A Brief Introduction to Matching-Score Level Fusion on Palmprint, Speech and Face Multimodal Biometrics

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Abstract

Biometric fusion is the use of multiple biometrics inputs or methods of processing to improve performance. The key purpose for biometric fusion are to improve system accuracy, efficiency, applicability, and robustness. Matching score level fusion is the most commonly used biometric information fusion strategy for each subsystem exploits one biometric trait to produce a matching score and then combine all to obtain the final matching score or decision for personal authentication. Many studies have been carried on large-scale biometrics systems for years like the palm print systems. While the matching score level fusion can be very effective, it should not be regarded as a panacea, since it adds complexity to data collection and system architecture.

Keywords: Fusion, Face recognition, Palmprint recognition, Speech recognition

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1 What is Biometric Fusion?

Biometric systems are automated means by which physical traits (or sometimes behavior) are used to identify a person, or verify a person's identity. [1] A variety of such systems have been implemented and used successfully over the years, including areas based on fingerprints, irises, facial images, hand geometry, among others. The successful implementation of biometric systems requires addressing a number of issues, including accuracy, efficiency, robustness, applicability and universality.

One method of dealing with many of the issues confronting biometric systems is to collect more data from each subject, and fuse the data, or the results of processing the data. The theory behind fusion is not limited to biometrics: biometric-based decisions are a special case of classification in the field of statistical pattern recognition, digital image processing and so on. The fusion methods are used in large diverse field as broader personal identification, analysis of medical test results. For years, various aspects of fusion have been integral part of the successful implementation of biometric systems, like the palm print systems.

1.1 Different Categories of Fusion:

The types of data or methods of processing used constitute the categories of fusion [2]:

- **Multi-sample**: fusion of multiple samples (images) acquired from the same source, such as multiple images of the same face, or recording of a speaker.
- **Multi-instance**: fusion if multiple instances of the same type of biometric, such as images of both irises, fingerprints from multiple fingers.
- **Multi-modal**: fusion of multiple types (or modalities) of biometrics, such as a combination of a subject's fingerprints, face, irises.
- **Metadata**: fusion of biometric inputs with other information, such as measures of sample quality, or demographic information such as gender, height, or age. Demographic information is sometimes described as soft biometrics.
- **Multi-algorithm**: fusion of multiple methods of processing for each individual sample. In practice, this usually means the use of multiple matchers, but can also apply to multiple methods of feature extraction.

1.2 Levels of Fusion:

As the Figure 1 shows, there are several stages in the process of obtaining an identity decision. A sample (image) is converted in feature extractor software into a template (machine representation, feature set). Matchers compare the template against temples from the gallery (database), and generates a system-specific matcher score (similarity score). [3] Decision software compares the matcher score to predetermined thresholds to make a match or non-match decision.

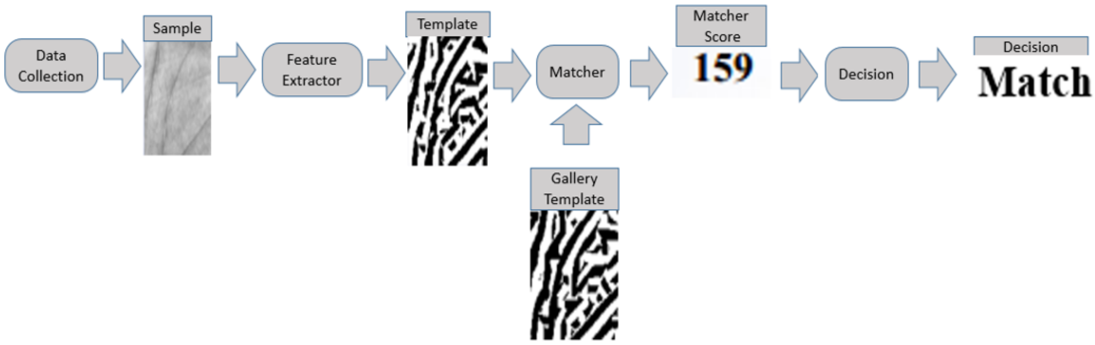

Figure 1: Stages of processing in a Palmprint System.

Therefore, those stages of processing will be imposed on different levels of fusion.

- **Feature Level Fusion:**

It can be broadly grouped into two classes:

- Directly combination different original biometric traits and then carrying out feature extraction on those combined biometric traits. This can be regarded as instance of multi-algorithmic biometrics and uses multiple presentations of a biometric trait to identify personal authentication.
- Combination of different features obtained by the feature extraction in their subsystems. It is typically viewed as multi-modal biometrics and use the same feature extraction algorithm and then combines these features to perform personal authentication.

- **Matching Score Fusion:**

Those matching scores produced by each subsystem on biometric traits are normalized and integrated to obtain the final matching score or final decision for personal authentication. Also, it is always viewed as the classification or combination problem to distinguish genuine matching from imposter matching. It is concluded that the combination performs better than the classification.

- In the first approach, the fusion can be viewed as a classification problem where a feature vector is constructed using the matching score output by the individual matchers.
- In the second approach, the fusion is viewed as a combination problem where individual matching scores are combined to generate a single individual matching scores are combined to generate a single scalar score using normalization techniques and fusion rules. The new single scalar score is then used to make a final decision.

- **Decision Level Fusion:**

It acts as classifier selection to integrate the multiple decisions to produce the final decision. Those decision level fusion rules contains Boolean conjunctions, classical inference, voting rules and weighted majority decision rule.

1.3 Purposes for Fusion

Fusion has been used successfully for years in large-scale automated palm print identification and face recognition systems, which combine multi-face and multi-palm-print data and multiple methods of processing; indeed, it is fair to say that multi-instance and multi-algorithm fusion are what have made very large-scale system practical. Nowadays, there is a tendency that more and more forms of fusion are used in a number of different types of biometric systems.

Biometrics fusions are intended to address a number of issues faced by the designers, implementers, and operators of biometric systems:

- **Accuracy:** Fusion is used very effectively to improve overall accuracy. Biometric system accuracy is generally stated in terms of maximizing the True Accept Rate (TAR) while minimizing the False Accept Rate (FAR).
- **Efficiency:** Fusion is used to increase efficiency, or to allow tradeoffs between efficiency and accuracy. System efficiency generally refers to throughput (processing time), computational requirements, and financial cost.
- **Robustness:** The inherent redundancy in a fused system increase the system's robustness. It is expected to have the ability of a system to continue to function as accurately as possible despite problems such as poor sample (image) quality and data integrity errors.
- **Applicability:** Applicability relates to the appropriateness of a system for a task—the need to work with legacy data often dictates the biometric modalities that can be used. A multimodal system is more applicable to a broad variety of uses than a uni-modal system, because it can be used in conjunction with multiple sources of legacy data.
- **Universality:** A system is designed to access to everyone despite the fact that some people may lack usable biometric samples for different reasons. Multi-modal and multi-instance systems can provide alternatives so that all people can use a system.

1.4 Comparison and Limitations of Biometric Fusion

As we show above, those three different levels have its own advantages and disadvantages. Feature level fusion can enable all traits to be used for personal authentication, but it may be not easy to combine feature vectors generated from different biometric traits and possibly non-compatible. Even worse, sometimes it is not feasible for users who don't possess all the biometric traits. However, decision level fusion has simple and straightforward implementation but not allow information of multiple biometric traits to be fully exploited. It makes sense that matching score fusion is on the medium stage between them and has more widely use among the biometric fusion areas despite the fact that it also meets various challenges.

Another issues should not be ignored is that collection additional data for fusion takes longer time, adds complexity and cost to the collection process. Collection of increased amount of biometric data is likely to increase public concerns about privacy issues and intrusiveness. The extract requirement for software and hardware for additional processing adds both complexity and cost to the system.

1.5 Question Answering

1.5.1 New Biometrics Technology ——Adaptive Biometric System

The categorization of multi-biometric technologies into three levels is not meant to imply that multiple biometric traits should be fused at only one of these three levels. Adaptive multi-biometrics is another attractive example of new methods in the field of biometrics. It will adaptively determine the weights for different biometric traits or select the most suitable biometric traits to conduct a varying multi-biometric implementation with various environments or conditions. Also it will determine the decision fusion rule and even threshold values for decision-making under different circumstance. Sometimes, it can be used on adaptive enrollment to improve the performance of system with a predetermined PIN just in case that the system forbid the genius customer to get in.

1.5.2 Other Biometrics Applications —— Mobile Payments Security

There are large areas where multi-biometrics are applied:

- Biometric Security
- Border Control/Airports
- Consumer/Residential Biometrics
- Financial
- Fingerprint & Biometric Locks
- Healthcare Biometrics
- Justice/Law Enforcement
- Logical Access Control
- Mobile Biometrics
- Time and Attendance
- ……

Our business plan is designed a platform to help the improvement of mobile payment security. The modal is based on the EZMCOM (https://www.ezmcom.com/). But we decide to make it more advanced based on what we have learned. So it will combine and fusion the Palmprint, Face, Speech to help identify customers and security. It also be improved with the help of adaptive biometric systems. The delated explanation will be displayed on Presentation sessions.

2 How do Matching Score Level Fusion Work?

2.1 Definition of Matching Score

Every comparison of two samples (images) processed in a matcher results in some measure of similarity or difference, which is known as the matching score. Biometric systems will make match or non-match decisions based on whether those scores exceed a predetermined threshold. An equal error rate (EER) is the score threshold at which the false accept and false reject rates are equal. Therefore, different application will have different threshold according to the matching score distributions and specific needs for FAR and FRR.

2.2 Fusions between Different Accurate Rate Matcher

It is notable that even in the case of a highly accurate matcher, fusion with additional data or other matchers will improve accuracy if that addition contributes useful information, and fusion is correctly implemented. Different feature extraction may initially have various accurate rate, so when some less accurate matcher has a distinctly separated distribution of the genuine and imposter scores, they can be valuable with the use of combination of the more accurate matcher.

2.3 Information Fusion in Multimodal Biometrics

Information fusion is a process of combining two or more modalities of biometrics that produces a better discriminating power in the feature space. Fusion at matching score level is known as fusion at the measurement or confidence level. The matched score output generated by biometrics matchers contain rich information about the input pattern after the feature extraction module.

3 Algorithms & Procedures for Different Subsystems

It is mentioned that the most important two steps to combine the matching scores including the normalization procedure and fusion rule. [4]

3.1 Normalization for Scores to Fuse

Those procedures are tend to project all the matching score into a proper section to go on.

Min-Max	$S_k^{'} = \frac{S_k - \min(S)}{\max(S) - \min(S)}$
Z-score	$S_k^{'} = \frac{S_k - mean(S)}{std(S)}$
Tanh	$S_k^{'} = \frac{1}{2}[\tanh(0.01\frac{S - mean(S)}{std(S)}) + 1]$
Median	$S_k^{'} = \frac{S_k - median(S)}{median(\lvert S_k - median(S)\rvert)}$
Logistic Norm	$S_k^{'} = \frac{1}{1 + A \cdot e^{-BS_{nm}}}$
Quadric Line-Quadric	$S_k^{'} = \begin{cases} \frac{1}{c - w/2} S_{nm}^2, & (S_{nm} \le c - w/2) \\ S_{nm}, & (c - w/2) < S_{nm} < (c + w/2) \\ (c + w/2) + \sqrt{(1 - c - w/2)(S_{nm} - c - w/2)}, & otherwise \end{cases}$

3.2 Fusion Rules

For the k-th user, S_{k1}, S_{k2}… S_{kR} denote the normalized matching scores of his R biometric traits.

3.2.1 General Matching Score Fusion Rule:

These rules integrate multiple normalized matching scores to produce the final matching score.

Simple-Sum	$S_k = \sum_{i=1}^{R} S_{ki}$
Product	$S_k = \prod_{i=1,2,\dots,R} S_{ki}$
Min-Score	$S_k = \min(S_{k1}, S_{k2}, \dots, S_{kR})$
Max-Score	$S_k = \max(S_{k1}, S_{k2}, \dots, S_{kR})$
Weighted Sum	$S_k = \sum_{n=1}^{R} w_n S_{kn}$
Weighted Product	$S_k = \prod_{n=1,\dots,R} S_{kn}^{w_n}$

3.2.2 Probability-Based Matching Score Fusion:

The rules of probability-based matching score fusion to fuse multi-biometric data at the matching score level is from the viewpoint of classification. We integrate multiple biometric traits with their posteriori probabilities. It will directly obtain the final authentication decision rather than the final matching score. The probabilities are considered as a special kind of matching score to discriminate the decision fusion.

Assign Z →ωj，if :

$$p^{-(R-1)}(\omega_j)\prod_i p(\omega_j \mid x_i) = \max_k p^{-(R-1)}(\omega_k)\prod_i p(\omega_k \mid x_i)$$

For a given sample represented by X1, X2 … XR, this rule computes the product:

$$p^{-(R-1)}(\omega_k)\prod_i p(\omega_k \mid x_i)$$

Sum	$(1-R)p(\omega_j) + \sum_{i=1}^{R} p(\omega_j \mid x_i) = \max_k((1-R)p(\omega_k) + \sum_{i=1}^{R} p(\omega_k \mid x_i))$
Max	$(1-R)p(\omega_j) + R\max_{i=1,\dots,R} p(\omega_j \mid x_i) = \max_{k=1,\dots,m}[(1-R)p(\omega_k) + R\max_{i=1,\dots,R} p(\omega_k \mid x_i)]$
Min	$p^{-(R-1)}(\omega_j)\min_{i=1,\dots,R} p(\omega_j \mid x_i) = \max_{k=1,\dots,m}(p^{-(R-1)}(\omega_k)\min_{i=1,\dots,R} p(\omega_k \mid x_i))$
Median	$\underset{i=1,2,\dots R}{median}(p(\omega_j \mid x_i)) = \max_{k=1,\dots,m} \underset{i=1,2,\dots R}{median}(p(\omega_k \mid x_i))$.

3.3 Palmprint Recognition Algorithms:

Compared with other biological features, palm print has some awesome features including larger areas, rich texture information with lower image resolution, easy to access, high recognition accurate rate, great stability and reliability.

3.3.1 Potential Palmprint Features:

- Geometry Features
  - Finger width
  - Length, width, thickness and area of a palm
- Texture Features
- Line Features
  - Principal lines
  - Wrinkles
- Point Features
  - Minutiae point
  - Delta point
  - Datum point
- Palm Vein (Anti-spoofing)

Two basic considerations in the design of a multispectral palmprint[5] systems are the color-absorptive and color-reflective characteristics of human skin and the light spectra to be used when acquiring images. We can design a system to obtain different bands of the image and feature extraction and matching for each band, by inter-spectral correlation analysis, it’s easy to use the score-level scheme to combine the results and minimize the overlapping effect on the fused score with the definition of a score-level fusion rule. In conclusion, different bands highlight different features of the palm, those features may provide discriminate capabilities. With the help of weighted sum, we can combine those cases for each spectrum and acquire the new distance with the weight for normalization.

[Continued on next page.]

3.3.2 Methodologies:

- **Structure-Based:** Lines and points as features.
  - Extraction of features: Line detection operator, edge detection operator
  - Representation of features: Line or feature points
  - Matching of features: Euclidean distance or Hausdor distance
  - **Evaluation**: Although it is simple and straightforward, the accurate rate is not high due to the loss of many information and the dependence on the detection operator makes it hard to recognize the small and fuzzy lines which contain plentiful matching information.

- **Statistical-Based:** The center of gravity, mean value, variance of the image as features.
  - Transformation on the images such as Fourier transform to extract the frequency domain information.
  - **Evaluation**: It views the palm image as the textural image and contains higher accurate rate and higher speed to deal with the images and the identity of the statistical makes it non-sensitive to the noise.

- **Subspace-Based:**
  - It view the palm image as the high-dimensional vectors or matrix and project it to the low-dimensional vectors or matrix. Representation and matching will be conducted in the low-dimension. The subspace-based methodologies contains linear and non-linear two parts.
  - **Evaluation**: This related algorithm has been widely adopted in face recognition. It has higher accuracy and smaller feature space. But it needs lot of training samples and different selection of samples has different influence on the result.

- **Coding-Based:**
  - The filtered image will be encoded with some rules. It will use Boolean operation to calculate the similarity of the Palmcodes. Three main process including: choose of the filter, encode rule, matching modes.
  - **Evaluation**: The use of amplitude and phase to help get the direction information and filter bank make the system effective and it has higher accurate rate and speed to match.

4 Exemplification

4.1 Face and Palmprint with Network Classifier

This section is to analyze and evaluates the performance of a personal authentication system with two-class separation criterion functions.[6] The matching scores generated from each of the two biometric traits are used as inputs of a neural network classifier. The claimed user identity is also used as a feature to neural network classifier.

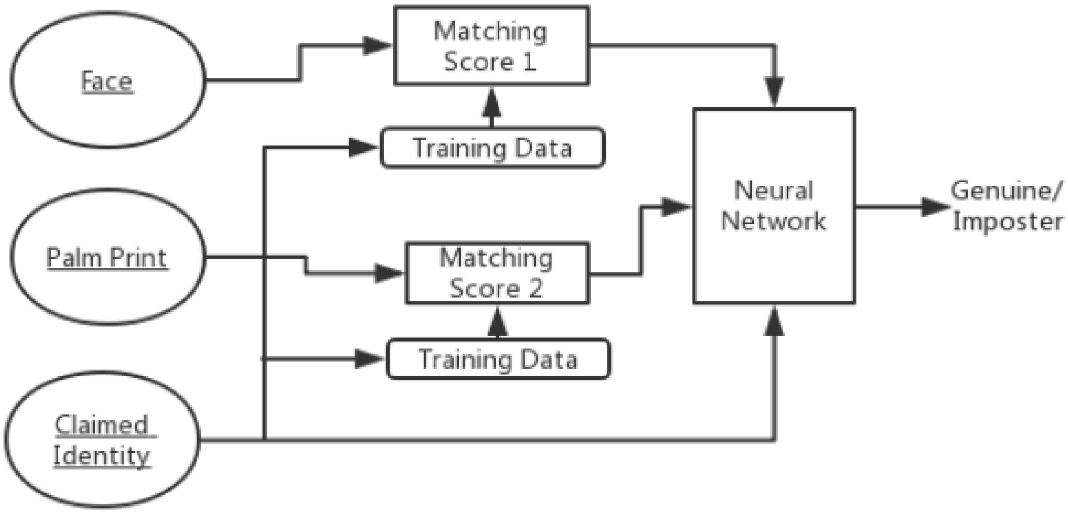

Figure 2: Neural Network Identification System

- Face: Eigenface Algorithm
- Palm Print: Four directional spatial masks to capture line features.
- Neural Networks-Based Classification: Use of forward-backward algorithm
- Performance:

	J_1	J_2	J_3	EER
Face	3.85(1.05)	2.11(0.00)	4.42(2.34)	8.33%(8.69%)
Palm print	4.38(1.03)	2.61(0.00)	8.61(3.71)	3.65%(4.32%)
Experiment using face and palm print	4.84(4.78)	3.04(2.99)	35.57(23.78)	0.84%(2.09%)

Conclusion: the experimental result shows that the proposed bimodal system can achieve a higher accuracy than the single biometric system using palm print or face image. It also shows the claimed user identity has significant effect in improving performance of the biometric system.

4.2 Face and Palmprint Fusion

Biomodal biometric verification system tries to improve the verification results of unimodal biometric systems based on palmprint or facial features by integrating them using fusion at the matching-score level. [7]

4.2.1 Prototype:

In the image-acquisition phase the palm and facial images are acquired using a low-cost scanner and a camera, respectively. The processing of these images, up until fusion, is carried out separately in the palmprint recognition and the face recognition subsystems.

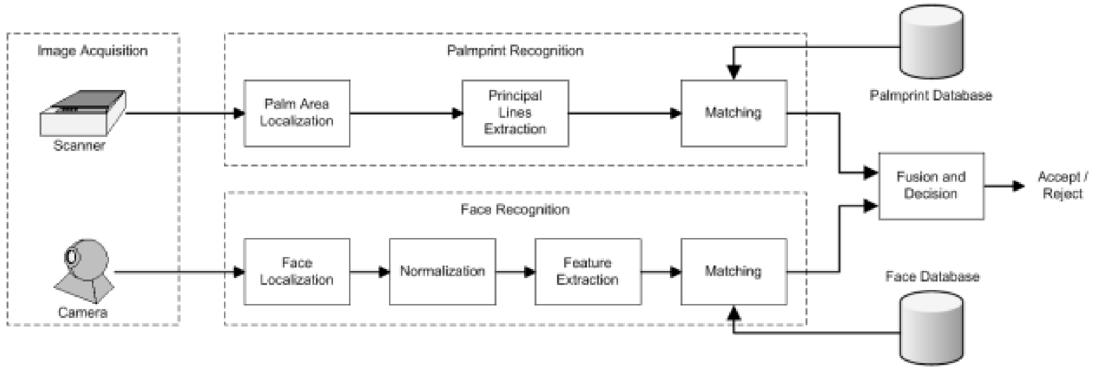

Figure 3: Block-diagram of the proposed multimodal biometric verification system

4.2.2 Palmprint recognition:

- Palm-area localization:
  - Gaussian smoothing and contrast enhancement to preprocess the palm images;
  - Standard global thresholding for segmentation;
  - contour-following for extraction
- Modified line-tracking: Convolve the grey-scale palmprint area by four line detection masks
- Palm matching: Adapted HYPER method.

The matching of the live-template and the template from the database is based on hypotheses generation and its evaluation:

- Generating hypotheses: Every palm line from the live-template is compared to every palm line from the database-template and a decision is made about whether to add this pair to the hypotheses collection. When the d_{gen} (average Euclidian distance calculated by the live-template and the database-template) is smaller than the threshold d_{gen_max}, then the pair of palm lines is added to the collection of hypotheses; otherwise, the lines are considered to be dissimilar.
- Evaluating hypotheses: Comparing every line segments and updating the matching measure for each segment. T_H is a threshold selected experimentally during the training phase. Then it is used to calculate the similarity measure Q for palmprint template pairs. The larger value of Q, the more similarity between them.

4.2.3 Face recognition:

- Face localization: Hough method and skin-color information
- Face normalization: geometry normalization, background removal and lighting normalization
- Feature extraction: K-L transform to a set of facial images eigenface technique.
- Face matching: Euclidean distance

4.2.4 Fusion:

We receive two sets of scores from the two independent matching modules: Euclidean distances from the face-template and the Similarity Measures from the palmprint-template. [8]

We need do normalization by using two transition functions to map the value into the interval [0, 1].

The final matching score was expressed as the total-similarity measure (TSM), which is calculated as a linear combination of the largest palm- and face-similarity measures.

The final decision is made by comparing the TSM with the verification threshold T.

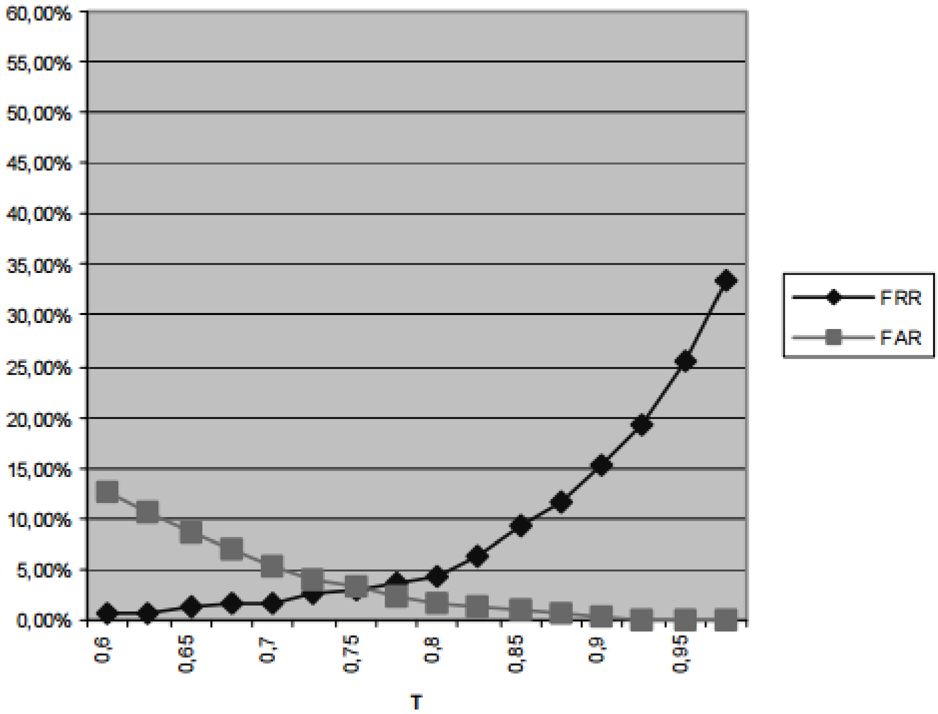

Figure 4: The verification results using the bimodal system depending on the threshold

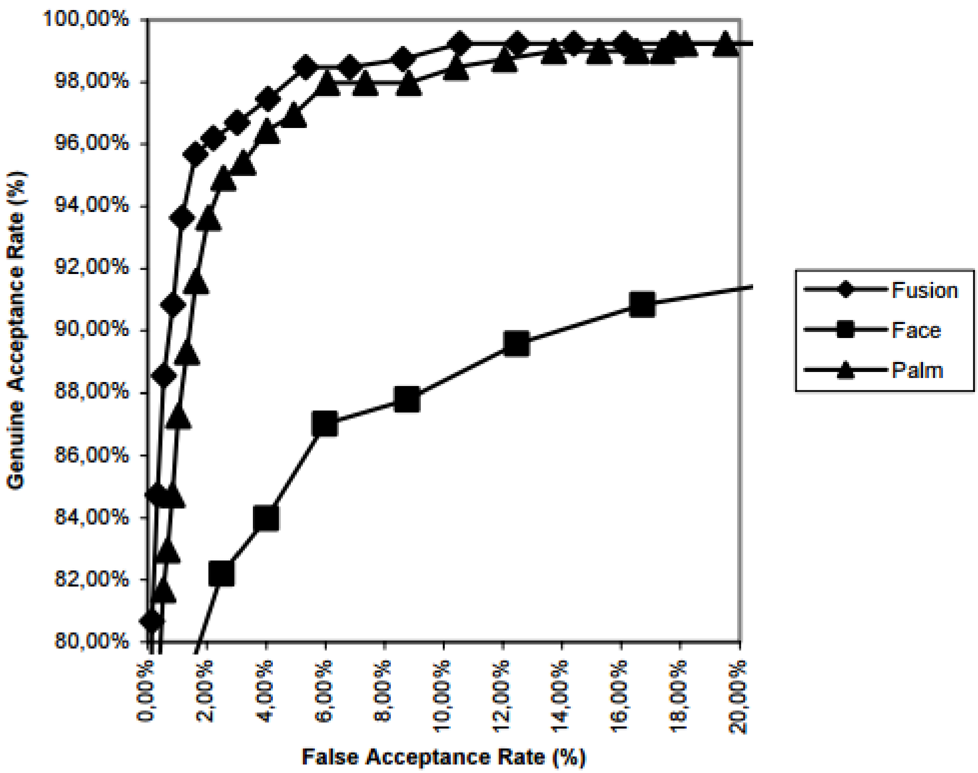

Figure 5: Comparison of unimodal and bimodal system verification results.

4.2.5 Conclusion:

At last, the matching scores from both recognition modules are combined into a unique matching score using fusion at the matching-score level. Based on this unique matching score, a decision about whether to accept or reject a user is made.

4.3 Palmprint and Speech Fusion

4.3.1 Prototype:

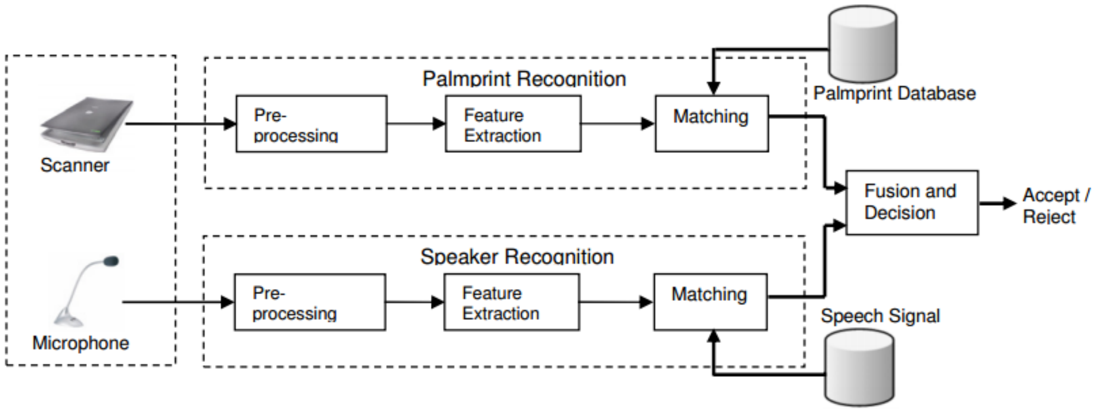

Figure 6: Block diagram of the proposed multimodal biometric verification system

4.3.2 Process:

Extract the features using Haar Wavelet transform method for palmprint and Subband based Cepstral Parameters (SBC) technique for speech. After getting the result, Min-Max will be used as the score normalization.[9] [10]

The weight a and b are calculated using FAR and FRR. MS_{FINAL} represents the final results:

$$MS_{FINAL} = \frac{1}{2}\ a * MS_{SPEECH} + b * MS_{PALM}$$

4.3.3 Conclusion:

It shows the multimodal system performs better than unimodal biometrics system.

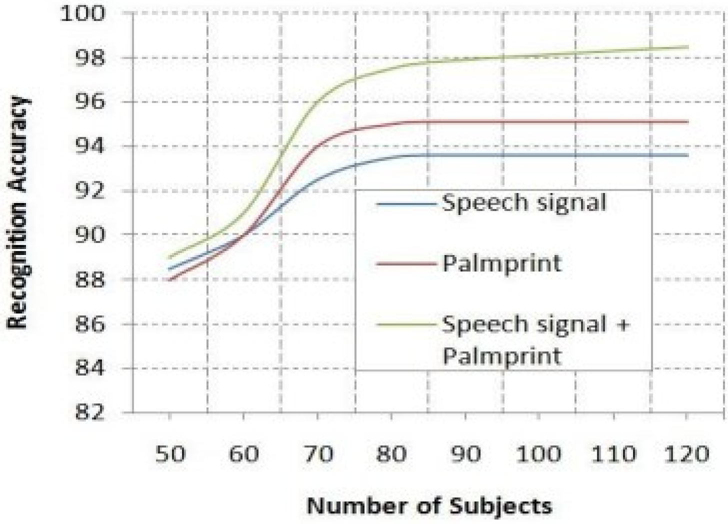

Figure 7: Accuracy graph for combined classifier

Trait	Algorithm	Accuracy (%)	FAR (%)	FRR (%)
Palmprint	Haar Wavelet	93.79	2.72	4.73
Speech signal	SBC+GMM	95.21	5.87	1.35
Fusion	Haar + SBC	98.47	1.36	0.87

Table individual and combined accuracy.

Whether the prototype of a biometric verification system based on the fusion of palmprint and facial features or the fusion of palmprint and speech features shows that although palmprint-based unimodal systems significantly outperform face-based unimodal systems, fusion at the matching-score level can still be used to improve the performance of the system.

The other reasons for including the face modality in biometric systems could be in the system usage for physical access where the additional subsystem can log the facial images of the people accessing the secure object. The psychological effects of such multimodal system should also not be disregarded; it is likely that a system using multiple modalities would seem harder to cheat to any potential impostors.

In the future, we need to focus on setting the user-specific weighting to different modalities to discuss the improvement of a system's performance.

5 Conclusion

Biometric fusion is defined broadly as the use of multiple types of biometric data or methods of processing to improve the performance of biometric systems. Fusion works by combining information from multiple sources. It is done to improve the accuracy, efficiency, and robustness of biometric systems. The specific examples of score-level fusion has explained those methods imposed on the process of fusion.

Matching score fusion can not only be applied between different biometric traits, but also distinct kinds of features generated from the same biometric trait such as the vein and line of palm. It is also considered that setting different weights for the matching scores of different biometric traits allows the multi-biometric system to perform better than the systems that assign the same set of weights to all the biometric traits.

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