Journal of Theoretical and Applied Information Technology
28th February 2017. Vol.95. No 4

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

TWINS MULTIMODAL BIOMETRIC IDENTIFICATION SYSTEM WITH ASPECT UNITED MOMENT INVARIANT

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ABSTRACT

In the field of pattern recognition twin's biometric identification is currently a popularly studied subject. In some situations, the mechanism of twins' biometric Identification leads to the finding a distinctive pattern of a person's biometric. Correspondingly, there has been considerable improvement made on the Unimodal biometric identification to identify identical twins with respect to its accuracy and reliability, with some traits that show sound performance. However, owing to great level of similarity, it is much more challenging to identify Identical twins as opposed to identifying non-twins. In order to deal with this problem, the application of more than one biometric trait is proposed; the Multimodal biometric system. Meanwhile, in pattern recognition it is crucial to extract and select features that are meaningful. This brings the attention to the major issue in twin handwriting-fingerprint identification: how to obtain features from numerous writing and styles twin handwriting-fingerprint so that the right person between twins can be reflected. Hence, the Aspect United Moment Invariant is proposed in this study as extraction of feature with identical twin multi-biometric identification.

Keywords: *Twin Multi-biometric, Global feature, Identification, Individuality, Aspect United Moment Invariant.*

1. INTRODUCTION

Biometric-based identification and verification systems will both be a main technology [1],[2]equipped with applications such as control of access to buildings and computers, decrease of fake transactions in electronic commerce, and dampen illegal immigration [9].Nonetheless, identical twins biometric identification appears to be a lot more difficult in comparison identifying non-twins due to substantial amount of identicalness found between these identical twins[6].This makes twins biometric Identification rather popular among researchers of pattern recognition and computer vision because in certain situations it is the only method that could lead to the discovery of the real person biometric of a pattern from a group of individuals[9], [10],[11],[12],[13],[21]. The Unimodal biometric identification for identical twins has lately improved significantly with respect to reliability and accuracy[6,14]and a number of the traits indicate good performance. Somehow, it should be noted that there are still issues plaguing even the best biometric traits of which are inherently linked to the technology itself. The past researches however, were focusing on the identification or verification of identical twins employing the Unimodal biometric system. Among those employed include Wonder Ears: Identification of Identical Twins from Ear Images by [14], 3D Face Recognition used for distinguish face for identical twins by [15],Analysis of Facial Marks to Distinguish Between Identical Twins by [10], Double Trouble: Differentiating Identical Twins by Face Recognition by [9].

As identical twins share single zygote, their genetic makeup will be similar. As such, identifying them would be more difficult. Thus, the use of more than one biometric trait is proposed to resolve this issue. The multimodal biometric system is one such system; it employs both physical and behavior trait. The multimodal biometric system comprises a combination of various sources from diverse biometric traits. Using this system, user who has no specific biometric identifier can still enroll and authenticate with other traits. This resolves the problem associated with enrollment and thus, the system is universal. So, multimodal biometric use to analyze the similar features to extract the unique characteristics of the features for further investigation of the written texts and patterns of minutiae versus original ones. Meanwhile, the past studies did not consider the global (holistic) features obtained from the cursive word or shape as one whole object for any biometric. Example is a study from [13].

2. INDIVIDUALITY OF TWINS MULTI-BIOMETRIC

The nature of a person is perceivable via his or her handwriting-fingerprint. The hypothesis constructed in [1],[2],[3],[4],[6] indicated that the individuality of a person with respect to writing and fingerprint style is evidenced by the fact that a person's handwriting-fingerprint is consistent. Figure 1 shows two pairs of samples in twins. From the figure, it is clear that the writings and fingerprints show only minor difference when the writings and fingerprints are produced by the same person in a pair of twins. Comparatively, there is more defined variance when the writings and fingerprints are produced by different persons in a pair of twins albeit the fact that the shape height is similar. Thus, even though the two persons are identical twins, there is still difference in terms of their handwriting and fingerprint. This difference is termed Individuality of Handwriting-fingerprint. This individuality can be measured by the variances. Here, the value of the person's feature (intra-class) has to be of lower than the value of different persons (inter-class) [4],[5],[6].If the features contains the smallest similarity error for one individual in a pair of twins (intra-class) and greatest similarity error for both individuals in a pair of twins (interclass), then the individual features are good as well as acceptable[7]. Hence, it is necessary to obtain individual features from the samples of handwritten-fingerprint. This will allow the identification of the individual in a pair of twins.

3. UNIQUE REPRESENTATION WITH GLOBAL FEATURES ON TWIN MULTI-BIOMETRIC IMAGES

Global features that can handle twin multi-biometric images for identification purpose is proposed in this study. This method is an adaptive method and it is used to extract feature extraction. Such usage will separately improve the class because for an individual twin class ,the method relocates the feature points to better places that would assure more efficient representation of individual characteristics of each biometric modality prior to their utilization in the matching process. Numerous researchers in the field of pattern recognition have their attention on identifying twin by employing the handwritten and fingerprint images shape [5],[8]. In visual domain, shape is an integral feature and in fact, shape is one of the fundamental features for illustrating the content of image [8]. However, it is not easy to extract features that accurately denote and illustrate the shape for a person in twins. Therefore, this study has the first objective of introducing a new mechanism for identical twins with Multimodal biometric identification with various modalities. Meanwhile an algorithm of Aspect United Moment Invariant (AUMI) [8] that can extract a good set of global features has been set as the second objective of this study. The features indicated denote the twin handwriting-fingerprint from the region as well as the boundary depiction of a word and shape of fingerprint. The features that are extracted from the AUMI algorithm then undergo the test of individuality of handwriting and fingerprint in the domain of twin identification.

Further, to analyze the efficiency of global features for minimizing the variation for intra-class while maximizing the variation for inter-class for Individuality of twins' handwriting-fingerprint in biometric Identification has been set as the third objective of this study. In order to attain this objective, a method comprising a procedure is employed. Such method use is crucial owing to that fact that the application of twin identification strictly requires the usage of technique that fulfils the 'individuality' of Multimodal biometric concept. Shown in Figure 2 is the study's overview that proposes a new procedure for improving the identification of a pair of twins' handwriting-fingerprint.

3.1 Twin handwriting-fingerprint Shape Representations

Techniques of shape representations and description for extracting features from an image in recognition of pattern are numerous. Two different approaches can generally be used when handling the shape of twin handwriting-fingerprint: the analytic (local / structural approach) and holistic (global approach). There are two methods in each approach: region-based or whole region shape method and contour-based or contour only method. In holistic approach, the image shape is represented in its entirety. On the other hand, in analytic approach, image is represented in sections. This study selects the holistic approach because the twin handwriting-fingerprint shape has to be extracted as one single entity that cannot be divided. As such,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

this study will include the exploration of global method in order to ascertain the most fitting technique for upholding the notion individuality of twin handwriting-fingerprint in the domain of twin biometric identification domain.

3.2 Aspect United Moment Invariant for Twin multi-Biometric

The extraction of individual features from Twin Multi-biometric shape requires an effective technique. As opposed to character, shape demonstrates greater level of individuality in handwriting [8],[16]. As such, the United Moment Invariant (UMI) [17] is chosen in this study to extract the global features from twin handwritten and fingerprint shape. UMI was created according to the Geometric Moment Invariant (GMI) [18] and the Improve Moment Invariant (IMI) [19]. As demonstrated by [19] , GMI is employable for region representation in separate circumstance. However, for boundary representation, the computational times are high. Owing to this, IMI is suggested for boundary and also for quicker computation.

However, the region and boundary of an image has to be extracted in a continuous and separate manner. This will assure the attainment of quality feature in representing an image [17]. As such, UMI is proposed [17] due to its capacity to effectively discriminate the image shape separately and continuously on both region and boundary .However, there are problems that are linked to the scaling factor employed in UMI [18].Hence, [8] suggested that the use of Aspect Invariant Moment (Aspect) scaling factor by [20] in Aspect United Moment Invariant. The invariant features are improved by this scaling factor with no normalization of size. This is why the Aspect's scaling is also included in the proposed AUMI algorithm; it can preserve the invarianceness of handwriting-fingerprint for twin in the X and Y direction. In fact, this is what characterizes the human's handwriting-fingerprint of twin. Using the scaling, the global word and the fingerprint features' shape are singly and continuously extracted from both region and boundary representation, with scale invarianceness from handwriting-fingerprint of twin.

Aspect United Moment Invariant [8] was formulated to have the capacity to extract global features from region and boundary of an object (word or shape) in a discrete and continuous manner, for denoting an individual in a twin. Such can be attained through the construction of fusion of Aspect's embedded scaling factor [20] into the UMI [17] (refer to Figure 3).This right away assumes the capacity of these two moment functions in to the proposed Aspect United Moment Invariant. The creation of UMI [17] has association with geometrical representation that considers GMI's Normalised Central Moment equations [18] and IMI's Boundary Representation [19]. Lastly, 8 features are shown in AUMI [8] with the formulation of UMI [17] below:

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

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

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

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

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

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

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

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

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

for $i = 1$ *to* 7 ; $\theta_i \leftarrow \log10\, \varphi_i$.

4 TWIN HANDWRITING WITH GLOBAL EXTRACTED FEATURE (GEF)

The sample of twin handwriting's extracted word images is shown in Tables 1, 2, 3,4 and 5. The sample comprises the original extracted features following the global feature. Here, Aspect Invariant Moment (Aspect), Aspect United Moment Invariant (AUMI), macro feature extraction (MFE), United Moment Invariant (UMI)and Geometric Moment Invariant (GMI)are included.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Tables 1, 2, 3, 4 and5 show that low inter-features variability does exist between both individuals in a twin. On the other hand, variability of height intra-features exists with the same individual in a twin.

5 TWIN FINGERPRINT WITH GLOBAL EXTRACTED FEATURE (GEF)

Tables6, 7, 8, 9 and10 show the shape images sample of the extracted twin fingerprint. The original extracted features and also the global feature are contained in these features. Geometrical minute feature extraction (GMFE), United Moment Invariant (UMI), Geometric Moment Invariant (GMI), Aspect Invariant Moment (Aspect) and Aspect United Moment Invariant (AUMI) are included.

A system of identification follows a set of features that is reflective of an individual's individuality and characteristics in a twin. Nonetheless, it is critical to extract and select only the meaningful features while for the context of twin identification, it is difficult to perform. The multi-biometric features that are stored in the data storage should be employed in identifying twin.

6 SIMILARITY MEASUREMENT

The measurement of uniqueness is performed with the Mean Absolute Error (MAE) function. Tables 11, 12 and 13present the example of MAE computation. Each person is presented by 4 images. The value of MAE provides the invarianceness of twin handwriting-fingerprint as well as the image of reference (first image) [8]. Small errors denote the closeness of the image to the image of reference. MAE's average is computed from the overall results' value.

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

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.

This study employs the MAE function as it matches to the individuality of the measurement of the individual twin handwriting-fingerprint in the domain of twin multi-biometric identification. In a pair of twins, each twin will possess the unique features or characteristic in handwriting-fingerprint. The MAE function allows the measurement of the variance between twin handwriting-fingerprint using two handwriting-fingerprints' similarity error obtained from detail characteristics in the column of feature. As such, to calculate the variance between two handwriting-fingerprint images for the each column's features from extracted invariant feature vector of image in this study. Lowest mean MAE value is considered as the most identical to the original image (reference image or first image) to be compared. Conversely, the highest mean MAE value indicates the most different. Also, MAE function has been grouped under robustness theory of statistical procedure and is also regarded as the solution that is simplest and most practical [8].

6.1 Intra-class and Inter-class with MAE

The value of MAE attained from thepriorprocess undergoes the intra-class and inter-class analysis. Intra-class is made of a group of features that are extractedfromthe same twin.Conversely, inter-class is formed by a group of features that are extractedfrom both twins. Smaller value of MAE is required for intra-class, for both handwriting word andshape of fingerprintof twin. For inter-class, the opposite is required.Such would demonstrate the individuality of twin handwriting-fingerprint.

The differences between the intra-classmeasurement (measurement of one individual in a twin) and the inter-class measurement (measurement ofboth individuals in a twin) with the application of the MAE function for the word and shape are shown inTables 11, 12 and 13 respectively. In Tables11 and 12which shows the intra-class, thevalues of MAE are less thanthose of MAEthat are presented in Table 13even thoughthe twin multi-biometricwas applied in both tables. As for the values of MAE inTables 11, 12 and 13they are analyzable for the individuality of twin handwriting-fingerprint verification. Tables 11 and 12, show MAE value that is lower. This indicates that the feature between the handwriting and fingerprint from the exact individual in a twin contains close feature value when contrasted with the handwriting and fingerprint from both twins (see Table 13).

Any function can be applied in the similarity measurement process as long as it complies with the rules of similarity measurement between twin's features. As for this study, the MAE function is selected because the data obtained are limited. In addition, the MAE function also matches with the individuality of the analysis of twin handwriting-fingerprint. With respect to the intra-class and inter-class analysis, comparison between intra-class and inter-class, the process of similarity measurement run. Here, it is necessary that the variance value for intra-class is smaller than the variance value of inter-class so that the requirement of the individuality of twin handwriting-fingerprint is satisfied. Then, it can be employed in the field of TI.

6.2 Result, Analysis and Interpretation

This study highlights the AUMI results as well. The purpose of presenting the results is to determine the applicability of the method in the domain of Twin multi-biometric identification. At the same time, comparison and analysis of the AUMI can also be performed with other techniques which will prove the hypothesis on the positive value of AUMI in the domain of TI. Table 14 presents the results of MAE value. As demonstrated by the results, there should be more exploration of AUMI algorithm in the context of the TI domain. The similarity error result indicates smaller Uniqueness of authorship for intra-class (same person in twin) when contrasted to that of inter-class (both persons in twin). This satisfies the notion of individuality of twin handwriting-fingerprint in the field of identification. In this regard, the value of MAE for intra-class (exact person in twin) is lower when compared to the MAE value of inter-class (both persons in twin) in terms of handwriting and fingerprint. This is caused by the ability of moment function as representation of image. Hence, the Uniqueness presentation analysis provides affirmation that AUMI is a valuable feature extraction technique in TMI domain. Also, it has been evidenced that extracted feature brings the distinctive features of individual in twin handwriting-fingerprint.

The unique characteristic or individual feature for handwriting-fingerprint of twin is demonstrated by the results above. With respect to inter-class (both twins), the similarity error should be greater while for intra-class (same individual) the similarity error should be smaller, in the notion of individuality of twin handwriting-fingerprint (see Figure 4). The features extracted with the AUMI algorithm appear closer for same individual in a twin while for different individuals in a twin, they appear more different. This leads to the attainment of MAE value that is smaller for intra-class but greater for the inter-class. Therefore, the proposed technique is indeed useful in the task of features extraction in TI field. Furthermore, many scholars, for instance [6],[21],have reported on the notion individuality of twin handwriting-fingerprint. Thus, it is hoped that this study will become part of the scientific substantiation of individuality of twin multi-biometric attainable with the application of the AUMI algorithm of MF in extraction of feature.

Somehow, this section's outcome will not be contrasted and analyzed to determine the best technique. The ensuing section will discuss the techniques' comparison. In this section, the AUMI algorithm is validated for to the notion of individuality of twin multi-biometric in the field of TI. This algorithm can be employed for the same individual in a twin and also for different individuals in a twin. As for the other three techniques, their outcomes also indicate their applicability for twin multi-biometric notion. Thus, in the field of TI, further examination of AUMI, UMI, Aspect and GMI technique of moment function and macro, geometrical minute is worthwhile.

7 COMPARISON OF PERFORMANCE BETWEEN TECHNIQUES

This section highlights the techniques (Macro, GMI, Aspect, UMI and AUMI) for twin handwriting in terms of their outcomes and (Geometrical minute, GMI, Aspect, UMI and AUMI) for twin fingerprint. This study also includes a comparative study as an attempt to find out the most fitting technique for twin handwriting-fingerprint individuality. Also, AUMI's ability in the extraction of features of twin handwritten-fingerprint word and shape image in the field of TI is also assessed in this study. As demonstrated, the individuality of the concept of twin handwriting-fingerprint for AUMI is proven. In comparison to that of the inter-class, the error of similarity for intra-class is smaller; that is, for the same individual and also for both individuals in a twin.

The analysis of variance between features for intra-class that is lower than that of inter-class has confirmed the Individuality of twin handwriting-fingerprint. Hence, in theory, the measurement of the finest technique of individuality of twin handwriting-fingerprint is possible with the application of the smallest MAE value for intra-class. With respect to inter-class in error measurement similarity, the highest MAE value is needed. With respect to intra-class, the lowest MAE value denotes that extracted features are most related, similar and bring greater individuality characteristic within a group of features. Conversely, for inter-class, the biggest MAE value means that the features are very different in comparison to the others and causes low individuality in that data set.

This section shows the outcomes of the intra-class and inter-class analysis. Table15, 16, 17 as well as18presents the result for both intra-class and inter-class. Four 20 twins are shown.

As shown by the outcomes in Tables 15 through 18, there appears an irregularity of the sequence of technique for the lowest MAE value with the exception of the AUMI technique. Specifically, the smallest value of MAE in most tables is indicated for AUMI. For comparison of intra-class and inter-class, consistency in the technique sequence is required. This allows the evaluation of the best technique. The best technique must possess smallest MAE value for intra-class and biggest MAE value for inter-class at the same time. Somehow, as demonstrated, AUMI satisfies the prerequisite. This is because the value scale for extracted invariant feature vector that is obtained from feature extraction has different nature for each technique. For instance, when compared to other techniques, for invariant feature vector, AUMI will generate the smallest value. As such, AUMI will consistently generate smallest MAE value for intra-class whereas for inter-class, AUMI generates largest value, as shown in table 19.

8 CONCLUSION

The purpose of this study is to show the AUMI technique's impact on the individuality in identical twin multi-biometric, 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. Further, this study presents the best technique that is measured by computing the mean between the smallest and largest MAE value is also highlighted in this study. It should be noted that each technique attains different scale value in extracted features. The experimental outcomes prove that AUMI creates the greatest individuality in addition to the investigation of other techniques of moment in the area of multi-biometric twin identification.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

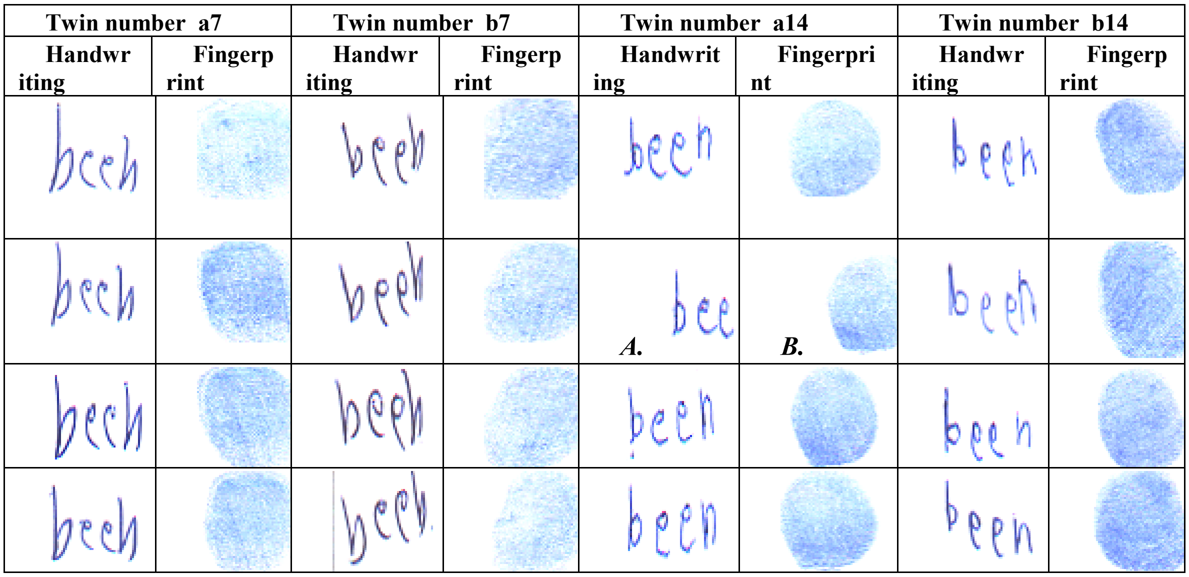


Figure 1: Handwriting-fingerprint for both person in twins.

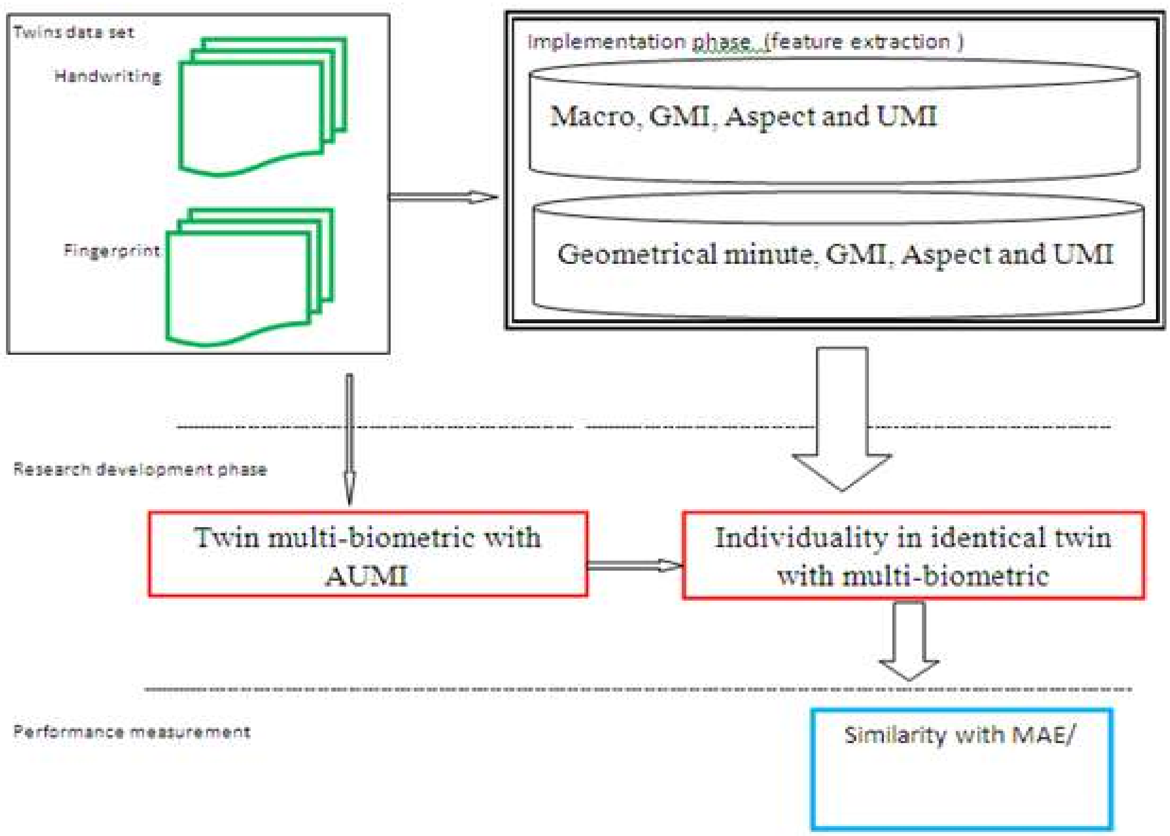


Figure 2: New Framework for multi-biometric identification for a pair of twins.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

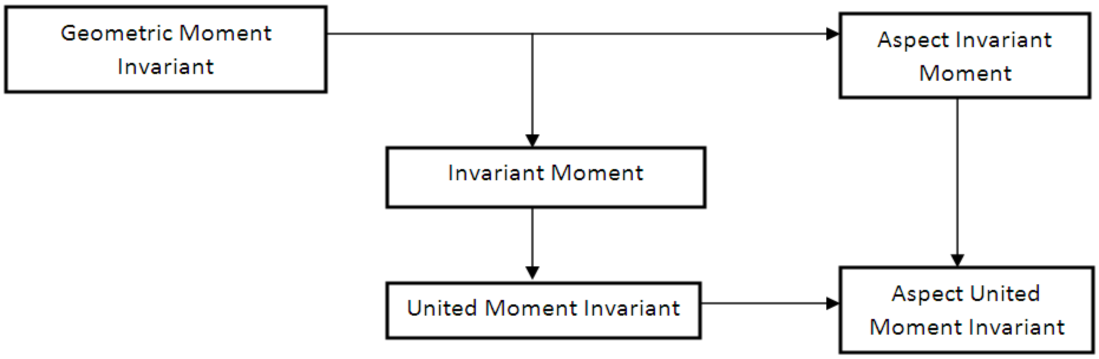


Figure 3: Aspect United Moment Invariant

Table 1: Invariant features of twin number 7 by GMI algorithm

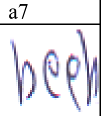
Image	F1	F2	F3	F4	F5	F6	F7
	18.9489	354.2521	2.5200	2.3977	5.7528	4.5015	9.6150
	19.5899	381.6335	2.6926	2.6496	7.0248	5.1721	6.4469
	18.8415	346.5908	2.3309	2.3254	5.4115	4.3299	1.2163
a7	19.0825	357.3562	2.5070	2.4411	5.9627	4.6084	7.1732
	18.7156	339.4583	2.3027	2.2954	5.2727	4.2285	1.6210
	19.2375	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
b7	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

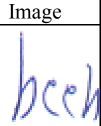
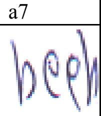
Image	F1	F2	F3	F4	F5	F6	F7
	18.8347	376.2823	7.0384	7.9596	1.8833	1.5714	4.9230
	18.2902	353.2250	6.4590	7.3065	1.5867	1.3663	4.1599
	18.0328	347.4064	6.1785	6.9915	1.4526	1.1928	3.8246
a7	18.3200	352.4048	6.4719	7.3206	1.5929	1.4439	4.2081
	18.7295	371.0281	6.7885	7.6793	1.7528	1.2949	4.5808
	18.6161	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
b7	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

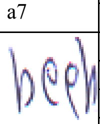
Image	F1	F2	F3	F4	F5	F6	F7	F8
	0.9933	0.9908	1.0003	0.9521	0.9555	1.0537	0.9610	2.0503
	0.9972	0.9964	1.0003	0.9847	0.9860	1.0170	0.9882	2.0156
	0.9881	0.9882	1.0004	0.9984	1.0098	1.0023	1.0102	2.0016
a7	0.9906	0.9893	1.0003	0.9743	0.9816	1.0284	0.9849	2.0264
	0.9844	0.9843	1.0004	0.9976	1.0125	1.0034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

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

Table 6: Invariant features of twin number 7by GMI algorithm

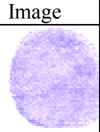
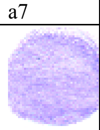
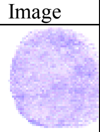
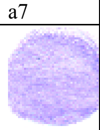
Image	F1	F2	F3	F4	F5	F6	F7
	20.0601	363.5930	2.5939	2.5712	6.6206	5.8891	3.8856
	20.4327	415.2668	2.6865	2.6790	7.1855	5.1489	1.1014
	21.8448	486.6713	4.4507	3.5393	1.2532	7.7199	4.7711
a7	29.3722	938.1759	1.8657	9.0555	8.2012	2.6159	6.3341
	34.5712	1.2134	1.9253	1.4308	2.0483	4.8979	9.0106
	48.0872	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

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 8: Invariant features of twin number 7 by UMI algorithm

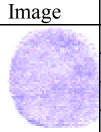
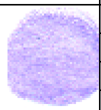
Image	F1	F2	F3	F4	F5	F6	F7	F8
 a7	0.9505	1.1418	1.0007	0.9927	1.2526	8.3991	8.6942	2.0074
	0.9973	0.9406	1.0006	0.9984	0.9430	1.0633	1.0614	2.0016
	1.0099	0.9985	1.0002	0.7955	0.7786	1.2719	0.7967	2.2570
	1.0428	0.9835	1.0001	0.4854	0.4390	2.1846	0.4936	3.0601
 b7	1.0076	0.9902	1.0003	0.7436	0.7248	1.3693	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
	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

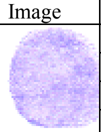
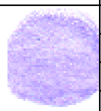
Image	F1	F2	F3	F4	F5	F6	F7	F8
 a7	1.0107	0.1690	1.7250	0.3358	0.0187	53.0042	1.9872	5.7168
	0.9910	0.1680	1.7248	0.3359	0.0193	52.2543	1.9999	5.7143
	0.9783	0.1527	1.7251	0.3358	0.0180	56.7789	2.1987	5.7170
	1.0094	0.0849	1.7244	0.3361	0.0094	105.1433	3.9566	5.7106
 b7	1.0109	0.0881	1.7217	0.3369	0.0098	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
	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

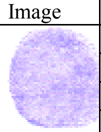
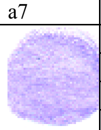
Image	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
 a7	178	162	184	190	183	168	167	159	192	209
	211	189	213	189	216	168	165	188	182	188
	213	209	174	208	210	147	153	200	209	206
	193	190	202	210	189	215	171	153	168	185
 b7	181	207	206	190	140	166	149	169	224	190
	229	216	219	220	140	175	185	195	232	216
	199	166	212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

Table 11: MAE from AUMI features for twin multi-biometric for a10

Image	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
	1.0230	0.1065	1.7242	0.3363	0.0115	84.9152	3.1569	5.7078	2.0710

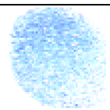
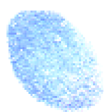
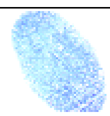
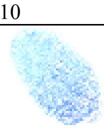
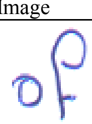
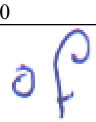
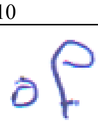
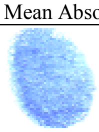
3a10									
 4a10	1.0272	0.1184	1.7242	0.3363	0.0127	76.7366	2.8398	5.7089	0.0662
Mean Absolute Error for handwriting a10									1.0926
 1a10	1.0119	0.1485	1.7240	0.3362	0.0164	60.2519	2.2644	5.7077	--
 *2a10*	1.0402	0.1253	1.7240	0.3362	0.0131	73.3963	2.6833	5.7079	3.4046
 3a10	1.0628	0.1288	1.7240	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 12: MAE from AUMI features for twin multi-biometric for b10

Image	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
 1b10	0.9765	0.1882	1.7252	0.3358	0.0223	46.0062	1.7844	5.7178	--

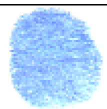
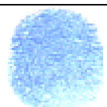
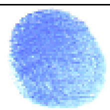
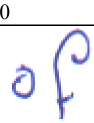
 2b10	0.9442	0.2601	1.7253	0.3356	0.0329	32.2016	1.2905	5.7202	3.6040
 3b10	1.0040	0.1724	1.7247	0.3359	0.0193	51.5573	1.9481	5.7139	1.4414
 4b10	1.0233	0.1531	1.7251	0.3358	0.0165	59.2351	2.1937	5.7166	3.4318
Mean Absolute Error for fingerprint b10									2.1193

Table 13: MAE from AUMI features for multi-biometric for twin number 10

Image	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

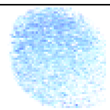
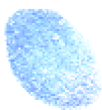
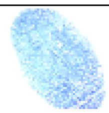
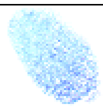
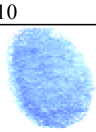
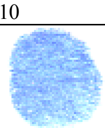
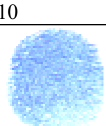
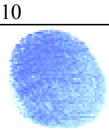
 1a10	1.0402	0.1253	1.7240	0.3362	0.0131	73.3963	2.6833	5.7079	--
 *2a10*	1.0628	0.1288	1.7240	0.3362	0.0129	72.9727	2.6111	5.7079	0.0653
 3a10	1.0516	0.1496	1.7244	0.3361	0.0153	60.2519	2.2462	5.7112	1.7029
 4a10	0.9765	0.1882	1.7252	0.3358	0.0223	46.0062	1.7844	5.7178	1.8386
 1b10	0.9442	0.2601	1.7253	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

Table 14: 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

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

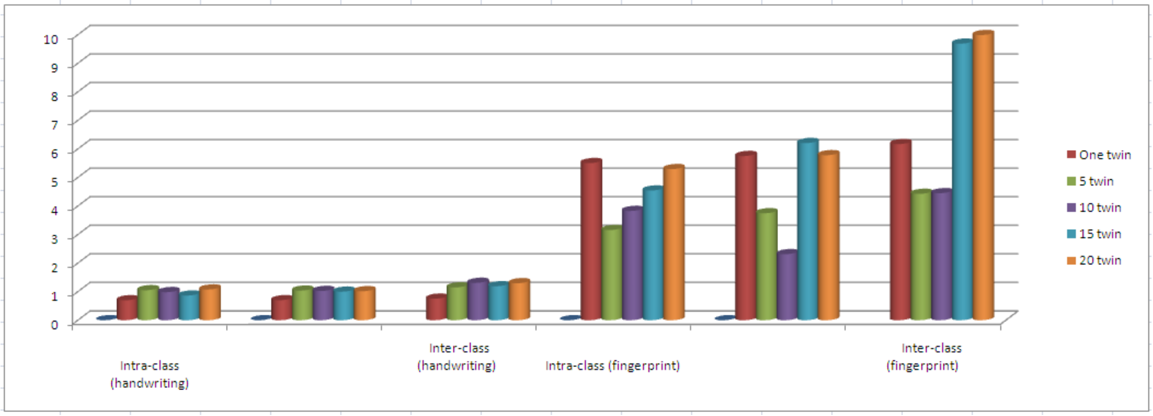


Figure 4: Graph of Uniqueness presentation for AUMI

Table 15: 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 16: 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 17: 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

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Table 18: 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