An Analytical Study on integration of Multibiometric Traits at Matching Score Level using Transformation Techniques

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Abstract— Biometric is one of those egressing technologies which are exploited for identifying a person on the basis of physiological and behavioral characteristic. However, unimodal biometric system faces the problem of lack of individuality, spoof attacks, non-universality, degree of freedom etc., which make these systems less precise and erroneous. In order to overcome these problems, multi biometric has become the favorite choice for verification of an individual to declare him as an imposte or a genuine. However, the fusion or integration of multiple biometric traits can be done at any one of the four module of a general multibiometric system. Further, achieving fusion at matching score level is more preferable due to the availability of sufficient amount of information present over there. In this paper we have presented a comparative study of normalization methodology which is basically used to convert the different feature vectors of individual traits in common domain in order to combine them as a single feature vector.

Keywords— Biometric, Multibiometric, Normalization, Unimodal, Unsupervised Learning rules, Imposter, Genuine.

1. INTRODUCTION

Biometric system is fundamentally a pattern recognition system. The Biometric is a Greek word in which 'bio' stands for life and 'metric' for the measurement. Biometrics has been used in the science that studies living organisms for the data analysis problems for a long period [1]. Different kinds of triats are use for authentication of individuality such as fingerprint recognition, hand geometry, facial recognition, iris recognition, key stroke recognition, signature recognition, gait recognition, DNA (De-oxyribo Nucleic Acid), voice recognition and palm print [2]. In the conventional approach of security, many password-cracking proficiencies being used today and the complexity necessary for passwords make these system a bit less preferable choice. Further, it is also easy for an application programmer to crack the password of someone, if any of these identity proof(token card and password) is lost by the individual which he is carrying along with him, then it might be used by an imposter and will create problems.To overcome of all these limitation, we use bio-metric techniques. In unimodal system, we use only one trait out of all for the identification [3]. In case of fingerprint recognition, user place his/her finger on the fingerprint sensor and is identified as a genuine one or as an imposter, but in due course of time when if the residual of the previous user remain present on the sensor may produces the false results and the right identity of individual will not be measured. In addition to this, facial recognition is highly dependent on the quality of the image, which is generally affected when low quality camera is used or due to the environmental factors. Many a time, facial recognition system fails in verification process of identical twins, or father-son. In Multimodal biometric systems, more than one physiological or behavioral characteristic are used for enrollment, verification, identification process or authentication of individuality. Multimodal biometric systems have some unique advantages over unimodal biometric in terms of accuracy, enrolment rates, and susceptibility to spoofing attacks [4]. In order to design a multi biometric system, the features of different biometric modalities are integrated at different modules of a general multi biometric system.

In multimodal biometric system the entropies of data can be combined at any one of four levels, namely sensor level, feature extraction level, matching score level and decision level, and fusion can occur at any level [5]. However it is beneficial to fuse the information at that level only where maximum amount of information can be accessed with ease. Due to the presence of sufficient amount of information at matching score level, it is best suited for fusion purpose. In this report we have briefly explored the problem and better solution for choosing sensors and fusion methods, and present a case study describing its impact on biometric systems.

2. NORMALIZATION

Normalization is a particular course of action intended to coordinate the fields and mutual exclusiveness of the information in a database in which relations among entropies are explicitly defined as approachable dimensions to minimize redundancy and dependency. The goal is to set apart the data so that accessions, omissions, and changes of a field can be made in just one table and then dispersed through with the rest of the database via the fixed relationships. Nevertheless, the objective of data normalization is to cut down and evenly eliminate data layoff. It is useful to minimize the discontinuities when covering the database structure, to make the data model more instructive to users, to keep away from preconception towards any particular form of questioning. Here, we have used two normalization methods to change the matching scores obtained from the finger print and face in common domain [6].

3. QUANTILE NORMALIZATION

Quantile normalization is a technique for making distributions identical in statistical properties [7]. To Quantile-normalize a test distribution to a reference distribution of the same length, sort the test distribution and sort the reference distribution. The highest entry in the test distribution then takes the value of the highest entry in the reference distribution, the next highest entry in the reference distribution, and so on, until the test distribution is a perturbation of the reference distribution. To Quantile normalize two or more distributions to each other, without a reference distribution, sort as before, and then set to the average of the distributions. So the highest value in all cases becomes the mean of the highest values, the second highest value becomes the mean of the second highest values, and so on. Quantile normalization is frequently used in microarray data analysis.Extending this approximation to N dimensions contributes us a technique of determining a common statistical distribution from multiple number of biometric modalities in the following steps.

1. A two dimensional matrix (X) of matching scores having N database of length M each obtained from different identifiers is available in MxN form.
2. Now, configure p = ($\frac{1}{\sqrt{N}}$,..., $\frac{1}{\sqrt{N}}$)
3. Sort each column of MxN matrix (X) of the matching scores to obtain the X_{sort}.
4. Successively each row of X_{sort} is Projected onto p to get X'_{sort}
5. Finally, X'_{sort} is rearranged having the same order of original X to obtained the X_{norm}.

4. DELTA NORMALIZATION

The delta normalization is a novel approach to convert the data in common domain and it helps to spread the whole statistical distribution in the range of 0 and 1, i.e. the minimum values approaches toward 0 and maximum toward 1 [8].this method is both functioning effectively and full-bodied in nature as it does not estimate the statistical distribution and cuts down the impression of outliers too. If δ is the archetype matching score then normalized scores δ' are given by.

$$\delta' = \frac{1}{2}\left(1 - \frac{\delta}{\sqrt{\delta^2 + \propto}}\right)$$

Here, α is a smoothing constant which takes out the infrequent and uncorrelated data from the statistical distribution. Usually we take the value of α approximately equal to the 100 and more as it gives better accuracy for higher value of α.

5. FUSION

Fusion is the method necessary for combining information from various single modality systems. The process of integrating the information from number of evidences to build-up a multi biometric system is called fusion. The information can be integrated or fused by fusion at any level. In this, information from different domains is transformed into a common domain [6].

5.1. Sum Rule

sum rule is helps in eliminating the problem of ambiguity during assortment of the database. Futhermore, after the normalization of finger and face data they are summed up to acquire the fused score. Here, input pattern is delegated to the class c such that.

$$c = argmax_j \sum_{i=1}^{R} \mathrm{P}\left(w_j \middle| \vec{\mathrm{X}}_{\mathrm{i}}\right)$$

5.2. Product Rule

The product rule renders a more inadvertent consequences than sum rule as it is based on the statistical influence of the feature vectores. The input pattern designated to the class c is given by.

$$c = argmax_j \prod_{i=1}^{R} \mathrm{P}\left(w_j \middle| \vec{\mathrm{X}}_{\mathrm{i}}\right)$$

5.3. Min Rule

Min rule of fusion dominate by considering a mimnum posterior probability which is accumulated out of all classifies. Therefore, the stimulus pattern designated to the class c such that[9].

$$c = \mathrm{argmax}_j \min_i P\left(w_j \mid \vec{x}_i\right)$$

5.4. Max rule

Max rule of fusion dominate by considering a maximum posterior probability which is accumulated out of all classifies. Therefore, the stimulus pattern designated to the class c such that[9].

$$c = \mathrm{argmax}_j \max_i P\left(w_j \mid \vec{x}_i\right)$$

6. MATCHING SCORE & DATABASE

To assess the execution of the normalization proficiencies with the fusion rules, the NIST- *Biometric Scores Set - Release 1 (*BSSR1), biometric database has been utilized. This database has a prominent amount of matching scores of faces and fingers, particularly derived for the fusion procedure.

7. FINGERPRINT MATCHING SCORE

Matching score for the fingerprint of 10 users have been considered for the experimental study.

Table 1. Matching scores of fingerprint of 10 users

Users	A	B	C	D	E	F	G	H	I	J
1	29	4	6	4	4	7	5	6	6	9
2	7	26	12	4	11	9	4	9	6	5
3	8	5	63	6	7	5	9	6	7	8
4	8	5	10	73	9	8	12	6	16	6
5	11	5	12	6	175	6	9	8	8	10
6	8	4	6	3	4	10	6	5	6	3
7	9	3	6	5	5	5	11	5	4	5
8	8	4	10	5	9	10	8	38	8	5
9	6	6	5	7	11	4	11	6	142	6
10	3	5	8	4	14	6	6	10	6	163

8. FACE MATCHING SCORE

Matching scores for the face of 10 users have been considered for the experimental study.

Table 2. Matching scores of face of 10 users

Users	A	B	C	D	E	F	G	H	I	J
1	.57	.53	.52	.55	.54	.54	.55	.55	.58	.52
2	.56	.78	.51	.51	.51	.52	.51	.54	.56	.52
3	.45	.52	.81	.49	.51	.54	.53	.50	.54	.58
4	.51	.53	.49	.82	.47	.51	.53	.51	.51	.52
5	.50	.55	.54	.50	.59	.54	.54	.52	.52	.51
6	.45	.49	.52	.52	.49	.67	.52	.47	.51	.52
7	.53	.57	.52	.53	.49	.50	.67	.52	.55	.52

8	.54	.54	.48	.53	.57	.49	.52	.77	.49	.51
9	.52	.53	.52	.53	.54	.50	.52	.50	.69	.52
10	.50	.52	.50	.55	.57	.52	.52	.60	.54	.58

9. NORMALIZED MATCHING SCORE

The matching scores considered previously have been applied in Quantile and delta normalization and the following tables are evaluated.

Table 3. Normalized matching scores of fingerprint of 10 users through Quantile normalization

Users	A	B	C	D	E	F	G	H	I	J
1	0.937	-0.467	-0.354	-0.467	-0.467	-0.298	-0.411	-0.354	-0.354	-0.411
2	0.263	-0.354	-0.017	-0.467	-0.074	-0.186	-0.467	-0.186	-0.354	-0.13
3	-0.24	-0.411	2.8469	-0.354	-0.298	-0.411	-0.186	-0.354	-0.298	-0.354
4	-0.24	-0.411	-0.13	3.4085	-0.186	-0.242	-0.017	-0.354	0.2072	-0.13
5	-0.07	-0.411	-0.017	-0.354	9.1371	-0.354	-0.186	-0.242	-0.242	-0.074
6	-0.24	-0.467	-0.354	-0.523	-0.467	-0.13	-0.354	-0.411	-0.354	-0.354
7	-0.19	-0.523	-0.354	-0.411	-0.411	-0.411	-0.074	-0.411	-0.467	-0.411
8	-0.24	-0.467	-0.13	-0.411	-0.186	-0.13	-0.242	1.4428	-0.242	0.3757
9	-0.35	-0.354	-0.411	-0.298	-0.074	-0.467	-0.074	-0.354	7.2837	-0.523
10	-0.24	-0.411	-0.242	-0.467	0.0949	-0.354	-0.354	-0.13	-0.354	1.2182

Table 4. Normalized matching scores of face of 10 users through Quantile normalization

Users	A	B	C	D	E	F	G	H	I	J
1	1.202	-0.269	-0.64	0.426	-0.142	-0.004	0.235	0.547	1.438	-0.685
2	0.843	9.3888	-1.007	-1.31	-0.987	-0.637	-1.23	0.136	0.903	-0.885
3	-3.32	-0.812	10.52	-1.96	-0.994	0.104	-0.29	-1.45	0.183	1.6488
4	-1.31	-0.472	-1.967	11.12	-2.655	-1.247	-0.46	-1.29	-1.08	-0.615
5	-1.37	0.2182	-0.036	-1.37	1.7858	0.04	0.173	-0.67	-0.88	-1.25
6	-3.47	-2.045	-0.867	-0.92	-2.111	5.12	-0.63	-2.61	-1.2	-0.931
7	-0.47	1.1465	-0.735	-0.31	-1.983	-1.503	4.936	-0.77	0.284	-0.893
8	0.158	-0.162	-2.274	-0.38	1.0883	-1.752	-0.78	9.14	-1.77	-0.997
9	-0.6	-0.306	-0.93	-0.51	0.0726	-1.511	-0.95	-1.71	6.058	-0.85
10	-1.45	-0.737	-1.42	0.577	1.3527	-0.628	-0.81	2.517	0.142	1.7597

Table 5. Normalized matching scores of fingerprint of 10 users through delta normalization

Users	A	B	C	D	E	F	G	H	I	J
1	0.473	0.186	0.257	0.186	0.186	0.287	0.224	0.257	0.257	0.224
2	0.431	0.257	0.384	0.186	0.37	0.334	0.186	0.334	0.257	0.354
3	0.312	0.224	0.494	0.257	0.287	0.224	0.334	0.257	0.287	0.257
4	0.312	0.224	0.354	0.495	0.334	0.312	0.384	0.257	0.424	0.354
5	0.37	0.224	0.384	0.257	0.499	0.257	0.334	0.312	0.312	0.37
6	0.312	0.186	0.257	0.144	0.186	0.354	0.257	0.224	0.257	0.257
7	0.334	0.144	0.257	0.224	0.224	0.224	0.37	0.224	0.186	0.224
8	0.312	0.186	0.354	0.224	0.334	0.354	0.312	0.484	0.312	0.442
9	0.257	0.257	0.224	0.287	0.37	0.186	0.37	0.257	0.499	0.144
10	0.312	0.224	0.312	0.186	0.407	0.257	0.257	0.354	0.257	0.48

Table 6. Normalized matching scores of face of 10 users through delta normalization

Users	A	B	C	D	E	F	G	H	I	J
1	0.0287	0.0269	0.0264	0.0277	0.027	0.0272	0.0275	0.0279	0.029	0.0263
2	0.0283	0.0391	0.0259	0.0255	0.0259	0.0264	0.0256	0.0274	0.0284	0.0261
3	0.023	0.0262	0.0406	0.0247	0.0259	0.0273	0.0268	0.0254	0.0274	0.0293
4	0.0255	0.0266	0.0247	0.0413	0.0238	0.0256	0.0266	0.0256	0.0258	0.0264
5	0.0255	0.0275	0.0272	0.0255	0.0295	0.0273	0.0274	0.0264	0.0261	0.0256
6	0.0228	0.0246	0.0261	0.026	0.0245	0.0337	0.0264	0.0239	0.0257	0.026
7	0.0266	0.0287	0.0263	0.0268	0.0247	0.0253	0.0335	0.0262	0.0276	0.0261
8	0.0274	0.027	0.0243	0.0267	0.0286	0.025	0.0262	0.0388	0.0249	0.0259
9	0.0264	0.0268	0.026	0.0265	0.0273	0.0253	0.026	0.025	0.0349	0.0261
10	0.0254	0.0263	0.0254	0.0279	0.0289	0.0264	0.0262	0.0304	0.0274	0.0294

10. FUSED SCORE

The resultant tables obtained after the normalization are fused together to get the fused score and are evaluated as followed.

Table7. Fused scores of 10 users using sum rule fusion through Quantile Normalization

Users	A	B	C	D	E	F	G	H	I	J
1	2.139	-0.735	-0.995	-0.041	-0.609	-0.302	-0.176	0.193	1.084	-1.096
2	1.107	9.034	-1.024	-1.777	-1.061	-0.823	-1.698	-0.050	0.548	-1.014
3	-3.566	-1.222	13.367	-2.310	-1.292	-0.306	-0.480	-1.804	-0.115	1.294
4	-1.552	-0.883	-2.097	14.531	-2.841	-1.489	-0.481	-1.641	-0.873	-0.745
5	-1.439	-0.192	-0.054	-1.726	10.923	-0.315	-0.013	-0.910	-1.126	-1.324
6	-3.714	-2.512	-1.221	-1.440	-2.578	4.990	-0.984	-3.021	-1.550	-1.286
7	-0.652	0.624	-1.089	-0.720	-2.394	-1.914	4.862	-1.180	-0.182	-1.303
8	-0.084	-0.628	-2.404	-0.793	0.902	-1.882	-1.024	10.583	-2.016	-0.621
9	-0.957	-0.660	-1.341	-0.813	-0.001	-1.978	-1.019	-2.065	13.342	-1.373
10	-1.688	-1.148	-1.662	0.110	1.448	-0.982	-1.161	2.387	-0.212	2.978

Table 8. Fused scores of 10 users using product rule fusion through Quantile Normalization

Users	A	B	C	D	E	F	G	H	I	J
1	1.126	0.125	0.227	-0.199	0.066	0.001	-0.096	-0.194	-0.510	0.281
2	0.222	-3.327	0.018	0.612	0.073	0.118	0.575	-0.025	-0.320	0.115
3	0.805	0.333	29.949	0.693	0.296	-0.043	0.055	0.514	-0.055	-0.584
4	0.317	0.194	0.255	37.912	0.494	0.302	0.008	0.456	-0.224	0.080
5	0.100	-0.090	0.001	0.486	16.317	-0.014	-0.032	0.162	0.214	0.092
6	0.840	0.955	0.307	0.479	0.985	-0.664	0.223	1.072	0.424	0.330
7	0.087	-0.599	0.261	0.127	0.814	0.617	-0.363	0.316	-0.133	0.367
8	-0.038	0.076	0.295	0.157	-0.202	0.227	0.189	13.187	0.429	-0.375
9	0.214	0.108	0.382	0.153	-0.005	0.705	0.070	0.606	44.127	0.445
10	0.350	0.303	0.344	-0.269	0.128	0.222	0.286	-0.327	-0.050	2.144

Table 9. Fused scores of 10 users using min rule fusion through Quantile Normalization

Users	A	B	C	D	E	F	G	H	I	J
1	0.937	-0.467	-0.640	-0.467	-0.467	-0.298	-0.411	-0.354	-0.354	-0.685
2	0.263	-0.354	-1.007	-1.311	-0.987	-0.637	-1.231	-0.186	-0.354	-0.885
3	-3.324	-0.812	2.847	-1.955	-0.994	-0.411	-0.294	-1.450	-0.298	-0.354
4	-1.310	-0.472	-1.967	3.409	-2.655	-1.247	-0.464	-1.287	-1.081	-0.615
5	-1.365	-0.411	-0.036	-1.371	1.786	-0.354	-0.186	-0.668	-0.883	-1.250
6	-3.472	-2.045	-0.867	-0.917	-2.111	-0.130	-0.630	-2.610	-1.195	-0.931
7	-0.466	-0.523	-0.735	-0.411	-1.983	-1.503	-0.074	-0.769	-0.467	-0.893
8	-0.242	-0.467	-2.274	-0.411	-0.186	-1.752	-0.782	1.443	-1.774	-0.997
9	-0.603	-0.354	-0.930	-0.514	-0.074	-1.511	-0.945	-1.711	6.058	-0.850
10	-1.446	-0.737	-1.420	-0.467	0.095	-0.628	-0.807	-0.130	-0.354	1.218

Table 10. Fused scores of 10 users using max rule fusion through Quantile Normalization

Users	A	B	C	D	E	F	G	H	I	J
1	1.202	-0.269	-0.354	0.426	-0.142	-0.004	0.235	0.547	1.438	-0.411
2	0.843	9.389	-0.017	-0.467	-0.074	-0.186	-0.467	0.136	0.903	-0.130
3	-0.242	-0.411	10.520	-0.354	-0.298	0.104	-0.186	-0.354	0.183	1.649
4	-0.242	-0.411	-0.130	11.123	-0.186	-0.242	-0.017	-0.354	0.207	-0.130
5	-0.074	0.218	-0.017	-0.354	9.137	0.040	0.173	-0.242	-0.242	-0.074
6	-0.242	-0.467	-0.354	-0.523	-0.467	5.120	-0.354	-0.411	-0.354	-0.354
7	-0.186	1.147	-0.354	-0.309	-0.411	-0.411	4.936	-0.411	0.284	-0.411
8	0.158	-0.162	-0.130	-0.383	1.088	-0.130	-0.242	9.140	-0.242	0.376
9	-0.354	-0.306	-0.411	-0.298	0.073	-0.467	-0.074	-0.354	7.284	-0.523
10	-0.242	-0.411	-0.242	0.577	1.353	-0.354	-0.354	2.517	0.142	1.760

Table11. Fused scores of 10 users using sum rule fusion through Delta Normalization

Users	A	B	C	D	E	F	G	H	I	J
1	0.501	0.213	0.284	0.213	0.213	0.314	0.251	0.285	0.286	0.250
2	0.459	0.296	0.410	0.211	0.396	0.361	0.211	0.362	0.286	0.380
3	0.335	0.250	0.534	0.282	0.313	0.251	0.361	0.283	0.314	0.287
4	0.338	0.250	0.378	0.537	0.358	0.338	0.411	0.283	0.450	0.380
5	0.395	0.251	0.411	0.283	0.529	0.285	0.362	0.339	0.338	0.396
6	0.335	0.210	0.283	0.170	0.210	0.387	0.284	0.247	0.283	0.283
7	0.361	0.172	0.284	0.250	0.248	0.249	0.403	0.250	0.213	0.250
8	0.340	0.213	0.378	0.250	0.363	0.379	0.339	0.522	0.337	0.468
9	0.284	0.284	0.250	0.313	0.397	0.211	0.396	0.282	0.534	0.170
10	0.338	0.250	0.338	0.214	0.436	0.284	0.283	0.384	0.285	0.509

Table12. Fused scores of 10 users using product rule fusion through Delta Normalization

Users	A	B	C	D	E	F	G	H	I	J
1	0.014	0.005	0.007	0.005	0.005	0.008	0.006	0.007	0.007	0.006
2	0.012	0.010	0.010	0.005	0.010	0.009	0.005	0.009	0.007	0.009
3	0.007	0.006	0.020	0.006	0.007	0.006	0.009	0.007	0.008	0.008
4	0.008	0.006	0.009	0.020	0.008	0.008	0.010	0.007	0.011	0.009
5	0.009	0.006	0.010	0.007	0.015	0.007	0.009	0.008	0.008	0.009
6	0.007	0.005	0.007	0.004	0.005	0.012	0.007	0.005	0.007	0.007
7	0.009	0.004	0.007	0.006	0.006	0.006	0.012	0.006	0.005	0.006
8	0.009	0.005	0.009	0.006	0.010	0.009	0.008	0.019	0.008	0.011
9	0.007	0.007	0.006	0.008	0.010	0.005	0.010	0.006	0.017	0.004
10	0.008	0.006	0.008	0.005	0.012	0.007	0.007	0.011	0.007	0.014

Table13. Fused scores of 10 users using min rule fusion through Delta Normalization

Users	A	B	C	D	E	F	G	H	I	J
1	0.029	0.027	0.026	0.028	0.027	0.027	0.028	0.028	0.029	0.026
2	0.028	0.039	0.026	0.026	0.026	0.026	0.026	0.027	0.028	0.026
3	0.023	0.026	0.041	0.025	0.026	0.027	0.027	0.025	0.027	0.029
4	0.026	0.027	0.025	0.041	0.024	0.026	0.027	0.026	0.026	0.026
5	0.025	0.027	0.027	0.025	0.029	0.027	0.027	0.026	0.026	0.026
6	0.023	0.025	0.026	0.026	0.025	0.034	0.026	0.024	0.026	0.026
7	0.027	0.029	0.026	0.027	0.025	0.025	0.033	0.026	0.028	0.026
8	0.027	0.027	0.024	0.027	0.029	0.025	0.026	0.039	0.025	0.026
9	0.026	0.027	0.026	0.027	0.027	0.025	0.026	0.025	0.035	0.026
10	0.025	0.026	0.025	0.028	0.029	0.026	0.026	0.030	0.027	0.029

Table14. Fused scores of 10 users using max rule fusion through Delta Normalization

Users	A	B	C	D	E	F	G	H	I	J
1	0.473	0.186	0.257	0.186	0.186	0.287	0.224	0.257	0.257	0.224
2	0.431	0.257	0.384	0.186	0.370	0.334	0.186	0.334	0.257	0.354
3	0.312	0.224	0.494	0.257	0.287	0.224	0.334	0.257	0.287	0.257
4	0.312	0.224	0.354	0.495	0.334	0.312	0.384	0.257	0.424	0.354
5	0.370	0.224	0.384	0.257	0.499	0.257	0.334	0.312	0.312	0.370
6	0.312	0.186	0.257	0.144	0.186	0.354	0.257	0.224	0.257	0.257
7	0.334	0.144	0.257	0.224	0.224	0.224	0.370	0.224	0.186	0.224
8	0.312	0.186	0.354	0.224	0.334	0.354	0.312	0.484	0.312	0.442
9	0.257	0.257	0.224	0.287	0.370	0.186	0.370	0.257	0.499	0.144
10	0.312	0.224	0.312	0.186	0.407	0.257	0.257	0.354	0.257	0.480

11. RESULT

The analytical consequences of a multibiometric system of rules for sum and product rule have been examined. The Genuine Acceptance Rate and False Acceptance Rate for delta and Quantile normalizations with two fusion strategies have been evaluated and are shown in table 15 and table 16. Threshold measures in table15 and table16 are the diagonal measures which are prevailed after the coalition of the transformed scores. The genuine acceptance rates and false rejection rates have been computed for some of the threshold values which are infact genuine matching score received after the integration.

Table 15. GAR and FRR for Quantile normalization with four fusion rules

	Sum			**Product**			**Min**			**Max**		
	Threshold	**GAR**	**FRR**	**Threshold**	**GAR**	**FRR**	**Threshold**	**GAR**	**FRR**	**Threshold**	**GAR**	**FRR**
Quantile Norm.	2.139	100	0	-3.327	82	18	-1.30	92	8	1.202	99	1
	4.990	100	0	-0.363	89	11	-0.354	96	4	4.936	100	0
	9.034	100	0	1.126	100	0	1.786	100	0	5.120	100	0
	10.92	100	0	29.94	100	0	2.847	100	0	9.389	100	0
	13.37	100	0	37.19	100	0	3.409	100	0	10.52	100	0
	14.53	100	0	44.12	100	0	6.058	100	0	11.12	100	0

Table 16. GAR and FRR for Delta normalization with four fusion rules

	Sum			**Product**			**Min**			**Max**		
	Threshold	**GAR**	**FRR**	**Threshold**	**GAR**	**FRR**	**Threshold**	**GAR**	**FRR**	**Threshold**	**GAR**	**FRR**
Delta Norm.	0.296	84	16	0.010	96	4	0.029	96	4	0.257	92	0
	0.387	91	9	0.014	100	0	0.033	100	0	0.354	97	0
	0.403	97	3	0.015	100	0	0.034	100	0	0.370	98	0
	0.501	100	0	0.017	100	0	0.035	100	0	0.473	100	0
	0.534	100	0	0.019	100	0	0.039	100	0	0.480	100	0
	0.537	100	0	0.020	100	0	0.041	100	0	0.495	100	0

CONCLUSION

The aim of substantial exercise shown in this paper is based on the elemental study of how more than one entity of biometric can be fused together to generate a more practicable and efficacious authentication system. Here, with two novel terminologies for the normalization of database have been used to fuse with sum rule and product rule fusion. The substantial eminence between these methods has built on the basis of genuine and false recognition rates. Furthermore, the Delta normalization function used for the normalization has given a reasonable performance over Quantile normalization method and has rendered superior GARs and FARs.

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