AN ONLINE BIOMETRIC AUTHENTICATION SYSTEM BASED ON EIGENFINGERS AND FINGER-GEOMETRY

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ABSTRACT

An approach to personal authentication using the fusion of the finger-geometry and the novel biometric features called eigenfingers at the score-matching level is presented in this paper. The online biometric system integrates finger-geometry features extracted from the four fingers and eigenfingers features extracted by means of the Karhunen-Loève (K-L) transform applied to the four finger strip-like regions. Additionally, the system has a liveness detection module, which uses an IR image of the dorsal surface of a hand. Authentication experiments were conducted on a database consisting of 1270 hand-images (127 persons). The verification results, EER = 0.04% and minimum TER = 0.04%, suggest that the system can be used in medium/high-security environments.

1. INTRODUCTION

Biometric person authentication is the process of determining whether someone is, in fact, who is declared to be, based on physicological and behavioural characteristics of an individual [1]-[3].

A prototype of an online bimodal biometric authentication system based on the fusion of a finger-geometry and a novel biometric feature called eigenfinger is described in the paper. The system has a liveness detection module capable of detecting liveness in biometric samples. The liveness detection module uses a thermal camera as input device. The infrared (IR) image of the dorsal surface of the hand is acquired at the same time as capturing the biometric sample (two or four fingers) by a scanner. The combination of eigenfinger and finger-geometry features and liveness detection increase anti-spoofing protection and makes the online biometric authentication more robust to fraudulent methods.

Many authentication systems utilizing the biometric features of a hand-geometry have been developed [4] – [8] over the past decade. Ribaric et al. [7] and Kumar et al. [8] combined line-like features of the palm and hand geometry into a multimodal biometric system for user authentication.

K–L-transform-based techniques have been widely used in the field of biometrics, particularly in face-recognition techniques (eigenfaces) [9], but they have also been used for palmprint recognition [10], lip tracking (eigenlips) [11] and hand-gesture recognition through hand contours (eigencontours) [12].

In general, multimodal biometric systems require fusion of information obtained from two or more biometric modalities. Various levels of fusion are possible [13], [14]: from feature-extraction level to decision level. Different multimodal biometric systems based on the fusion of hand-geometry and palmprint features [7], [8], and face, fingerprint and hand-geometry features [15], [16] have been described.

Liveness detection, as an anti-spoofing protection in a biometric system, ensures that biometric being captured is an actual measurement from the live person who is present at the time of capturing. There are several approaches to liveness detection of the hand, for example: IR and near-IR measurements of hand vein patterns, hand thermograms [17], and photo-plethysmography [18].

2. SYSTEM DESCRIPTION

Figure 1 shows the block-diagram of the proposed biometric authentication system. First, images (visible and infrared) are acquired simultaneously using a scanner and a thermal camera. Scanner images are used as samples for the biometric authentication, while the IR images are used for liveness detection. Some standard procedures are then applied in order to segment these images. In the next phase, the liveness detection is performed on the segmented infrared image. If the liveness detection module claims the hand is alive, the biometric system proceeds with extraction of the biometric features from the scanner image. Otherwise, the process is terminated and the user is rejected.

Two kinds of biometric features are extracted: (i) Eigenfinger features extracted by means of the K-L transform applied to the previously extracted and normalized finger subimages; (ii) Finger geometry features extracted from the hand contour.

Each of these features is matched to the templates stored in the database. Matching scores are combined using fusion at the

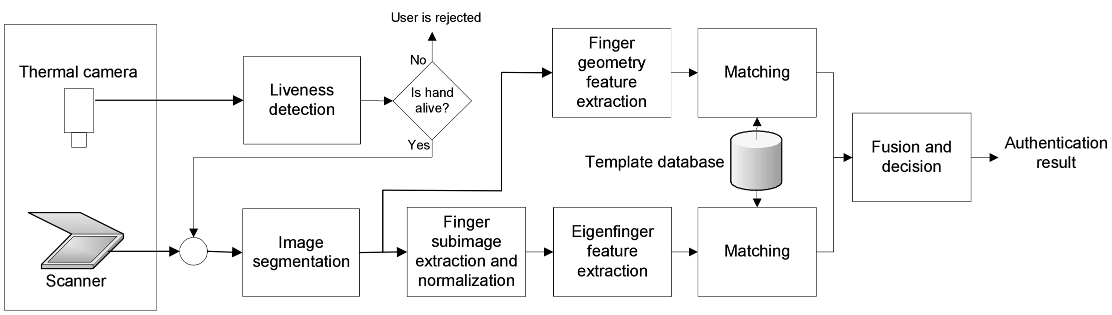
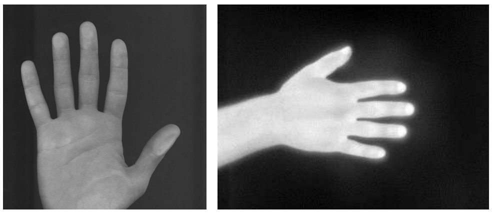


Figure 1: Block diagram of the proposed biometric authentication system

matching score level, and finally, an authentication decision is made by thresholding.

2.1 Image acquisition

Visual images and IR images are acquired using a scanner and a thermal camera, respectively. A scanner is used to capture palmar images of the hand in a 180 dpi (dots per inch) resolution and 256 gray levels. The user is required to put his/her hand on the scanner with the fingers spread naturally; there are no pegs, or any other hand-position constrainers. The infrared camera is used to simultaneously capture the dorsa hand images at the relatively low resolution of 320x240 pixels. We used ThermaCAM(TM) PM695 infrared camera with spectral range of 7.5μm – 13.0μm. An example of such image pair is presented in the Figure 2.

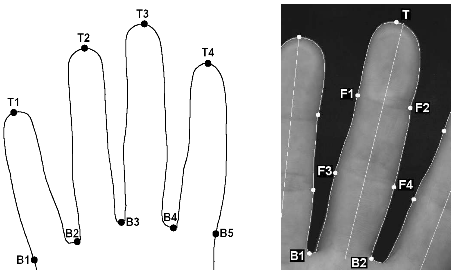


a) b)

Figure 2: An example of the acquired images, a) Scanner image, b) IR image

2.2 Image segmentation

The scanner images are first binarized using global thresholding. A contour-following algorithm is applied to a binarized image to extract the hand contour. The hand contour is then processed in order to find some points relevant for the geometry and eigenfinger feature extraction. The extracted hand contour and the relevant points are shown in the Figure 3 a). Finally, the line of symmetry of each finger (Fig. 3 b)) has to be found using four additional points marked with F1-F4 on the Figure 3b).



a) b)

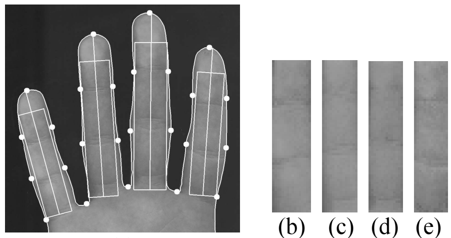
a) Hand contour with relevant points, b) Processed finger on the hand image

2.3 Eigenfinger template generation

The first step towards the eigenfinger template generation is locating the finger-strip regions to be extracted on each finger. The finger-strip regions are defined with respect to the finger line of symmetry and relevant points as shown on the Figure 4a). The selected finger-strip region contains the folds of the skin corresponding to the places between the phalanxes of the finger. These folds of the skin and their positions, as well as texture of the skin contribute to the discriminatory characteristics of the region.

The regions of interest in the original grey-scale images vary in size and orientation from image to image, so before using the K-L transform, they need to be normalized. Geometry normalization is applied to the grey-scale image to obtain the finger-strip subimages: the little-finger subimage is normalized to 16 x 64 pixels, and the ring-, middle- and index-finger subimages to 14 x 64 pixels. After the subimages have been extracted, a lighting normalization using histogram fitting [19] is applied.

The examples of normalized finger-strip subimages are shown on Figures 4 b) – 4 e).



(b) (c) (d) (e)

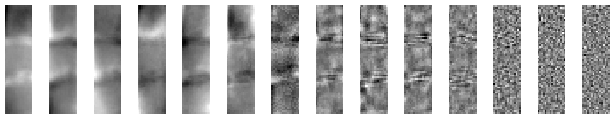
(a)

Figure 4. a) Original hand image with the regions of interest marked on it, b) normalized little-finger subimage, c) normalized ring-finger subimage, d) normalized middle-finger subimage, e) normalized index-finger subimage

We use the K-L transform, which is a well-known technique in biometrics [9], for feature extraction.

The basis vectors of the K–L transform are calculated by finding the largest m eigenvectors of the covariance matrix of the set of images. In the case of finger-strip images, we will call the eigenvectors *eigenfingers*. The subspace spanned by these eigenvectors' is referred as the finger-space. In our system, four finger-spaces are created, one for each finger considered. We calculated the finger-spaces using the training set of our database, consisting of 550 images of 110 persons.

Some of the little-finger eigenfingers obtained using our database are presented in the Figure 5. They are ordered in the falling order of their appropriate eigenvalues, and their ordinal numbers are shown.



$k = 1$ 2 3 4 5 10 20 30 40 50 100 200 300 400

Figure 5: Some little-finger eigenfingers obtained from our database, in the falling order of the appropriate eigenvalues. k denotes the eigenfinger's ordinal number

The largest eigenfingers carry the useful information (in the sense of image representation) and only they are used as the basis for the finger-space, while the information carried by the smaller eigenvectors is lost in the process of encoding. Based on the preliminary recognition experiments on the training database, we chose $m = 100$ for the dimensionality of all four finger spaces.

The feature vector from an unknown finger subimage can be obtained by projecting the image onto a corresponding finger-space. Thus, the eigenfinger template extracted from each sample consists of four 100-component vectors $\mathbf{F_i}$; i = 1, 2, 3, 4, one for each of the four fingers considered (1 – little finger, 2 – ring finger, 3 – middle finger, 4 – index finger).

2.4 Finger-geometry template generation

Figure 6 illustrates the finger geometry measurements taken from the hand contour. Six measurements (five widths and length) are taken for each of the considered fingers (Figure 6). Thus, the finger-geometry template extracted from each sample consists of a 24-component vector $\mathbf{G}$, in the case when four fingers are considered, or a 12-component vector, in the case when two fingers are considered.

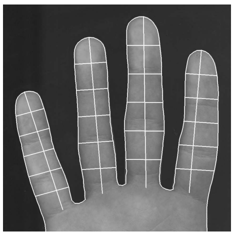


Figure 6: Finger geometry measurements

2.5 Matching, fusion and decision

A template in our system is represented by five feature vectors: four eigenfinger feature vectors $\mathbf{F_i}$; i = 1, 2, 3, 4 and a finger-geometry feature vector **G**. In order to verify or identify a user, the matching process between the live-template and the templates from the database has to be performed. The matching between corresponding feature vectors is based on the Euclidean distance. In general, when matching two templates, **X** and **Y**, five Euclidean distances are obtained: $D^F_i(\mathbf{X}, \mathbf{Y})$; i = 1, 2, 3, 4 and $D^G(\mathbf{X}, \mathbf{Y})$.

Since these distances come in different ranges, a normalization first has to be performed, so that they can be combined into the unique matching score. The normalization is carried out by means of five transition functions, $S^F_i(D)$; i = 1, 2, 3, 4 and $S^G(D)$ which were determined experimentally from the training set of the database [7].

The normalized outputs of the six matching modules are combined using fusion at the matching-score level. The fusion is expressed by means of the total similarity measure TSM(X,Y)

$$TSM(X,Y) = w^G S^G(D^G(X,Y)) + \sum_{i=1}^{4} w_i^F S_i^F(D_i^F(X,Y)) \quad (1)$$

where w^F_i; i = 1, 2, 3, 4 and w^G are weight factors associated with each of the hand parts and fulfil the condition

$$w^G + \sum_{i=1}^{4} w_i^F = 1 \quad (2)$$

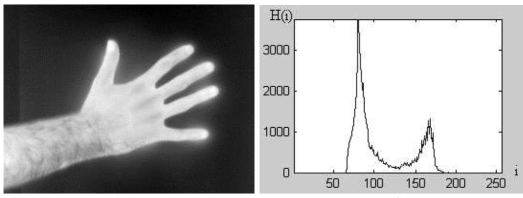
In our system the weights are set proportionally to the preliminary unimodal recognition results. In the case the two fingers (middle- and index-finger) are considered the weights are set to $w^F_1 = 0$, $w^F_2 = 0$, $w^F_3 = 0.337$, $w^F_4 = 0.330$ and $w^G = 0.333$. In the case the four fingers are considered the weights are set to $w^F_1 = 0.197$, $w^F_2 = 0.201$, $w^F_3 = 0.202$, $w^F_4 = 0.197$ and $w^G = 0.202$.

The decision in our system is based on thresholding. If two templates, **X** and **Y** have TSM(X,Y) ≥ T, where T is the threshold, they are considered to belong to the same person. Otherwise, they are considered to belong to different persons.

3. LIVENESS DETECTION

The goal of a liveness detection module is to extract characteristic features of the live hand from the infrared images and use this features to make a decision whether the sample represents a live hand or not. Two kinds of features are proposed: (i) Histogram of the entire image (including background); (ii) Temperature distributions from the two characteristic regions of dorsa hand images.

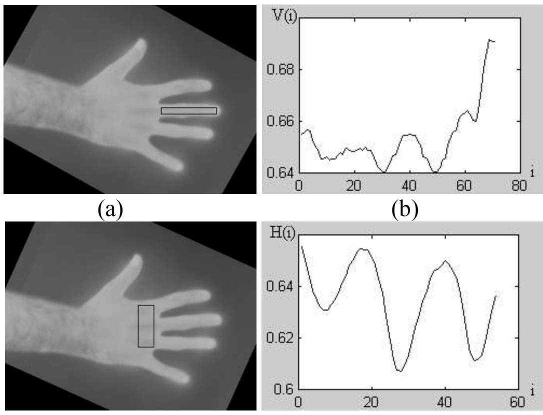
Image histogram H(i) carries the information about the distribution of the temperature (represented by gray-scale levels i = 0, 1, 2, …, 255) in the infrared image. One such histogram is shown on Figure 8. Two prominent peeks can be noticed in the histogram, one corresponding to the background temperature, and the other to the hand temperature.



(a) (b)

Figure 8: a) Infrared image, b) Corresponding histogram

We selected two regions of the hand with characteristic temperature distributions – the middle-finger area, and the back of the hand area marked on the Figure 9 a) and Figure 9 c), respectively. We observe the normalized vertical projection V(i) of the finger region, and the normalized horizontal projection H(i) of the back of the hand region. The obtained projections from Figure 9 a) and c) can be seen on Figure 9 b) and d), respectively. There, some characteristics of the live hand can be observed. For example, the tip of the finger is much warmer from the rest of the finger, and the areas on the back of the hand, where the metacarpal bones are located are colder than the areas between the bones.



(c) (d)

Figure 9: a) Infrared hand image with finger region marked, b) Vertical projection of the finger region, c) Infrared hand image with back of the hand region marked, d) Horizontal projection of the back of the hand region

We propose a multi-layer perceptron (MLP) to classify these features (histogram and two projections) into the live hand or non-live classes. However, this would require substantial number of training samples that yet have to be collected, so this part of the system is not implemented fully at this time.

4. EXPERIMENTAL RESULTS

Authentication experiments were conducted on a database consisting of two mutually exclusive sets: a training set and a test set. The training set consisted of 550 visual hand-images of 110 persons and was used for the generation of eigen-basis, obtaining the transition functions $S^F_i(D)$; i = 1, 2, 3, 4 and $S^G(D)$ and the weights w^F_i; i = 1, 2, 3, 4 and w^G. The test set consisted of 1270 visual hand-images of 127 persons (10 images per person) and was used exclusively for the evaluation of the system performance. None of the persons involved in the acquisition of the test set was involved in the acquisition of the training set. Out of 127 persons in the test set, 57 played the role of clients, while the remaining 70 played the role of impostors. Out of ten images for each client, seven were used for enrolment, and the remaining three were used for testing. All ten of the impostor samples, for each impostor, were used for testing.

Identification

In the identification experiments each of the test client samples tried to be successfully identified by the system. Also, each of the test impostors tried to be identified as any of the clients enrolled in the system. The identification setup makes for 171 (57x3) client experiments and 700 (70x10) impostor experiments. The results of the experiments are shown in Table 1.

Verification

In the verification experiments each of the test client samples tried to be successfully verified using his/her own ID. Each of the impostors tried to be verified using IDs of all clients. The verification setup makes for 171 (57x3) client experiments and 39900 (70x10x57) impostor experiments. The results are shown in Table 1.

Experimental results of all experiments, both identification and verification, are expressed in the terms of the EER (Equal Error Rate) and the minimum TER (Total Error Rate). The threshold values corresponding to the EER and the minimum TER are also given in the Table 1.

We tested both unimodal performance of the system (using only finger-geometry features or using only eigenfinger features), as well as bimodal performance of the system. The above experiments were made using features from two fingers (index- and middle-finger) and using features from four fingers (little-, ring-, middle- and index-finger).

Features used	Identification results		Verification results	
	EER T	Minimum TER T	EER T	Minimum TER T
2 Fingers - geometry	5.29% 0.910	7.17% 0.975	0.43% 0.860	0.43% 0.860
2 Fingers – eigenfingers	7.86% 0.885	14.33% 0.900	1.75% 0.780	2.10% 0.875
2 Fingers – geometry + eigenfingers	1.75% 0.825	2.92% 0.900	0.18 0.750	0.18 0.750
4 Fingers - geometry	1.75% 0.645	3.34% 0.675	0.26% 0.510	0.26% 0.510
Fingers – eigenfingers	3.51% 0.840	5.79% 0.850	0.26% 0.780	0.26% 0.780
4 Fingers – geometry + eigenfingers	1.17% 0.760	2.03% 0.775	0.04% 0.710	0.04% 0.710

Table 1: Experimental results

5. CONCLUSION

We have developed a prototype of an online biometric authentication system based on the finger-geometry features and the novel biometric features called eigenfingers. The experimental results, obtained on a database of 1270 images of 127 persons show the effectiveness of our system in the sense of EER = 1.17% and the minimum TER = 2.03% for identification, and EER = 0.04% and minimum TER = 0.04% for verification.

The results show the feasibility of the eigenfinger features for biometric authentication as well as effects of fusion at the matching-score level on improving the system's accuracy. The preliminary work on the liveness detection module reveals the number of features that can be collected from the IR images of the hand and used for the liveness detection.

In the future, we plan to test the system on a larger database collected over a longer period of time. We also plan to collect more IR images and continue the work on the liveness detection module of the system, as well as try to use the features obtained from the IR images as biometric features for authentication.

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