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A Multimodal Biometric System using Global Features for Identical Twins Identification

[1,2,3]Bayan Omar Mohammed and [1,2]Siti Mariyam Shamsuddin

[1]*UTM Big Data Centre, IbnuSina Institute for Scientific and Industrial Research, Universiti Teknologi Malaysia, Johor, Malaysia*
[2]*Faculty of Computing, Universiti Teknologi Malaysia, Johor, Malaysia*
[3]*College of Science and Technology, University of Human Development, Sulaimani, KRG, Iraq*

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Corresponding Author:
Bayan Omar Mohammed
UTM Big Data Centre,
IbnuSina Institute for Scientific and Industrial Research,
Universiti Teknologi Malaysia,
Johor, Malaysia
Email: bayan.omar@uhd.edu.iq

Abstract: Pattern recognition studies are currently focusing on twin's biometric identification. The system of twins' biometric Identification can potentially differentiate the individual's biometric pattern. With the new Unimodal biometric identification, identical twins are precisely and reliably identified, with well exposure of certain traits. However, it is much more challenging to identify identical twins as they share so many similarities between them, as opposed to identifying the non-twins. Therefore, this study proposes the use of more than one biometric trait with global features. Pattern recognition application includes extracting and selecting meaningful features and this has brought to the key question in twin handwriting-fingerprint identification: How to obtain features from many writing styles and shapes of twin handwriting-fingerprint in order that the reflection of the right person between twins can be obtained. Global with Aspect United Moment Invariant for the extractions of global feature using the identical twin multi-biometric identification is thus proposed by this study.

Keywords: Identical Twin, Global Features, Multimodal Biometric, Identification, AUMI, Similarity Measurement

Introduction

Biometric-based identification and verification systems will soon be leaders in the technology of human identification (Koda *et al*., 2016; Karahan *et al*., 2016). These systems are equipped with applications that control access to premises as well as computers and the ability to decrease fraudulent transaction incidences in electronic commerce and dampen unauthorized immigration (Hamid and Faez, 2013). Somehow, in the case of twins, identifying their biometric is difficult unlike identifying non-twins. As Eliabeth *et al*. (2015) had stated: The amount of similarities shared by identical twins is astonishing. Thus, in the arena of pattern recognition and computer vision, twins' biometric identification has been the researched subject among many. In certain situations in fact, it is the only method that could identify an actual person's biometric pattern from a group of individuals (Muhammed and Shamsuddin, 2017; Hamid and Faez, 2013; Narayanan and Shmatikov, 2005; Umair *et al*., 2009; Neves and Proenc, 2016).

The unimodal biometric identification for identical twins is now considerably more accurate and reliable (Eliabeth *et al*., 2015; Leng and Shamsuddin, 2012; Muhammed and Shamsuddin, 2012) and certain traits exhibit sound performance. Still, there are issues with respect to the technology itself. Further, among the past works on identical twins' identification or verification with the application of the Unimodal biometric system include: Wonder Ears, which employs images of ears to identify identical twins (Nejati *et al*., 2012), new multimodal database from the biometric traits of twins (Hamid and Faez, 2013). Discriminability between the fingerprints of twins (Jain *et al*., 2001), DNA analysis (Jain *et al*., 2002), computational discriminability analysis on the fingerprints of twins (Liu and Srihari, 2009), '3D Face Recognition' method to recognize the face of identical twins (Vipin *et al*., 2011), facial marks analysis to differentiate identical twins (Srinivas *et al*., 2012), 'Double Trouble' method for recognising identical twins' by face (Paone *et al*., 2014). However, Muhammed and Shamsuddin (2012) opined that all these

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studies were physiological in nature which means that changes are not likely to happen to them.

For sharing one zygote, identical twins have identical genetic makeup. Thus, it is difficult to identify them (Fig. 1). The application of more than one biometric trait with Global features is thus recommended as a solution to this problem, hence, the introduction of the multimodal biometric system employing both the physical and behaviour trait. A combination of countless sources obtained from countless biometric traits is employed in this system. Employing this system, without exact biometric identifier, user is still able to enrol as authentication can still be done using other traits. Thus, enrolment problem can be solved using this system, proving the universality of this system. Multimodal biometric is thus usable in the analysis of identical features to allow the extraction of features' unique characteristics, after which, further examination of the written texts and minutiae patterns versus the original ones, can performed. Additionally, in the past works for twins' biometric, the global (holistic) features of the cursive word or shape were not treated as one whole object.

Individuality of Twins Multi-Biometric

As theorized by some scholars (Kauba *et al*., 2016; Easwaramoorthy *et al*., 2016; Eliabeth *et al*., 2015), a person's handwriting-fingerprint can represent his/her nature. This shows that the permanency of writing and fingerprint style of a person, just like their personality. This study obtained the data in UHD for 20 twins. Here, 4 samples were produced by each twin for each biometric. Figure 2 presents the samples from the exact individual in pairs of twins as well as samples with differing pairs. As evidenced, both the writings and fingerprints demonstrate more similarity being generated by both individuals in a pair of twins. Nevertheless, there appears dissimilarity when the writings and fingerprints are generated by the different pair. A minor difference has also been discovered in the writings and fingerprints that the exact individual in a pair of twins produce.

Fig. 1: A pair of identical twins from the identical twins dataset

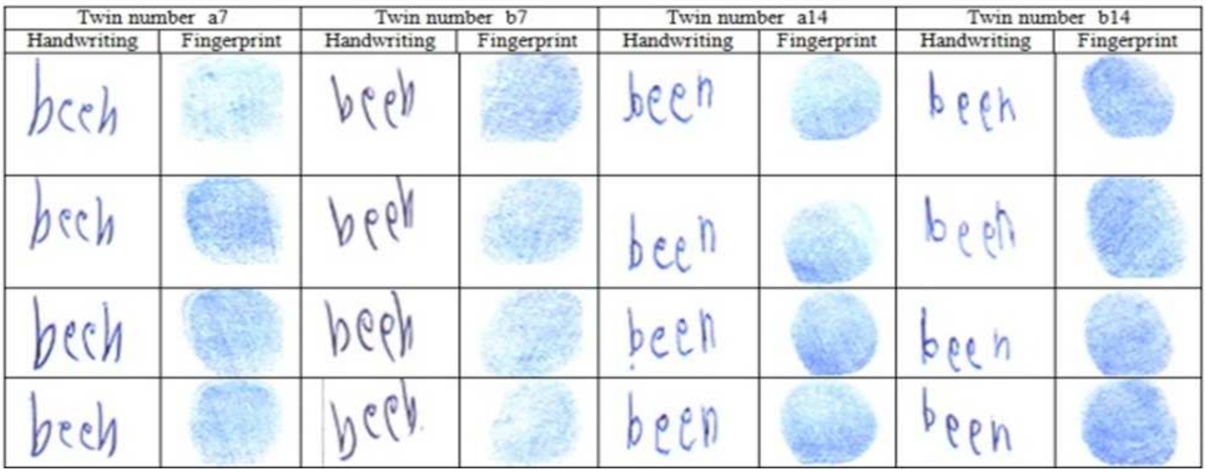


Fig. 2: Handwriting-fingerprint for both person in twins

Defined difference appears to be present in writings and fingerprints that both individuals in a pair produce even though the height of shape seems similar in identical twins. Based on these findings, it can be said that even identical twins differ particularly in terms of handwriting and fingerprint, which has been termed 'Individuality of Handwriting-fingerprint' which is assessable using the variances. Here, as suggested by Easwaramoorthy *et al*. (2016), Patil *et al*. (2016) and Eliabeth *et al*. (2015), the value of the person's feature or the intra-class, should be lower than that of different persons or the inter-class. Additionally, features with the least similarity error for one person in a pair of twins (intra-class) and the most similarity error for both individuals in a pair of twins (inter-class) demonstrate the soundness as well as acceptableness of individual features (Patil and Wagh, 2016). This shows the need to obtain the individual features from the samples of handwritten-fingerprint to allow the identification of the individual in a pair of twins.

Unique Representation with Global Features in Identical Twin

The global features that could handle images of twin multi-biometric for identification purpose are proposed in this study. This method is employed to extract feature and it is an adaptive method. Using this method, the class is discretely improved since it relocates the feature points of individual twin's class to better places, which assures more efficient depiction of individual characteristics for each biometric modality prior to their usage in the matching process. Identification of twins with the shape of handwritten and fingerprint have been presented by many pattern recognition researchers (Patil *et al*., 2016; Muhammed and Shamsuddin, 2012; 2017). Meanwhile, the visual domain comprises the application of shape feature and according to Azah *et al*. (2010), shape is also a key feature in describing image content. It is however, not easy to extract features that accurately denote and exemplify the shape of a twin in identical pair. Thus, the proposal of a state-of-the-art system for identical twins becomes the first objective of this study. The proposed system comprises Multimodal biometric identification with the incorporation of countless modalities.

Further, the inclusion of algorithm of Aspect United Moment Invariant (AUMI) from Azah *et al*. (2010) is this study's second objective. The use of AUMI allows the extraction of a good set of global features which denote the twin handwriting-fingerprint from the region and the boundary representation of a fingerprint in terms of word and shape. In the process of identifying twin, the AUMI extracted features endure the test of individuality of handwriting and fingerprint.

Meanwhile, this study's next objective is to analyse the efficiency of global features. This is for minimising the variation for intra-class while maximising the variation for inter-class for twins' handwriting-fingerprint's individuality in the context of biometric Identification. A method comprising a procedure is used to achieve this purpose and this method is crucial since twin identification demands a technique that fulfils the 'individuality' of Multimodal biometric. Figure 3 illustrates the new proposed procedure for achieving better identification of handwriting-fingerprint of pair of twins.

Multi-Biometric Shape Representations for Identical Twin

The pattern recognition field has generated countless methods for shape representation and depiction of features extraction from an image. Using two different approaches, twin handwriting-fingerprint shape can be handled, generally. These approaches are: Analytic (local/structural) approach and holistic (global) approach. There are two methods to each approach which are: Region-based or whole region shape method and contour-based or contour only method. For the purpose of this study, the holistic approach has been chosen. This approach involves the depiction of the whole image shape, which is appropriate for this study because the twin handwriting-fingerprint shape has to be extracted as one single entity. In other words, it cannot be divided. Also, as assurance of the application of the most appropriate technique to preserve the individuality concept of twin handwriting-fingerprint in twin biometric identification, this study has selected the global method exploration. Meanwhile, as for the other approach, that is, the analytic approach, it involves image depiction in segments.

AUMI with Twin Multi-Biometric

The extraction of individual features from Twin Multi-biometric shape demands an effective technique. With respect to handwriting, Azah *et al*. (2010) and Zhang and Lu (2002) mentioned shape as opposed to character, to demonstrate greater individuality level. Thus, the United Moment Invariant (UMI) (Yinan *et al*., 2003) is useful for global features' extraction from the handwriting and shape of fingerprint produced by twins. UMI was formulated based on Hu (1962) Geometric Moment Invariant (GMI) and Chen (1993) Improve Moment Invariant (IMI). In this context, the feasibility of GMI for representation of region in subtle situation has been proven in the work of Chen (1993), but considering that boundary representation requires high computational times, IMI is proposed for boundary and quicker computation.

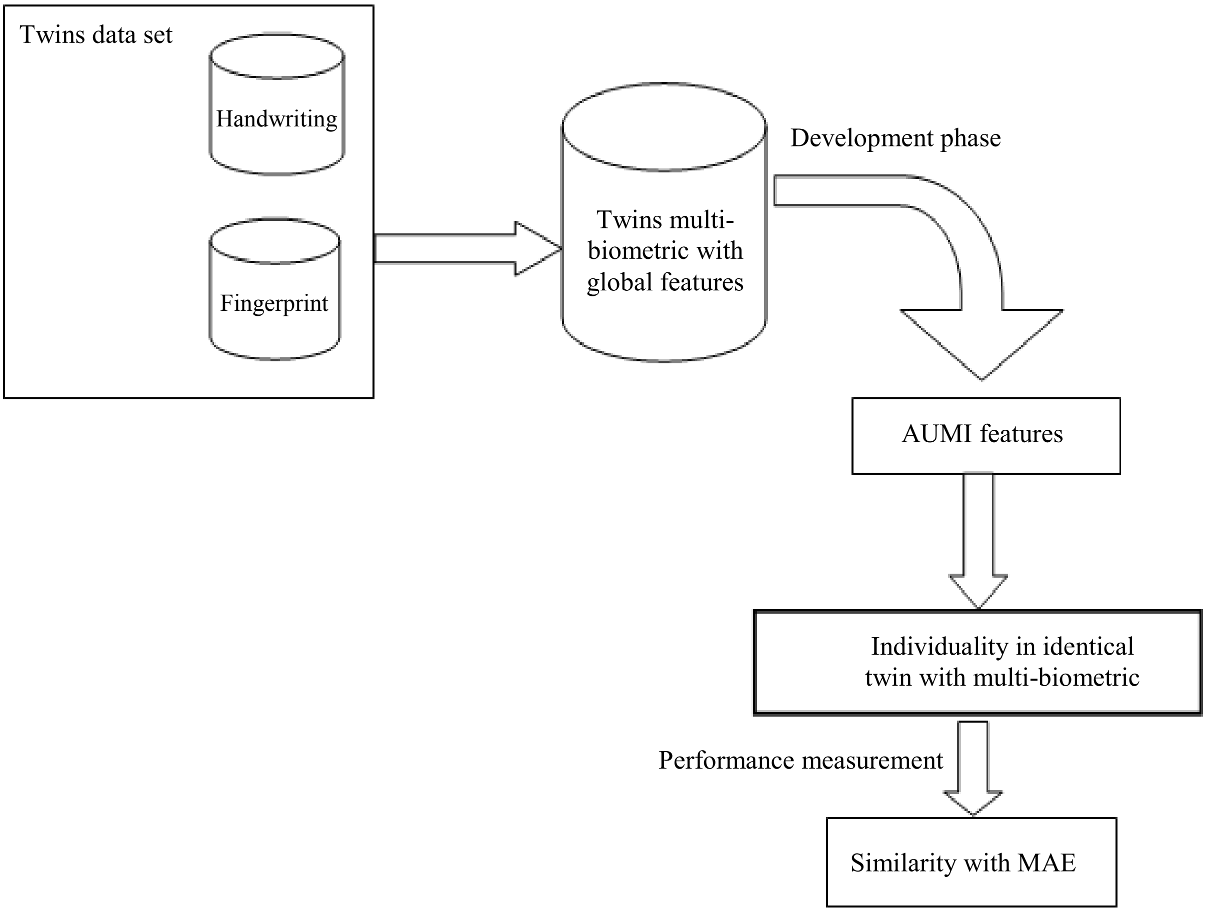


Fig. 3: New Framework for multi-biometric identification for a pair of twins

The image's region and boundary need to be constantly and independently extracted to assure quality feature in image representation (Yinan *et al*., 2003). Here, Yinan *et al*. (2003) proposed the use of UMI because of its capacity in effectively separating the shape of image consistently on region as well as on boundary. However, there are issues regarding the scaling factor utilised in UMI (Hu, 1962), which have led to the recommendation by Azah *et al*. (2010) of the use of the scaling factor of Aspect Invariant in Aspect United Moment formulated by Feng and Keane (1994). The application of this scaling factor enhances the invariant features without normalization of size. Therefore, the proposed AUMI algorithm also includes the aspect's scaling. With the use of this scaling, the invarianceness of handwriting-fingerprint for twin could be preserved in the direction of X and Y, characterizing the human's handwriting-fingerprint of twin. Also, the scaling enables the consistent and subtle extraction of the global word and the fingerprint features shape from both region and boundary representation by way of invarianceness from twin's handwriting-fingerprint.

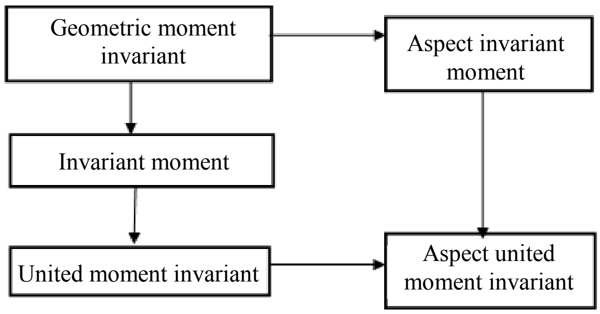


Fig. 4: Aspect United Moment Invariant

Azah *et al*.'s (2010) AUMI allows the global features' extraction from the region and boundary of (word or shape) in separate and continuous manner as representation of an individual in a twin. Here, the fusion embedded scaling factor of Aspect is created (Feng and Keane, 1994) into the UMI (Yinan *et al*., 2003), as can be referred in Fig. 4. This instantly assumes the capacity of these two functions of moment into the proposed Aspect United Moment Invariant. Yinan *et al*.'s (2003) UMI has association with geometrical representation that considers Normalized Central Moment equations of GMI (Hu, 1962) and Boundary Representation of IMI (Chen, 1993). Lastly, Azah *et al.*'s (2010) AUMI comprises 8 features with the construction of Yinan *et al.* (2003) UMI, as shown below:

$$\theta_1 = \frac{\sqrt{\varnothing_2}}{\varnothing_1} \quad (1)$$

$$\theta_2 = \frac{\varnothing_6}{\varnothing_1\varnothing_4} \quad (2)$$

$$\theta_3 = \frac{\sqrt{\varnothing_5}}{\varnothing_4} \quad (3)$$

$$\theta_4 = \frac{\varnothing_3}{\varnothing_2\varnothing_4} \quad (4)$$

$$\theta_5 = \frac{\varnothing_1\varnothing_6}{\varnothing_1\varnothing_3} \quad (5)$$

$$\theta_6 = \frac{\left(\varnothing_1 + \sqrt{\varnothing_2}\right)\varnothing_2}{\varnothing_6} \quad (6)$$

$$\theta_7 = \frac{\varnothing_1\varnothing_5}{\varnothing_3\varnothing_6} \quad (7)$$

$$\theta_8 = \frac{\varnothing_3 + \varnothing_4}{\sqrt{\varnothing_5}} \quad (8)$$

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

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

Twin Multi-Biometric with Global Extracted Feature (GEF)

Table 1 shows the extracted word images sample of handwriting produced by twin. What can be seen in the table are the original extracted features after the global feature, which are the Aspect Invariant Moment (Aspect), United Moment Invariant (UMI), Aspect United Moment Invariant (AUMI) as well as macro feature extraction (MFE).

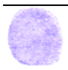
Table 2 illustrates the extracted the sample of twin's fingerprint images of shape. Both the original extracted features and the global feature are shown in the table and they include Geometrical minute feature extraction (GMFE), United Moment Invariant (UMI), Aspect Invariant Moment (Aspect), Geometric Moment Invariant (GMI), as well as Aspect United Moment Invariant (AUMI).

The system of identification employs a group of eatures that denotes the individuality and characteristics of an individual in a twin and only the vital features are extracted and selected. Somehow, in twin identification, extraction and selection are rather difficult to perform. This calls for the utilisation of the multi-biometric features from the data storage in identifying twin.

Table 1: Invariant features of twin number 7 by different algorithms

		F1	F2	F3	F4	F5	F6	F7	F8
GMI	a	19.5899	381.6335	2.6926	2.6496	7.0248	5.1721	6.4469	--
	b	19.2375	361.0587	2.5265	2.4890	6.1995	4.7262	5.4285	--
Aspect	a	18.8347	376.2823	7.0384	7.9596	1.8833	1.5714	4.9230	--
	b	18.1444	344.3009	6.4421	7.2856	1.5778	1.2334	4.1239	--
UMI	a	0.9933	0.9908	1.0003	0.9521	0.9555	1.0537	0.9610	2.0503
	b	0.9844	0.9843	1.0004	0.9976	1.0125	1.0034	1.0135	2.0024
AUMI	a	1.0280	0.0900	1.7240	0.3362	0.0096	100.9817	3.7346	5.7076
	b	1.0336	0.0946	1.7239	0.3363	0.0100	96.5498	3.5544	5.7088
Macro	a	7.3061	3.1300	2.1606	0.7039	9.3260	9.3260	0.2293	8.6080
	b	7.6824	2.3400	1.8381	0.7216	5.8710	1.5393	0.1691	6.2170

Table 2: Invariant features of twin number 7 by different algorithms

		F1	F2	F3	F4	F5	F6	F7	F8
GMI	a	20.0601	363.5930	2.5939	2.5712	6.6206	5.8891	3.8856	--
	b	20.2399	37.8910	2.6470	2.6291	6.9262	2.3313	2.8285	--
Aspect	a	8.4807	70.6361	1.6392	1.8510	1.0192	2.6367	2.6340	--
	b	7.3566	58.9641	9.0411	1.0253	3.1206	3.1206	8.2568	--
UMI	a	0.9505	1.1418	1.0007	0.9927	1.2526	8.3991	8.6942	2.0074
	b	1.0379	1.0189	1.0003	0.2933	2.7728	3.4749	2.8784	4.4102
AUMI	a	1.0107	0.1690	1.7250	0.3358	0.0187	53.0042	1.9872	5.7168
	b	1.0109	0.0881	1.7217	0.3369	0.0098	100.9343	3.8238	5.6906
Geometrical	a	178.0000	162.0000	184.0000	190.0000	183.0000	168.0000	167.0000	159
minute	b	199.0000	166.0000	212.0000	209.0000	198.0000	200.0000	167.0000	182

Similarity Measurement with MAE

Mean Absolute Error (MAE) measures uniqueness and the example of MAE calculation can be referred in Tables 3 to 5. As can be seen from the tables, there are 4 images employed for the representation of each individual. The value of MAE denotes the invarianceness of twin handwriting-fingerprint and it also offers the first image or reference image (Muhammed and Shamsuddin, 2017). The occurrence of small errors means that the image is almost identical to the reference image. The value of the overall results is used to compute MAE's average. MAE computation is as expressed below:

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

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

MAE matches with the individuality measurement of the individual twin handwriting-fingerprint in twin multi-biometric identification. Thus, this study has chosen the use of MAE function. Each twin of a pair has distinct features or characteristic with respect to their handwriting-fingerprint. The MAE function is used to measure the variance between twins' handwriting-fingerprint. Here, two handwriting-fingerprints' similarity error obtained from detailed characteristics in the column which denote feature, is used. Thus, the variance between two handwriting-fingerprint images for the features obtained from each column from the image's extracted invariant feature vector can be calculated. If low mean and standard division MAE value is attained, then, there is high similarity between the image and the reference or first image. On the other hand, if mean and standard division MAE value is high, then, there is low similarity between the image and the reference or first image. Simply stated, lowest value signifies highest similarity and vice versa. The classification of MAE function under robustness theory of statistical procedure has also been mentioned by other studies (e.g., Muhammed and Shamsuddin, 2012; 2017) and MAE function is also regarded as the most practicable and simplest solution. The pseudo code for this process is exhibited in Fig. 5.

Table 3: Intra-class MAE from AUMI features for twin multi-biometric for a10

Image	F1	F2	F3	F4	F5	F6	F7	F8	MAE
Handwriting									
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									
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

Table 4: Intra-class MAE from AUMI features for twin multi-biometric for b10

Image	F1	F2	F3	F4	F5	F6	F7	F8	MAE
Handwriting									
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									
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 5: Inter-class MAE from AUMI features for multi-biometric for twin number 10

Image	F1	F2	F3	F4	F5	F6	F7	F8	MAE
Handwriting									
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									
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

```
r = reference image;
c = current image;
 for c = 1 to no_of_writer {
    for i = 1 to no_of_features
       sum_feature = abs(ci - ri);
    mean_feature_c = sum_feature/no_of_features;
    sum_mean = sum_mean + mean_feature_c;
   }
MAE = sum_mean / no_of_writer;
```

Fig. 5: Pseudo code of MAE analysis

Similarity measurement with Intra-class and Inter-class with AUMI

The analyses of intra-class and inter-class were performed on the obtained value of MAE. Intra-class contains features extracted from the exact twin or one twin. On the other hand, inter-class includes features extracted from both in a twin or different twin. Word of writing and fingerprint shape produced by twin for intra-class both necessitate smaller MAE value. Comparatively, the inter-class needs bigger MAE value. Thus, the individuality of twin handwriting-fingerprint would be observable.

Presented in Tables 3 through 9 are the intra-class measurement (measurement of one person in a twin or one twin) and the inter-class measurement (measurement of both persons in a twin or different twin) with respect to difference. Here, the MAE function is employed for shape and word. The intra-class can be referred in Tables 3, 4, 6 and 8. Here, the values of MAE are lower than those presented in Tables 5, 7 and 9; all tables employ the twin multi-biometric. In Tables 3 through 9, the analysability of MAE values is demonstrated in the twin handwriting-fingerprint verification with respect to individuality. As for Tables 3 and 4, lower MAE value can be seen which shows that as proven by Table 5, the feature between the handwriting and fingerprint from the same person in a twin demonstrates close feature value when it is contrasted with the handwriting and fingerprint produced by both twins. Lower MAE value can also be seen in Tables 6 and 8 which shows that as proven by Table 9, the feature between the handwriting and fingerprint produced by both persons in a twin evidences close feature value when it is contrasted with the handwriting and fingerprint produced by different twins.

Table 6: Intra-class MAE from AUMI features for handwriting for twin number 1 and 2 (a, b)

F1	F2	F3	F4	F5	F6	F7	F8	MAE
Handwriting Twin 1 (a,b)								
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)								
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

Table 7: Inter-class MAE from AUMI features for handwriting for twin number 1 and 2 (a, b)

F1	F2	F3	F4	F5	F6	F7	F8	MAE
Handwriting Twin 1 and 2 (a,b)								
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

The similarity measurement process can apply any function that is in compliant with the similarity measurement rules between twin's features. This study has chosen MAE function because MAE function can be employed on limited data (as this study has). Also, MAE function demonstrates its appropriateness with the individuality of the analysis of twin handwriting-fingerprint. With respect to the analysis of intra-class and inter-class, comparison between intra-class and inter-class, the process of similarity measurement run. For this matter, the value of variance for intra-class should be lower than that of inter-class. This will guarantee that the individuality requirement of the twin handwriting-fingerprint is satisfied in order that it becomes pertinent in TI.

Experiment Result

The outcomes of AUMI are highlighted in this work. This will allow the determination of this method's applicability in Twin multi-biometric identification. Comparison and analysis are also made involving AUMI and other techniques, so that the hypothesis on AUMI's positive value in TI can be determined. Accordingly, Table 10 presents the MAE value outcomes and as can be construed, more exploration on AUMI algorithm should be carried out in the TI domain. Also, the outcome of similarity error demonstrates the presence of smaller Uniqueness of authorship for intra-class (same individual in twin or both individuals in a twin) when comparison is

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performed with that of inter-class (both individuals in twin or different twin). This finding satisfies the individuality notion of twin handwriting-fingerprint in identification arena. Here, in terms of handwriting and fingerprint, lower value of MAE for intra-class is obtained in comparison to the value of MAE obtained for inter-class. This is factored by the fact that moment function is a representation of image.

Table 8: Intra-class MAE from AUMI features for fingerprint for twin number 1 and 2 (a, b)

F1	F2	F3	F4	F5	F6	F7	F8	MAE
Fingerprint Twin 1 (a,b)								
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)								
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 9: Inter-class MAE from AUMI features for fingerprint for twin number 1 and 2 (a,b)

F1	F2	F3	F4	F5	F6	F7	F8	MAE
Fingerprint Twin 1 and 2 (a,b)								
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

Table 10: Uniqueness presentation with twin multi-biometric identification

	Intra-class (handwriting)			Intra-class (fingerprint)		
Twin	a	b	Inter-class (handwriting)	a	b	Inter-class (fingerprint)
One twin	0.69840	0.702700	0.755700	5.506100	5.752900	6.170300
5 twin	1.05090	1.038160	1.149260	3.159780	3.748200	4.427920
10 twin	0.98417	1.024620	1.310340	3.829320	2.313170	4.450940
15 twin	0.86576	1.001100	1.190767	4.544347	6.207867	9.690447
20 twin	1.07769	1.016375	1.296195	5.292855	5.780635	9.989795

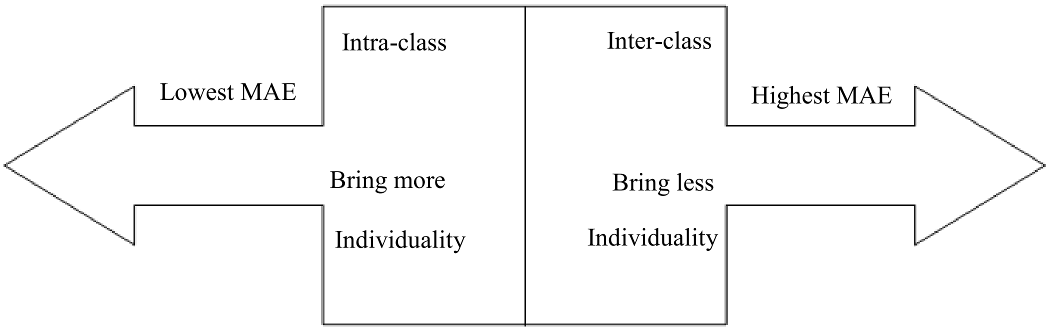

Fig. 6: Connection between MAE values

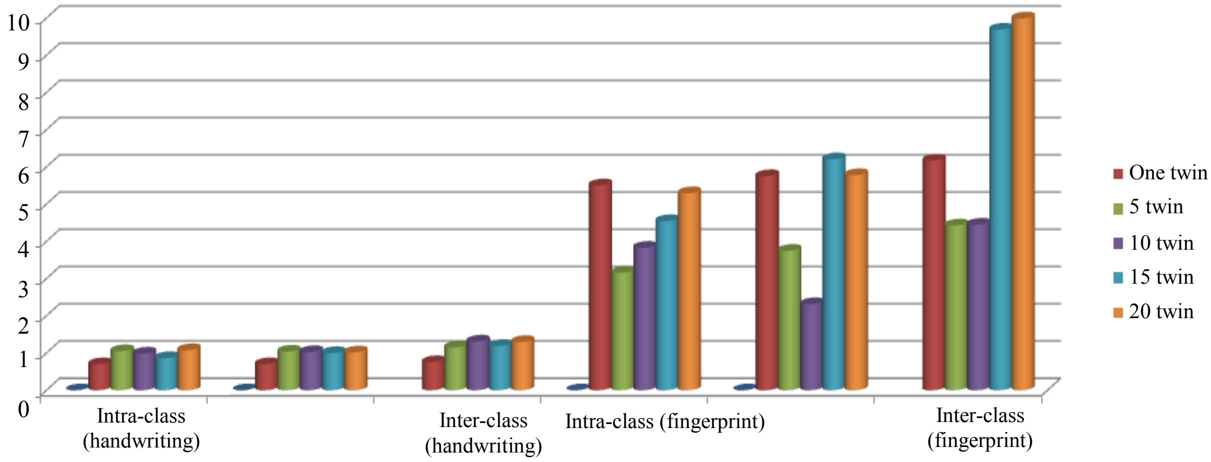

Fig. 7: Graph of Uniqueness presentation for AUMI

As such, AUMI's effectiveness in TMI feature extraction has been verified by the analysis of uniqueness presentation. Furthermore, in twin handwriting-fingerprint, the extracted feature appears to present the individual's distinct features.

The relation between these two values of MAE in technique capacity assessment for the discovery of the best technique is depicted in Fig. 6.

The notion of individuality in twin handwriting-fingerprint requires that the similarity error is greater for inter-class (both twins) and lesser for intra-class (same person); Figure 7 can be referred. It appears that the features extracted with the AUMI algorithm are closer for the exact person in a twin but more dissimilar for different persons in a twin. This has led to lesser MAE value for intra- class while the MAE value for the inter-class becomes larger, evidencing the practicability of the proposed technique in features extraction in the context of TI. Additionally, the notion of individuality relating to twin handwriting-fingerprint has been mentioned in several works including Eliabeth *et al*. (2015) and Pervouchine and Leedham (2007). Some empirical validation of individuality of twin multi-biometric with the AUMI algorithm of MF in the extraction of feature is offered in this work.

However, this section's result will not be considered in the best technique determination. Additionally, the next section will present the comparison of techniques. In particular, AUMI algorithm for the notion of individuality embraced by twin multi-biometric in the arena of TI will be validated. AUMI is practicable for the same person in a twin as well as for different persons in a twin. Also, three techniques also demonstrate their fittingness for the concept of twin multi-biometric, as can be seen from the outcomes they generate. Therefore, more in-depth exploration should be made on AUMI, UMI, Aspect, GMI technique of moment function as well as macro and geometrical minute with IT.

Intra-Class (Same Person in a Twin) and Inter-Class (Both Persons in a Twin) Result and Performance between Techniques

This section presents the outcomes generated by Macro, GMI, Aspect, UMI and AUMI in the context of twin handwriting. Geometrical minute, GMI, Aspect, UMI and AUMI are discussed in the context of twin fingerprint, with the additional inclusion of the findings of relevant study in order to determine the most fitting technique for twin handwriting-fingerprint's individuality. AUMI's capacity in the extraction of features of twin handwritten-fingerprint word and shape image in the context of TI is examined in this study and the algorithm efficiently has fulfilled the individuality of the twin handwriting-fingerprint. For intra-class, similarity error is found to be smaller, while that of inter-class; it is found to be larger. Inter-class and intra-class refers to both persons and the exact person, respectively, in a twin.

For intra-class, the analysis of variance between features generates lower value, as opposed to the analysis performed on inter-class, which demonstrates affirmation on the Individuality of twin handwriting-fingerprint. Thus, for intra-class, the most advanced technique of individuality of twin handwriting-fingerprint can be measured using the smallest MAE value. As for inter-class, the biggest MAE value is required for the measurement of similarity error, whereas for intra-class, the smallest MAE value is required for the same purpose. This demonstrates that the extracted features are the most linked and similar, while showing more characteristic of individuality inside a group of features. In the context of inter-class, gaining the largest MAE value signifies that the features are very distinct from others, resulting in low individuality level in the dataset.

This section discusses the outcomes generated from the analysis of the intra-class and inter-class comprising MEA with mean and standard deviation (refer Tables 11 through 16). Four sets of samples for each biometric from 20 twins are employed.

Intra-Class (Same twin) and Inter-Class (Different Twin) Result and Comparison Technique

This section comprises the discussion on the outcomes obtained from the analysis on both the intra-class and inter-class. Tables 17 through 26 can be referred for the intra-class (same twin) and inter-class (different twin) outcomes. Here, four sets of handwriting and four sets of fingerprint from 20 twins are shown.

As evidenced by Tables 17-26, there is irregularity in terms of the technique arrangement for the lowest MAE value with mean and standard deviation, with the exception of AUMI. Here, AUMI shows the smallest MAE value in almost all tables. A technique must be consistent so that intra-class and inter-class can be compared with one another, which will lead to the determination of the best technique. The best technique concurrently has the smallest MAE value for intra-class and the biggest MAE value for inter-class. Among the tested techniques in this study, AUMI is the best technique. The value scale for the extracted invariant feature vector produced by feature extraction contains characteristics that are different. As proof, in comparison to other techniques, AUMI will generate the smallest value for invariant feature vector, demonstrating its consistency in generating the smallest MAE value for intra-class and biggest MAE value for inter-class, as shown in Table 27.

Table 11: Calculation of mean and standard deviation for AUMI

	Intra-class (handwriting)		Intra-class (fingerprint)							
Twin	a	b	a	b	Mean	Standard deviation	Inter-class (handwriting)	Inter-class (fingerprint)	Mean	Standard deviation
One twin	0.698400	0.702700	5.506100	5.752900	3.165025	2.847514	0.755700	6.170300	3.463000	3.828700
5 twins	1.050900	1.038160	3.159780	3.748200	2.249260	1.411701	1.149260	4.427920	2.788590	2.318363
10 twins	0.984170	1.024620	3.829320	2.313170	2.037820	1.344376	1.310340	4.450940	2.880640	2.220740
15 twins	0.865760	1.001100	4.544347	6.207867	3.154769	2.653940	1.190767	9.690447	5.440607	6.010181
20 twins	1.077690	1.016375	5.292855	5.780635	3.291889	2.599895	1.296195	9.989795	5.642995	6.147304
Mean	0.935384	0.956591	4.466480	4.760554	2.779752		1.140452	6.945880	4.043166	
Standard deviation	0.155711	0.142563	0.985293	1.668426		0.730530	0.225700	2.736989		1.911777

Table 12: Calculation of mean and standard deviation for GMI

	Intra-class (handwriting)		Intra-class (fingerprint)							
Twin	a	b	a	b	Mean	Standard deviation	Inter-class (handwriting)	Inter-class (fingerprint)	Mean	Standard deviation
One twin	5.573000	3.505300	4.548600	5.124400	4.687825	0.892913	2.80040	15.38670	9.093550	8.899858
5 twins	5.017060	3.920140	45.78400	50.08234	26.20089	25.15955	3.28166	33.31978	18.30072	21.24016
10 twins	4.198270	3.981390	56.70813	41.93724	26.70626	26.80251	3.04288	33.67116	18.35702	21.65746
15 twins	4.313453	4.183793	54.17597	37.29115	24.99109	24.92360	3.073113	33.30669	18.18990	21.37837
20 twins	5.835410	4.333975	47.34950	43.76792	25.32170	23.42141	3.387275	30.59107	16.98917	19.23599
Mean	4.987439	3.984920	41.71324	35.64061	21.58155		3.117066	29.25508	16.18607	
Standard deviation	0.731413	0.314497	21.27037	17.66513		10.88159	0.227935	7.851050		5.390356

Table 13: Calculation of mean and standard deviation for Aspect

	Intra-class (handwriting)		Intra-class (fingerprint)							
Twin	a	b	a	b	Mean	Standard deviation	Inter-class (handwriting)	Inter-class (fingerprint)	Mean	Standard deviation
One twin	1.447500	0.949700	14.06670	4.926600	5.347625	6.075970	1.362900	4.861300	3.112100	2.473742
5 twins	2.865500	2.455080	82.39698	53.19492	35.22812	39.45089	1.480800	46.90434	24.19257	32.11929
10 twins	3.410860	3.198690	55.34073	41.42899	25.84482	26.63960	1.841810	32.16461	17.00321	21.44146
15 twins	1.824000	4.108500	57.11473	34.93319	24.49511	26.47380	1.587900	1.824000	1.705950	0.166948
20 twins	4.913280	2.687370	60.59422	44.48573	28.17015	28.91235	2.200155	4.913280	3.556718	1.918469
Mean	2.892228	2.679868	53.90267	35.79389	23.81716		1.694713	18.13351	9.914110	
Standard deviation	1.376835	1.156961	24.77899	18.46367		12.10177	0.333308	20.25808		14.36687

Table 14: Calculation of mean and standard deviation for UMI

	Intra-class (handwriting)		Intra-class (fingerprint)							
Twin	a	b	a	b	Mean	Standard deviation	Inter-class (handwriting)	Inter-class (fingerprint)	Mean	Standard deviation
One twin	0.015100	0.005100	0.320000	0.855700	0.298975	0.398887	0.007600	0.380300	0.193950	0.263539
5 twins	0.013760	0.015220	0.715680	0.456020	0.300170	0.346490	0.009760	0.327580	0.168670	0.224733
10 twins	0.015150	0.013190	0.698400	0.453700	0.295110	0.339436	0.009930	0.495920	0.252925	0.343647
15 twins	0.015620	0.015547	0.779427	1.568773	0.594842	0.742450	0.010133	0.646620	0.328377	0.450064
20 twins	0.025195	0.013455	0.710440	1.269090	0.504545	0.604943	0.012370	0.549525	0.280948	0.379826
Mean	0.016965	0.012502	0.644789	0.920657	0.398728		0.009959	0.479989	0.244974	
Standard deviation	0.004653	0.004267	0.184272	0.494878		0.179197	0.001692	0.128473		0.090215

Table 15: Calculation of mean and standard deviation for Macro

	Intra-class (handwriting)						
Twin	a	b	Mean	Standard deviation	Inter-class (handwriting)	Mean	Standard deviation
One twin	0.694100	0.284200	0.489150	0.289843	0.505700	0.505700	0.505700
5 twins	0.645760	0.547220	0.596490	0.069678	0.405180	0.405180	0.405180
10 twins	0.699420	0.553160	0.626290	0.103421	0.417180	0.417180	0.417180
15 twins	0.673300	0.638387	0.655844	0.024687	0.429180	0.429180	0.429180
20 twins	0.710505	0.674430	0.692468	0.025509	0.433245	0.433245	0.433245
Mean	0.684617	0.539479	0.612048		0.438097	0.438097	
Standard deviation	0.025579	0.152814		0.109725	0.039352		0.039352

Table 16: Calculation of mean and standard deviation for Geometrical minute

	Intra-class (fingerprint)						
Twin	a	b	Mean	Standard deviation	Inter-class (fingerprint)	Mean	Standard deviation
One twin	51.56250	75.62500	63.59375	17.01476	32.45310	32.45310	32.45310
5 twins	46.82500	57.32500	52.07500	7.424621	28.77500	28.77500	28.77500
10 twins	57.22863	45.55857	51.39360	8.251979	31.39877	31.39877	31.39877
15 twins	32.12500	27.62500	29.87500	3.181981	23.96880	23.96880	23.96880
20 twins	46.55494	42.64804	44.60149	2.762595	26.78768	26.78768	26.78768
Mean	46.85921	49.75632	48.30777		28.67667	28.67667	
Standard deviation	9.311773	17.91939		5.743082	3.442864		3.442864

Table 17: Calculation of mean and standard deviation for AUMI with Intra-class and Inter-class for handwriting

AUMI	Mean intra-class	standard deviation intra-class	Inter-class
Twin (1,2)	0.662400	0.066750880	0.8822
Twin (1,...,5)	0.959400	0.561415711	1.3235
Twin(1,...,10)	1.215410	0.772118980	2.6528
Twin(1,...,15)	1.134663	0.762484227	1.3437
Twin(1,...,20)	1.159055	0.697907828	2.5505

Table 18: Calculation of mean and standard deviation for UMI with Intra-class and Inter-class for handwriting

UMI	Mean Intra-class	Standard deviation intra-class	Inter-class
Twin (1,2)	0.01015	0.003323402	0.0046
Twin (1,...,5)	0.0098	0.00429127	0.0018
Twin(1,...,10)	0.009045	0.005909362	2.6528
Twin(1,...,15)	0.010147	0.005398501	0.0018
Twin(1,...,20)	0.01298	0.012503246	0.0015

Table 19: Calculation of mean and standard deviation for GMI with Intra-class and Inter-class for handwriting

GMI	Mean Intra-class	standard deviation intra-class	Inter-class
Twin (1,2)	4.906600	1.885712	2.1638
Twin (1,...,5)	3.436220	1.722402	2.4285
Twin(1,...,10)	3.120160	1.576148	0.6372
Twin(1,...,15)	2.929344	1.676507	0.3585
Twin(1,...,20)	3.494950	1.808673	0.2493

Table 20: Calculation of mean and standard deviation for Aspect with Intra-class and Inter-class for handwriting

Aspect	Mean Intra-class	standard deviation intra-class	Inter-class
Twin (1,2)	1.3273000	0.066185	1.038900
Twin (1,...,5)	1.2769400	0.524883	0.615900
Twin(1,...,10)	1.7398800	0.752517	0.280600
Twin(1,...,15)	1.5595375	0.663759	0.196000
Twin(1,...,20)	2.1491900	0.168500	2.221547

Table 21: Calculation of mean and standard deviation for Macro with Intra-class and Inter-class for handwriting

Macro	Mean Intra-class	standard deviation intra-class	Inter-class
Twin (1,2)	0.47075	0.049426764	0.2879
Twin (1,...,5)	0.40518	0.094443142	0.1375
Twin(1,...,10)	0.41718	0.148020521	0.4553
Twin(1,...,15)	0.41718	0.087087560	0.1960
Twin(1,...,20)	0.46161	0.146029730	0.0419

Table 22: Calculation of mean and standard deviation for AUMI with Intra-class and Inter-class for fingerprint

AUMI	Mean Intra-class	standard deviation intra-class	Inter-class
Twin (1,2)	3.737950	2.991415238	6.8941
Twin (1,...,5)	4.364500	1.765268414	6.1811
Twin(1,...,10)	3.909640	1.625751286	6.7887
Twin(1,...,15)	4.354938	3.100190322	7.3110
Twin(1,...,20)	4.587275	2.720654340	7.2035

Table 23: Calculation of mean and standard deviation for UMI with Intra-class and Inter-class for fingerprint

UMI	Mean Intra-class	standard deviation intra-class	Inter-class
Twin (1,2)	0.250700	0.183282078	0.1191
Twin (1,...,5)	0.327580	0.267001361	0.0673
Twin(1,...,10)	0.419910	0.481040616	0.0317
Twin(1,...,15)	0.595947	0.617032208	0.0299
Twin(1,...,20)	0.487162	0.556085108	0.0199

Table 24: Calculation of mean and standard deviation for GMI with Intra-class and Inter-class for fingerprint

GMI	Mean Intra-class	standard deviation intra-class	Inter-class
Twin (1,2)	28.98820	19.23543	14.8771
Twin (1,...,5)	33.31978	16.86477	6.53870
Twin(1,...,10)	33.67116	13.06800	4.12390
Twin(1,...,15)	33.30669	12.38446	42.1358
Twin(1,...,20)	30.59107	12.13054	2.02350

Table 25: Calculation of mean and standard deviation for aspect with Intra-class and Inter-class for fingerprint

Aspect	Mean Intra-class	standard deviation intra-class	Inter-class
Twin (1,2)	4.858066667	3.6802	3.430599
Twin (1,...,5)	46.90434000	3.6804	85.41617
Twin(1,...,10)	32.16461000	1.8467	59.72388
Twin(1,...,15)	29.40896667	1.3589	49.08535
Twin(1,...,20)	34.26115000	1.2451	49.16043

Table 26: Calculation of mean and standard deviation for geometrical minute with Intra-class and Inter-class for fingerprint

Geometrical minute	Mean Intra-class	standard deviation intra-class	Inter-class
Twin (1,2)	27.13280	7.524040416	19.6758
Twin (1,...,5)	28.77500	4.397706389	7.31250
Twin(1,...,10)	28.10781	4.806303191	3.92480
Twin(1,...,15)	26.13646	5.544032737	2.91630
Twin(1,...,20)	25.14220	5.831024929	2.29570

Table 27: Mean for All techniques

	Mean	
Techniques	Intra-class	Inter-class
AUMI	2.779752	4.043166
GMI	21.58155	16.18607
Aspect	23.81716	9.914110
UMI	0.398728	0.244974
Macro	0.612048	0.438097
Geometrical minute	48.30777	28.67667
Standard deviation		
AUMI	0.730530	1.911777
GMI	10.88159	5.390356
Aspect	12.10177	14.36687
UMI	0.179197	0.090215
Macro	0.109725	0.039352
Geometrical minute	5.743082	3.442864

Conclusion

A novel framework for identical twins is introduced in this study. The proposed framework utilises a technique known as AUMI in its determination of individuality in identical twin multi-biometric. AUMI provides the verification to twin multi-biometric in twin Identification (TI) fulfilling the individuality requirement. Representation of individuality is the focal point of this study, specifically the individuality of twin multi-biometric which is illustrated by Moment Function (MF) during the extraction of feature. The representation of individuality is elaborated in terms of procedure. Also, the technique deemed most applicable is recommended. In the context of this study, the technique in question involves mean and standard division calculation between the smallest and biggest MAE value. In terms of the extracted features, each technique acquires distinctive value of scale. The obtained outcomes show that AUMI produces the highest individuality. This study also scrutinises other techniques of moment in multi-biometric twin identification.

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Author's Contributions

Bayan Omar Mohammed: Designed the literature review plan and organized the study and contributed to the writing of the manuscript.

Siti Mariyam Shamsuddin: The main research supervisor, advised and supervised in the review process of this systematic study.

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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