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GLOBAL FEATURES WITH IDENTICAL TWINS BIOMETRIC IDENTIFICATION SYSTEM

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ABSTRACT

Studies in pattern recognition domain currently revolve around twin's biometric identification. The twins' biometric Identification system may lead to the discovery of a distinguishing pattern of a biometric of an individual. A significant improvement can also be seen in the Unimodal biometric identification; it allows accurate and reliable identification of identical twins with good performance of certain traits. However, since the similarity level is very high, Identical twins' identification is much more difficult when compared to that of non-twins. Hence, the use of more than one biometric trait with global features is proposed. Further, pattern recognition requires the extraction and selection of meaningful features, which leads to the key issue in the identification of twin handwriting-fingerprint, that is, the question of how to acquire features from many writing and styles twin handwriting-fingerprint to enable the reflection of the right person between twins. This study thus proposes the global with Aspect United Moment Invariant for global feature extractions with the application of identical twin multi-biometric identification with Inter-class and Intra-class .

Keywords: *Identical Twin, Global Features, Multi-Biometric, Identification, Unique Representation, Aspect United Moment Invariant, Similarity.*

1. INTRODUCTION

Biometric-based identification and verification systems will become a leading technology [2,3]. The systems are armed with applications that provide access control to buildings and computers while reducing the incidences of deceitful transactions in electronic commerce and discouraging unlawful immigration [10]. However, it is much more difficult to identify the identical twins' biometric as opposed to identifying non-twins because as stated by [7], identical twins share astounding amount of similarities. For this reason, identification of twins biometric has been the subject of research among many researchers in the domain of pattern recognition and computer vision; it should be noted that in some circumstances, it is the one method that could result in the discovery of the biometric pattern of a real person from a group of persons[1,10,11,12,13,14,24].

There appears to be considerable improvement in the unimodal biometric identification for identical twins particularly in terms of accuracy and reliability [7,15,26]. Additionally, some traits demonstrate good performance. Nonetheless, there remain issues related to the technology itself. The past studies were revolving around the identification or verification of identical twins with the use of the Unimodal biometric system such as Wonder Ears: Identification of Identical Twins from Ear Images [15], 3D Face Recognition used for distinguish face for identical twins [16], Analysis of Facial Marks to Distinguish Between Identical Twins [11], Double Trouble: Differentiating Identical Twins by Face Recognition [10].

Sharing single zygote causes the identical twins to have similar genetic makeup which makes their identification difficult (see Figure 1). The usage of more than one biometric trait with Global features is thus proposed in order to solve this problem. This brings to the multimodal biometric system that uses the physical and also the behavior trait. This system includes a mix of many sources from various biometric traits. This system allows user with no exact biometric identifier to still enroll and authenticate with other traits. Such allowance solves the issue linked with enrollment. The system is therefore universal. Thus, multimodal biometric use to analyze the similar features to extract the

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unique characteristics of the features for further investigation of the written texts and patterns of minutiae versus original ones. Further, the past researches did not treat the global (holistic) features of the cursive word or shape as one complete object for any twins biometric. A study by [14] can be referred for example.

Fig. 1. A Pair Of Identical Twins From The Identical Twins Dataset

2. UNIQUENESS OF TWINS MULTI-BIOMETRIC

A person's nature is represent able by his/her handwriting-fingerprint and this has been mentioned in the hypothesis of some studies [4,5,7] noting a person's individuality in their style of writing and fingerprint style; their style of writing and fingerprint style that is also consistent. Data collected in UHD for 46 twins and each individual 4 samples for each biometric, Samples from same individual in pairs of twins and samples with different pairs are presented in Figure 2. As shown, the writings and fingerprints show more similarity being produced by both individuals in a pair of twins. However, difference is shown when the writings and fingerprints are produced by the different pair. Also, there is small difference to the writings and fingerprints generated by the same individual in a pair of twins and defined difference when the writings and fingerprints are produced by the both individual in a pair, although the height of shape appears to be the same in identical twins. This means that even identical twins differ especially with respect to handwriting and fingerprint. Such difference, which his called Individuality of Handwriting-fingerprint, is measureable by the variances. In this context, the value of the person's feature or the intra-class, must be less than that of different persons or the inter-class [5,6,7]. [8] reported that features that have the smallest similarity error for one individual in a pair of twins (intra-class) and largest error of similarity for both individuals in a pair of twins (inter-class) denote the soundness sand acceptableness of individual features. Thus, attaining the individual features from the handwritten-fingerprint samples is important so that the individual in a pair of twins can be identified.

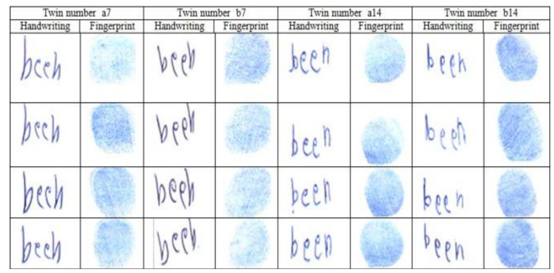

Fig. 2. Handwriting-Fingerprint For Both Person In Twins.

2.1 Individuality with global features in identical twin

This study introduces the global features with the capacity in handling twin multi-biometric images for the purpose of identification. As an adaptive method, this method is for feature extraction. It discretely improves the class because for the class of individual twin, the method repositions the points of feature to better places. This guarantees more efficient representation of individual characteristics for each biometric modality before they are used in the process of matching. Many pattern recognition researchers have been focusing on twin identification utilizing the handwritten and fingerprint images shape [5,26,29]. The field of visual includes the use of shape feature; shape is among the core features for the illustration of content of image [9]. Nonetheless, extracting features that precisely symbolize and illustrate the shape for a person in twins is difficult. Hence, in this study, the first objective is to introduce a new system for identical twins with Multimodal biometric identification using many modalities.

On the other hand, the second objective of this study includes an algorithm of Aspect United Moment Invariant (AUMI) [9]. AUMI has the capacity to extract a good set of global features. Such features represent the twin handwriting-fingerprint from the region. They also denote the depiction of boundary of a word and shape of fingerprint. In twin identification, the features

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extracted from the AUMI algorithm then go through the individuality test of handwriting and fingerprint.

The third objective is to perform analysis on the efficiency of global features for the purpose of variation minimization for intra-class and variation maximization for inter-class for Individuality of twins' handwriting-fingerprint in biometric Identification. For this purpose, this study uses a method that contains a procedure. It is an important method because twin identification necessitates a technique that satisfies the 'individuality' of the notion of Multimodal biometric. The proposed new procedure to improve the identification of a pair of twins' handwriting-fingerprint is presented in Figure 3.

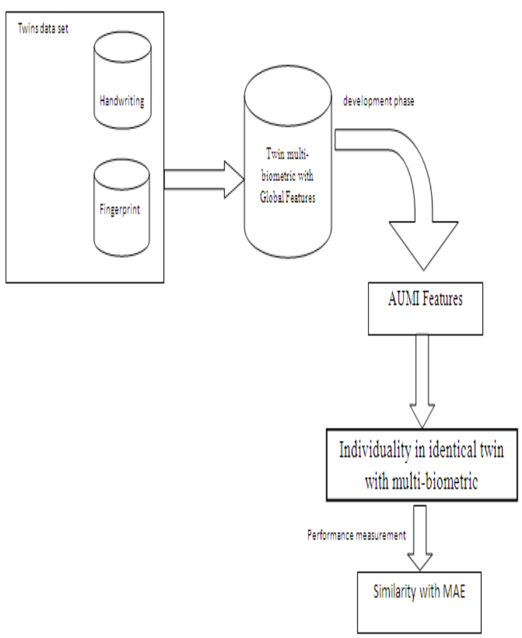

Fig. 3. New Framework For Multi-Biometric Identification For A Pair Of Twins.

2.2 Twin Multi-Biometric Shape Representations

Within the domain of pattern of recognition, there are many available shape representation methods and illustration of extraction of features from an image. The handling of the twin handwriting-fingerprint shape can generally be done using two different approaches namely the analytic (local / structural)approach and holistic (global) approach. Each approach comprises two methods namely region-based or whole region shape method and contour-based or contour only method. The holistic approach entails the representation of the entire image shape while the analytic approach entails the representation of image in sections. The holistic approach is selected in this study because in the context of this study, it is required that the twin handwriting-fingerprint shape is extracted as one single entity; is not divisible. Further, the exploration of global method is included in this study. This will ensure the most suitable technique for the preservation of individuality concept of twin handwriting-fingerprint in twin biometric identification.

2.3 Aspect United Moment Invariant with Twin multi-Biometric

Effective technique is important in extracting the individual features from Twin Multi-biometric shape. In the context of handwriting, shape shows higher level of individuality in comparison to character, [9,19]. This is the reason for selecting the United Moment Invariant (UMI) [20] for the extraction the global features from the handwriting of twin and shape of fingerprint. The creation of UMI was grounded on the Geometric Moment Invariant (GMI) [21] and the Improve Moment Invariant (IMI) [22]. In relation to this, [22] evidenced the employability of GMI for region representation in discreet setting. However, representation of boundary has high computational times and thus, IMI is suggested (for boundary and faster computation).

It should be noted however, that the extraction of the region and boundary of an image has to be done continuously and separately. This, as stated by [20], will guarantee that quality feature is obtained in image representation. [20] proposed UMI because it could effectively and continuously distinguish separate the image shape on both region and boundary. Somehow, [21] mentioned the issues associated with the factor of scaling used in UMI. For this reason, [9] suggested the application of [23] Aspect Invariant Moment (Aspect) scaling factor in Aspect United Moment Invariant. This scaling factor improves the invariant features without size normalization. Aspect's scaling is thus included in the AUMI algorithm proposed due to its ability in preserving the invarianceness of handwriting-fingerprint for twin in the direction of X and Y; this characterizes the human's handwriting-fingerprint of twin. With the usage of scaling, the global word and the shape of

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fingerprint features are continuously and discreetly extracted from both region and boundary representation using scale invarianceness from handwriting-fingerprint of twin.

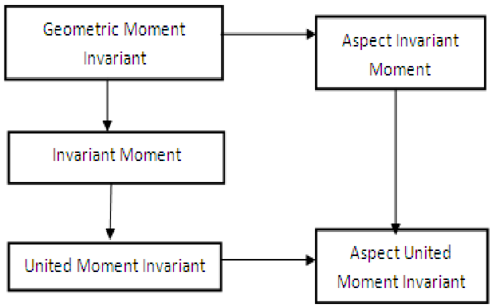


Fig. 4 Aspect United Moment Invariant

Aspect United Moment Invariant by (9) can extract global features from an object's region and boundary of (word or shape) separately and continuously manner to represent an individual in a twin. This is attainable through the creation of fusion embedded scaling factor of Aspect [23] into the UMI [20] (see Figure 4). Immediately, this assumes the capability of these two moment functions into the recommended Aspect United Moment Invariant. UMI by [20] is linked with geometrical representation that takes into account GMI's Normalized Central Moment equations (21) and IMI's Boundary Representation [22]. Finally, AUMI by [9] shows 8 features with UMI's construction [20] below:

$$\theta_1 = \frac{\sqrt{\phi_2}}{\phi_1} \quad (1)$$

$$\theta_2 = \frac{\phi_6}{\phi_1 \phi_4} \quad (2)$$

$$\theta_3 = \frac{\sqrt{\phi_5}}{\phi_4} \quad (3)$$

$$\theta_4 = \frac{\phi_5}{\phi_3 \phi_4} \quad (4)$$

$$\theta_5 = \frac{\phi_1 \phi_6}{\phi_1 \phi_3} \quad (5)$$

$$\theta_6 = \frac{(\phi_1 + \sqrt{\phi_2})\phi_3}{\phi_6} \quad (6)$$

$$\theta_7 = \frac{\phi_1 \phi_5}{\phi_3 \phi_6} \quad (7)$$

$$\phi_8 = \frac{\phi_3 + \phi_4}{\sqrt{\phi_5}} \quad (8)$$

As φ_i denotes large values, the natural logarithm is employed. As such, below is obtained

for $i = 1$ *to* 7 ; $\theta_i \leftarrow \log 10\ \varphi_i$.

3 TWIN MULTI-BIOMETRIC WITH GLOBAL EXTRACTED FEATURE (GEF)

Tables 1, 2, 3, 4 and 5, present the sample of the extracted word images of twin's handwriting. The sample consists of the original extracted features after the global feature. Among the included are the Aspect Invariant Moment (Aspect), United Moment Invariant (UMI), Aspect United Moment Invariant (AUMI), macro feature extraction (MFE) and Geometric Moment Invariant (GMI).

Table 1. Invariant Features Of Twin Number 7 By GMI Algorithm

Image	F1	F2	F3	F4	F5	F6	F7
 a7	18.9489	354.2521	2.5200	2.3977	5.7528	4.5015	9.6150
	19.5899	381.6335	2.6926	2.6496	7.0248	5.1721	6.4469
	18.8415	346.5908	2.3309	2.3254	5.4115	4.3299	1.2163
	19.0825	357.3562	2.5070	2.4411	5.9627	4.6084	7.1732
 b7	18.7156	339.4583	2.3027	2.2954	5.2727	4.2285	1.6210
	19.2375	361.0587	2.5265	2.4890	6.1995	4.7262	5.4285
	20.0445	392.8424	2.8450	2.8207	7.9609	5.5885	5.1561
	19.2749	360.1698	2.5479	2.5100	6.1995	4.7600	5.5050

Table 2. Invariant Features Of Twin Number 7 By Aspect Algorithm

Image	F1	F2	F3	F4	F5	F6	F7
 a7	18.8347	376.2823	7.0384	7.9596	1.8833	1.5714	4.9230
	18.2902	353.2250	6.4590	7.3065	1.5867	1.3663	4.1599
	18.0328	347.4064	6.1785	6.9915	1.4526	1.1928	3.8246
	18.3200	352.4048	6.4719	7.3206	1.5929	1.4439	4.2081
 b7	18.7295	371.0281	6.7885	7.6793	1.7528	1.2949	4.5808
	18.6161	366.8255	6.7355	7.6190	1.7254	1.2656	4.4770
	18.1444	344.3009	6.4421	7.2856	1.5778	1.2334	4.1239
	18.4553	360.0841	6.5980	7.4648	1.6561	1.1341	4.3045

Table 3. Invariant Features Of Twin Number 7 By UMI Algorithm

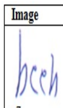
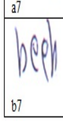
Image	F1	F2	F3	F4	F5	F6	F7	F8
 a7	0.9933	0.9908	1.0003	0.9521	0.9555	1.0537	0.9610	2.0503
	0.9972	0.9964	1.0003	0.9847	0.9860	1.0170	0.9882	2.0156
	0.9881	0.9882	1.0004	0.9984	1.0098	1.0023	1.0102	2.0016
	0.9906	0.9893	1.0003	0.9743	0.9816	1.0284	0.9849	2.0264
 b7	0.9844	0.9843	1.0004	0.9976	1.0125	1.0034	1.0135	2.0024
	0.9877	0.9870	1.0003	0.9858	0.9967	1.0158	0.998	2.0144
	0.9888	0.9884	1.0003	0.9920	1.0023	1.0090	1.0036	2.0080
	0.9846	0.9839	1.0004	0.9858	0.9998	1.0159	1.0020	2.0144

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Table 4. Invariant Features Of Twin Number 7 By AUMI Algorithm

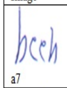
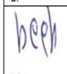
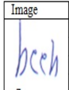
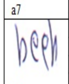
Image	F1	F2	F3	F4	F5	F6	F7	F8
	1.028	0.0900	1.7240	0.3362	0.0096	100.9817	3.7346	5.7076
	1.0288	0.0892	1.7240	0.3362	0.0095	101.9277	3.7680	5.7077
	1.0227	0.0933	1.7241	0.3362	0.0101	96.9143	3.6030	5.7086
a7	1.0282	0.0892	1.7239	0.3362	0.0088	100.9817	4.0847	5.7076
	1.0299	0.1048	1.7241	0.3363	0.0112	86.8850	3.2071	5.7088
	1.0299	0.1022	1.7240	0.3363	0.0110	88.8466	3.2885	5.7077
	1.0336	0.0946	1.7239	0.3363	0.0100	96.5498	3.5544	5.7088
b7	1.0299	0.1077	1.7240	0.3363	0.0116	84.1434	3.1228	5.7077

Table 5. Invariant Features Of Twin Number 7 By Macro Algorithm

Image	F1	F2	F3	F4	F5	F6	F7	F8
	8.1681	2.5000	1.9624	0.7451	7.124	1.5422	0.1775	8.079
	4.7929	2.5500	1.8342	0.7451	7.079	1.5401	0.2057	6.526
	7.3061	3.1300	2.1606	0.7039	9.326	9.326	0.2293	8.608
a7	7.4947	2.7900	2.1044	0.7373	6.308	1.541	0.2029	8.271
	7.6824	2.3400	1.8381	0.7216	5.871	1.5393	0.1691	6.217
	5.9056	2.8600	2.0889	0.7333	5.917	1.5414	0.2208	6.555
	4.633	3.2800	2.3596	0.7196	5.355	1.5457	0.2663	7.347
b7	5.7884	2.9000	2.3194	0.7294	8.147	1.5436	0.2249	6.754

As can be seen in Tables 1, 2, 3, 4 and 5, there is low inter-features variability between the individuals in a twin. Meanwhile, there appears variability of height intra-features with the same individual in a twin.

As can be seen in Tables 6, 7, 8, 9 and10,are the extracted twin fingerprint's sample shape images. These features comprise the original extracted features as well as the global feature. Among the included are the Geometrical minute feature extraction (GMFE), United Moment Invariant (UMI), Aspect Invariant Moment (Aspect), Geometric Moment Invariant (GMI) and Aspect United Moment Invariant (AUMI).

Table 6. Invariant Features Of Twin Number 7by GMI Algorithm

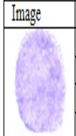
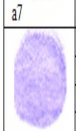
Image	F1	F2	F3	F4	F5	F6	F7
	20.0601	363.5930	2.5939	2.5712	6.6206	5.8891	3.8856
	20.4327	415.2668	2.6865	2.6790	7.1855	5.1489	1.1014
	21.8448	486.6713	4.4507	3.5393	1.2532	7.7199	4.7711
a7	29.3722	938.1759	1.8657	9.0555	8.2012	2.6159	6.3341
	34.5712	1.2134	1.9253	1.4308	2.0483	4.8979	9.0106
	48.0872	2.4909	1.5261	4.4735	2.0023	2.1919	2.3298
	39.0116	1.7261	4.8869	1.9229	3.6991	8.6324	3.4421
b7	20.2399	37.891	2.6470	2.6291	6.9262	2.3313	2.8285

Table 7. Invariant Features Of Twin Number 7 By Aspect Algorithm

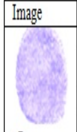
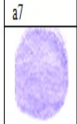
Image	F1	F2	F3	F4	F5	F6	F7
	20.0601	363.5930	2.5939	2.5712	6.6206	5.8891	3.8856
	20.4327	415.2668	2.6865	2.6790	7.1855	5.1489	1.1014
	21.8448	486.6713	4.4507	3.5393	1.2532	7.7199	4.7711
a7	29.3722	938.1759	1.8657	9.0555	8.2012	2.6159	6.3341
	34.5712	1.2134	1.9253	1.4308	2.0483	4.8979	9.0106
	48.0872	2.4909	1.5261	4.4735	2.0023	2.1919	2.3298
	39.0116	1.7261	4.8869	1.9229	3.6991	8.6324	3.4421
b7	20.2399	37.891	2.6470	2.6291	6.9262	2.3313	2.8285

Table 8. Invariant Features Of Twin Number 7 By UMI Algorithm

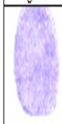
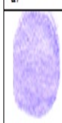
Image	F1	F2	F3	F4	F5	F6	F7	F8
	0.9505	1.1418	1.0007	0.9927	1.2526	8.3991	8.6942	2.0074
	0.9973	0.9406	1.0006	0.9984	0.9430	1.0633	1.0614	2.0016
	1.0099	0.9985	1.0002	0.7955	0.7786	1.2719	0.7967	2.2570
a7	1.0428	0.9835	1.0001	0.4854	0.4390	2.1846	0.4936	3.0601
	1.0076	0.9902	1.0003	0.7436	0.7248	1.3693	0.7509	2.3450
	1.0379	1.0189	1.0003	0.2933	2.7728	3.4749	2.8784	4.4102
	1.0650	11.507	1.0002	0.3936	3.9924	0.2352	0.0342	3.5407
b7	0.9579	4.3810	1.0010	0.9952	4.7424	2.2014	2.2717	2.0048

Table 9. Invariant Features Of Twin Number 7 By AUMI Algorithm

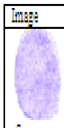
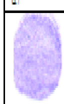
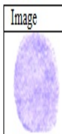
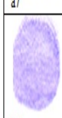
Image	F1	F2	F3	F4	F5	F6	F7	F8
	1.0107	0.1690	1.7250	0.3358	0.0187	53.0042	1.9872	5.7168
	0.9910	0.1680	1.7248	0.3359	0.0193	52.2543	1.9999	5.7143
	0.9783	0.1527	1.7251	0.3358	0.0180	56.7789	2.1987	5.7170
a7	1.0094	0.0849	1.7244	0.3361	0.0094	105.1433	3.9566	5.7106
	1.0109	0.0881	1.7217	0.3369	0.0098	100.9343	3.8238	5.6906
	1.0438	0.0126	1.7229	0.3366	0.0013	732.5799	26.7907	5.6984
	1.0077	0.0074	1.7236	0.3364	8.2513	1.2030	45.4722	5.7035
b7	0.9404	0.1815	1.7251	0.3358	0.0232	45.9228	1.8497	5.7176

Table 10. Invariant Features Of Twin Number 7 By Geometrical Minute Algorithm

Image	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
	178	162	184	190	183	168	167	159	192	209
	211	189	213	189	216	168	165	188	182	188
	213	209	174	208	210	147	153	200	209	206
a7	193	190	202	210	189	215	171	153	168	185
	181	207	206	190	140	166	149	169	224	190
	229	216	219	220	140	175	185	195	232	216
	199	166	212	209	198	200	167	182	169	192
b7	186	183	202	204	187	158	140	149	172	214

In an identification system, a set of features reflecting the individuality and characteristics of a person in a twin is followed. It is however important to extract and choose only the important features. However, in identification of twin, it is not easy to do. The features of multi-biometric in the data storage should be used in twin identification.

4 SIMULATION WITH MAE

The Mean Absolute Error (MAE) function is used to measure uniqueness. Tables 11, 12 and 13 show the example of the calculation of MAE .Here, 4 images are used to present each individual. As stated by [9], the MAE value offers the invariancenes of twin handwriting-fingerprint aside from providing the first image or reference image.

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15th December 2017. Vol.95. No 23

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Small errors mean that the image is close to the reference image. The average of MAE is calculated from the value of the overall results.

$$MAE = \frac{1}{n}\sum_{i=1}^{f} |(x_i - r_i)| \quad (9)$$

Where:
n denotes the number of images;
x_i represents the current image;
r_i denotes the image of reference or location measure;
f represents the number of features;
i denotes the feature column of image.

Since it corresponds to the measurement's individuality of the individual twin handwriting-fingerprint in twin multi-biometric identification, the MAE function is used in this study. Each twin of a pair will have the unique features or characteristic in terms of handwriting-fingerprint. Using the MAE function, the variance measurement between twins' handwriting-fingerprint can be performed with two handwriting-fingerprints' similarity error gathered from detail characteristics in the column that represents feature. This allows the calculation of variance between two handwriting-fingerprint images for the features of each column from the extracted invariant feature vector of image. Low mean MAE value means high similarity to the original image (reference image or first image) while high mean MAE value means low similarity. As such, lowest value denotes the highest similarity while highest value denotes highest difference. Azah et al. (2010) mentioned the classification of MAE function under robustness theory of statistical procedure. Also, MAE function appears to be the most feasible and simplest solution.

4.1 Intra-class and Inter-class with MAE

The intra-class and the inter-class analyses were conducted on the obtained MAE value. Intra-class comprises features extracted from the same twin or one twin while inter-class comprises features extracted from either twins or different twin. Both handwriting word and shape of fingerprint of twin for intra-class requires smaller MAE value. On the other hand, larger MAE value is required for inter-class. This would show the individuality of twin handwriting-fingerprint.

Tables 11 through 17 present the intra-class measurement (measurement of one individual in a twin or one twin) and the inter-class measurement (measurement of both individuals in a twin or different twin) in terms of difference, using the MAE function for shape and word. In particular, Tables 11, 12, 14 and 16 present the intra-class where the MAE values are lower than the MAE values shown in Tables 13,15 and 17 (it should be noted even that the twin multi-biometric was used in all tables). Tables 11 through 17 demonstrate the analyzability of MAE values for the individuality of the verification of twin handwriting-fingerprint. Meanwhile, Tables 11 and 12, show lower MAE value. What can be inferred is that, as can be seen in Table 13, the feature between the handwriting and fingerprint from the exact individual in a twin shows close feature value when differentiated with the handwriting and fingerprint from both twins. Tables 14 and 16 show lower MAE value, demonstrating that, , as can be seen in Table 17,the feature between the handwriting and fingerprint from the both individual in a twin contains close feature value when differentiated with the handwriting and fingerprint from difference twins.

Table 11. MAE From AUMI Features For Twin Multi-Biometric For A10

Handwriting									
Image name	F1	F2	F3	F4	F5	F6	F7	F8	MAE
1a10	1.0323	0.1000	1.7242	0.3363	0.0126	76.9720	2.8343	5.7091	--
2a10	1.0209	0.1055	1.7242	0.3363	0.0115	85.5333	3.1863	5.7079	2.2331
3a10	1.0230	0.1065	1.7242	0.3363	0.0115	84.9152	3.1569	5.7078	2.0710
4a10	1.0272	0.1184	1.7242	0.3363	0.0127	76.7366	2.8398	5.7089	0.0662
Mean Absolute Error for handwriting a10									1.0926
Fingerprint									
Image name	F1	F2	F3	F4	F5	F6	F7	F8	MAE
1a10	1.0119	0.1485	1.7240	0.3362	0.0164	60.2519	2.2644	5.7077	--
2a10	1.0402	0.1253	1.7240	0.3362	0.0131	73.3963	2.6833	5.7079	3.4046
3a10	1.0628	0.1288	1.7240	0.3362	0.0129	72.9727	2.6111	5.7079	3.2855
4a10	1.0516	0.1496	1.7244	0.3361	0.0153	60.2519	2.2462	5.7112	0.0160
Mean Absolute Error for fingerprint a10									1.6765

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Table 12. MAE From AUMI Features For Twin Multi-Biometric For B10

Handwriting									
Image name	F1	F2	F3	F4	F5	F6	F7	F8	MAE
1b10	1.0260	0.1186	1.7240	0.3362	0.0127	76.4993	2.8347	5.7085	---
2b10	1.0274	0.1164	1.7240	0.3362	0.0125	78.0525	2.8889	5.7080	0.4029
3b10	1.0230	0.1187	1.7240	0.3362	0.0128	76.1647	2.8316	5.7076	0.0855
4b10	1.0206	0.1105	1.7240	0.3362	0.0120	81.6596	3.0431	5.7078	1.3459
Mean Absolute Error for handwriting b10									0.4586
Fingerprint									
Image name	F1	F2	F3	F4	F5	F6	F7	F8	MAE
1b10	0.9765	0.1882	1.7252	0.3358	0.0223	46.0062	1.7844	5.7178	---
2b10	0.9442	0.2601	1.7253	0.3356	0.0329	32.2016	1.2905	5.7202	3.6040
3b10	1.0040	0.1724	1.7247	0.3359	0.0193	51.5573	1.9481	5.7139	1.4414
4b10	1.0233	0.1531	1.7251	0.3358	0.0165	59.2351	2.1937	5.7166	3.4318
Mean Absolute Error for fingerprint b10									2.1193

Table 13. MAE From AUMI Features For Multi-Biometric For Twin Number 10

Handwriting									
Image name	F1	F2	F3	F4	F5	F6	F7	F8	MAE
1a10	1.0209	0.1055	1.7242	0.3363	0.0115	89.5333	3.1863	5.7079	--
2a10	1.0323	0.1000	1.7242	0.3363	0.0126	76.9720	2.8343	5.7091	1.6175
3a10	1.0230	0.1065	1.7242	0.3363	0.0115	84.9152	3.1569	5.7078	0.5813
4a10	1.0272	0.1184	1.7242	0.3363	0.0127	76.7366	2.8398	5.7089	1.6456
1b10	1.0260	0.1186	1.7240	0.3362	0.0127	76.4993	2.8347	5.7085	1.6757
2b10	1.0274	0.1164	1.7240	0.3362	0.0125	78.0525	2.8889	5.7080	1.4746
3b10	1.0230	0.1187	1.7240	0.3362	0.0128	76.1647	2.8316	5.7076	1.7176
4b10	1.0206	0.1105	1.7240	0.3362	0.0120	81.6596	3.0431	5.7078	1.0029
Mean Absolute Error for handwriting a10 , b10									1.2144
Fingerprint									
Image name	F1	F2	F3	F4	F5	F6	F7	F8	MAE
1a10	1.0402	0.1253	1.7240	0.3362	0.0131	73.3963	2.6833	5.7079	--
2a10	1.0628	0.1288	1.7240	0.3362	0.0129	72.9727	2.6111	5.7079	0.0653
3a10	1.0516	0.1496	1.7244	0.3361	0.0153	60.2519	2.2462	5.7112	1.7029
4a10	0.9765	0.1882	1.7252	0.3358	0.0223	46.0062	1.7844	5.7178	1.8386
1b10	0.9442	0.2601	1.7253	0.3356	0.0329	32.2016	1.2905	5.7202	3.5545
2b10	1.0040	0.1724	1.7247	0.3359	0.0193	51.5573	1.9481	5.7139	5.3565
3b10	1.0233	0.1531	1.7251	0.3358	0.0165	59.2351	2.1937	5.7166	2.8338
4b10	1.0119	0.1485	1.7240	0.3362	0.0164	60.2519	2.2644	5.7077	1.7023
Mean Absolute Error for fingerprint a10, b10									2.1317

Any function is applicable in the process of similarity measurement with the condition that it adheres with the rules of similarity measurement between twin's features. The MAE function is appropriate for this study due to limited data obtained aside from the fact that MAE function matches with the individuality of the twin handwriting-fingerprint analysis. In terms of the intra-class and inter-class analysis, comparison between intra-class and inter-class, the process of similarity measurement run. In terms of this, the variance value for intra-class must be less than the variance value of inter-class to assure the fulfillment of the requirement of the individuality of twin handwriting-fingerprint so that it becomes applicable in TI.

Table 14. Intra-Class MAE From AUMI Features For Handwriting For Twin Number 1 And 2 (A,B)

Handwriting Twin 1 (a,b)								
F1	F2	F3	F4	F5	F6	F7	F8	MAE
1.0354	0.1152	1.7242	0.3361	0.0122	79.4867	2.9178	5.7093	--
1.0326	0.1130	1.7242	0.3361	0.0120	80.8020	2.9741	5.7093	0.1721
1.0330	0.1072	1.7242	0.3362	0.0114	85.2382	3.1368	5.7089	0.7478
1.0339	0.1018	1.7239	0.3362	0.0110	89.7995	3.3039	5.7071	1.3397
1.0358	0.1018	1.7240	0.3362	0.0110	87.6847	3.2193	5.7079	1.0645
1.0336	0.1132	1.7241	0.3362	0.0110	80.7376	2.9702	5.7084	0.1637
1.0346	0.1013	1.7239	0.3363	0.0107	90.2566	3.3188	5.7069	1.3988
1.0332	0.1068	1.7242	0.3362	0.0113	85.5679	3.1482	5.7089	0.7904
Average MAE								0.7096
Handwriting Twin 2 (a,b)								
F1	F2	F3	F4	F5	F6	F7	F8	MAE
1.0318	0.1098	1.7241	0.3362	0.0117	83.1055	3.0619	5.7089	--
1.0347	0.0976	1.7239	0.3362	0.0103	93.6710	3.4440	5.7071	1.3708
1.0299	0.1026	1.7241	0.3362	0.0109	88.7336	3.2760	5.7082	0.7316
1.0300	0.1024	1.7241	0.3362	0.0109	88.9304	3.2831	5.7082	0.7571
1.0311	0.1046	1.7241	0.3362	0.0111	87.1319	3.2127	5.7087	0.5230
1.0322	0.1076	1.7242	0.3362	0.0114	84.8370	3.1241	5.7091	0.2246
1.0315	0.1087	1.7242	0.3362	0.0116	83.9064	3.0919	5.7091	0.1041
Average MAE								0.0988

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Table 15. Inter-Class MAE From AUMI Features For Handwriting For Twin Number 1 And 2 (A,B)

Handwriting Twin 1 and 2 (a,b)								
F1	F2	F3	F4	F5	F6	F7	F8	MAE
1.0347	0.0976	1.7239	0.3362	0.0103	100.6710	3.4440	5.7071	---
1.0299	0.1026	1.7241	0.3362	0.0109	88.7336	3.2760	5.7082	0.7573
1.0300	0.1024	1.7241	0.3362	0.0109	88.9304	3.2831	5.7082	0.7446
1.0311	0.1046	1.7241	0.3362	0.0111	87.1319	3.2127	5.7087	0.8615
1.0322	0.1076	1.7242	0.3362	0.0114	84.8370	3.1241	5.7091	1.0106
1.0315	0.1087	1.7242	0.3362	0.0116	83.9064	3.0919	5.7091	1.0709
1.0325	0.0988	1.7240	0.3362	0.0105	92.4349	3.4045	5.7078	0.5175
1.0318	0.1098	1.7241	0.3362	0.0117	83.1055	3.0619	5.7089	1.1229
1.0354	0.1152	1.7242	0.3361	0.0122	79.4867	2.9178	5.7093	1.3583
1.0326	0.1130	1.7242	0.3361	0.0120	80.8020	2.9741	5.7093	1.2725
1.0330	0.1072	1.7242	0.3362	0.0114	85.2382	3.1368	5.7089	0.9847
1.0339	0.1018	1.7239	0.3362	0.0110	89.7995	3.3039	5.7071	0.6886
1.0358	0.1018	1.7240	0.3362	0.0110	87.6847	3.2193	5.7079	0.8261
1.0336	0.1132	1.7241	0.3362	0.0110	80.7376	2.9702	5.7084	1.2766
1.0346	0.1013	1.7239	0.3363	0.0107	90.2566	3.3188	5.7069	0.6590
1.0332	0.1068	1.7242	0.3362	0.0113	85.5679	3.1482	5.7089	0.9633
Average MAE								0.8822

Table 16. Intra-Class MAE From AUMI Features For Fingerprint For Twin Number 1 And 2 (A,B)

Fingerprint Twin 1 (a,b)								
F1	F2	F3	F4	F5	F6	F7	F8	MAE
1.0481	0.1603	1.7238	0.3362	0.0165	57.7984	2.0979	5.7069	0
1.0169	0.1505	1.7235	0.3364	0.0165	59.6604	2.2343	5.7044	0.2553
1.0107	0.1611	1.7248	0.3359	0.0178	55.5587	2.0847	5.7148	0.2877
1.0226	0.1603	1.7259	0.3354	0.0261	37.4212	1.3818	5.7253	2.6437
0.9363	0.1749	1.7240	0.3361	0.0226	47.3295	1.9214	5.7090	1.3475
0.9024	0.2053	1.7237	0.3361	0.0285	38.8720	1.6370	5.7095	2.4491
0.9756	0.2902	1.7253	0.3355	0.0344	29.8335	1.1563	5.7221	3.6430
0.8951	0.2053	1.7240	0.3356	0.0282	39.6290	1.6370	5.7090	2.3554
Average MAE								1.6227
Fingerprint Twin 2 (a,b)								
F1	F2	F3	F4	F5	F6	F7	F8	MAE
1.0564	0.0629	1.7239	0.3363	0.0064	148.4058	5.3458	5.7064	0
1.0490	0.0616	1.7240	0.3363	0.0063	150.5808	5.4608	5.7070	0.2874
1.0644	0.0611	1.7239	0.3362	0.0061	184.0403	5.5053	5.7070	4.4756
1.0305	0.1353	1.7248	0.3359	0.0144	67.4441	2.4819	5.7149	10.4927
1.0178	0.1602	1.7237	0.3363	0.0175	56.1404	2.0994	5.7059	11.9574
1.0142	0.1418	1.7242	0.3361	0.0156	63.2681	2.3703	5.7100	11.0309
1.0305	0.0901	1.7238	0.3363	0.0096	101.1057	3.7337	5.7062	6.1211
1.0178	0.1021	1.7239	0.3362	0.0110	100.8608	3.2916	5.7073	6.2103
Average MAE								6.3219

Table 17. Inter-Class MAE From AUMI Features For Fingerprint For Twin Number 1 And 2 (A,B)

Fingerprint Twin 1 and 2 (a,b)								
F1	F2	F3	F4	F5	F6	F7	F8	MAE
1.0644	0.0611	1.7239	0.3362	0.0061	184.0403	5.5053	5.7070	0
1.0481	0.1603	1.7238	0.3362	0.0165	57.7984	2.0979	5.7069	8.1110
1.0169	0.1505	1.7235	0.3364	0.0165	59.6604	2.2343	5.7044	7.9876
1.0107	0.1611	1.7248	0.3359	0.0178	55.5587	2.0847	5.7148	8.2548
1.0226	0.1603	1.7259	0.3354	0.0261	37.4212	1.3818	5.7253	9.4328
0.9363	0.1749	1.7240	0.3361	0.0226	47.3295	1.9214	5.7090	8.7847
0.9024	0.2053	1.7237	0.3361	0.0285	38.8720	1.6370	5.7095	9.3355
0.9756	0.2902	1.7253	0.3355	0.0344	29.8335	1.1563	5.7221	9.9324
0.8951	0.2053	1.7240	0.3356	0.0282	39.6290	1.6370	5.7090	9.2886
1.0178	0.1602	1.7237	0.3363	0.0175	56.1404	2.0994	5.7059	8.2165
1.0142	0.1418	1.7242	0.3361	0.0156	63.2681	2.3703	5.7100	7.7532
1.0305	0.0901	1.7238	0.3363	0.0096	101.1057	3.7337	5.7062	5.2984
1.0178	0.1021	1.7239	0.3362	0.0110	88.8608	3.2916	5.7073	6.0929
1.0564	0.0629	1.7239	0.3363	0.0064	148.4058	5.3458	5.7064	2.2378
1.0490	0.0616	1.7240	0.3363	0.0063	150.5808	5.4608	5.7070	2.0950
1.0305	0.1353	1.7248	0.3359	0.0144	67.4441	2.4819	5.7149	7.4841
Average MAE								6.8941

4.2 Result, Analysis and Interpretation

The AUMI results are discussed in this study to determine if the method is suitable for Twin multi-biometric identification. AUMI is also compared and analyzed with other techniques. This will ascertain the hypothesis on AUMI's positive value in TI. As shown by the MAE value results in Table 18, AUMI algorithm should be explored more in the field of TI. As indicated by the similarity error result, there appears smaller Uniqueness of authorship for intra-class (same person in twin or both in a twin) when comparison is made with that of inter-class (both persons in twin or difference twin), fulfilling the conception of individuality of twin handwriting-fingerprint in identification field. In this context, the value of MAE for intra-class is lower when as opposed to the MAE value of inter-class with respect to handwriting and fingerprint because moment function is a representation of image. The Uniqueness presentation analysis therefore verifies the usefulness of AUMI in feature extraction in TMI. Moreover, in twin handwriting-fingerprint, extracted feature has been shown to bring the unique features of individual.

Table 18. Uniqueness Presentation With Twin Multi-Biometric Identification

Twin	Intra-class (handwriting)		Inter-class (handwriting)	Intra-class (fingerprint)		Inter-class (fingerprint)
	a	b		a	b	
One twin	0.6984	0.7027	0.7557	5.5061	5.7529	6.1703
5 twin	1.0509	1.03816	1.14926	3.15978	3.7482	4.42792
10 twin	0.98417	1.02462	1.31034	3.82932	2.31317	4.45094
15 twin	0.86576	1.0011	1.190767	4.544347	6.207867	9.690447
20 twin	1.07769	1.016375	1.296195	5.292855	5.780635	9.989795

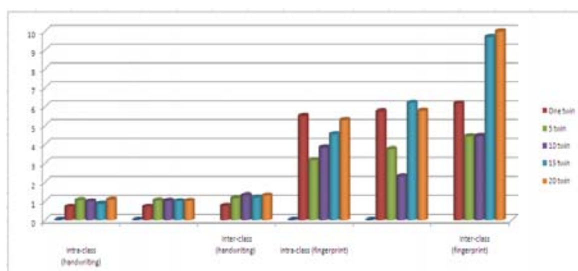

Fig. 5. Graph Of Uniqueness Presentation For AUMI

In satisfying the conception of individuality of twin handwriting-fingerprint, the similarity error has to be higher for inter-class (both twins) but smaller for intra-class (same individual), as can be referred in Figure 5. The features extracted using the AUMI algorithm seem closer for same individual in a twin but more different for different individuals in a twin, causing the production of

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smaller MAE value for intra-class and bigger MAE value for the inter-class. This proves the usefulness of the proposed technique in extraction of features in TI. Additionally, there have been reports from many studies (e.g. Sh. et al., 2015; Pervouchine et al., 2007)on the conceptualization of twin handwriting-fingerprint in terms of individuality. This study is therefore hoped to offer some scientific validation of individuality of twin multi-biometric using the AUMI algorithm of MF in feature extraction.

Somehow, the determination of the best technique will not include the comparison and analysis of the result of this section. Comparison of technique is highlighted in the following section. This section highlights the validation of AUMI algorithm for the individuality conception of twin multi-biometric in TI field. This algorithm is applicable for both the same individual in a twin and for different individuals in a twin. With respect to the results of the other three techniques also prove their appropriateness for the concept of twin multi-biometric. This is the reason why in the context of TI, AUMI, UMI, Aspect and GMI technique of moment function and macro, geometrical minute should be explored in more depth.

5 PERFORMANCE BETWEEN TECHNIQUES

The techniques of Macro, GMI, Aspect, UMI and AUMI for twin handwriting are presented in this section with respect to their results. Meanwhile, the Geometrical minute, GMI, Aspect, UMI and AUMI are highlighted in this section in the domain of twin fingerprint. Further, a comparative study is included as well. The purpose is to discover the technique that is most appropriate for twin handwriting-fingerprint individuality. Besides that, this study also examines the capacity of AUMI in extracting the features of twin handwritten-fingerprint word and shape image in TI and proved the individuality of the twin handwriting-fingerprint concept for AUMI. As opposed to the inter-class, the error of similarity for intra-class is smaller. This refers to the same individual and both individuals in a twin.

The analysis of variance between features for intra-class is lower than that of inter-class. This affirms the Individuality of twin handwriting-fingerprint. This makes possible the measurement of the most sophisticated technique of individuality of twin handwriting-fingerprint with the use of the smallest MAE value for intra-class. Meanwhile, inter-class in error measurement similarity requires the highest MAE value and lowest value of MAE for intra-class, showing that the extracted features are most associated, identical and demonstrate more individuality characteristic within a set of features. For inter-class, obtaining the largest MAE value means that the features show great level of difference as opposed to the others which leads to low level of individuality in that data set.

This section comprises the presentation of the intra-class and inter-class analysis results. Table 19-27 can be referred, Four 20 twins are shown.

Table 19. Intra-Class And Inter-Class For 5 Twins

Technique	Intra-class (handwriting)		Inter-class (handwriting)	Intra-class (fingerprint)		Inter-class (fingerprint)
	a	b		a	b	
AUMI	1.0509	1.03816	1.14926	3.15978	3.7482	4.42792
GMI	5.01706	3.92014	3.28166	45.784	50.08234	33.31978
Aspect	2.8655	2.45508	1.4808	82.39698	53.19492	46.90434
UMI	0.01376	0.01522	0.00976	0.71568	0.45602	0.32758
Macro	0.64576	0.54722	0.40518	---	---	---
Geometrical minute	---	---	---	46.825	57.325	28.775

Table 20. Intra-Class And Inter-Class For 10 Twins

Technique	Intra-class (handwriting)		Inter-class (handwriting)	Intra-class (fingerprint)		Inter-class (fingerprint)
	a	b		a	b	
AUMI	0.98417	1.02462	1.31034	3.82932	2.31317	4.45094
GMI	4.19827	3.98139	3.04288	56.70813	41.93724	33.67116
Aspect	3.41086	3.19869	1.84181	55.34073	41.42899	32.16461
UMI	0.01515	0.01319	0.00993	0.6984	0.4537	0.49592
Macro	0.69942	0.55316	0.41718	---	---	---
Geometrical minute	---	---	---	57.22863	45.55857	31.39877

Table 21. Intra-Class And Inter-Class For 15 Twins

Technique	Intra-class (handwriting)		Inter-class (handwriting)	Intra-class (fingerprint)		Inter-class (fingerprint)
	a	b		a	b	
AUMI	0.86576	1.0011	1.190767	4.544347	6.207867	9.690447
GMI	4.313453	4.183793	3.073113	54.17597	37.29115	33.30669
Aspect	1.824	4.1085	1.5879	57.11473	34.93319	29.40897
UMI	0.01562	0.015547	0.010133	0.779427	1.568773	0.64662
Macro	0.6733	0.638387	0.42918	---	---	---
Geometrical minute	---	---	---	32.125	27.625	23.9688

Table 22. Intra-Class And Inter-Class For 20 Twins

Technique	Intra-class (handwriting)		Inter-class (handwriting)	Intra-class (fingerprint)		Inter-class (fingerprint)
	a	b		a	b	
AUMI	1.07769	1.016375	1.296195	5.292855	5.780635	9.989795
GMI	5.83541	4.333975	3.387275	47.3495	43.76792	30.59107
Aspect	4.91328	2.68737	2.200155	60.59422	44.48573	34.26115
UMI	0.025195	0.013455	0.01237	0.71044	1.26909	0.549525
Macro	0.710505	0.67443	0.433245	---	---	---
Geometrical minute	---	---	---	46.55494	42.64804	26.78768

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Table 23. Intra-Class And Inter-Class For 2 Twins

	Handwriting			Fingerprint		
Technique	Intra-class		Inter-class	Intra-class	Inter-class	Inter-class
	Twin 1 (a ,b)	Twin 2 (a ,b)	Twin 1,2 (a ,b)	Twin 1 (a ,b)	Twin 2 (a ,b)	Twin 1,2 (a ,b)
AUMI	0.6152	0.7096	0.8822	5.8532	1.6227	6.8941
UMI	0.0078	0.0125	0.0046	0.3803	0.1211	0.1191
GMI	3.5732	6.2400	2.1638	15.3867	42.5897	14.8771
Aspect	1.3741	1.2805	1.0389	4.8613	9.7129	3.6802
Macro	0.5057	0.4358	0.2879	--	--	--
Geometrical minute	--	--	--	32.4531	21.8125	19.6758

Table 24. Handwriting Intra-Class And Inter-Class For 10 Twins

Technique	Intra-class										Inter-class
	Twin 1 (a ,b)	Twin 2 (a,b)	Twin 3 (a,b)	Twin 4 (a,b)	Twin 5 (a,b)	Twin 6 (a,b)	Twin 7 (a,b)	Twin 8 (a,b)	Twin 9 (a,b)	Twin 10 (a,b)	Twins (1,2,3,4,5,6,7,8,9,10)
AUMI	0.6152	0.7096	1.0564	0.5198	1.8960	0.6385	0.8575	1.6672	2.595	1.2144	2.6528
UMI	0.0078	0.0125	0.0048	0.0157	0.0082	0.0030	0.0227	0.0046	0.0046	0.0108	0.0027
GMI	3.5732	6.2400	1.7271	3.2123	2.4285	1.4264	2.3763	2.1435	2.6346	5.4397	0.6372
Aspect	1.3741	1.2805	1.6464	1.0578	2.0564	1.5887	1.8578	1.8465	3.2866	2.4345	0.2806
Macro	0.5057	0.4358	0.2741	0.4662	0.3441	0.3504	0.5341	0.3556	0.4505	0.4553	0.0776

Table 25. Handwriting Intra-Class And Inter-Class For 20 Twins

Technique	Intra-class									
	Twin 1 (a ,b)	Twin 2 (a,b)	Twin 3 (a,b)	Twin 4 (a,b)	Twin 5 (a,b)	Twin 6 (a,b)	Twin 7 (a,b)	Twin 8 (a,b)	Twin 9 (a,b)	Twin 10 (a,b)
AUMI	0.6152	0.7096	1.0564	0.5198	1.8960	0.6385	0.8575	1.6672	2.595	1.2144
UMI	0.0078	0.0125	0.0048	0.0157	0.0082	0.0030	0.0227	0.0046	0.0046	0.0108
GMI	3.5732	6.2400	1.7271	3.2123	2.4285	1.4264	2.3763	2.1435	2.6346	5.4397
Aspect	1.3741	1.2805	1.6464	1.0578	2.0564	1.5887	1.8578	1.8465	3.2866	2.4345
Macro	0.5057	0.4358	0.2741	0.4662	0.3441	0.3504	0.5341	0.3556	0.4505	0.4553

Technique	Intra-class										Inter-class
	Twin 11 (a,b)	Twin 12 (a,b)	Twin 13 (a,b)	Twin 14 (a,b)	Twin 15 (a,b)	Twin 16 (a,b)	Twin 17 (a,b)	Twin 18 (a,b)	Twin 19 (a,b)	Twin 20 (a,b)	Twins (1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20)
AUMI	1.1474	1.1684	0.5738	0.5248	1.3437	1.0484	1.7835	1.0068	0.5180	0.7174	2.5505
UMI	0.0152	0.0044	0.0104	0.0152	0.0075	0.0167	0.0614	0.0065	0.0070	0.0158	0.0015
GMI	1.6337	3.2232	2.1229	6.6658	2.0223	5.5860	7.5088	3.2277	3.0767	3.6303	0.2493
Aspect	0.7727	2.0961	1.5348	1.5623	1.5879	1.2292	11.2399	1.7519	2.2920	1.5182	0.1685
Macro	0.3366	0.5383	0.3568	0.5537	0.4805	0.3113	0.5929	0.4178	0.5234	0.9491	0.0419

Table 26. Fingerprint Intra-Class And Inter-Class For 10 Twins

Technique	Intra-class										Inter-class
	Twin 1 (a ,b)	Twin 2 (a,b)	Twin 3 (a,b)	Twin 4 (a,b)	Twin 5 (a,b)	Twin 6 (a,b)	Twin 7 (a,b)	Twin 8 (a,b)	Twin 9 (a,b)	Twin 10 (a,b)	Twins (1,2,3,4,5,6,7,8,9,10)
AUMI	5.8532	1.6227	3.5767	5.2672	5.5027	5.5027	3.421	4.3481	1.8704	2.1317	6.7887
UMI	0.3803	0.1211	0.1692	0.7717	0.1956	1.6753	0.2883	0.1631	0.2991	0.1354	0.0317
GMI	15.3867	42.5897	39.5634	53.0801	15.979	26.0057	28.109	42.9508	26.3606	46.6866	4.1239
Aspect	4.8613	9.7129	7.8165	9.6201	12.5109	40.6226	11.6471	18.2924	6.4504	10.1119	1.8467
Geometrical minute	32.4531	21.8125	32.3594	29.7344	27.5156	25.25	33.2656	24.3281	20.9531	33.4063	3.9248

Table 27. Fingerprint Intra-Class And Inter-Class For 20 Twins

Technique	Intra-class									
	Twin 1 (a ,b)	Twin 2 (a,b)	Twin 3 (a,b)	Twin 4 (a,b)	Twin 5 (a,b)	Twin 6 (a,b)	Twin 7 (a,b)	Twin 8 (a,b)	Twin 9 (a,b)	Twin 10 (a,b)
AUMI	5.8532	1.6227	3.5767	5.2672	5.5027	5.5027	3.421	4.3481	1.8704	2.1317
UMI	0.3803	0.1211	0.1692	0.7717	0.1956	1.6753	0.2883	0.1631	0.2991	0.1354
GMI	15.3867	42.5897	39.5634	53.0801	15.979	26.0057	28.109	42.9508	26.3606	46.6866
Aspect	4.8613	9.7129	7.8165	9.6201	12.5109	40.6226	11.6471	18.2924	6.4504	10.1119
Geometrical minute	32.4531	21.8125	32.3594	29.7344	27.5156	25.25	33.2656	24.3281	20.9531	33.4063

Technique	Intra-class										Inter-class
	Twin 11 (a,b)	Twin 12 (a,b)	Twin 13 (a,b)	Twin 14 (a,b)	Twin 15 (a,b)	Twin 16 (a,b)	Twin 17 (a,b)	Twin 18 (a,b)	Twin 19 (a,b)	Twin 20 (a,b)	Twins (1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20)
AUMI	2.554	2.722	14.4458	5.4006	5.4602	2.9337	4.8807	3.3155	5.3268	5.6098	7.2035
UMI	1.3931	0.2272	2.0646	0.5276	0.5276	0.1098	0.4801	0.0655	0.2864	0.3494	0.0199
GMI	38.0898	11.0456	35.979	35.6386	42.1358	25.6573	23.8347	10.0447	24.1364	28.5479	2.0235
Aspect	9.1913	11.0867	55.0904	17.5442	26.5758	29.4279	131.7001	5.3541	11.9772	65.6292	1.2451
Geometrical minute	14.7656	28.9219	22.5625	20.75	23.9688	15.4688	31.125	25.7188	20.125	18.3594	2.2957

Tables 19-27 show irregularity of the sequence of technique for the lowest MAE value. However, the AUMI technique shows exception; the smallest MAE value in nearly all tables is shown for AUMI. It is important that the technique has consistency in order to enable comparison of intra-class and inter-class, which in turn will enable the evaluation of the best technique. A technique that has smallest MAE value for intra-class and largest MAE value for inter-class simultaneously is considered as the best technique. In relation to this, AUMI fits the bill; for every technique, the scale of value for extracted invariant feature vector gained from feature extraction has dissimilar nature. AUMI for example, will produce the smallest value for invariant feature vector; as opposed to other techniques. This means that AUMI will unfailingly produce the smallest MAE value for intra-class and largest value for inter-class. Table 28 can be referred.

Table 28. Mean For All Techniques

Techniques	Intra-class	Inter-class
AUMI	2.779752	4.043166
GMI	21.58155	16.18607
Aspect	23.81716	9.91411
UMI	0.398728	0.244974
Macro	0.612048	0.438097
Geometrical minute	48.30777	28.67667

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6 CONCLUSION

This study brings forth a new framework for identical twins. In particular, this framework employs the technique of AUMI to determine the individuality in identical twin multi-biometric. Such method verifies twin multi-biometric in twin Identification (TI) in terms of individuality. This study brings to the table Uniqueness representation. It is to prove the individuality of twin multi-biometric owing to the application of Moment Function (MF) in the task of feature extraction. The procedure of individuality representation is highlighted. The most appropriate technique is suggested. Such technique comprises the computation of mean between the smallest and largest MAE value. In extracted features, each technique obtains unique scale value. As evidenced by the results, the use of AUMI demonstrates the highest individuality. Other moment techniques in multi-biometric twin identification were also explored.

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9. ETHICS

The corresponding author confirms that the other authors have read and approved the manuscript and there is no ethical issue involved. This paper is original and contains unpublished material.

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