|| Volume 5 || Issue 11 || November 2020 || ISSN (Online) 2456-0774
INTERNATIONAL JOURNAL OF ADVANCE SCIENTIFIC RESEARCH
AND ENGINEERING TRENDS

MULTIMODAL BIOMETRIC INTELLIGENT SYSTEM TO IMPROVE FACE RECOGNITION

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***Abstract*: - Face recognition is one of the most active and promising fields of computer vision due to its various applications in many areas such as robotics, intelligent user interfaces, authentication in security systems and face search in video databases. Possible avenues for improved performance include the use of a different source of biometric information, and / or the combination of information from multiple sources. One problem of face recognition is the fact that different faces could seem very similar; therefore a discrimination task is needed. One other possible biometric source is the ear. A very simple multi-biometric combination technique is used. The normalized, masked ear and face images of a subject are concatenated to form a combined face-plus-ear image.**

Keywords: *- Multimodal Biometric, Face Recognition, Unimodal Biometric, Ear Recognition.*

I INTRODUCTION

Multiple biometric approaches are proposed integrating three-dimensional face appearance with ear appearance, three-dimensional face shape, and the pattern of heat emission on face. A single source biometric recognition method, such as face, has been shown to improve its identification rate by incorporating other biometric sources.

The investigation of multi biometrics involves a variety of sensors. For the recognition task, each sensor captures different aspects of human facial features; for example, appearance representing the levels of brightness on surface reflectance by a light source, shape data representing depth values defined at points on an object, and the pattern of heat emitted from an object.

II MULTIMODAL BIOMETRIC SYSTEM

A new evaluation scheme is to design to assess the improvement gained by multiple biometrics. Because multi-modal recognition employs multiple samples of facial data, it is also possible that the improvement achieved over considering multiple samples from all modalities for recognition. Therefore, this evaluation scheme will determine the recognition accuracy gained by multiple modality approach and multiple sample approach. A new algorithm based on soft computing for 2D face recognition is proposed for handling expression variation.

It uses an Artificial Neural Network (ANN) with surface registration based technique for 3D face recognition. Evaluate and compare the performance of approaches to 2D face recognition based on Artificial Neural Network. The proposed 3D face recognition method is fully automatic to use to initialize the 2D matching. This is the study to compare the ANN and Support Vector Machine (SVM) approach to 2D face recognition, and propose a multiple-region approach to coping with expression variation in 2D face recognition etc.

III THE PHASES OF BIOMETRIC RECOGNITION

A. Image Acquisition

In this background or scenes unrelated to face will be eliminated. The system can detect a face in real-time. The face detection system is also robust against illumination variance and works well with different skin color and occlusions such as beards, moustache and with head cover. Its purpose is to seek and then extracts a region which contains only the face. Adaboost algorithm is applied. The outputs of the system are the rectangle which contains face features, and image which contains the extraction of the detection face features.

B. Preprocessing

It is to reduce or eliminate some of the variations in face due to illumination. It normalized and enhanced the face image to improve the recognition performance of the system. By performing normalization processes, the system robustness against scaling, posture, facial expression and illumination is increased. The techniques are Histogram Equalization, and Homomorphic filtering.

- Histogram equalization – It is to produce an image with equally distributed brightness levels over the whole brightness scale. It is usually done on too dark or too bright images in order to enhance image quality and to improve face recognition performance.
- Homomorphic filtering – In general a high-pass filter is used to separate and suppress low frequency components while still passing the high frequency components in the signal.

TABLE 1 COMPARISON OF DIFFERENT DATABASE

DATABASE	DESCRIPTION	LIMITATIONS
AT & T Database	Contains face images of 40 persons, with 10 images of each. Images were shot always against a dark background.	Limited number of people
Oulu Physics	Includes frontal color images of 125 different faces. Each face was photographed 16 times, using 1 of 4 different illuminants (horizon, incandescent, fluorescent, and daylight) in combination with 1 of 4 different camera calibrations (color balance settings). The images were captured under dark room conditions.	(1) Although this database contains images captured under a good variety of illuminant colors, and the images are annotated for illuminant, there are no variations in the Lighting angle. (2) all of the face images are basically frontal (with some variations in pose angle and distance from the camera)
XXM2VTS	Consists of 1000 Gigabytes of video sequences and speech recordings taken of 295 subjects at one-month intervals over a period of 4 months (4 recording sessions). Significant variability in appearance of clients (such as changes of hairstyle, facial hair, shape and presence or absence of classes) is present in the recordings. During each of the 4 sessions a “speech” video sequence and a “head rotation” video sequence was captured. This database is designed to test systems designed to do multimodal (video + audio) identification of humans by facial and voice features.	It does not include any information about the image acquisition parameters, such as illumination angle, illumination color, or pose angle.
Yale	Contains frontal grayscale face images of 15 people, with 11 face images of each subject, giving a total of 165 images. Lighting variations include left-light, center-light, and right-light. Spectacle variations include with-glasses and without-glasses. Facial expression variations include normal, happy, sad, sleepy, surprised, and wink.	(1) limited number of people (2) while the face images in this database were taken with 3 different lighting angles (left, center, and right) (3) since all images are frontal, there are no pose angle variations. (4) Environmental factors (such as the presence or absence of ambient light) are also not described.

MIT	Contains 16 subjects. Each subject sat on a couch and was photographed 27 times, while varying head orientation. The lighting direction and the camera zoom were also varied during the sequence.	(1) Although this database contains images that were captured with a few different scale variations, lighting variations, and pose variations, these variations were not very extensive, and were not precisely measured. (2)There was also apparently no effort made to prevent the subjects from moving between pictures.
CMU PIE	Contains images of 68 subjects that were captured with 13 different poses, 43 different illumination conditions, and 4 different facial expressions. Two sets of images were captured – one set with ambient lighting present, and another set with ambient lighting absent.	(1) There was clutter visible in the backgrounds of these images. (2) The exact pose angle for each image is not specified.
UMIST	Consists of 564 grayscale images of 20 people of both sexes and various races. (Image size is about 220 x 220.) Various pose angles of each person are provided, ranging from profile to frontal views.	(1) No absolute pose angle is provided for each image. (2) No information is provided about the illumination used – either its direction or its color temperature.
The University of Stirling online database	Was created for use in psychology research, and contains pictures of faces, objects, drawings, textures, and natural scenes. A web-based retrieval system allows a user to select from among the 1591 face images of over 300 subjects based on several parameters, including male, female, grayscale, color, profile view, frontal view, or 3/4 view.	(1) no information is provided about the illumination used during the image capture. (2) Most of these images were also captured in front of a black background, making it difficult to discern the boundaries of the head of those subjects with dark hair.
FERET	Contains face images of over 1000 people. It was created by the FERET program, which ran from 1993 through 1997. The database was assembled to support government monitored testing and evaluation of face recognition algorithms using standardized tests and procedures.	(1) it does not provide a very wide variety of pose variations. (2) there is no information about the lighting used to capture the images.
Kuwait University face database	The in-house built database consists of 250 face acquired from 50 people with five images per face. There is a total 250 gray level images (5 images x 50 people). Facial images are normalized to sizes 24 x 24, 32 x 32, and 64 x 64). Images were acquired without any control of the laboratory illumination. Variations in lighting, facial expression, size, and rotation, are considered.	(1) Limited number of people. (2) It does not include any information about image acquisition parameter, such as pose angle.

TABLE 2 FACE IDENTIFICATION RESEARCH SURVEY

Database	Reference	Method	% of Correct Identification
FERET	[1]	Eigenfeatures	95%
	[2]	Eigenface	95%, 85%, 64% correct classifications averaged lighting, orientation over, size variation.
	[3]	Graph matching	86.5% - 111 faces of 15 degree rotation, 66.4% - 110 faces of 30 degree rotation.
	[4]	SVM	Identification performance is 77.78% versus 54% for PCA. Verification performance is 93% versus 87% for PCA.
	[5]	SVM + 3D morphable model	98%
	[6]	SVM+PCD	99% for verification , 98% for recognition
AR	[7]	LEM	96.43%
	[8]	SVM+PCA SVM+ICA	92.6% 94%
YALE	[9]	SVM+PCA SVM+ ICA	99.3% 99.3%
	[10]	Boosted parameter – based combined classifier	99.5%
ORL	[11]	Hidden Markov Model	87%
	[2]	SVM, Nearest Center Classification	91.21% for SVM , 84.86% for NCC
	[13]	Eigenface	90%
	[14]	PDBNN	96%
	[13]	MRF	86.95%
	[14]	Boosted parameter based combined classifier	100 %
Bern University face database	[9]	LEM	100%

C. Feature Extraction

The purpose is to extract the feature vectors or information which represents the face. The feature extraction algorithms used are PCA, LDA.

the rectangle which contains face features, and image which contains the extraction of the detection face features.

D. Classification

The purpose is to map the feature space of a test data to a discrete set of label data that serves as template. The classification techniques used are ANN, Euclidean Distance, Normalized Correlation, Support Vector Machine.

IV SUPPORT VECTOR MACHINE

Before Support Vector Machine is a binary classification method that finds the optimal linear decision surface between two classes. The decision surface is nothing but a weighted combination of the support vectors. In other words, the support vectors decide the nature of the boundary between the two classes.

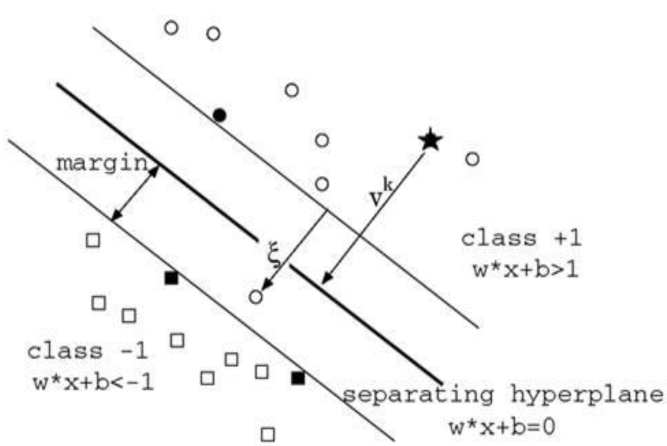

Figure 1 Weighted Combination of the Support Vector Machine

Support Vector Machine is a classifier derived from statistical learning theory. The SVM is a popular method because of its ability to solve many non-linear classification problems with good results. One of the initial relevance using SVM regarding vision computing applications is for face detection, where the discrimination is between two classes; face and non-face. SVM extended to multiclass problems which suit the application of a face recognition task, i.e., to recognize more than two person face images and described as K class problems.

V CONCLUSION

Multimodal biometric systems address numerous problems observed in single modal biometric systems. The complex methods employed to find a good combination of multiple biometric modality and various level of fusion applied to get the best possible recognition result are discussed in this paper. The prior work has shown the performance evaluation of the multimodal system under the different trait combination scheme, identification rate and databases. The combination of face and ear modality are suggested and the proposed framework of the biometric system is given. In this paper, table 1 claims that multi biometrics improve over a single biometric system and uncorrelated modalities are used to achieve performance in multimodal system.

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