

Fusion of Face and Voice for a Multimodal Biometric Recognition System

Balaka Ramesh Naidu, P.V.G.D Prasad Reddy

Abstract - Biometric authentication system takes a primary role in the present modern society, computers are becoming a part of everyday life. It provides more security than the traditional systems. In traditional authentication systems password, pin-number, or signature is used for identification but these can be lost, stolen or subject to spoofing attacks. This paper introduces combination of two individual human traits, face and voice signal which are used for identification. The biometric authentication system with two traits supports more security and reliability than the single source of identification system.

This paper presents a biometric recognition system integrating face and voice signal based on score level fusion. The features are extracted individually from the preprocessed traits and then classified the data using Gaussian mixture model. After classification, fuse the traits to make the training dataset. Test data is compared with the training dataset and then display the result whether the individual is genuine or an impostor. Performance measures like False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and Failure To Capture (FTC) are calculated and performance evaluated. It is proved that the proposed biometric system overcomes the limitations of individual biometric systems and also meets the less response time as well as the good accuracy requirements.

Keywords: Biometric System, Face recognition, Voice recognition, Score level fusion, FAR, FRR, EER, FTC.

I. INTRODUCTION

Biometric characteristics are of two types. They are behavioral characteristics and physiological characteristics. Physiological characters are face, fingerprint, hand geometry and palm print [1]. Behavioral character refers to speech, keystroke, and gait. This paper introduces both the behavioral and physiological characteristics for biometric recognition. The combination of these two traits provides more reliability than any other individual biometric system. In this paper mainly focus is given on fusion (i.e., mixture) of two sources of information with the goal of improving the accuracy of biometric systems. Individual biometric personalities like IRIS, DNA, Voice recognition, Fingerprint, Retina, and Finger-vein can be labeled as uni-biometric systems because it rely on a single biometric source for recognition [2]. Uni-biometric systems have some disadvantages like background noise, noisy data, blurred, low quality of illumination biometric trait of the authentic

user [3]. Integrating two traits can significantly enhance the recognition performance of a biometric system as well as increasing the security and decreasing the failure rate. The storage requirements, processing time, and the computational demands of a multimodal biometric system are much higher than a uni-modal system. According to Sanderson and Paliwal [4] various levels of fusion can be classified into two broad categories: fusion before matching and fusion after matching. Fusion of these three biometric traits is carried out at the matching score level. Based on the proximity of feature vector and template, each subsystem computes its own matching score. These individual scores are finally combined into a total matching score, which is passed to the decision module [5]. Recently, Ziou and Bhanu [6] proposed a multimodal biometric system based on the fusion of face features with gait features at feature level. A multimodal biometric system based on the integration of face and fingerprint trait at feature extraction level was presented. These two traits are the most widely accepted biometrics in most applications. There are also other advantages in multimodal biometric systems, including the ease of use, robustness to noise, and the availability of low cost, off-the-shelf hardware for data acquisition [7]. Gyaourova et al. [8] fused IR-based face recognition with recognizable based face recognition at feature level, reporting a substantial development in recognition performance as compared to matching individual sensor modalities.

II. PROPOSED MULTIMODAL SYSTEM

To overcome the troubles faced in individual biometric recognizers of voice signal, palm print, fingerprint and face, a novel combination is projected for the recognition system. The integrated system provides anti spoofing measures, efficiency, robustness, and more security.

III. FACE FEATURE EXTRACTION

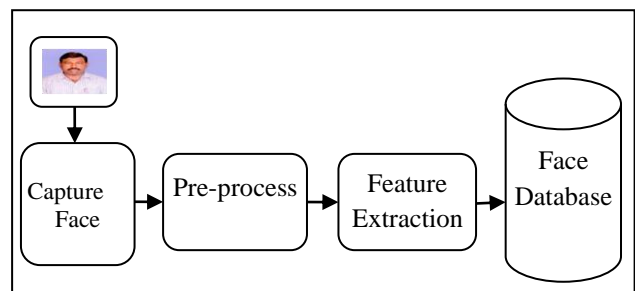


Fig.1 Steps involved in Face feature extraction

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Image acquisition is done using camera and later converted into 256 x 256 pixel size in two dimensional formats with fixed size. In second stage, each of the image trait is compressed by using DCT (Discrete Cosine Transform) technique. After compression extract features from an image by using HOG (Histogram of Oriented Gradients). The result is in the format of vector called feature descriptor [9]. Feature descriptor simplifies the extraction of useful information and discards extraneous information from an image. Using feature descriptor the image cannot be viewed but it is useful for image reorganization and object detection [10]. After obtaining a feature vector then, the data is classified using (GMM) Gaussian mixture model. GMM is parametric representation of based on sum of weighted Gaussian distributions. This model is commonly used in continuous measurements or features in biometric traits. Each component is defined by its mean and covariance, and the mixture is defined by a vector of mixing proportions [11]. GMM is used in classification, signal processing, speaker recognition and language identification [12, 14]. The mathematical notation of Gaussian mixture model is given in Eq. (1).

$$P(x) = W_1 P_1(x) + W_2 P_2(x) + W_3 P_3(x) + \dots + W_n P_n(x) \quad (1)$$

Where, $P(x)$ is mixture component, $W_1, W_2, W_3, \dots, W_n$ is mixer weight or coefficient and $P_i(x)$ is density function where $i = 1, 2, 3, \dots, n$.

The most common distribution is the Gaussian (Normal) density function in which each of the components are the Gaussian distributions, each one with their own mean and variance parameters as given in below Eq. (2).

$$P(x) = W_1 N(x|\mu_1, \Sigma_1) + W_2 N(x|\mu_2, \Sigma_2) + W_3 N(x|\mu_3, \Sigma_3) + \dots + W_n N(x|\mu_n, \Sigma_n) \quad (2)$$

Where, μ_i^s are the means, Σ_i^s are the covariance matrix of individual components (PDF) and $P_i(x)$ is result of density functions.

IV. VOICE RECOGNITION

Conversation is one of the most important communication channels for human beings. To help security in communications, speech recognition technologies have been developed in biometric system. In this study, voice data is extracted individually of several users by using microphones without interference of any other sounds. The Fast Fourier Transform is used to extract the features from input voice and then distributed using Gaussian mixture model and finally fusion with face dataset [13, 14]. The acquiring of voice dataset is shown in Fig. 2.

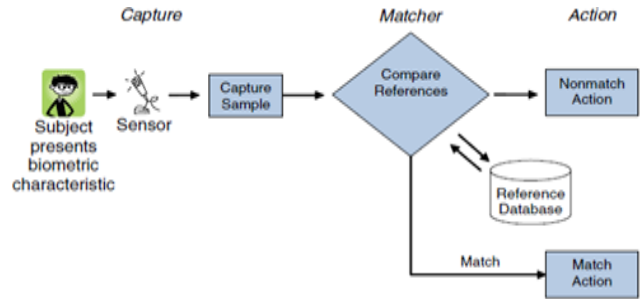


Fig.2 Steps involved in voice feature extraction

V. FUSION

Fusion is the process of combining two or more things together to form a single entity [15]. There are four standard fusion types including feature level fusion, score level fusion, decision level fusion and sensor level fusion.

Feature Level Fusion:

Feature sets are acquired from sensor, where each feature set is represented as a vector. Then the vectors are concatenated which results in a new feature vector with higher dimensionality representing a person's identity in a different hyperspace.

Score Level Fusion:

This technique is also known as measurement or confidence level fusion. It uses scores from different modalities and then concatenates feature vector sets into single feature vector based on either maximum or minimum score. The final result is a new feature vector fusion set is considered based on maximum score.

Decision Level Fusion:

In this resulting feature vectors from each sensor require to be classified into two classes like either reject or accept. After that a final decision is based on majority of a vote scheme.

Sensor Level Fusion:

Fusion at the sensor level is performed by integrating information from different sensors before feature extraction takes place. In this study, the score level fusion is applied in multimodal biometric authentication system.

VI. RESULTS AND DISCUSSIONS

The performance measures considered for evaluating the systems include FAR, FRR, EER, and FTC which are calculated both in uni-modal and multimodal biometric authentication systems. Experiments are conducted on one thousand different traits and the measured values are shown for two hundred traits in the Table I and Table II.

TABLE I Performance measures FAR, FRR, FTC, and EER in Uni-Modal biometric system.

S.No	FACE -FAR	VOICE-FAR	FACE-FRR	VOICE-FRR	FACE-FTC	VOICE-FTC	FACE-EER	VOICE-EER
1	0.025	0.021	0.022	0.025	0.017	0.024	--	--
2	0.02	0.028	0.018	0.027	0.02	0.024	--	--
3	0.019	0.023	0.026	0.019	0.019	0.029	--	--

4	0.026	0.02	0.021	0.02	0.019	0.027	--	--
5	0.019	0.03	0.026	0.022	0.017	0.021	--	--
6	0.027	0.029	0.025	0.028	0.016	0.026	--	--
7	0.024	0.024	0.02	0.023	0.018	0.021	0.024	--
8	0.023	0.021	0.023	0.02	0.017	0.024	--	--
9	0.025	0.02	0.026	0.024	0.018	0.027	--	--
10	0.021	0.023	0.022	0.021	0.017	0.025	--	--
11	0.022	0.026	0.027	0.027	0.018	0.025	--	0.027
12	0.027	0.025	0.024	0.024	0.02	0.026	--	0.024
13	0.02	0.021	0.018	0.028	0.019	0.026	--	--
14	0.02	0.02	0.023	0.028	0.016	0.025	0.02	--
15	0.024	0.027	0.023	0.024	0.018	0.026	--	--
16	0.021	0.023	0.024	0.023	0.02	0.03	--	--
17	0.027	0.022	0.019	0.024	0.016	0.021	--	--
18	0.027	0.029	0.026	0.026	0.018	0.02	--	0.026
19	0.027	0.026	0.024	0.021	0.018	0.024	--	--
20	0.027	0.024	0.019	0.024	0.019	0.023	--	--
21	0.025	0.024	0.026	0.026	0.02	0.024	--	0.026
22	0.024	0.021	0.019	0.023	0.018	0.02	--	--
23	0.025	0.023	0.019	0.024	0.016	0.021	--	--
24	0.028	0.028	0.019	0.022	0.02	0.028	0.028	--
25	0.023	0.022	0.025	0.021	0.016	0.03	--	--
26	0.021	0.029	0.023	0.023	0.017	0.024	--	0.023
27	0.018	0.022	0.017	0.021	0.019	0.023	--	--
28	0.021	0.022	0.021	0.024	0.016	0.023	--	--
29	0.027	0.025	0.018	0.025	0.017	0.02	--	--
30	0.018	0.023	0.021	0.02	0.015	0.029	--	--
31	0.024	0.021	0.02	0.027	0.018	0.025	--	--
32	0.022	0.024	0.022	0.025	0.017	0.026	--	--
33	0.026	0.03	0.018	0.023	0.02	0.02	--	--
34	0.024	0.025	0.024	0.024	0.018	0.029	--	0.024
35	0.022	0.026	0.018	0.026	0.017	0.029	--	--
36	0.02	0.023	0.019	0.025	0.016	0.027	--	--
37	0.027	0.022	0.02	0.023	0.016	0.021	--	--
38	0.025	0.023	0.021	0.028	0.016	0.026	--	--
39	0.024	0.027	0.02	0.022	0.015	0.021	--	--
40	0.021	0.025	0.02	0.023	0.017	0.029	--	--
41	0.022	0.027	0.022	0.022	0.018	0.023	--	0.022
42	0.023	0.029	0.022	0.027	0.017	0.028	--	--
43	0.019	0.026	0.026	0.019	0.018	0.029	--	--
44	0.02	0.029	0.018	0.026	0.019	0.029	--	--
45	0.021	0.028	0.019	0.028	0.017	0.027	--	--
46	0.025	0.022	0.026	0.029	0.018	0.02	--	--
47	0.018	0.022	0.026	0.023	0.018	0.023	--	--
48	0.023	0.025	0.026	0.027	0.02	0.028	--	--
49	0.021	0.023	0.019	0.025	0.015	0.024	--	--
50	0.025	0.022	0.019	0.023	0.016	0.027	--	--
51	0.026	0.025	0.02	0.028	0.016	0.026	--	--
52	0.02	0.023	0.024	0.021	0.016	0.029	--	--
53	0.018	0.03	0.021	0.022	0.017	0.026	--	--
54	0.024	0.024	0.021	0.02	0.015	0.023	0.024	--
55	0.025	0.028	0.023	0.024	0.019	0.028	--	--
56	0.02	0.029	0.022	0.026	0.016	0.027	--	--
57	0.019	0.028	0.027	0.02	0.019	0.025	--	--
58	0.024	0.028	0.018	0.025	0.015	0.028	--	--
59	0.019	0.022	0.025	0.024	0.019	0.029	--	--
60	0.023	0.029	0.021	0.029	0.019	0.022	--	--

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61	0.024	0.024	0.025	0.026	0.019	0.022	0.024	--
62	0.02	0.02	0.026	0.023	0.02	0.024	0.02	--
63	0.025	0.022	0.018	0.028	0.019	0.024	--	--
64	0.024	0.029	0.025	0.021	0.018	0.029	--	--
65	0.022	0.023	0.023	0.021	0.016	0.025	--	--
66	0.024	0.024	0.027	0.027	0.017	0.03	0.024	0.027
67	0.018	0.028	0.018	0.028	0.017	0.027	--	--
68	0.018	0.022	0.025	0.021	0.018	0.029	--	--
69	0.022	0.03	0.019	0.022	0.019	0.022	--	--
70	0.02	0.021	0.018	0.026	0.016	0.024	--	--
71	0.02	0.025	0.02	0.022	0.016	0.026	--	--
72	0.026	0.025	0.019	0.026	0.016	0.027	--	--
73	0.026	0.025	0.023	0.024	0.017	0.027	--	--
74	0.019	0.029	0.025	0.026	0.015	0.025	--	--
75	0.019	0.028	0.019	0.025	0.016	0.022	--	--
76	0.025	0.025	0.025	0.019	0.02	0.028	0.025	--
77	0.022	0.024	0.021	0.02	0.017	0.029	--	--
78	0.02	0.027	0.018	0.02	0.019	0.027	--	--
79	0.02	0.024	0.021	0.019	0.019	0.026	--	--
80	0.026	0.024	0.021	0.026	0.015	0.024	--	--
81	0.026	0.029	0.025	0.019	0.019	0.026	--	--
82	0.025	0.025	0.025	0.022	0.017	0.026	0.025	--
83	0.018	0.027	0.024	0.024	0.018	0.022	--	0.024
84	0.02	0.025	0.025	0.024	0.019	0.021	--	--
85	0.027	0.02	0.017	0.019	0.016	0.021	--	--
86	0.024	0.023	0.02	0.026	0.018	0.022	--	--
87	0.026	0.027	0.025	0.026	0.019	0.023	--	--
88	0.019	0.025	0.02	0.024	0.017	0.025	--	--
89	0.024	0.029	0.026	0.027	0.016	0.03	--	--
90	0.027	0.023	0.02	0.028	0.016	0.025	--	--
91	0.027	0.028	0.023	0.02	0.017	0.024	--	--
92	0.023	0.024	0.023	0.022	0.015	0.025	--	--
93	0.027	0.024	0.023	0.021	0.02	0.024	--	--
94	0.026	0.026	0.017	0.026	0.017	0.021	0.026	--
95	0.02	0.026	0.019	0.022	0.016	0.025	--	--
96	0.025	0.026	0.026	0.024	0.02	0.022	--	--
97	0.023	0.028	0.026	0.023	0.019	0.023	--	--
98	0.022	0.029	0.024	0.025	0.019	0.022	--	--
99	0.026	0.029	0.019	0.021	0.018	0.022	--	--
100	0.021	0.029	0.018	0.029	0.019	0.026	--	--
101	0.024	0.027	0.018	0.023	0.019	0.022	--	--
102	0.026	0.029	0.02	0.021	0.015	0.02	--	--
103	0.021	0.021	0.027	0.024	0.016	0.025	0.021	--
104	0.026	0.02	0.026	0.028	0.019	0.029	--	--
105	0.023	0.021	0.022	0.027	0.016	0.02	--	--
106	0.021	0.028	0.025	0.022	0.018	0.028	--	--
107	0.02	0.024	0.021	0.029	0.017	0.023	--	--
108	0.025	0.023	0.019	0.026	0.017	0.022	--	--
109	0.025	0.024	0.026	0.027	0.019	0.029	--	--
110	0.024	0.029	0.019	0.02	0.016	0.022	--	--
111	0.023	0.022	0.022	0.028	0.02	0.03	--	--
112	0.02	0.028	0.023	0.027	0.016	0.03	--	--
113	0.023	0.028	0.019	0.02	0.02	0.025	--	--
114	0.026	0.027	0.018	0.024	0.017	0.02	--	--
115	0.023	0.025	0.022	0.024	0.016	0.022	--	--
116	0.021	0.022	0.024	0.023	0.017	0.022	--	--
117	0.027	0.026	0.025	0.019	0.018	0.021	--	--

118	0.023	0.027	0.017	0.023	0.02	0.026	--	--
119	0.025	0.022	0.022	0.022	0.016	0.025	--	0.022
120	0.023	0.022	0.022	0.026	0.019	0.025	--	--
121	0.024	0.026	0.018	0.022	0.017	0.029	--	--
122	0.025	0.023	0.018	0.02	0.019	0.021	--	--
123	0.024	0.029	0.025	0.029	0.017	0.028	--	--
124	0.028	0.023	0.025	0.026	0.019	0.022	--	--
125	0.026	0.02	0.019	0.025	0.016	0.027	--	--
126	0.025	0.023	0.027	0.028	0.019	0.022	--	--
127	0.022	0.027	0.017	0.022	0.019	0.021	--	--
128	0.02	0.03	0.022	0.022	0.018	0.021	--	0.022
129	0.022	0.026	0.024	0.02	0.017	0.026	--	--
130	0.023	0.03	0.023	0.026	0.017	0.022	--	--
131	0.027	0.025	0.024	0.021	0.019	0.021	--	--
132	0.025	0.029	0.024	0.022	0.02	0.024	--	--
133	0.021	0.029	0.024	0.019	0.015	0.025	--	--
134	0.023	0.021	0.025	0.029	0.016	0.024	--	--
135	0.023	0.026	0.026	0.024	0.019	0.027	--	--
136	0.019	0.025	0.02	0.023	0.018	0.03	--	--
137	0.026	0.022	0.018	0.024	0.016	0.024	--	--
138	0.023	0.025	0.019	0.026	0.02	0.022	--	--
139	0.024	0.027	0.017	0.022	0.02	0.024	--	--
140	0.024	0.025	0.025	0.02	0.017	0.024	--	--
141	0.019	0.028	0.025	0.026	0.016	0.024	--	--
142	0.027	0.024	0.021	0.025	0.018	0.02	--	--
143	0.021	0.025	0.018	0.021	0.018	0.026	--	--
144	0.026	0.022	0.02	0.028	0.016	0.025	--	--
145	0.023	0.022	0.017	0.028	0.02	0.028	--	--
146	0.028	0.022	0.025	0.028	0.018	0.025	--	--
147	0.022	0.024	0.026	0.02	0.016	0.026	--	--
148	0.018	0.029	0.019	0.023	0.018	0.029	--	--
149	0.028	0.027	0.02	0.025	0.019	0.025	--	--
150	0.021	0.028	0.026	0.02	0.018	0.02	--	--
151	0.027	0.023	0.027	0.023	0.017	0.026	--	--
152	0.019	0.025	0.024	0.022	0.018	0.028	--	--
153	0.02	0.026	0.026	0.024	0.019	0.022	--	--
154	0.02	0.023	0.026	0.026	0.016	0.026	--	0.026
155	0.019	0.022	0.022	0.023	0.016	0.02	--	--
156	0.025	0.021	0.022	0.023	0.018	0.026	--	--
157	0.023	0.022	0.021	0.026	0.018	0.021	--	--
158	0.019	0.029	0.018	0.028	0.018	0.03	--	--
159	0.019	0.026	0.021	0.027	0.02	0.025	--	--
160	0.025	0.024	0.017	0.027	0.015	0.024	--	--
161	0.027	0.025	0.019	0.027	0.02	0.022	--	--
162	0.025	0.029	0.022	0.027	0.019	0.021	--	--
163	0.019	0.029	0.024	0.025	0.017	0.029	--	--
164	0.019	0.024	0.017	0.027	0.016	0.028	--	--
165	0.027	0.029	0.02	0.022	0.02	0.023	--	--
166	0.021	0.028	0.019	0.021	0.018	0.026	--	--
167	0.02	0.022	0.023	0.023	0.018	0.024	--	0.023
168	0.019	0.026	0.022	0.022	0.019	0.024	--	0.022
169	0.022	0.022	0.027	0.025	0.017	0.027	0.022	--
170	0.02	0.021	0.024	0.028	0.018	0.027	--	--
171	0.019	0.022	0.019	0.027	0.016	0.022	--	--
172	0.018	0.023	0.023	0.029	0.017	0.022	--	--
173	0.024	0.028	0.022	0.021	0.019	0.027	--	--
174	0.023	0.022	0.023	0.022	0.018	0.023	--	--

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175	0.023	0.022	0.026	0.019	0.017	0.022	--	--
176	0.023	0.023	0.021	0.026	0.018	0.024	0.023	--
177	0.019	0.02	0.023	0.019	0.017	0.022	--	--
178	0.025	0.029	0.018	0.02	0.019	0.025	--	--
179	0.027	0.029	0.025	0.022	0.015	0.027	--	--
180	0.02	0.028	0.019	0.027	0.017	0.023	--	--
181	0.022	0.028	0.025	0.024	0.019	0.029	--	--
182	0.025	0.022	0.023	0.02	0.016	0.025	--	--
183	0.023	0.024	0.018	0.021	0.019	0.023	--	--
184	0.022	0.028	0.02	0.02	0.016	0.024	--	0.02
185	0.021	0.025	0.022	0.023	0.016	0.027	--	--
186	0.025	0.025	0.025	0.026	0.017	0.025	0.025	--
187	0.024	0.029	0.02	0.022	0.02	0.025	--	--
188	0.018	0.029	0.019	0.029	0.017	0.021	--	--
189	0.02	0.022	0.024	0.019	0.015	0.029	--	--
190	0.025	0.029	0.017	0.023	0.019	0.021	--	--
191	0.022	0.03	0.027	0.019	0.018	0.022	--	--
192	0.019	0.022	0.019	0.026	0.017	0.029	--	--
193	0.025	0.024	0.027	0.023	0.015	0.023	--	--
194	0.021	0.025	0.019	0.024	0.016	0.025	--	--
195	0.021	0.022	0.021	0.022	0.019	0.029	--	--
196	0.027	0.021	0.021	0.022	0.018	0.023	--	--
197	0.018	0.027	0.023	0.02	0.02	0.02	--	--
198	0.019	0.03	0.023	0.028	0.018	0.022	--	--
199	0.025	0.024	0.02	0.024	0.018	0.021	--	--
200	0.019	0.023	0.022	0.022	0.017	0.027	--	0.022

In biometric recognition system, FAR incorrectly accept an access attempt by an unauthorized user. That is number of false acceptances divided by the number of identification attempts. FRR incorrectly rejects an access attempt by an authorized user. FRR is number of false recognitions divided by the number of identification attempts. FTC is errors encountered at the sensor level and EER is a threshold set to evaluate the performance of the recognition are shown

in Table I and Table II. From the Table I, it is observed that performance metric in aspect of FAR is 0.025 for face trait and 0.021 for voice trait. The other performance metric FRR is 0.022 for face trait and 0.025 for voice trait. It is also noted that the third metric FTC is 0.017 for face trait and 0.024 for voice trait. The fourth metric EER is 0.021 for face trait and 0.024 for voice trait.

TABLE II Performance measures on FAR, FRR, FTC and EER in Multimodal biometric system.

S.No	FACE & VOICE-FAR	FACE & VOICE-FRR	FACE and VOICE-FTC	FACE & VOICE-EER	S.No	FACE & VOICE-FAR	FACE & VOICE-FRR	FACE & VOICE-FTC	FACE & VOICE-EER
1	0.017	0.011	0.031	--	101	0.016	0.016	0.027	0.016
2	0.013	0.016	0.028	--	102	0.015	0.012	0.031	--
3	0.016	0.011	0.027	--	103	0.017	0.015	0.029	--
4	0.015	0.016	0.032	--	104	0.013	0.013	0.029	0.013
5	0.015	0.012	0.029	--	105	0.014	0.015	0.027	--
6	0.013	0.014	0.033	--	106	0.014	0.012	0.026	--
7	0.013	0.016	0.032	--	107	0.017	0.012	0.031	--
8	0.014	0.016	0.035	--	108	0.016	0.014	0.032	--
9	0.013	0.015	0.031	--	109	0.016	0.012	0.028	--
10	0.017	0.011	0.032	--	110	0.016	0.013	0.026	--
11	0.014	0.016	0.027	--	111	0.015	0.013	0.032	--
12	0.012	0.011	0.027	--	112	0.015	0.012	0.027	--
13	0.016	0.011	0.029	--	113	0.014	0.014	0.035	0.014
14	0.017	0.015	0.026	--	114	0.014	0.014	0.027	0.014
15	0.012	0.016	0.029	--	115	0.014	0.012	0.032	--
16	0.016	0.016	0.034	0.016	116	0.013	0.013	0.031	0.013
17	0.013	0.013	0.032	0.013	117	0.015	0.016	0.032	--

18	0.014	0.012	0.025	--	118	0.013	0.014	0.034	--
19	0.015	0.016	0.03	--	119	0.015	0.014	0.035	--
20	0.015	0.014	0.026	--	120	0.016	0.015	0.034	--
21	0.012	0.013	0.035	--	121	0.016	0.013	0.035	--
22	0.015	0.013	0.026	--	122	0.016	0.015	0.026	--
23	0.012	0.016	0.026	--	123	0.014	0.012	0.03	--
24	0.016	0.013	0.028	--	124	0.016	0.014	0.033	--
25	0.013	0.012	0.029	--	125	0.015	0.013	0.028	--
26	0.016	0.013	0.032	--	126	0.015	0.015	0.028	0.015
27	0.012	0.016	0.034	--	127	0.014	0.014	0.031	0.014
28	0.013	0.012	0.031	--	128	0.016	0.012	0.027	--
29	0.012	0.016	0.032	--	129	0.013	0.014	0.026	--
30	0.014	0.012	0.031	--	130	0.017	0.011	0.031	--
31	0.016	0.015	0.033	--	131	0.015	0.015	0.032	0.015
32	0.017	0.016	0.035	--	132	0.014	0.011	0.026	--
33	0.015	0.015	0.032	0.015	133	0.016	0.013	0.026	--
34	0.015	0.012	0.034	--	134	0.015	0.016	0.03	--
35	0.016	0.011	0.032	--	135	0.013	0.013	0.026	0.013
36	0.016	0.014	0.026	--	136	0.017	0.011	0.031	--
37	0.016	0.014	0.026	--	137	0.015	0.016	0.034	--
38	0.016	0.013	0.03	--	138	0.012	0.013	0.032	--
39	0.013	0.014	0.029	--	139	0.016	0.015	0.029	--
40	0.016	0.016	0.029	0.016	140	0.016	0.013	0.035	--
41	0.016	0.015	0.026	--	141	0.016	0.014	0.027	--
42	0.017	0.014	0.033	--	142	0.014	0.014	0.025	0.014
43	0.016	0.014	0.03	--	143	0.016	0.012	0.03	--
44	0.016	0.013	0.027	--	144	0.016	0.013	0.03	--
45	0.014	0.015	0.026	--	145	0.016	0.011	0.027	--
46	0.016	0.016	0.033	0.016	146	0.015	0.013	0.028	--
47	0.013	0.012	0.028	--	147	0.014	0.015	0.033	--
48	0.012	0.012	0.035	0.012	148	0.014	0.015	0.032	--
49	0.017	0.014	0.031	--	149	0.016	0.016	0.028	0.016
50	0.013	0.014	0.029	--	150	0.016	0.016	0.032	0.016
51	0.013	0.013	0.029	0.013	151	0.016	0.013	0.028	--
52	0.014	0.014	0.03	0.014	152	0.012	0.014	0.028	--
53	0.013	0.014	0.031	--	153	0.012	0.012	0.03	0.012
54	0.016	0.013	0.028	--	154	0.013	0.015	0.029	--
55	0.015	0.014	0.031	--	155	0.016	0.014	0.032	--
56	0.015	0.014	0.032	--	156	0.013	0.012	0.028	--
57	0.014	0.015	0.033	--	157	0.013	0.012	0.034	--
58	0.014	0.016	0.034	--	158	0.013	0.016	0.033	--
59	0.012	0.016	0.028	--	159	0.015	0.015	0.033	0.015
60	0.014	0.011	0.032	--	160	0.015	0.014	0.028	--
61	0.015	0.014	0.03	--	161	0.016	0.014	0.035	--
62	0.013	0.013	0.031	0.013	162	0.016	0.016	0.034	0.016
63	0.014	0.012	0.031	--	163	0.015	0.012	0.031	--
64	0.014	0.014	0.032	0.014	164	0.012	0.012	0.028	0.012
65	0.017	0.013	0.035	--	165	0.015	0.011	0.029	--
66	0.013	0.015	0.028	--	166	0.017	0.012	0.026	--
67	0.016	0.012	0.032	--	167	0.012	0.013	0.033	--
68	0.013	0.012	0.026	--	168	0.013	0.013	0.035	0.013
69	0.012	0.013	0.026	--	169	0.016	0.012	0.025	--
70	0.015	0.014	0.035	--	170	0.015	0.013	0.031	--
71	0.015	0.014	0.033	--	171	0.012	0.013	0.03	--
72	0.015	0.013	0.032	--	172	0.014	0.016	0.027	--
73	0.013	0.011	0.03	--	173	0.016	0.013	0.025	--
74	0.016	0.012	0.03	--	174	0.014	0.013	0.034	--

Fusion of Face and Voice for a Multimodal Biometric Recognition System

75	0.016	0.014	0.025	--	175	0.014	0.014	0.03	0.014
76	0.013	0.011	0.032	--	176	0.013	0.014	0.035	--
77	0.013	0.013	0.025	0.013	177	0.016	0.015	0.032	--
78	0.013	0.012	0.026	--	178	0.014	0.015	0.034	--
79	0.013	0.011	0.03	--	179	0.015	0.015	0.034	0.015
80	0.017	0.013	0.03	--	180	0.017	0.011	0.025	--
81	0.016	0.016	0.029	0.016	181	0.015	0.012	0.032	--
82	0.014	0.015	0.026	--	182	0.015	0.014	0.03	--
83	0.015	0.012	0.029	--	183	0.017	0.012	0.028	--
84	0.016	0.014	0.031	--	184	0.016	0.015	0.03	--
85	0.016	0.014	0.035	--	185	0.016	0.012	0.026	--
86	0.015	0.011	0.034	--	186	0.015	0.016	0.029	--
87	0.016	0.015	0.03	--	187	0.012	0.014	0.029	--
88	0.013	0.015	0.027	--	188	0.015	0.011	0.026	--
89	0.014	0.016	0.029	--	189	0.017	0.013	0.031	--
90	0.015	0.016	0.026	--	190	0.013	0.011	0.027	--
91	0.015	0.011	0.035	--	191	0.015	0.015	0.026	0.015
92	0.012	0.015	0.03	--	192	0.017	0.014	0.029	--
93	0.017	0.014	0.035	--	193	0.015	0.013	0.027	--
94	0.013	0.016	0.032	--	194	0.017	0.012	0.035	--
95	0.015	0.012	0.026	--	195	0.015	0.016	0.031	--
96	0.012	0.015	0.029	--	196	0.015	0.015	0.034	0.015
97	0.015	0.012	0.025	--	197	0.014	0.011	0.032	--
98	0.014	0.014	0.026	0.014	198	0.013	0.016	0.029	--
99	0.014	0.015	0.029	--	199	0.014	0.015	0.026	--
100	0.016	0.015	0.03	--	200	0.015	0.012	0.034	--

From Table II, it is noticed that performance metrics of FAR, FRR, FTC and EER are 0.017, 0.011, 0.031 and 0.016 respectively for face and voice multimodal biometric recognition system. Experiments are conducted on 1000 traits but performance measures are shown only 200 traits in table I and table II

In this experimental results are divided into three different individual biometric authentication systems. In the first phase, performance measures of face biometric authentication system are represented in graphical form. All the graphs from Fig. 3 to Fig.5 are represented for five hundred traits. Fig.3 (a) shows that FAR value ranges from 0.018 to 0.028. From Fig. 3(a) & Table I, it is observed that, 18 to 28 numbers of impostors are accepted out of one thousand attempts. Fig. 3(b) shows that FRR value falls in the range of 0.017 to 0.027. From Fig. 3(b) & Table I, it is also observed that, the system rejects 17 to 27 genuine users out of one thousand attempts. Similarly Fig. 3(c) shows that FTC value ranges from 0.015 to 0.020. From the Fig. 3(c) & Table I, it is also observed that the system fails to capture 15 to 20 face traits out of one thousand attempts.

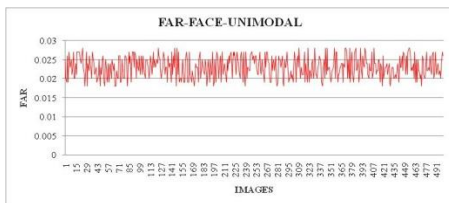


Fig.3 (a). Performance measures of FAR plot for face dataset model

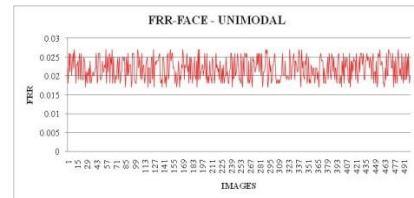


Fig.3(b). Performance measures of FRR plot for face dataset model

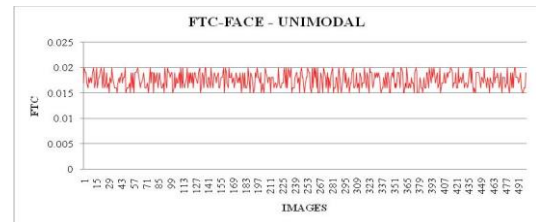


Fig.3(c). Performance measures of FTC plot for face dataset model

In the second phase, performance measures of voice biometric authentication system are represented in graphical form. In voice trait biometric system, FAR performance plot is shown in Fig. 4(a). From Fig. 4(a) & Table I, it is observed that the FAR value ranges from 0.020 to 0.030 and it means this system accepts 20 to 30 impostors out of one thousand attempts. From Fig. 4(b) & Table I, it is also observed that, the FRR value ranges from 0.019 to 0.029 and the system rejects 19 to 29 genuine users out of one thousand attempts. From Fig. 4(c) & Table I, it is also observed that FTC value ranges from 0.020 to 0.030. This means that the system fails to capture 20 to 30 traits out of one thousand attempts.

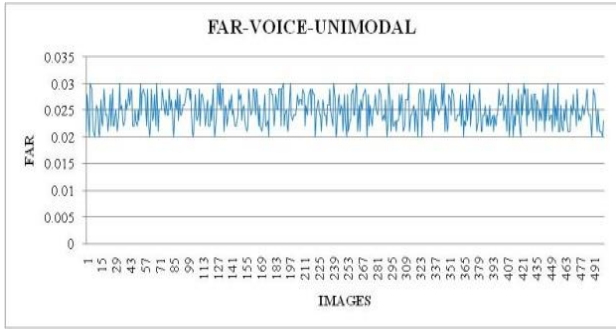


Fig.4 (a). Performance measures of FAR plot for voice dataset model.

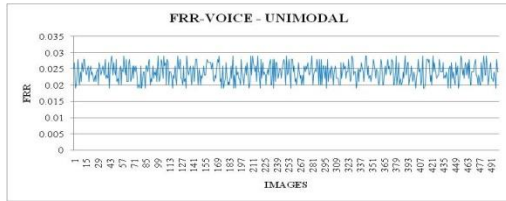


Fig.4(b). Performance measures of FRR plot for voice dataset model

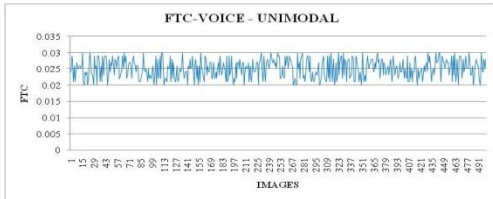


Fig.4(c). Performance measures of FTC plot for voice dataset model

In third phase, experiments are conducted on both face image and voice trait model which are shown in graphical representation. In face-voice multimodal biometric system, FAR performance plot is shown in Fig. 5(a). From Fig. 5(a) & Table II, it is observed that the FAR value falls in the range from 0.012 to 0.017 which means this system accepts 12 to 17 unauthorized users out of one thousand attempts. From Fig. 5(b) & Table II, it is observed that the FRR value is in the range from 0.011 to 0.016 which means this model rejects 11 to 16 genuine users out of one thousand attempts. It is also observed from Fig. 5(c) & Table II that FTC values fall in the range between 0.025 and 0.035 that is this system fails to capture 25 to 35 biometric traits out of one thousand attempts.

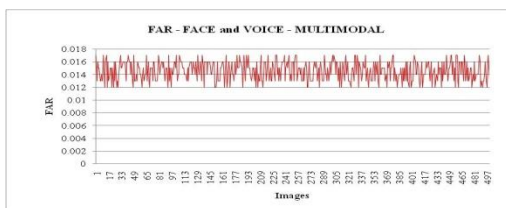


Fig.5 (a). FAR plot for face and voice data set model

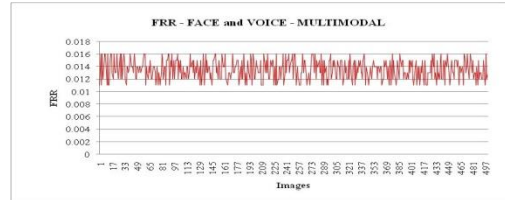


Fig.5 (b). FRR plot for face and voice data set model

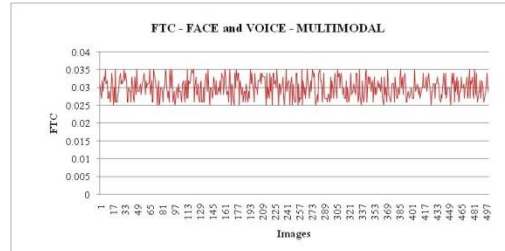


Fig.5 (c). FTC plot for face and voice data set model

Discussions:

- In Unimodal biometric authentication system for which experimental values represented in Table I & Fig. 3(a), 4(a) for FAR, it is observed that ,
 - FAR value of face trait model ranges between 0.018 and 0.028 and voice ranges between 0.020 and 0.030. From these statistics, it is observed that FAR value is better in facial trait when compared to voice trait model.
- With reference to FRR, which is represented in Table I & Fig. 3(b), 4(b)
 - The FRR value ranges are between 0.017 and 0.027 for face image and are between 0.019 and 0.029 for voice trait model. From these values, it is observed that FRR value is better in facial trait when compared to voice trait model.
- In multimodal biometric authentication system, FAR performance of face and voice traits are shown in Table II & Fig. 5(a)
 - The FAR value ranges are between 0.012 and 0.017. This system accepts 12 to 17 unauthorized users out of one thousand attempts. After evaluating unimodal and multimodal, it is observed that multimodal system shows better results when both face and voice traits are integrated.
- In perspective of FRR performance of face and voice traits are shown in Fig. 5(b) & Table II,
 - The values of FAR ranges are between 0.011 and 0.016. This system accepts 11 to 16 unauthorized users out of one thousand attempts. In FRR perspective also this multimodal shows better results when both face and voice traits are integrated.
- In case of FTC for uni-modal which is shown in Fig. 3(c) for face & Fig.4(c) for voice,
 - The values of FTC ranges are between 0.015 and 0.020 for face image traits and ranges are between 0.020 and 0.030 for voice traits. It is observed that FTC value is better in facial trait when compared to voice trait.

- In multimodal, FTC performance of face and voice measures are shown in Fig.5(c) & Table II,
 - The FTC value ranges are between 0.025 and 0.035. This system fails to capture 25 to 35 biometric traits out of one thousand attempts. It can be noticed that poor results are obtained when both face and voice traits are integrated.

VII. VII.CONCLUSIONS

In this study, a new biometric authentication system is developed which combines both face image and voice trait by using score level fusion. Many experiments are conducted by taking 1000 samples of face image and voice traits and the performance of the system is evaluated basing on FAR, FRR, FTC and EER. As per the results and evaluation it can be concluded that the proposed model improves the recognition performance when compared to traditional recognition and uni-modal recognition. Multimodal recognition model supports high security, confidentiality and it is achieved by different compression methods, feature extraction and fusion techniques.

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