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INDIVIDUALITY REPRESENTATION USING MULTIMODAL BIOMETRICS WITH ASPECT UNIETED MOMENT INVARIANT FOR IDENTICAL TWINS

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ABSTRACT

In essence, a biometric system comprises a pattern recognition system that obtains a person's biometric data from which a feature is set and then extracted. Upon setting the feature, it is compared to the template set stored in the database. Biometric identification systems need to not only have the capacity to distinguish between individuals but to also be capable of distinguishing individuals with nearly identical biometric signatures, such as identical twins. Multimodal biometric systems are therefore currently more popular because of their higher accuracy level in comparison to unimodal biometric systems in the context of identical twins. Comparatively, these systems require the extraction and selection of meaningful features. This paper introduces a new method for a multimodal biometric system using the Aspect United Moment Invariant for global feature extractions to detect identical twins. An experimental data set comprised of 1600 images from 100 pairs of identical twins collected from the Kurdistan region in Iraq is utilized.

Keywords: *Multi-Biometric, Identical Twin, Identification, Global Features, Aspect United Moment Invariant (AUMI).*

1. INTRODUCTION

Both biometric-based identification and verification systems are becoming primary technologies [1, 2, 4]. These systems are utilized in many applications, including controlling access to buildings and computers, reductions in false transactions in electronic commerce, and methods to reduce illegal immigration [6]. However, an efficient biometric identification system for twins is far more challenging compared to a system that identifies non-twins because of the significant similarity between twin individuals [6,8]. As such, among pattern recognition and computer vision researchers, the identification of a twin biometric is quite popular. This is also because in some cases, this method is the only one that can distinguish a specific person's biometric pattern from a group of people due to its high accuracy [3,9,10].

There have been significant improvements to unimodal biometric identification systems for identical twins, particularly in terms of their accuracy and reliability [17]. Additionally, several traits demonstrate sound performance. However, even the best biometric traits are plagued with issues that are being linked to the technology itself. In addition, past studies concentrated on the identification or verification of identical twins using unimodal biometric systems. The systems used include Wonder Ears, such as the Identification of Identical Twins from Ear Images in [11], and 3D Face Recognition to differentiate identical twins' faces by [12]. [8] used an Analysis of Facial Marks to Distinguish between Identical Twins, [7] used Double Trouble: Differentiating Identical Twins by Face Recognition, and the individuality of twin handwriting was used by [13]. However, [19] all these studies were physiological in nature, which means that changes, were unlikely to occur.

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Identical twins are from one zygote, and they therefore possess an identical genetic makeup (see Figure 1). This makes their identification more difficult. Thus, to resolve this issue, more than one biometric trait should be employed. Thus, the multimodal biometric system is appropriate because it uses both physical and behavioural traits. This system is made up of a combination of various biometric traits from numerous sources. This system allows users with no specified biometric identifier to still enrol and be authenticated using other traits, thus solving the enrolment issues. Worded simply, the multimodal biometric system is a universal system. Meanwhile, good and detailed features must be obtained as they are recorded and used as input to a classifier to guarantee a good performance in a twin's biometric identification. So, multimodal biometric use to analyze the similar features to extract the unique characteristics of the features forRepresentation Algorithm further investigation of the written texts and patterns of minutiae versus original ones. Meanwhile, the AUMI features obtained from the cursive word or shape as one whole object for any biometric.

Figure 1: A Pair of Identical Twins from the Identical Twins Dataset

2. FEATUER EXTRACTION

[14] AUMI allows the extraction of global features from the region and boundary (word or shape) in a separate and continuous manner to represent an individual. Here, the fusion embedded scaling factor of aspect is created [22] into the United Moment Invariant [18], as shown in Figure 2.

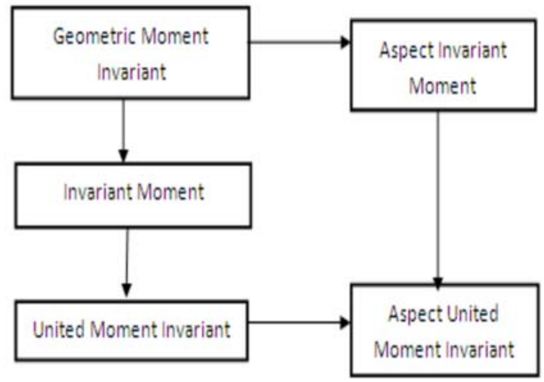

Figure 2: Aspect United Moment Invariant Structure by [14,16]

This instantly combines the capacities of these two functions of moment into the proposed AUMI. The [18] United Moment Invariant has an association with the geometrical representation that considers the normalized central moment equations of Geometric Moment Invariant [19] and the boundary representation of IMI [21]. Finally, AUMI comprises 8 features with the construction of the [18] UMI, as shown below:

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

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

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

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

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

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

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

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

The features of the AUMI satisfy the individuality of the concept of the twin's handwriting-fingerprint [14, 16], and the outcomes

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demonstrate a lower intra-class value for the variance between features for the mean absolute error (MAE) in comparison to the value for the inter-class. This is the reason why the features of the AUMI were explored and employed in the domain of twin biometric identification in this study. The AUMI presents the striking individual features in the extracted invariant feature. In the context of a twin's biometric identification, getting features that denote the twin's handwriting-fingerprint from numerous writing styles and shapes is the main purpose [14, 15, 16]. The AUMI is primarily concerned with obtaining the twin's handwriting-fingerprint's unique features. The purpose of employing algorithms is to extract individual features.

3. INDIVIDUALITY REPRESEANTATION PROCEDURE

Individuality representation procedure measures the capacity of [14] AUMI technique for individuality of the concept of twin handwriting-fingerprint. This procedure is made up of three processes: global features extraction from moment representation, similarity measurement of variance between features and intra-class and inter-class analysis. This method requires the engagement of the MF and TI domains. As such, the processes in the individuality representation procedure are linked to both areas. The proposed new procedure to improve the identification of a pair of twins' handwriting-fingerprint is presented in Figure 3.

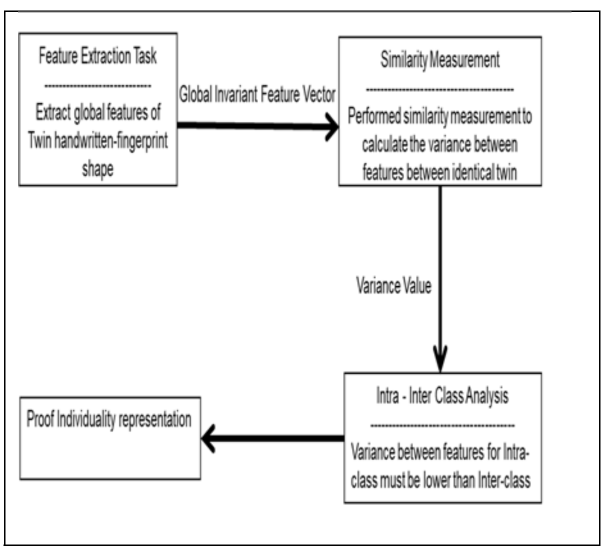

Figure 3: New Framework For Multi-Biometric Identification For a Pair Of Twins.

4. SIMILARITY MEASUREMENT

Mean Absolute Error (MAE) function measures similarity in the method of individuality representation to determine the mean of variance between features in a group of data. MAE function is a statistical function of measuring similarity error. It computes the mean variance's absolute value from the reference data. [20] describes this function as the entire mean deviation from every mean in the data set. Equation (9) below illustrates MAE function.

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

Where:
n: is number of image.
x_i: is the current image.
r_i: is the reference image or location measure.
f: is the number of features.
i: is the feature's column of image.

MAE function is employed in this study due to its ability to correspond with the individuality of the measurement of twins handwriting-fingerprint in the domain of Twins Identification. Twins will each has the exact features or characteristics in his/her handwriting-fingerprint. The MAE function allows the measurement of the variance between handwriting-fingerprint with error of similarity of two handwritings-fingerprints from detailed characteristics in the column of features. As such, to calculate the variance between two handwritten-fingerprints words and shapes images for the each column's features from extracted invariant feature vector of word and shape image in this study. The lowest value of MAE is the most identical to the original image. It is regarded as the reference image (first image) for comparison purpose. On the other hand, the highest value of MAE is regarded as the most different. Also, MAE function is grouped under the theory of robustness of statistical procedure and the simplest practical solution [20]. Tables 1 until 4 present a sample computation of MAE value for twins handwriting word and shape of fingerprint respectively for twins a7 and b7, extracted using the GMI technique.

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Table 1: Example of MAE from GMI for the word 'been' for twin a7

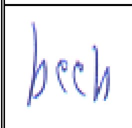
Image	F1	F2	F3	F4	F5	F6	F7	MAE
	18.9489	354.2521	2.5200	2.3977	5.7528	4.5015	9.6150	--
	19.5899	381.6335	2.6926	2.6496	7.0248	5.1721	6.4469	8.3894
	18.8415	346.5908	2.3309	2.3254	5.4115	4.3299	1.2163	4.2354
	19.0825	357.3562	2.5070	2.4411	5.9627	4.6084	7.1732	1.5132
Mean Absolute Error								3.5345

Table 2: Example of MAE from GMI for the word 'been' for twin b7

Image	F1	F2	F3	F4	F5	F6	F7	MAE
	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	6.9429
	20.0445	392.8424	2.8450	2.8207	7.9609	5.5885	5.1561	15.8410
	19.2749	360.1698	2.5479	2.5100	6.1995	4.7600	5.5050	6.7682
Mean Absolute Error								7.3880

Table 3: Example of MAE from GMI of fingerprint for twin a7

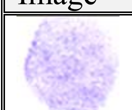
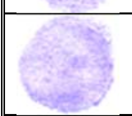
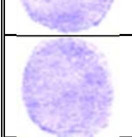
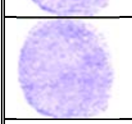
Image	F1	F2	F3	F4	F5	F6	F7	MAE
	22.0001	471.3585	3.8032	3.6822	1.3569	7.9836	1.8012	--
	28.6572	895.2590	9.0647	7.4851	5.6048	2.2192	1.9288	112.4405
	28.7231	855.6641	7.8401	7.8250	6.1287	5.5025	3.5522	102.0531
	21.8701	467.4235	3.6728	3.5565	1.2667	7.6697	1.6294	1.2243
Mean Absolute Error								53.9294

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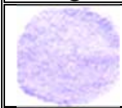
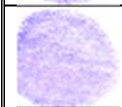
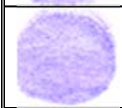
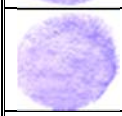
Table 4: Example of MAE from GMI of fingerprint for twin b7

Image	F1	F2	F3	F4	F5	F6	F7	MAE
	19.5385	352.7799	2.6055	2.4217	5.8746	4.5188	1.1804	--
	16.8247	230.5387	2.7294	1.5612	2.4470	2.2347	1.5711	33.0104
	16.3309	219.0293	3.3267	1.5295	2.3482	2.0570	1.8948	36.3186
	15.7280	213.5134	1.6836	1.2907	1.6703	1.8430	6.8208	39.4126
Mean Absolute Error								27.1854

Variance between twins handwriting-fingerprint words and shape images with the image of reference is computed with every feature's column. Thus, comparison is made between the first column feature of an image with that of the reference image. The first row is where the reference image is placed. All feature's columns of an image is contrasted with feature's columns of the reference image to attain the whole variance between these two images as a whole. It is important that the variance value is positive as this process is to compute the difference between two images rather than the value of the invariant feature vector itself. As such, the computation involves absolute function. Prior to the calculation of all mean variance of all images, the summary of all variance of all columns' features is computed to obtain the mean of variance for that image. For this set of data, the final mean value attained in this process is termed the MAE value.

5. RESULT, ANALYSIS AND INTERPRETATION

The outcomes of the AUMI with individuality representation with twins multimodal biometrics are presented in this chapter. This ascertains if AUMI is applicable to be used for twins multimodal biometrics identification domain. It also allows for comparison and analysis between AUMI and other techniques to prove the hypothesis that the exploration of AUMI useful in Twins Identification (TI) domain.

5.1 Proving Individuality of Twins Multimodal Biometrics Representation

A technique's capacity is measurable via the comparison of range or gaps between MAE values for intra-class and inter-class. The linkage between these two MAE values in order to discover the best technique is illustrated in the form of a diagram in Figure 4.

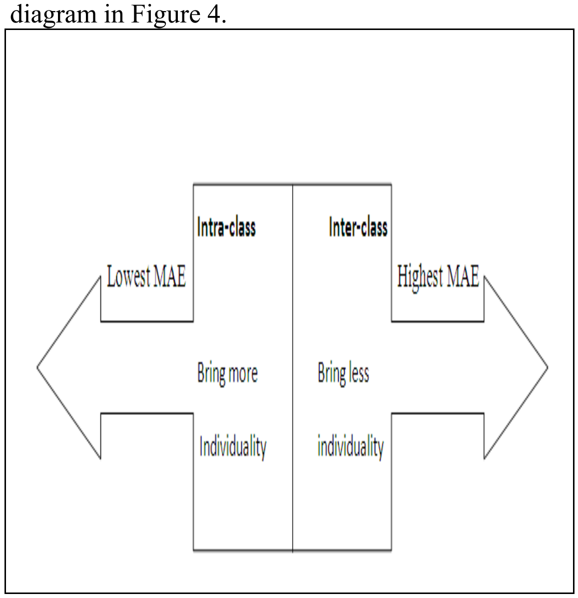
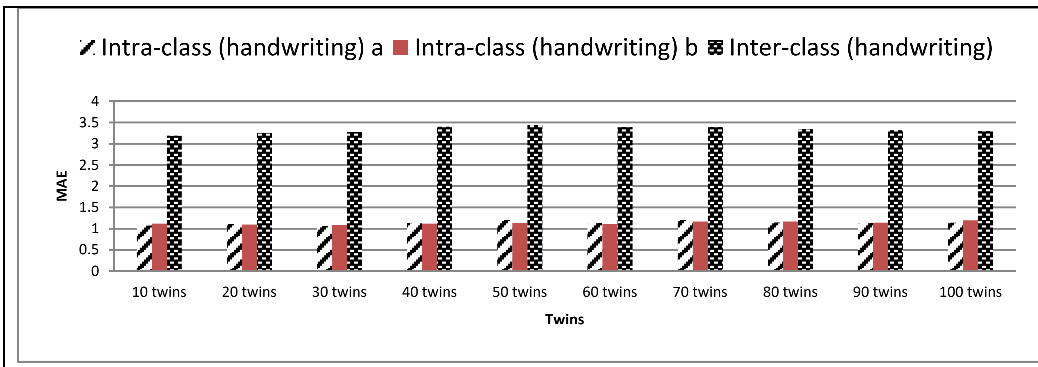


Figure 4: Connection between MAE values

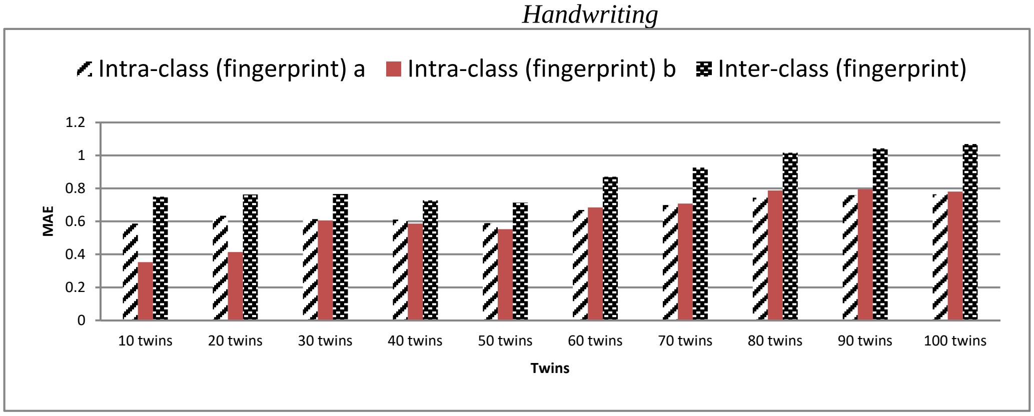
As demonstrated by MAE value outcomes in Table 5, AUMI algorithm should be explored further in the TI domain. The outcome for similarity error denotes the individuality of authorship for intra-class (same person in twins) is smaller compared to inter-class (both persons in twins). It fulfills the concept of individuality of twins handwriting-fingerprint in TI. Here, the MAE value for intra-class (same person in twins) is lower in comparison to inter-class (both persons in twins) for handwriting-fingerprint owing to the capacity of moment function as image representation. As such, this analysis of individuality representation affirms the usefulness of AUMI as a technique of feature extraction for the domain of twins multi-biometric identification (TMI). Also, extracted feature has been proven to bring the unique features of individual in twins handwriting-fingerprint.

Table 5: AUMI Individuality representation for twins handwriting-fingerprint identification

Twin	Intra-class (handwriting)		Inter-class (handwriting)	Intra-class (fingerprint)		Inter-class (fingerprint)
	a	b		a	b	
10 twins	1.074	1.120	3.190	0.587	0.353	0.750
20 twins	1.106	1.098	3.260	0.634	0.414	0.763
30 twins	1.065	1.088	3.277	0.614	0.605	0.766
40 twins	1.138	1.119	3.404	0.611	0.587	0.727
50 twins	1.207	1.127	3.440	0.590	0.553	0.714
60 twins	1.137	1.104	3.391	0.669	0.685	0.871
70 twins	1.200	1.169	3.390	0.699	0.708	0.926
80 twins	1.145	1.170	3.344	0.744	0.788	1.017
90 twins	1.135	1.143	3.317	0.759	0.795	1.043
100 twins	1.142	1.193	3.296	0.764	0.781	1.069



Handwriting



Fingerprint

Figure 5: Graph of individuality representation for AUM

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The above results demonstrate the unique characteristic or individual feature for twins handwriting-fingerprint. For inter-class (both individuals in a pair of twins), the similarity error should be bigger than that of intra-class (same individual in a pair of twins) for the concept of individuality of twins handwriting-fingerprint (refer to Figure 5). As shown, the extracted features with the AUMI algorithm are closer for same individual in comparison to both individuals in a twin. Such causes smaller MAE value for intra-class in comparison to that of the inter-class.

6. PERFORMANCE COMPARISON

The outcomes for each technique for twins handwriting-fingerprint (GMI, Aspect, UMI and AUMI) are discussed in this section alongside a comparative study for discovering the finest technique for individuality of twins handwriting-fingerprint. At the same time, this study attempts to assess the capacity of AUMI in features extraction of twins handwriting-fingerprint word and shape image in the domain of TI. As indicated, the individuality of twins handwriting-fingerprint concept for the technique of AUMI is affirmed. Similarity error for intra-class is smaller in comparison to that of the inter-class (same individual and both individuals in a twin).

Individuality of twins handwriting-fingerprint has been affirmed by the analysis of variance between features for intra-class that is lower than that of inter-class. As such, theoretically, the best technique of individuality for twins handwriting-fingerprint is measurable using the smallest MAE value for intra-class. As for inter-class similarity error measurement, the biggest MAE value is required. For intra-class, the smallest MAE value is to affirm that extracted features are most linked, identical and bring higher individuality characteristic in a set of features. On the other hand, for inter-class, the greatest MAE value denotes that the features are highly distinct from one another and bring low individuality in that data set.

6.1 Results of Intra-class and Inter-class Analyses for Each Individual Twins

The results for intra-class and inter-class analyses are exhibited in this section. Table 6. through Table 9 present the outcome for intra-class for 100 twins.

Table 6: Mean and standard deviation for AUMI

Twins	Intra-class (handwriting)		Intra-class (fingerprint)		Mean	Standard deviation	Inter-class (handwriting)	Inter-class (fingerprint)	Mean	Standard deviation
	a	b	a	b						
10 twins	1.074	1.120	0.587	0.353	0.784	0.374	3.190	0.750	1.970	1.725
20 twins	1.106	1.098	0.634	0.414	0.813	0.345	3.260	0.763	2.011	1.765
30 twins	1.065	1.088	0.614	0.605	0.843	0.269	3.277	0.766	2.021	1.775
40 twins	1.138	1.119	0.611	0.587	0.864	0.305	3.404	0.727	2.066	1.893
50 twins	1.207	1.127	0.590	0.553	0.869	0.345	3.440	0.714	2.077	1.928
60 twins	1.137	1.104	0.669	0.685	0.899	0.256	3.391	0.871	2.131	1.782
70 twins	1.200	1.169	0.699	0.708	0.944	0.277	3.390	0.926	2.158	1.742
80 twins	1.145	1.170	0.744	0.788	0.962	0.227	3.344	1.017	2.181	1.645
90 twins	1.135	1.143	0.759	0.795	0.958	0.209	3.317	1.043	2.180	1.607
100 twins	1.142	1.193	0.764	0.7819	0.970	0.228	3.296	1.069	2.182	1.574
Mean	1.135	1.133	0.667	0.6275	0.890		3.331	0.865	2.098	
Standard deviation	0.045	0.034	0.069	0.1548		0.054	0.077	0.139	0.079	0.113

Table 7: Mean and standard deviation for GMI

Twins	Intra-class (handwriting)		Intra-class (fingerprint)		Mean	Standard deviation	Inter-class (handwriting)	Inter-class (fingerprint)	Mean	Standard deviation
	a	b	a	b						
10 twins	4.198	3.981	1.634	1.501	2.828	1.459	3.042	1.492	2.267	1.095
20 twins	5.835	4.333	1.550	1.513	3.308	2.140	3.387	1.445	2.416	1.372
30 twins	6.366	4.177	1.593	1.617	3.438	2.298	3.265	1.488	2.376	1.256

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40 twins	6.029	4.328	1.614	1.638	3.402	2.165	3.253	1.484	2.368	1.250
50 twins	5.571	4.732	1.634	1.624	3.390	2.062	3.449	1.479	2.464	1.392
60 twins	5.504	4.884	1.640	1.647	3.419	2.065	3.459	1.493	2.476	1.390
70 twins	6.109	5.088	1.630	1.631	3.614	2.328	3.518	1.471	2.494	1.447
80 twins	5.991	5.158	1.634	1.647	3.608	2.296	3.517	1.482	2.500	1.438
90 twins	6.407	5.287	1.627	1.635	3.739	2.476	3.556	1.467	2.511	1.477
100 twins	6.140	5.392	1.636	1.628	3.697	2.406	3.624	1.466	2.545	1.525
Mean	5.815	4.736	1.619	1.608	3.445		3.407	1.477	2.442	
Standard deviation	0.640	0.502	0.027	0.054		0.311	0.174	0.0147	0.0842	0.128

Table 8: Mean and standard deviation for Aspect

Twins	Intra-class (handwriting)		Intra-class (fingerprint)		Mean	Standard deviation	Inter-class (handwriting)	Inter-class (fingerprint)	Mean	Standard deviation
	a	b	a	b						
10 twins	3.410	3.198	1.327	1.247	2.296	1.168	1.841	1.171	1.506	0.473
20 twins	4.913	2.687	1.477	1.328	2.601	1.656	2.200	1.267	1.733	0.659
30 twins	4.363	2.533	1.586	1.525	2.502	1.324	2.260	1.413	1.837	0.599
40 twins	3.930	2.330	1.658	1.613	2.383	1.082	1.999	1.472	1.735	0.372
50 twins	3.866	2.574	1.691	1.678	2.452	1.031	2.041	1.536	1.788	0.356
60 twins	3.764	2.603	1.750	1.759	2.469	0.951	2.036	1.603	1.819	0.305
70 twins	4.158	2.587	1.797	1.803	2.587	1.111	2.101	1.644	1.873	0.323
80 twins	4.222	2.612	1.829	1.848	2.628	1.123	2.087	1.681	1.884	0.286
90 twins	4.071	2.647	1.857	1.872	2.612	1.040	2.098	1.705	1.901	0.277
100 twins	4.021	2.642	1.853	1.879	2.599	1.016	2.061	1.714	1.887	0.245
Mean	4.072	2.641	1.682	1.655	2.513		2.072	1.521	1.796	
Standard deviation	0.397	0.218	0.175	0.226		0.197	0.112	0.188	0.118	0.141

Table 9: Mean and standard deviation for UMI

Twins	Intra-class (handwriting)		Intra-class (fingerprint)		Mean	Standard deviation	Inter-class (handwriting)	Inter-class (fingerprint)	Mean	Standard deviation
	a	b	a	b						
10 twins	0.015	0.013	0.698	0.453	0.295	0.339	0.009	0.495	0.252	0.343
20 twins	0.026	0.013	0.710	1.269	0.504	0.604	0.012	0.549	0.280	0.379
30 twins	0.021	0.034	2.327	1.113	0.874	1.095	0.026	0.909	0.467	0.624
40 twins	0.020	0.031	1.949	1.010	0.752	0.923	0.022	0.781	0.402	0.537
50 twins	0.021	0.028	1.850	1.090	0.747	0.890	0.020	0.794	0.407	0.546
60 twins	0.020	0.171	1.732	1.219	0.786	0.826	0.103	0.811	0.457	0.500
70 twins	0.027	0.152	4.269	1.281	1.432	1.973	0.091	1.225	0.658	0.801
80 twins	0.026	0.244	3.879	1.354	1.376	1.767	0.144	1.184	0.664	0.735
90 twins	0.031	0.220	5.614	1.384	1.813	2.603	0.131	1.465	0.798	0.943
100 twins	0.031	0.200	5.197	1.389	1.704	2.405	0.119	1.403	0.761	0.907
Mean	0.0242	0.111	2.823	1.157	1.028		0.068	0.962	0.515	
Standard deviation	0.005	0.095	1.787	0.279		0.838	0.054	0.340	0.193	0.208

The results presented in Tables 6 through 9 demonstrate that AUMI fulfilled this requirement. The MAE value for intra-class twins multimodal biometrics handwriting-fingerprint generated by AUMI is always lowest while having the highest MAE value for inter-class twins multimodal biometrics handwriting-fingerprint. As depicted in Table 8, UMI, GMI and Aspect gives the lowest MAE value for inter-class and heights MAE for intra-class.

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Table 10: Mean and standard deviation for all techniques

Techniques	Mean Intra-class	Mean Inter-class
AUMI	0.8909	2.0982
GMI	3.4450	2.4422
Aspect	2.5132	1.7969
UMI	1.0288	0.5152
Standard deviation		
AUMI	0.0543	0.1136
GMI	0.3116	0.1287
Aspect	0.1977	0.1416
UMI	0.8383	0.2088

The mean and standard deviation for all techniques are calculated and presented in Table 10 for the final result. The highest value is defined as the best technique because it gives the largest range of MAE value for inter-class and intra-class. Result in experimental results proved that the hypothesis of extracted features by using the AUMI bring more individuality in twins handwriting-fingerprint. It is then followed by UMI, Aspect and GMI.

7. CONCLUSION

The purpose of this study is to demonstrate the impacts of the AUMI technique and to verify the individuality of twins multimodal biometrics in the domain of twin identification (TI). In order to offer verification to the individuality of twin multi-biometric in the field of twin Identification (TI). Representation of individuality is highlighted in this study so that the individuality of twin multi-biometric is demonstrated by the utilization of Moment Function (MF) when extracting the feature. This study also highlights the individuality representation procedure This study also presented the best technique to compute the mean and standard division between the smallest and largest MAE value. A technique's capacity in the extraction of individual features is crucial since individual features are the key in the identification of a twin. Technique that generates the highest MAE for inter-class and lowest MAE for intra-class extracted features for twins individuality will generate successful process of identification in TI domain. As demonstrated by the experimental results, the AUMI technique proposed generates the highest MAE for inter-class and lowest MAE for intra-class compared to other existing techniques in the domain of TI.

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