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A SINGLE SENSOR HAND BIOMETRIC MULTIMODAL SYSTEM

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ABSTRACT

Nowadays the question of identifying a person assumes a major role in many applications. To circumvent the limitations of traditional identity recognition mechanisms (e.g., passwords or ID cards), modern security control procedures often exploit people biometrics.

This paper proposes a multimodal biometric system for personal recognition, based on three different biometrics computed from the same hand image. Features extracted from each of the five finger surface areas are fused at score level into a single biometric mode. Hand geometry, palmprint and finger surface biometric features are finally fused at decision level to come to a recognition decision.

The achieved recognition results of FAR=0.31%, FRR=0.80% and a maximum recognition rate of 98.28% indicate that this work should be continued and might be considered for high security applications.

1. INTRODUCTION

Reliable and secure access control systems are often required for many applications, ranging from border control security checks to the access to restricted areas, or even to control the presence of employees at the workplace, among others. The need for improved security systems has been accompanied by a growing research interest in biometric technologies. Biometric recognition systems target the automatic recognition of a person's identity based on physical, physiological or behavioural characteristics (something a person is or produces).

A major advantage of biometric features is that they cannot be easily stolen or lost, and typically are unique for each person. Fingerprints are among the most used biometric features, but many others have been considered, such as face, hand geometry, palmprints, iris, voice, signature, or gait, among others. Recent systems often combine multiple biometrics to increase recognition accuracy and reliability.

Biometric systems need to capture an individual's unique biometric features, which are converted into a digital format, called template. This template is then enrolled into a database or some other secure storage location (e.g. a smart card) and later used for comparison with new samples, to determine whether there is a match for recognition purposes.

Biometric systems' performance is usually measured by the type and frequency of errors, namely: acceptance of impostors as true users – false acceptance rate (FAR) – and rejection of legitimate users – false rejection rate (FRR).

Also an equal error rate (EER) is often considered, corresponding to the operation point for which the FRR and FAR have equal values. Another relevant measure is the failure to enroll (FTE), indicating the portion of the population for whom the system fails to complete the enrolment process, according to the conditions specified by the pre-processing block.

Several types of biometric features can be extracted from hand images: (i) hand geometry features, such as hand shape, palm area, width and length of fingers and other measurements; (ii) palmprint characteristics, like principal lines, wrinkles, feature points, and skin texture; (iii) fingerprint or finger-strip features, composed of the ridges, furrows and texture on the surface of the finger.

In this paper the biometric features to be exploited for recognition are the hand geometry, the texture of the palmprint and the texture of finger surfaces – see Figure 1. A special focus is put on the surface of fingers, as this feature has only recently started being investigated as biometric for recognition purposes [1][2][3].

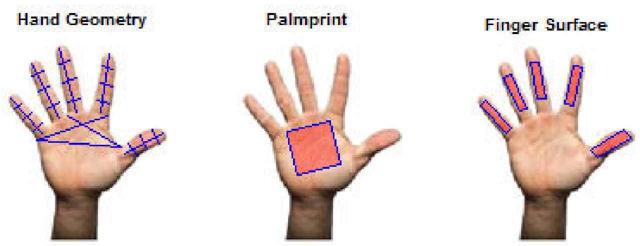

Figure 1 – Hand features to be used as biometric identifiers.

Individual hand features, like finger width and length or palm area are usually considered for hand geometry [4][5]. Other times shape-based hand recognition algorithms [6] are considered. In this paper a selection of finger lengths, widths, perimeters and palm based measurements are used.

For palmprint biometrics, several techniques have been actively researched in the past, like: algebraic approaches analysing statistical data [1][7] examination of the palm line features [7]; texture-based approaches [7]. This paper uses an algebraic approach to extract palm features.

For finger surface analysis two main approaches have been considered in the literature: one analyzing the texture of the inner surface [1][2][3], the other looking at the curvature of knuckle surface of the fingers [8]. This paper takes the first approach.

In the remainder of this paper, the three proposed biometrics and the way to combine their partial results (fusion) are described in Section 2, recognition results are presented and discussed in Section 3, and conclusions are drawn in Section 4.

2. SYSTEM DESCRIPTION

The architecture of the proposed multimodal biometric recognition system is shown in Figure 2. The system is used for both user enrolment and recognition purposes. Enrolment consists in the acquisition of a set of hand images from each user. These images are pre-processed and a feature template is generated for each biometric modality. The templates are then stored in the template database.

At recognition time, a hand image is sensed, pre-processed and templates for each of the three biometrics are generated. The acquired templates are tested by the corresponding matching modules, being compared with those stored in the database. The final step is the fusion block, which combines the information obtained from the three different modalities to produce a recognition decision.

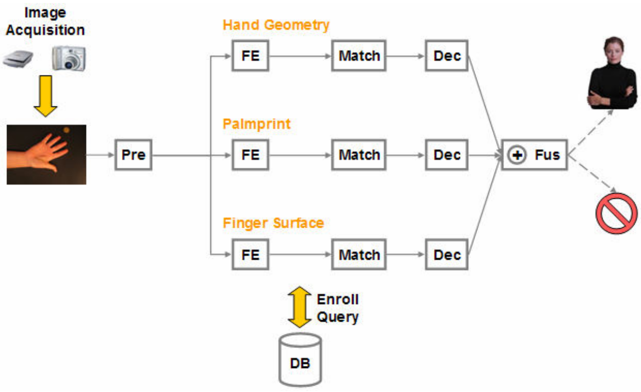

Figure 2 – Proposed system architecture.

No sophisticated hardware is needed for image acquisition of hand images, either for enrolment or recognition purposes. A medium resolution digital camera, a tripod for image stability and a well defined environment (i.e., image background), or in alternative a digital scanner, can be used. A computer is then needed to run the recognition algorithms.

2.1 Pre-processing

To simplify the segmentation of hand images a constant background that contrasts with skin colour is selected.

After hand image capture, it is pre-processed to segment the hand region, leading to a black and white silhouette used as a mask in subsequent processing steps.

The hand binary mask is used to detect a set of relevant hand points that will serve as reference points for the three biometric modalities analysed in this paper. Notably, the fingertips and finger-webs, illustrated in Figure 3, are taken as hand reference points. To find the hand feature points locations, a combination of two commonly used techniques is employed: radial distance to a reference point and contour curvegram [6]. Since the first is sensitive to rotation and the second produces a noisy data plot, the combination of both techniques allows a more robust reference point localization.

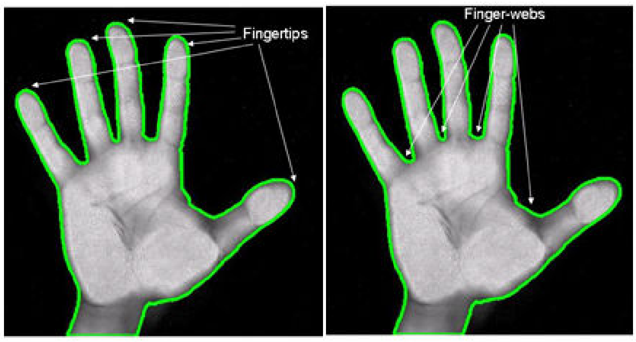

Figure 3 – Fingertip and finger-web locations on a hand image.

2.2 Hand Geometry

For recognition based on the hand geometry biometric, a subset of the features discussed in the literature are used [4][5]: five finger lengths, twenty finger widths (four for each finger), five palm based measurements, and five finger perimeters – see Figure 4.

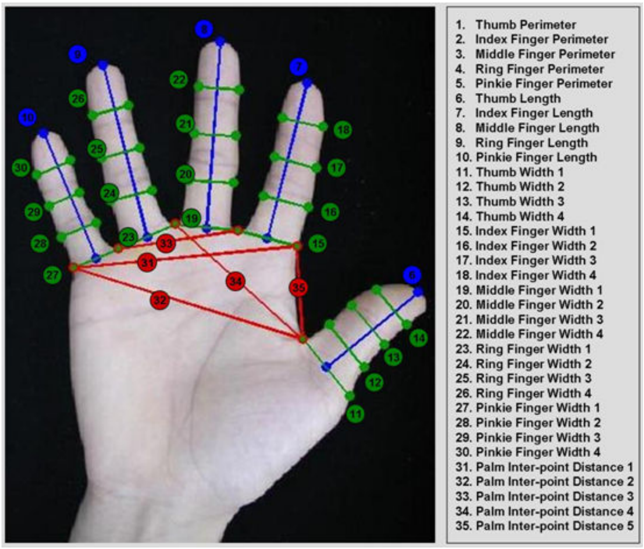

Figure 4 – Hand geometry template features.

Those 35 features are then statistically analysed for discriminability, to select only the best performing ones, in terms of the ratio between interclass and intraclass variability of each feature. The most discriminant features present the highest ratio values.

Interclass variability evaluates how much a specific feature varies between different users' hands, based on the standard deviation. This value is desirably high, indicating that the specific feature is different for most users.

Intraclass variability evaluates the variation of a specific feature regarding each user's set of hand images. A good feature should not vary much for different images of the same hand, meaning the feature will always be extracted with a similar value.

After a statistical analysis of the test database, the 25 features with highest ratio (i.e., the most discriminant) are selected as the default hand geometry feature set for usage in the multimodal biometric system being developed.

As the values of the selected measurements have different value ranges, the comparison of two different feature measurements will also assume significant differences: for instance a finger perimeter is significantly greater than a finger width. As a consequence, the feature values need to be normalized, in order to guarantee that fair distance measurements are used in the subsequent matching phase. The final set of biometric feature measurements is arranged into a feature vector.

2.3 Palmprint

For palmprint analysis, a region-of-interest (ROI) of the hand is first extracted. The ROI for palmprint recognition purposes is usually a square region in the central part of the palm.

To obtain the palm ROI, the previously identified hand feature points are used as reference. The middle points of the line segments that define the beginning of the index and pinky fingers are used as vertices of a square region of the palm [7], from where features will be extracted.

Since for different hand images the ROIs will be of diverse sizes and orientations, normalization is required. The ROI image is converted to grayscale and resized to a fixed size using bicubic interpolation, so that features can be accurately extracted and compared with other samples.

Due to performance considerations, regarding the processing speed of the palmprint recognition algorithms used, the ROI is resized to 16x16 pixels. This size, smaller than the ones usually considered in the literature, that range from 64x64 [1] to 300x300 [5], nevertheless allows achieving a reasonably good recognition performance, which is a useful input to the multimodal recognition system being proposed, via the fusion with the other extracted biometrics.

As a final step, the ROI image is converted into a template vector consisting of luminance values. This template vector is then linearly transformed into a more discriminating feature vector by means of statistical analysis algorithms. The entire process described above is illustrated in Figure 5.

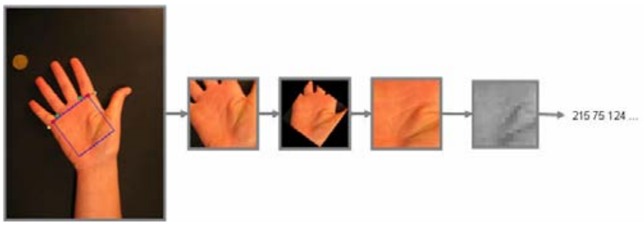

Figure 5 – Palmprint's ROI processing procedure.

An optimal technique, in view of class separability purposes, is Linear Discriminant Analysis [9], which is used in this project for both palmprint and finger surface analysis.

2.4 Finger Surface

To analyze the finger surfaces, a region of interest (ROI) for each finger needs to be extracted. This is done by finding the largest rectangle area lying inside the contour of the finger in a region bounded at about 1/8 and 7/8 of the finger length. An example of the final set of finger surface ROIs, formed by rectangular areas for the thumb, index, middle, ring and pinky finger, is shown in Figure 6.

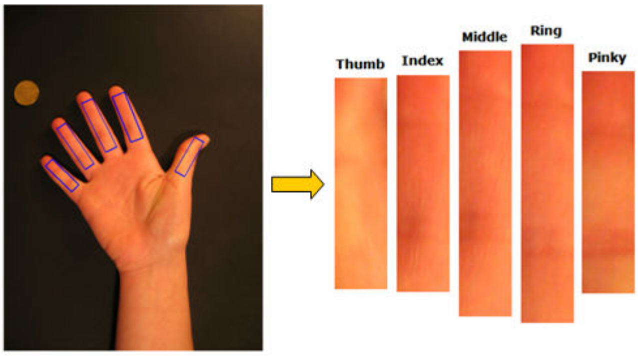

Figure 6 – Extracted ROIs for the five fingers.

The image of each finger's ROI is converted to gray scale. Then, its size is normalized by resizing the ROI to a standard size, again using bicubic interpolation. To guarantee a fast processing while maintaining the recognition ability, the ROI is resized to 32x8 pixels. This size is smaller than those typically used in the available literature, which ranges from 64x16 [1][3] to 128x32 [2]. In spite of using of a smaller ROI size, the recognition rates of the proposed algorithm, achieved from the fusion of the five fingers' results, are good.

Finally, the ROI image is vectorized into a template consisting of luminance values. While in [1][2][3] the Principal Component Analysis (PCA) algorithm is used to extract features from this type of template, this paper proposes the usage of the Linear Discriminant Analysis (LDA) algorithm [9], due to its higher discriminability characteristics.

2.5 Fusion

A multimodal biometric system requires an integration of the various individual biometrics, to allow making a decision on the user's identity. This is the step of biometric data fusion. Recently the interest in multimodal biometric systems has increased, with results showing this is a worthwhile investment and promising research area. The fusion methods adopted in the literature include weighted combination of scores, support vector machines, decision templates, and behaviour knowledge space methods [10].

Two different levels of fusion are applied in this paper: score level fusion is used for the five finger surface features, by computing their mean score; and decision level fusion is applied for data fusion of the various modalities, based on the majority vote rule. For three modalities, as is the case, a minimum of two accept votes is needed for a final acceptance decision.

3. EXPERIMENTAL RESULTS

The test of the proposed biometric recognition system consists in the evaluation of the matching modules and the fusion block represented in Figure 2.

The matching algorithms generate a score for each template comparison based on the distance between the tested and stored feature vectors. The Euclidean distance metric is used, as it achieves good results at a low computation cost [4]. The lowest distance score value indicates the best match.

A flag, set by the pre-processing stage, indicating if the template belongs to a right of left hand is used to eliminate unnecessary template matching comparisons. Database templates belonging to users that enrolled using a different hand than that of the query template are not considered for comparison. The matching procedure is illustrated in Figure 7.

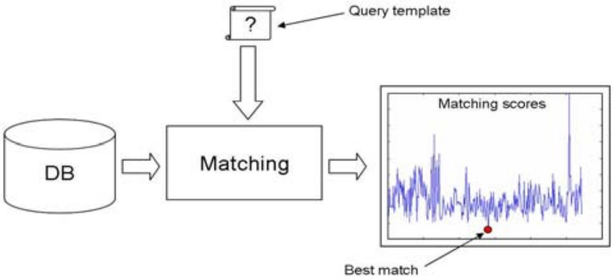

Figure 7 – The matching procedure.

Whenever the best matching score exceeds a predefined threshold the recognition attempt is considered as an impostor access, otherwise the recognition attempt is considered a client access and the system assumes the user has been correctly identified. When several database templates scores are below the threshold, the one with lowest score should correspond to the correct user identity.

Different thresholds can be chosen in order to achieve the desired FAR or FRR levels of operation, depending on the application considered for the biometric system. For instance, high-security applications require a FAR close or equal to zero.

The results presented in the following were obtained considering the UST Hand Image Database [11].

The test database enrolment produced a FTE value of 8.2%. Most of the failed registrations, approximately 95%, are due to poor image acquisitions: the hand crosses two image borders, e.g. a finger is not completely captured by the sensing device. This type of error should be corrected at the image capture stage, by requiring a correct placement of the hand, always within the camera view.

The results for the finger surface biometric recognition, after the fusion of individual finger features, are illustrated in Figure 8. This biometric generates a good separation of clients and impostors in the score distribution, as can also be seen in Figure 9. Also, only one test image of the 564 users[1] of the UST database is scored outside the top ten matching scores.

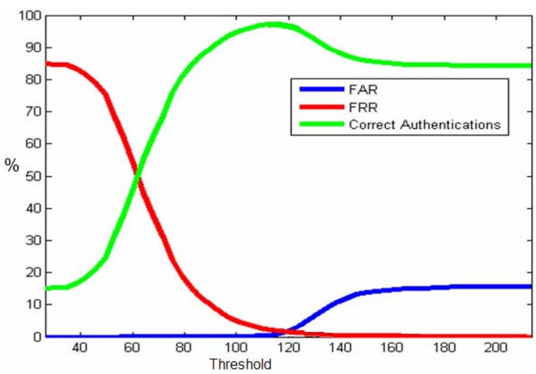

Figure 8 – Finger surface performance measures.

[1] Left and right hands of the same person are considered as different users.

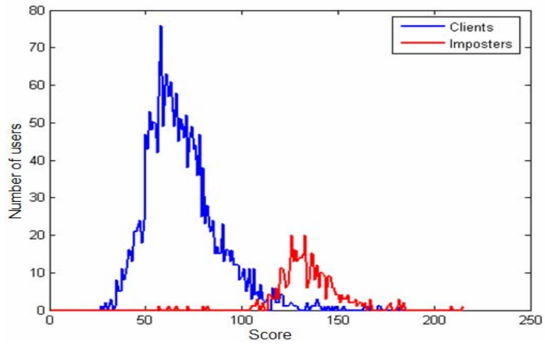

Figure 9 – Finger surface client/impostor score distribution.

The score level fusion of the individual finger surface scores into a single biometric greatly improves recognition rates and the EER, compared to the usage of individual finger results, as shown in Figure 10.

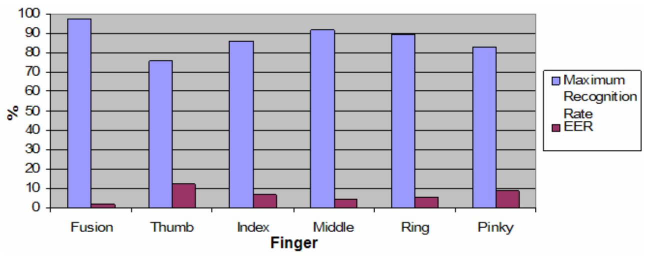

Figure 10 – Finger surface recognition performance rates.

Using threshold values that maximize the correct recognition rates for each individual biometric, after fusion a FAR of 0.31% was obtained, as illustrated in Table 1.

Table 1 – Results for thresholds equivalent to maximum correct authentications.

	Hand Geometry	Palmprint	Finger Surface	Multimodal Fusion
Recognition Rate	91.65%	86.19%	97.25%	96.80%
FAR	3.55%	4.12%	0.46%	0.31%
FRR	4.80%	9.69%	2.29%	2.90%

As the table shows, by applying decision level fusion, the majority vote method leads to a reduced overall FAR. By adequately adjusting the thresholds of each biometric mode to achieve reduced individual FRR values, the overall FRR is also reduced, while the recognition rate is increased when compared to each individual biometric modality. It is for instance possible to set these thresholds to achieve a correct recognition rate (after fusion) of 98.28%, with a FAR of 0.92% and a FRR of 0.80%, as illustrated in Figure 11.

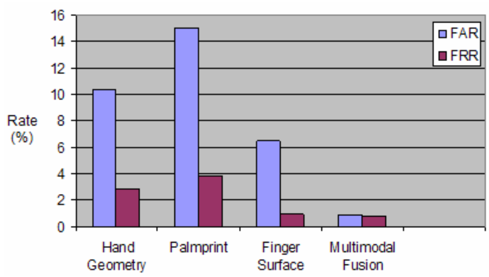

Figure 11 – Error rates for thresholds equivalent to a low FRR.

The GUI of the developed biometric recognition application, which when run against an entire database also provides the statistical data and graphs needed to assess the system's performance, is illustrated in Figure 12.

Figure 12 – The GUI of the biometric recognition application.

4. CONCLUSIONS

This paper proposes a multimodal biometric recognition system that exploits several modalities present in hand images. Image acquisition is based on a simple setup, using fairly inexpensive equipment. From a single acquired image, several biometric features are computed: hand geometry, palmprint, and finger surface. Different sensors for each biometric mode are not required, nor does it need specific hand placement as in pegged image acquisition devices. These characteristics make the system practical and easy to use.

The proposed multimodal biometric system has shown that the usage of multiple biometrics improves performance in comparison to systems using a single biometric. The combined results are better than the best of the individual biometric recognition results.

Compared to the literature, the proposed system is able to achieve a performance similar to the other hand recognition multimodal systems [1][3][5]. In reference [1], a maximum recognition rate of 99.28% and an EER of 0.58% were achieved by fusion of palmprint and finger surface features. Another multimodal system [5], using bimodal fusion of palmprint and hand geometry features, was able to achieve a maximum recognition rate of 98.59% and a 0% FAR. Using finger surface and hand geometry fusion [3], performance results with a maximum recognition rate of 97.97% and an EER of 1.71% were also reported.

From the individual biometrics considered, hand geometry and finger surface biometrics achieved the expected performance values – similar to the results described in [3][5]. The palmprint modality did not obtain the performance shown in other work [5], mainly due to the small size of the normalized ROIs considered here, which was nevertheless considered sufficient for integration in the multimodal recognition platform, while keeping the computational cost, both for feature extraction and for feature matching, lower than those of the alternative solutions. The selected option could make sense for large databases.

Future work will focus on the comparison of different fusion algorithms, for example considering a weighted score level fusion for each finger, so that individual finger performance is also taken into consideration. Other matching classifiers shall be investigated and compared, such as Hamming or Mahalanobis distance, and Gaussian Mixture Models. Also the usage of the so-called soft-biometrics, such as the size of the hand, can be used to speed up the recognition procedure.

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