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Philosophy design of single-trait based multi-feature biometric system

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ABSTRACT

This paper presents new techniques for designing a simple and reliable multifeatured biometric system based on a single trait source. First, a one-to-one relationship between the feature's edge and its associated angle is utilized after extracting the contrast feature using the gray-level co-occurring matrix (GLCM) method. Secondly, the classifying stage is modified to process one-dimensional vectors rather than the whole feature's template. That means whatever the template size is, the matching operation is always processing a one-dimensional vector called a mean-feature vector which requires low storage and less computation complexity. Finally, for comparison purposes, the performances of the three biometric systems are calculated for recognizing 170 subjects taken from four facial databases. These comparisons are made using three error distance measurements. The recognition rates of the angle-based feature were very competitive to the regular edge-based results; however, the overall recognition accuracy is highly improved after fusing the decision of the two unibiometric systems using the Logic-OR operator. The fused system performance was satisfactory and it shows that the decision fusion of the single source trait based multifeatured system has promising performance represented by accuracy improvement, low storage, and low matching time.

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1. INTRODUCTION

The feature detection and extraction methods are definitely the processes of dimension reduction for subject information. The subject description should be maintained after applying those two operations, where the original features are reduced to be more appropriate for selecting, combining, or comparing operations. Recently, most modern applications have turned their intelligent systems into multimodal, also called multifeatured biometric systems, where the multimodal system can improve security, accuracy, and availability in an efficient manner. In machine learning, there are many factors that affect the performance of the biometric system for recognizing humans accurately, such factors are feature detection, feature extraction, template generation, or classification, however, system complexity and time-consuming are the major two disadvantages of such systems [1]–[4].

The main goal of this work is to eliminate or highly reduce these two disadvantages by designing a single trait unibiometric system that functions like a multifeatured one. Therefore, a modification in the feature extraction stage is required to ensure that all multimodal elements exist, this modification includes generating a second feature from the same single trait, this step will set down the multimodal complexity to a unimodal level. The time-consuming of the multifeatured system can be overcome by the one-dimensional feature vector, which is the second modification step that accelerates the classification/matching processes and eliminates the second disadvantage factor of the multifeatured system. The two modification techniques will be demonstrated in detail next sections.

This paper is organized as follows: section 2 is the other researchers' related work, and section 3 demonstrates the motivation of this work, while the modification techniques in the feature extraction and classification stages are illustrated in sections 4 and 5 respectively. The three modal comparison results are tabulated, graphed, and discussed in section 6. The recognition accuracy results of the two biometric systems are comprehensively compared in section 7. Finally, section 8 summarizes the conclusion of this work.

2. RELATED WORK

A comparison between unimodal and bimodal biometric systems using three essential parameters, false acceptance rate (FAR), false rejection rate (FRR), and equal error rate (EER). The performance and reliability have been improved after merging the face and iris features in a bimodal biometric system [5]. Iula and Micucci [6] success improved the recognition rate of a multimodal ultrasound system by fusing two unimodal biometrics, a 3D palmprint, and 3D hand geometry features with score-level fusion. The face and fingerprint features are fused in match score-level fusion based on a convolution neural network (CNN). The multimodal biometric system is evaluated on the University of California Irvine (UCI) machine learning repository and the system achieved promising human recognition results [7].

The motivations for designing multi-biometric systems with high-security assured, high-accuracy recognition, and overcoming limitations like noisy sensor data and non-universality were applied by [8] for choosing high-significance data for fusion in the design of a multimodal biometric system. A hybrid feature for designing deep learning CNN based on a fusion of three biometric traits: faces, iris, and fingerprints using principal component analysis (PCA) and adaptive weighting for feature extraction and feature fusion respectively. The fused results provide better accuracy in comparison to the unimodal method [9]. The performance of the unibiometric vs. multibiometric systems is analyzed and demonstrated [10]. The challenges that face the unimodal biometric system are addressed and the work has approved that the deep learning algorithm CNN produced higher accuracy than other deep learning algorithm visual geometry group (VGG) such as VGG-16 and VGG-19.

Guarino *et al.* [11] defined soft biometric traits as information like gender or age group that have been extracted from the human body via smartphones. The combining of multiple touch gestures with the intermediate and late fusion learning of CNN algorithms has achieved 94% gender recognition and 99% aged-group recognition. Galdi *et al.* [12] adopted a novel system that combines the iris recognition of the user and his mobile identity to overcome the sensor interoperability problem that resulted from different embedded sensors, each sensor creates its own data source which exceeds the biometric systems limitations and ability to compare biometric data originated by different sensors. The authentication security level of the proposed design is upgraded to five which is something the user is, plus something the user has.

All the above-related works considered two or more human traits in their multimodal biometric systems. The researches [13], [14] is the most related to our proposal. It considered facial images for recognizing 130 people taken from three databases. The design complexity is reduced by applying the phase congruency as a confident feature detection and extraction method. Their works did not aim to design a multi-featured system nor apply any fusion technique, but it proved experimentally that the mean vector of the olivetti research laboratory (ORL) face dataset had achieved 14.49 seconds faster than the regular template feature. Hereby, our work proposal aims to construct a robust and reliable multifeatured prototype model that utilizes the design simplicity in the unibiometric structure and functions like a multimodal system, where the weakness in some stages or phases in the multimodal systems are fixed and modified using some explained techniques next sections.

3. MOTIVATION: UNIBIOMETRIC VS. MULTIBIOMETRIC SYSTEM

A motivation in biometric systems is primarily intended for recognizing an individual in an easy way and enabling an automated action related to that recognition, while the main motive of multimodal biometrics is to enhance the identification and authentication of an individual by integrating the features of these modalities from acquired data. The unimodal system uses a single biometric resource or trait to distinguish a subject while the multimodal biometrics combines more than two resources to complete the operation, it fuses the acquired information from multiple biometric sensors, samples, algorithms, or traits to enhance the recognition accuracy. The traits might be physiological or behavioral human characterization [10], [14]–[20].

In this work, the motivation is started by generating the gradient-angle features which are a one-to-one map of their gradient-edge features. At this time, the multi-featured biometric system is satisfied and it is ready to be utilized by one of the fusion levels efficiently. The "OR-logic" is considered here to fuse the final decision of the two unibiometric systems according to the logic addition rule. Moreover, the computations and storage are significantly optimized by largely decreasing the matching/classification time when the mean vector of the edge and angle features is considered instead of large-size templates. Figure 1 illustrates those modifications clearly.

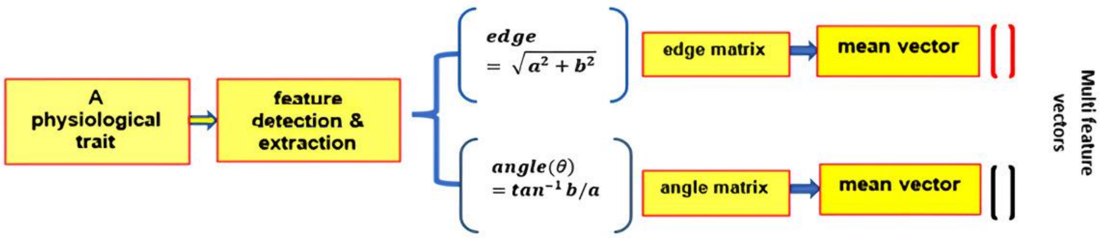


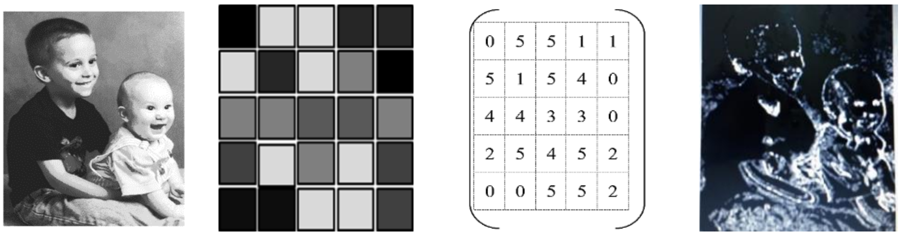
Figure 1. The general structure of single-trait based multi-feature biometric system

4. FEATURE DERIVATION

The prototype is designed to be applicable to any physical trait. Therefore, a modification in the feature extraction stage is introduced to create or more precisely to differentiate the angle-based feature matrix from its associated edge matrix. Figure 1 explains the general structure of a multi-featured biometric system based on a single trait. It explains the modification in the feature extraction stage for obtaining a second biometric feature. The gray-level co-occurrence matrix (GLCM) is applied to obtain the second-moment texture description. It finds how many pixel-pairs with specific gray level values and spatial relationships are occurred or is repeated in the image, in another word it obtains the second-order statistical texture features like contrast, correlation, variance, entropy, angular second moment, inverse difference moment, energy, dissimilarity, and homogeneity [21]–[23]. The contrast feature is considered here to measure the difference between the largest and the smallest pixel values in a sub-image. Figure 2 shows an example of the GLCM contrast feature that is obtained from applying (1) to the boys image.

$$\sum_{i,j=0}^{N-1} P_{i,j}\,(i-j)^2 \tag{1}$$

Where, P, is the pixel value, when i and j are equal, the cell is on the diagonal and $(i - j) = 0$, so they are given a weight of 0. If i and j differ by 1, there is a small contrast, and the weight is 1. If i and j differ by 2, the contrast is increasing and the weight is 4. The weights continue to increase exponentially as $(i - j)$ increases. The newly generated features, the edge-angle features can be utilized in one of four fusion levels as explained next section, where the recognition accuracy can be highly improved after fusing the decisions using Logic-OR operators as shown in Table 1.



original image gray-level co-occurrence matrix contrast feature

Figure 2. Gray level co-occurrence matrix feature extraction example

Table 1. Multibiometric decision fusion using Logic-OR

Unibiometric system decision		Multibiometric system
Edge-based probability	Angle-based probability	Decision fusion
0	0	0
0	1	1
1	0	1
1	1	1

5. FUSION RESOURCES AND FUSION LEVELS

There are four methods by which biometric features can be fused to construct the basic concept of the multimodal system, they are: i) feature level; ii) rank level; iii) score level, and iv) decision level. These fusion levels can be utilized in each of the fusion resource categories which is explained in Figure 3. Those five fusion categories are applied according to practical needs or security requirements [24]–[26].

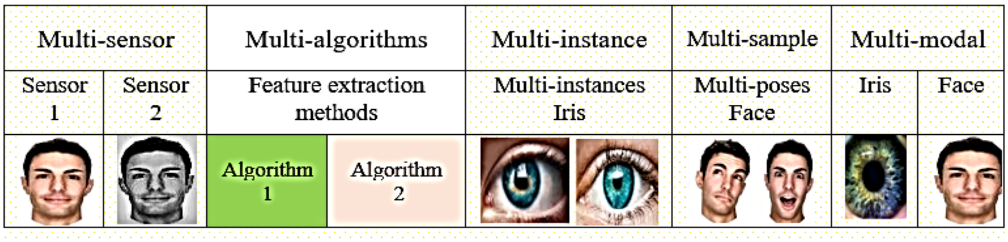


Figure 3. Multibiometric system fusion resources

6. STORAGE AND TIME OPTIMIZATION TECHNIQUE

The second modification step is computing the mean vector of templates, where the training and classifying processes have been optimized by largely reducing the size of the feature matrices to one-dimensional arrays, in another word the biometric system will process $F_{(\mathrm{m}\times 1)}$ featured vector rather than $F_{(\mathrm{m}\times \mathrm{n})}$ featured matrix. The modification step has been explained in Figure 4, where the mean vector is applied during the training/matching process, i.e., for any template size like $(m \times n)$, the technique will save $(n-1)$ time units for each template, for example, if a unimodal biometric system has to recognize fifty (50) persons, each person has five images (one for a test and four as training), the mathematical calculations needed for matching one person is:

$$Cal_{(Total)} = Cal_{(FAR,49)} + Cal_{(FRR,1)}$$

$$Accuracy\ (\%) = 1 - \frac{(FAR + FRR)}{2} \times 100 \quad (2)$$

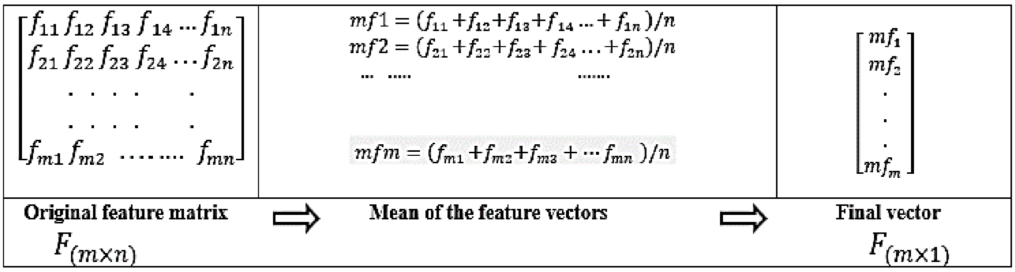


Figure 4. Generation of the average feature vector

Therefore, the mathematical operation for testing one person is illustrated in Table 2. Hereby, for 10,000 $template_{(\mathrm{m}\times\mathrm{n})}$ comparison operations there are 10,000 $averaging_{(\mathrm{m}\times 1)}$ operations, so the difference between the two operations is $10{,}000_{(\mathrm{m}\times\mathrm{n}-1)}$ comparison operations, i.e., if one $template_{(\mathrm{m}\times\mathrm{n})}$ requires 1 µs to complete the comparison process, a one $averaging_{(\mathrm{m}\times 1)}$ vector needs µs/n to complete the same operation. That means the biometric system based on the mean vector will accelerate the system classification time by $[\frac{\mu s}{n} \times (n-1)] \times 10{,}000$. If n=256, the acceleration time would be ≈ 9,961 µs.

Table. 2 Example of fifty subjects' biometric system comparison operations

No. of subjects	No. of test images per subject	No. of templates per class	No. of classes	Total of comparison operations
50	1	4	50	50×1×4×50=10,000

7. COMPARISON RESULTS

In this experiment, a comparison amongst three error distance measures (Cosine, Manhattan, and Euclidian) and four facial datasets; augmented reality (AR) [27], ORL, visible-thermal paired (VIS-TH), and unique formula identifier (UFI) [28] has been made to evaluate the performance of the two unimodal biometric systems individually, where the recognition accuracy of the edge-based feature and angle-based feature is calculated. After that, the performance of the multifeatured biometric system is carried out after fusing the individual edge-angle recognition accuracies using the “OR" operator rule as explained in Table 2. This step will highly improve the decision results, even if the dataset contains occlusion, poor contrast, and multiple poses like VIS-TH and UFI datasets. Table 3 summarizes the recognition accuracy rates of the 170 subjects for the two unimodal systems and their fusion results.

a) Unimodal performances

It is worth noticing that the unimodal applying angle-based feature has competitive recognition results to the edge-based feature, where both of them utilize the averaging feature vector in the training/matching stage. The angle-based feature system satisfied maximum recognition accuracies (98%, 98%, and 96%) for the AR dataset when the error is measured by the Cosine, Manhattan, and Euclidian distance measurements respectively. However, the edge-based feature system achieved the highest recognition rates (95%, 82%, and 87%) compared to the angle rates (77%, 67%, and 72%) when the rates are carried by the ORL, VIS-TH, and UFI datasets respectively. The lowest recognition rates for the angle-based feature are mostly associated with the UFI and VIS-TH datasets as they contain the most difficult dataset images, also there is no specific constraint on the other distance measurements such as Manhattan or Euclidian as they own the same effects on the rates of the edge-based feature. Moreover, Table 3 indicates that the angle-based feature has relatively high rates (98%, 90%, 92%, and 82%) when the error is measured by the Cosine distance for UFI or VIS-TH datasets.

b) OR-fused performance

The multifeatured model has been tested by 170 subjects, they are distributed on four facial databases with a different number of test and class images. The impact of the average vector and decision fusion have clearly noticeable in the system results. The maximum accuracy is satisfied with the Cosine distance measurement (100%) while Euclidian distance is stamped with the lowest accuracy rate (65%) as illustrated in Table 3. The decision fusion has succeeded in raising the accuracy rates from 60% to 90% for the edge-based feature of the UFI dataset and Cosine distance, while the angle-based feature accuracy is raised from 60% to 87% when the distance measure is Euclidian and the dataset is the ORL. As explained in Table 3, all fused results have a significant improvement in recognition accuracies that are built on a single-trait source unimodal biometric system and apply a mean-feature vector ($F_{(\mathrm{m}\times 1)}$) with a simple “OR” operator. Figure 5 illustrates the accuracy rates for the two proposed biometric systems in all situations, it reflects the outcomes of Table 3 in a simple graph mode.

Table 3. Recognition accuracy for single-trait based multi-feature biometric system

Datasets, subject	Classification Accuracy (%)								
	Cosine			Manhattan			Euclidian		
	Edge	Angle	Fusion	Edge	Angle	Fusion	Edge	Angle	Fusion
AR, 50	92	98	100	94	98	98	78	96	98
ORL, 40	90	90	95	95	77	97	77	60	87
VIS-TH, 40	87	92	95	82	67	85	57	56	65
UFI, 40	60	82	90	67	66	72	87	72	92

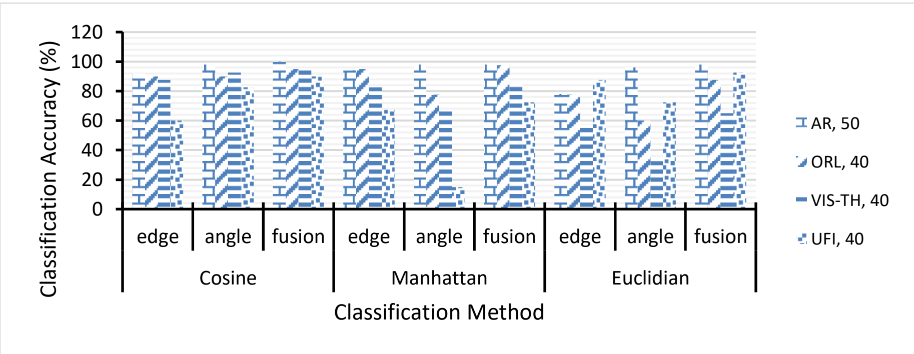


Figure 5. Recognition accuracy for single trait based multi-feature biometric system

8. CONCLUSION

In this paper, a simple and reliable single trait unimodal biometric system was implemented to function like a multimodal system after introducing two modification techniques. First, the one-to-one relationship of the edge-angle feature was derived and utilized as a multimodal biometric system. Secondly, the mean-feature vectors are computed to be used in training and matching stages rather than the whole template size, this will accelerate the comparison operations and reduce the matching delay that resulted from the large-template dimensions. The "OR" decision fusion raised the recognition accuracy for all subjects, even for low quality datasets like the UFI and VIS-TH. The experimental result was run on 170 subjects, taken from four facial datasets. The relatively high performance of the adopted proposal has approved that a single-trait source can be considered as a multifeatured biometric system in any design in the future after fusing the decisions using logic-OR or logic-AND operators. The highest fusion rate was 100% with the AR dataset and cosine measurement, while the UFI had the lowest fused rate 65% using the Euclidian measurement.

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