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Mean-Discrete Algorithm for Individuality Representation

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ABSTRACT

A biometric is one of the common types of pattern recognition, which acquires biometric data from a person. From these data, a feature is established and extracted where these features can be used to identify individual. Exiting works in biometric Identification concentrate on unimodal biometric identification. As such, using features that are uniquely belonging to a person would decrease fraud possibility. Hence, owing to their great accurateness, multimodal biometric systems have become more favored compared with unimodal biometric systems in identification. However, these systems are highly complex. We proposed Mean-Discrete feature-based fusion algorithm for person detection. Its viability and advantage over the unimodal biometric systems are highlighted.

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1. Introduction

Biometrics refers to the robotic method for distinguishing an individual built on their bodily or behavioral traits for example fingerprints, voice, face, iris, signature, or gait [1]. These behaviors are referred to as biometric modalities or biometric signals. Concluded the previous several years, a quantity of various biometric modalities [2-4] have been discovered in order to use in different applications ranging from private device entree to border resistor systems [5].

A Unimodal biometric system operates a single biometric cue, may encounter difficulties corresponding to the lost information for example occluded face, disadvantaged data quality for example dry fingerprint, interfere between identities such as partial discriminability such as hand geometry or face images of twins [6]. In such states, the compulsory to use multiple biometric cues to recover recognition accuracy, for instance, a margin control system may use both fingerprints and face in order to found the identity of an individual [7-8].

Such systems of biometric have been successful in certain real-life applications. An individual's fingerprints, face, ear and irises are inherently image based and necessitate the procedures of image processing, pattern recognition,

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and computer vision in order to enable implementation. On the other hand, an individual's speech, keystrokes, signature and hand geometry are used in the signal processing and pattern recognition. There have been some attempts to combine multiple biometrics (9) (audio-video, faces- fingerprints, etc.).

Multimodal biometric system combines many biometric traits from multitude of sources. In the context of enrolment, the use of this system enables the enrolment of users even though they have no identified biometric identifier. Such ability becomes a solution to the problems of enrolment, and these abilities therefore prove the universality of multimodal biometric system. Some multimodal biometric systems have been proposed using different modalities in recent years, including the following. Making multimodal biometric system suitable owing to the use of both physical and behavioral traits in its application [10-11]. In 2018, projected multi-biometric systems built on genuine-impostor score fusion [12]. In 2019, projected a multimodal biometric system mixing with 3 complementary biometric behaviors, namely, finger vein, iris and finger print depend on an optimum score level combination model [13].

In 2019, projected multi-factor authentication based on multimodal biometrics (MFA-MB) [14]. In 2020, projected score level combination on face–iris multimodal biometric system [15].

There are countless of representations in multi-biometric systems, which have led to the presence of vast variance between features for one individual. Somehow, there is small variance in the context of individual's comparison, making it necessary to engage one more process. This is to enable the unique features to be represented from the pool of multi-biometric features. During the process, many representations obtained from multi-biometric representations of a person are merged and converted into a uni-representation. The merging and conversion are done before the execution of the identification task. As a result, the level of variance in the data between the person is decreased. However, the majority of past researches were focusing on the discrete feature extraction methods of each individual's biometric. Hence, this study presents the application of Mean-Discrete feature based fusion algorithm in order to combine these features with individual's handwriting-fingerprint.

2. Uniqueness in Multibiometric Representation

Choosing greatest predominant features stand-in as an input to a classifier is very exciting to become well execution in the procedure of recognition. In the context of this study, the features, which are usually classed individually, are representatives of the individual handwriting-fingerprint particularly, with respect to word and shape. Furthermore, the individual classification of features allows the identification of an individual within a group of individuals. Accordingly, this study presents the feature-based fusion in order that the performance of identification in the arena of an individual biometric identification can be improved.

For the purpose, individual features would be needed, whereas the extracted features are often in multi-representations, for this purpose, individual features for each individual within are employed together. Arguably, such usage will increase the performance of individual identification. These are called a Mean-Discrete feature vector and this method is used following the process of feature extraction. Mean-Discrete feature vector carries the generalized features of global features possessed by individuals. In the model of identification, the features are generalized prior to the classification task. This generates better outcome. Relevantly, the framework proposed in this study is shown in summarized form in Figure 1.

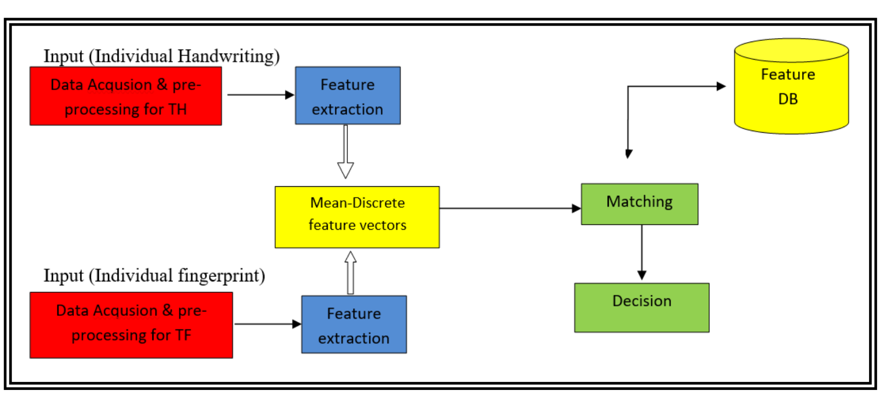


Fig. 1 – Proposed new framework for individual multi-biometric.

3. Extraction of the Feature

Features extraction is a converting the input data to a set of features. Feature extraction is an unusual representative of dimensionality decrease approaches. Breakdown with the large number of variable quantities normally needs a huge amount of memory, a classification algorithm or calculation control, which over fits the training sample and generalizes poorly to new samples. When the input data is too large to be managed, the input data are converted to a reduced representation set of features. Clearly, it's significant to choose type of feature extraction technique because it's the important, factor in the act of pattern recognition systems [16]. Choice type of feature extraction is reliant on the request. Various features are suggested to distinguish hand written digits and characters. They are Furies Transform, Invariant Moments, Geometric Moments, Characteristic Loci and others [17-18]. In the present work, Geometric moments realize individual handwriting-fingerprint have been used. Geometric Moment is utlized in object recognition and pattern recognition requests. A set of distinctive features calculated for an object must be skilled of identifying the same object with another possible various extent and location [19].

The geometric moments are depicted by the following computational steps [19]

1) Input and read the data of image from top-bottom and left-right hand.

2) Calculate the threshold the image data to extract the target process zone.

3) Calculate the moment value of the image, m_{pq} till 3rd according to the following expression

$$m_{pq}' = \iint_{\delta} (x')^p (y')^q f'(x', y') dx' dy' \; ; \quad p, q = 0, 1, 2, \ldots \tag{1}$$

4) Compute the intensity moment, (x_0, y_0) of image according to the following expression

$$x_0 = m_{10} / m_{00} \; ; \qquad y_0 = m_{01} / m_{00}.$$

5) Calculate the central moments, η_{pq} according to the following expression

$$\mu_{pq} = \iint_{\delta} (x - x_0)^p (y - y_0)^q f(x, y) dx dy \; ; \quad p, q = 0, 1, 2, \ldots \tag{2}$$

6) Calculate normalized central moment, η_{pq} in order to utilized in image scaling until 3rd order according to the following expression

$$\gamma = (p + q + 2)/2, \quad \eta_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{\gamma/2}} \quad , p + q \le 3. \tag{3}$$

7) Calculate geometric moments, Φ_1 0 to 0 Φ_4 with respect to concerning the translation, rotation and scale "geometric moment invariants" invariants according to the following expression:

$$\phi_1 = \eta_{20} + \eta_{02} \tag{4}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{5}$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{6}$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{7}$$

The purpose of employing algorithms is to extract individual features. Eventually, such use accurately reflects the handwriting-fingerprint of the individual. Conversely, for a multi-biometric representing an individual belonging to a same person, the directly extracted individual features do not directly represent the unique features of an individual biometric. As such, prior to the measurement task, additional processes should be included. This study proposes use of the Mean- Discrete feature based fusion algorithm prior to the identification task.

4. Proposed Mean-Discrete Algorithms

Mean-Discrete algorithm encompasses a global combination that proposed from discretization [20] and the statistical mean along with the moment function for multi-biometric. In this study, the individual features vector was obtained from features extracted from the image of individual handwriting-fingerprint word and shape utilizing GM. Using this approach, the global shape of an image is represented holistically. The format use for the extracted individual features vector is of real value [21]. In addition, the extracted unique features vector as seen in the form of multi-representations. Meanwhile, the MAE value range is used in measuring the technique's ability to make differentiation between the intra-class and inter-class. In this regard, bigger ranges or gaps denote sounder performance of identification. Utilizing the multi-representations of features, the value range of Mean Absolut Error (MAE) is calculated. Further, the individuality of the individual handwriting-fingerprint is computed utilizing the uni-representation of features with MAE. The uni-representation of individual features is formed using the process of the Mean- Discrete feature-based fusion.

4.1. Proposed Mean-Discrete feature-based fusion

Owing to the performance of the collective process on the task of identification, Mean-Discrete Algorithm is dubbed as global combination as well. Furthermore, owing to it's reliance on each attribute for each feature within the dataset, the Mean-Discrete Algorithm also becomes part of the global characteristic class. Such reliance allows the calculation of Mean-Discrete value for each attribute for each multi-biometric of individual. The application of Mean-Discrete feature vector leads to improved representation of data for the individual handwriting-fingerprint's individuality. Accordingly, the Mean-Discrete algorithm methodologies are presented in this section. Mean-Discrete algorithm is used at the feature level and it entails a blend of individual multiple features for the concluding decision-making. In the task of feature extraction of a multi-biometric for each person, GM used in producing the columns of seven-feature vector, and for the process of Mean-Discrete, seven features are generated from the individual's handwriting-fingerprint. For this reason, it is not impossible to keep the initial amount of invariant feature vector columns within the moment function that is utilized within the feature extraction task. Accordingly, the following section provides the elaboration of the process of Mean-Discrete feature-based fusion, and Figure 2 presents the Mean-Discrete process proposed in this study.

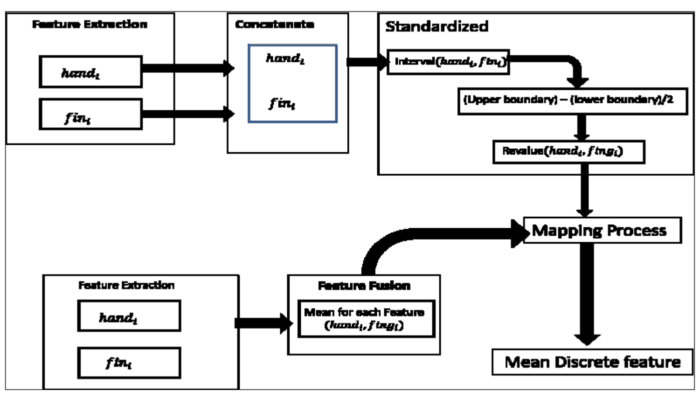


Fig. 2 – Process of Mean-Discrete (Uni-representation) Features.

The process of Mean-Discrete feature-based fusion entails the labeling of the person's class, and the conversion of the multi-representation features into uni-representation features. In the line of Mean-Discrete, first concatenate individual handwriting-fingerprint then the intervals are computed using the minimum (Fe_{min}) and maximum (Fe_{max}) feature vectors for an individual. The line of Mean-Discrete line entails a line of invariant feature vectors. This line begins from the minimum (Fe_{min}) invariant feature vector value and finishes with the maximum (Fe_{max}) invariant feature vector value for an individual. An interval encompasses the average of the line of Mean-Discrete apportioned using a number of columns within the invariant feature vector. The calculation of the width (wd) of an interval can be found using the following equation

$$wd = (Fe_{max} - Fe_{min})/f \quad (8)$$

where:

Fe_{min}: smallest value of invariant feature vector of the person.

Fe_{max}: largest value of invariant feature vector of the person.

f: quantity of columns in the invariant features vector.

The width describes the interval's cut points. It also computes the value of representation value. The 'f' value denotes seven for the number of columns of the feature from GM. Meanwhile, the cut point denotes the intervals' divider within the line of Mean-Discrete. For invariant feature vectors with similar interval, they have the exact value of representation. For each interval, the value of representation (Revalue) comprises the average of an interval computed using the following formula: Revalue = (Upper boundary − lower boundary)/2 .

The value of representation value for all intervals (1-7) denotes the invariant feature vector that is in the following range: in mapping process if Mean Handwiting-fingerprint ≤ Lower boundary and if Mean Handwiting-fingerprint ≤ Upper boundary. Meanwhile, mean features for each individual are computed using the invariant feature vectors of the individual's handwriting and fingerprint. Seven features were formed in this study, which represents the number of columns of a quantity for GM features stratified for the individual's multi-biometric; these features are called the Mean-Discrete feature vector. Vector symbolizes the individuality of the individual's handwriting-fingerprint to the person.

Table 1 and Table 2 illustrate the conversion of the individual's multi-biometric feature vector for a Mean-Discrete feature vector.

Table 1 - Real Data for fingerprint and handwriting for individual number 7.

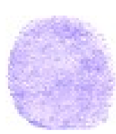
Image	F1	F2	F3	F4	F5	F6	F7
	18.9489	354.2521	2.5200	2.3977	5.7528	4.5015	9.6150
	19.5899	381.6335	2.6926	2.6496	7.0248	5.1721	6.4469
	18.8415	346.5908	2.3309	2.3254	5.4115	4.3299	1.2163
	19.0825	357.3562	2.5070	2.4411	5.9627	4.6084	7.1732
	20.0601	363.5930	2.5939	2.5712	6.6206	5.8891	3.8856
	20.4327	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
	29.3722	938.1759	1.8657	9.0555	8.2012	2.6159	6.3341

Table 2 - Mean-Discrete fingerprint and handwriting for individual number 7.

F1	F2	F3	F4	F5	F6	F7
65.08	448.2	65.08	65.08	65.08	65.08	65.08
65.08	576.0	65.08	65.08	65.08	65.08	65.08
65.08	576.0	65.08	65.08	65.08	65.08	65.08
65.08	448.2	65.08	65.08	65.08	65.08	65.08

Table 1 and 2 describe the seven columns of the invariant feature vectors in the GM, the Mean-Discrete procedure is achieved depending on the data in this table. Table 2 illustrates a Mean-Discrete process for individual number 7, while Table 3 illustrates a Mean-Discrete feature vector obtained by a Mean-Discrete algorithm procedure, the features obviously perform a general individual features for each one individual.

Table 3 - Mean- Discrete feature for Individual an example.

Individual 11	[60.71, 299.4, 60.71, 60.71, 60.71, 60.71, 60.71]
	[60.71, 538.2, 60.71, 60.71, 60.71, 60.71, 60.71]
	[60.71, 418.8, 60.71, 60.71, 60.71, 60.71, 60.71]
	[60.71, 418.8, 60.71, 60.71, 60.71, 60.71, 60.71]
Individual 17	[26.01, 176.0, 26.01, 26.01, 26.01, 26.01, 26.01]
	[26.01, 176.0, 26.01, 26.01, 26.01, 26.01, 26.01]
	[26.01, 26.01, 26.01, 26.01, 26.01, 26.01, 26.01]
	[26.01, 176.0, 26.01, 26.01, 26.01, 26.01, 26.01]
Individual 25	[30.72, 327.6, 30.72, 30.72, 30.72, 30.72, 30.72]
	[30.72, 327.6, 30.72, 30.72, 30.72, 30.72, 30.72]
	[30.72, 268.2, 30.72, 30.72, 30.72, 30.72, 30.72]
	[30.72, 387.0, 30.72, 30.72, 30.72, 30.72, 30.72]

5. Experiment & Results

Mean-Discrete algorithm generates more accurate results of identification task results; for this reason, it is of value to the context of this study. Within the context of multi-representation analysis, the individuality of the individual's handwriting-fingerprint is this study's focal point. The individual's multi-biometric identification has been improved using the variance between similarity errors or features of inter-class and intra-class, and the improved aspect is its individuality. An example of the execution of identification with a current accuracy in individual's identification task shows the feasibility of Mean-Discrete data in generating better performance. In other words, the prospect of attaining better level of individuality of an individual's handwriting-fingerprint for Mean-Discrete feature based fusion data utilization is proven in this work. Comparison was made between this study's outcomes of the uni-representation analysis with the Mean-Discrete feature based fusion data and those from the analysis of multi-representation.

5.1. Intra- and inter-class Analyses

The proposed Mean-Discrete method computes the individuality of individual's handwriting-fingerprint for the feature vector of Mean-Discrete. Then, using the MAE function, analyses of intra- and inter-class were carried out. For the identical and different biometrics, the variance it seems between features of the intra-class (exact individual) smaller when compared to the variance between features of an inter-class (different individual). The use of Mean-Discrete data in this study led to the production of superior outcomes; better individuality of the individual's handwriting-fingerprint was attained. In addition, for the intra-class with the Mean-Discrete feature, the attained MAE value seems smaller than that of the intra-class with the un-Mean-Discrete feature. Inter-class attained with the Mean-Discrete feature, the MAE value seems bigger as opposed to the use of un-Mean-Discrete feature. These results affirm the supposition that the suggested Mean-Discrete algorithm can enhance the individuality of an individual's handwriting-fingerprint corresponding to a uni-representation for the individual features. The outcomes of analysis of the uni-representation of the Mean-Discrete algorithm are detailed in the following tables and figures.

Table 4 - Multi-biometric with MAE Intra-class.

Individual's	Mean-Discrete -Feature Intra-class Handwriting-Fingerprint	Un-Mean-Discrete-Feature Intra-class Handwriting-Fingerprint
individual 1,..., 5	1.27708	3.37849
individual 1,..., 10	1.863575	3.263735
individual 1,..., 20	1.8985125	4.200255
Individual 1,..., 30	2.09827	5.178683
Individual 1,..., 40	2.208132	7.468086
Individual 1,..., 50	2.312474	5.881737
Mean	1.276341	4.895164
Standard division	1.072805	1.619778

Table 5 - Multi-biometric with MAE Inter-class.

Individual's	Mean-Discrete	Un-Mean-Discrete
individual 1,...,5	2.14022	1.26666
individual 1,...,10	2.74552	1.28458
individual 1,...,20	4.323025	1.47306
individual 1,...,30	3.39878	1.637747
individual 1,...,40	3.518627	1.82877
individual 1,...,50	3.7836772	1.9118276
Mean	3.484975	1.567107
Standard division	2.300031	0.272479

Figures 3 and 4 show the comparison the uni-representation of the Mean-Discrete feature and the multi-representation of the un-Mean-Discrete feature for an individual and different individual, respectively.

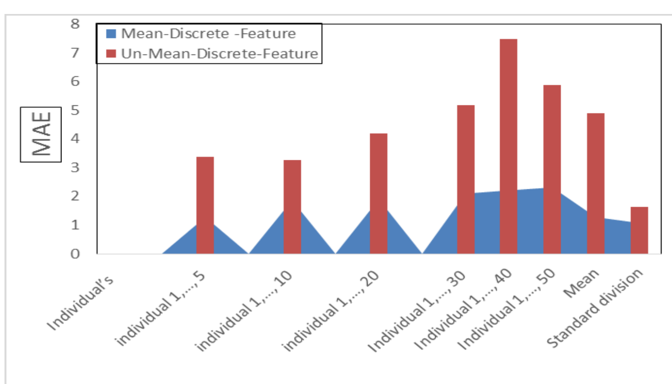


Fig. 3 – Uni-representation (Mean-Discrete) comparison for intra-class.

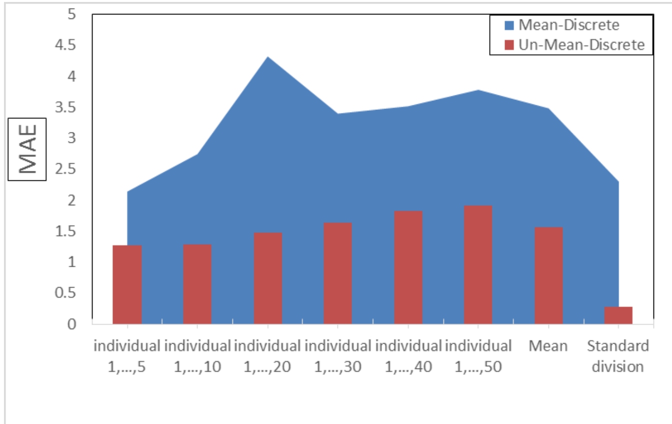


Fig. 4 – Uni- representation (Mean-Discrete) comparison for inter-class.

5.2. Analysis on the classification Accuracy of the proposed Mean-Discrete Algorithm with Identification Performance

The identification performance was evaluated in an experiment. Here, a technique of Mean-Discrete was conducted. In addition, in this study, the proposed Mean-Discrete algorithm is Mean-Discrete feature-based fusion. Two examples are demonstrated with various number of testing datasets and training. In the first example, both Mean-Discrete data, individual handwriting, individual fingerprint Concatenate and Discretization Match Score-based Fusion (DMS) [22], individual datasets are split into two: 70% for training data, 30% for testing data. For the second example, 80% training data, 20% testing data. The training process is implemented using SGD Text, SMO, ZeroR with WEKA tool and using the eight (8) and ten (10) fold cross validation, In this experiment, the data sets comprise of 800 data which are broken down into two categories with 50 individual. Table 6, 7, 8 and 9 with figures 8 and 9 can be referred.

Table 6 - Provide the accuracy for classification process for Mean-Discrete feature-based fusion with all Methods for Split Percentage of 70% Training and 30% of Testing.

Methods	SGD Text	SMO	ZeroR	J48
Mean-Discrete	89.009	89.0099	86.0594	83.0198
Handwriting	6.9406	3.9802	10.8614	4.9406
Fingerprint	5.9703	4.5678	17.9208	45.2513
Concatenate	13.4456	12.4567	4.8835	34.1253
DMS	4.0404	4.0404	1.0101	00

Table 7 - Provide the accuracy for classification process for Mean-Discrete feature-based fusion with all Methods for Split Percentage of 80% Training and 20% of Testing.

Methods	SGD Text	SMO	ZeroR	J48
Mean-Discrete	90.625	92.9899	92.9293	87.9798
Handwriting	12.75	8.5	8.75	5.25
Fingerprint	4.25	3.75	12.5	12.5
Concatenate	7.0625	5.0625	4.0625	8.0625
DMS	5	5	00	1.25

Table 8 - Provide the accuracy for Mean-Discrete feature-based fusion with all Methods for eight (8) folds Cross Validation.

Methods	SGD Text	SMO	ZeroR	J48
Mean-Discrete	88.1227	90.8711	93.4793	97.2478
Handwriting	20.2957	14.782	23.0376	11.2832
Fingerprint	22.0301	13.5188	15.2757	13.2732
Concatenate	20.5414	8.5106	3.7547	6.7584
DMS	7.5377	7.0350	4.5226	1.5075

Table 9 - Provide the accuracy for Mean-Discrete feature-based fusion with all Methods for ten (10) folds Cross Validation.

Methods	SGD Text	SMO	ZeroR	J48
Mean-Discrete	87.4956	84.4956	83.8548	87.8723
Handwriting	20.5414	14.0301	14.5363	11.0276
Fingerprint	11.2782	11.2782	10.2757	17.5263
Concatenate	8.6333	9.6333	2.8786	7.5094
DMS	7.035	7.035	3.517	2.0101

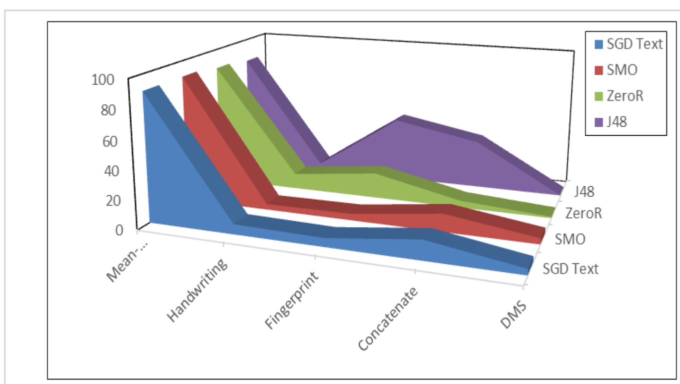


Fig. 5 – Visualization for Mean-Discrete with all Methods 70% training and 30% testing.

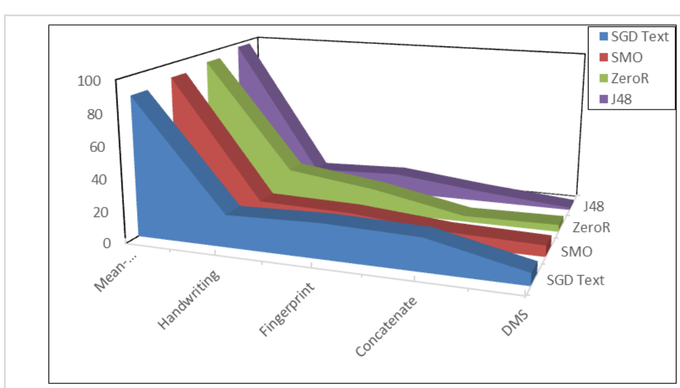


Fig. 6 – Visualization for Mean-Discrete with all Methods for eight (8) folds Cross Validation.

As suggested by the outcomes presented in Table 6,7,8,9 and figures 8,9 for the overall Methods, the Mean-Discrete feature-based fusion have significantly higher accuracy in comparison to individual handwriting, individual fingerprint, DMF and Concatenate data. This is caused by the improvement of the individuality of feature representations in Mean-Discrete feature-based fusion and this has been highlighted in the earlier section. The features are symbolized with feature fusion for multi-biometric to the similar person, resulting in smaller variation between features in intra-class and greater variation between features in inter-class.

6. Conclusion

This study attempted to improve the individuality in handwriting-fingerprint through the demonstration of Mean-Discrete feature based fusion algorithm. Mean-Discrete method converts the multi-representations of individual features into a uni-representation with the technique of Mean-Discrete algorithm. The data representation signifies an individual's generalized features. The conventional approach and the proposed approach were compared with one another and then, the task of similarity measurement was executed. Using these approaches, the handwriting-fingerprints produced by individual were identified. Then, the obtained outcomes were scrutinized. With the application of the Mean-Discrete feature, the individual features are represented in a manner that is systematic with representation that is more informative. Also, the variance between the features of intra-class and those of inter-class appears to be improved. Hence, better performance is generated with the application of the proposed method particularly with respect to accuracy. The application of the algorithm with the Mean-Discrete process is demonstrated in this study. Then, it appears that using Mean-Discrete data enhances the individuality of handwriting-fingerprint for both inter-class and intra-class features, as well as for the performance of classification.

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REFERENCES

[1] A. Jain, A. Ross and K. Nandakumar, "Introduction to Biometrics: A Textbook", Springer Publishers, (2011).
[2] A. K. Jain and S. Z. Li, "Handbook of face recognition", Springer Publishers, (2011).
[3] M. J. Burge and K. Bowyer, "Handbook of iris recognition", Springer Publishers, (2013).
[4] D. Maltoni, D. Maio, A. K. Jain and S. Prabhakar, "Handbook of fingerprint recognition", Springer Publishers, (2009).
[5] A. K. Jain, K. Nandakumar and A. Ross, "50 years of biometric research: Accomplishments, challenges, and opportunities", Pattern Recognition Letters, 79, (2016), pp. 80 – 105.
[6] Singh M., Singh R. and Ross A., "A Comprehensive Overview of Biometric Fusion", Science Direct Information Fusion, 52, (2019), pp.187-205.
[7] Spain airports implement a multi-biometric solution, https://www.secureidnews.com/news-item/ spain-airports-implement-a-multi-biometric-solution/.
[8] Multi-biometrics: the future of border control, https://www.idemia.com/news/ multi-biometrics-future-border-control-2016-04-21.
[9] A. Jain and D. Zongker, "Feature Selection: Evaluation, Application and Small Sample Performance", IEEE Trans. On Pattern Analysis and Machine Intelligence, vol. 19 (2), (1997), pp. 153 – 158.
[10] A. S. Al Waisy, R. Qahwaji, S. Ipson, S. Al Fahdawi and T. A. M. Nagem, "A multi biometric iris recognition system based on a deep learning approach", Pattern Anal Applic, vol. 21, (2018), pp. 783–802.
[11] B. Lakshmi Priya and M. Pushpa Rani. "Authentication of Identical Twins Using Tri Modal Matching", World Congress on Computing and Communication Technologies (WCCCT), IEEE, vol. 1, (2019), pp. 30-33.
[12] W. Kabir, A. Omair, M. and M. N. S. Swamy, "Normalization and Weighting Techniques Based on Genuine-impostor Score Fusion in Multi-biometric Systems", IEEE Trans. Inf. Forensics Secur., vol. 13, (8), (2018), pp. 1989-2000.
[13] G. S. Walia, T. Singh, K. Singh and N. Verma, "Robust Multimodal Biometric System based on Optimal Score Level Fusion Model", Expert Syst. Appl., (2019), pp. 116, 364–376.
[14] A. Mansour, M. Sadik, E. Sabir and M. Jebbar, "AMBAS: An autonomous multimodal biometric authentication system", Int. J. Auton. Adapt. Commun. Syst., vol. 12, (2019), pp. 187–217.
[15] A. Basma, B. Larbi, B. Toufik and R. Messaoud, "Face–Iris Multimodal Biometric Identification System", Electronics, vol. 9 (1), (2020), pp. 85.
[16] Trier and A. K. Jain. "Feature Extraction Methods for Character Recognition- A Survey", Pattern Recognition, vol. 29 (4), (1996), pp. 641- 662.
[17] H. Takahashi, "A Neural Net OCR using geometrical and zonal pattern features", In Proc. 1th. Conf. Document Analysis and Recognition, (1991), pp. 821-828.
[18] K. Azmi, R. Kabir and E. Badi, "Recognition Printed Letters wit Zonong Features", Iran Computer Group, vol. 1, (2003), pp. 29-37.
[19] R. Muralidharan and C. Chandrasekar, "Combining local and global feature for object recognition using SVM KNN", International Conference on Pattern Recognition, Informatics and Medical Engineering (PRIME-2012), pp. 215-219.
[20] K. M. Azah, S. M. Shamsuddin and A. Abrahamz, "Improvement of authorship invarianceness for individuality representation in writer identification", Neural Network World, vol. 3, (2010), pp. 371-387.
[21] B. O. Mohammed and S. M. Shamsuddin, "Twins multimodal biometric identification system with aspect united moment invariant", Journal of Theoretical and Applied Information Technology, vol. 95, (2017), pp. 2895.
[22] L. Wong Yee, S. M. Shamsuddin, "Multimodal Biometric Identification with Improved Discretization based Matching Score Fusion Scheme", PhD thesis. UTM, (2015).