropy and contrast of the input image based on that value any of the one algorithm is selected dynamically on the fly. Selection of algorithm depends on quality vector which suggests which algorithm is best suitable for the input image. for this we have taken different algorithm range of quality vector. If image quality is good a simple algorithm in selected otherwise a complex algorithm is selected that give good performance in low quality images as well .simple algorithm which are generally fast and require less computation are used for good quality images while a low quality image is processed by a complex algorithm which require more computation and may take more time than other algorithm.

3.2 Calculation of Quality Vector

3.2.1 Pose angle estimation: For face images, pose is a major covariate that determines the usability of the face image. Even a good quality face image may not be useful during recognition due to pose variations. Pose is estimated based on the geometric relationship between face, eyes, and mouth. Depending upon the yaw, pitch and roll values of the estimated pose, a composite score is computed for denoting face quality.

In face recognition, pose variations can reduce the amount of overlapping biometric features required for recognition. Therefore, it is important to include the head position or angle as a pose parameter in the quality vector. In this research, a fast single view algorithm [17] is used for estimating the pose of a face image. The output of the algorithm is the pose angle which serves as the first element in the quality vector.

In a computer vision context, head pose estimation is the process of inferring the orientation of a human head from digital image. It requires a series of processing steps to transform a pixel-based representation of a head into a high-level concept of direction. Similar to other facial vision processing steps an ideal head pose estimator must demonstrate invariance to a variety of image-changing factors [18]. These factors include physical phenomena like camera distortion, multisource non-Lambertian ,projective geometry,lighting, as well as biological appearance such as facial expression and the presence of accessories like glasses and hats.

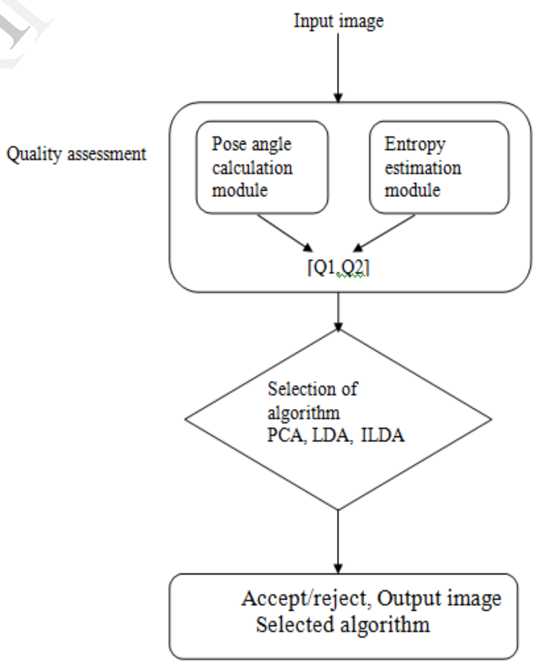
There are following steps used for pose angle estimation first one is detecting bounding box which detects the head position in an image after that face alignment is done and in the end estimation or normalization is done which produces actual angle for an image.

3.2.2. Entropy calculation : Entropy for an image provide information contain of an image. It is also a vital parameter for image quality measurement. Density of an image can be measured by entropy calculation for an image . Entropy of an image is a quantity which is used to describe the properties of an image such as the amount of information which must be coded for by a compression algorithm [19]. Low entropy images, such as those containing a lot of black sky have very little contrast and large runs of pixels with the same or similar DN values. An image that is perfectly flat will have an entropy of zero or very low entropy . Consequently, they can be compressed to a relatively small size images. On the other hand, high entropy images such as an image of heavily cratered areas on the moon have a great deal of contrast from one pixel to the next and consequently cannot be compressed as much as low entropy images [20].

$$\text{Entropy} = -\sum_{i} P_i \log_2 P_i$$

In the above expression, P_i is the probability that the difference between 2 adjacent pixels is equal to i, and $\log_2$ is the base 2 logarithm.

3.3 Flowchart for propose method



4. Result and Analysis

For our work we have taken Indian face dataset [21] which contained images of 40 distinct subjects with eleven different poses of each individual. The files are in JPEG format. The size of each image is 640x480 pixels, with 256 grey levels per pixel. Platform used in this dissertation work for implementation is MATLAB 7.4. A database of 40 different samples are created which is divided into training set and recognized set. Image which is to be recognized is store in recog set. These recog images are compared with the data stored in training set. Table shows selected algorithm for different images with their quality parameters.

Table 5.1 Different algorithm selected based on image quality vector

S. NO.	QUALITY VECTOR		SELECTED ALGORITHM
	POSE ANGLE	ENTROPY	
1	43	6.952	PCA
2	67	7.317	LDA
3	67	6.978	PCA
4	08	7.011	LDA
5	43	7.290	ILDA
6	34	7.223	ILDA
7	48	7.153	LDA
8	15	6.9082	PCA
9	9	6.9574	PCA
10	18	7.3631	LDA
11	19	7.1342	LDA
12	10	7.2941	LDA
13	59	7.1325	LDA
14	31	7.2759	LDA
15	54	7.1830	LDA
16	03	7.1300	PCA
17	64	7.2167	LDA
18	72	7.0761	ILDA
19	51	7.1428	LDA
20	49	6.9947	LDA
21	71	7.1774	LDA
22	60	7.1861	LDA
23	78	7.2233	ILDA
24	16	7.2998	LDA
25	72	7.1995	ILDA
26	08	7.011	LDA
27	43	7.290	ILDA
28	34	7.223	ILDA
29	48	7.153	LDA
30	15	6.9082	PCA
31	9	6.9574	PCA
32	18	7.3631	LDA
33	19	7.1342	LDA
34	10	7.2941	LDA
35	59	7.1325	LDA
36	34	7.223	ILDA
37	48	7.153	LDA
38	15	6.9082	PCA
39	9	6.9574	PCA
40	18	7.3631	LDA

5. Conclusion And Future Work

We noticed that proposed dynamic selection algorithm overcome the stand alone PCA, LDA and ILDA. And this algorithm require less computational time and give higher accuracy .But due to three algorithms data base is large and require larger storage than single algorithm.
The success of this dissertation proves the feasibility of using proposed algorithm in training face recognition systems. Future work includes the expansion of the system to include a wider range of rotations, illumination and quality parameter of images conditions. Extension of pose and illumination invariance would involve training on synthetic images over a larger range of views and conditions.

Another area of improvement is the accuracy in face detection, which was not explored in depth in this thesis. Face detection accuracy will improve by using a more number of images. Finally, the number of faces currently in the database is not large and could be increased. However, increasing the number of people causes additional issues. First, the speed of the system will decrease significantly with additional users. How to improve feature extraction method to make the classification more easily and more quickly is expected to research deeply in the future.

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