Single-sensor multi-instance fingerprint and eigenfinger recognition using (weighted) score combination methods

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Abstract: When multiple instances of single biometrics can be acquired from a single input simultaneously, a multiple-step acquisition at additional transaction time cost can be avoided. We present a rotation-invariant, peg-free multi-instance Fingerprint and Eigenfinger-based biometric system extracting multiple features from a palmar scan of the hand. Our evaluation targets (a) rankings of individual fingers with respect to Minutiae and Eigenfinger features; (b) fusion of multi-instance intra-feature (Minutiae or Eigenfinger) matching scores; (c) cross-feature compared to intra-feature performance; (d) optimal weights for weighted versions of five score-level fusion methods Max, Median, Min, Product and Sum, and (e) aspects of computational demands for hand-based identification discussing the usage of serial classifier combinations instead of classically employed parallel ones. We examine results of an experimental approach to the problem of finding a suitable fusion method by investigating the effect of matcher-specific combination weights on recognition accuracy and compare cross-feature and intra-feature score combinations.

Keywords: hand biometrics; score-level combination; multi-instance fusion; eigenfingers; fingerprint; serial classifiers.

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1 Introduction

Multimodal biometric systems make use of multiple evidences of the same identity to recognize a person in order to cope with unsatisfactory performance, flexibility in case of failure to acquire single biometrics, and security of unimodal systems. Depending on the type of information used in the fusion process, five different integration scenarios have been identified in [1]: multiple sensors, multiple samples, multiple biometrics, multiple instances and multiple matching algorithms. We concentrate on the multiple instances configuration, since this scenario can be expected to combine largely independent information (in contrast to multiple sensors when sensing the same instance, multiple samples and multiple matching algorithms) without the necessity of additional sensors (such as for multiple biometrics scenarios).

1.1 Objectives

There are many different modalities related to the human hand, most commonly used are according to [2]: Fingerprint, Hand and finger geometry, and Palmprint. Originally, different sensing devices have been developed for these modalities (see [3, 4]) and typically, only one instance (i.e. finger) is acquired for verification or identification. This approach bears the risk of a rather high FER (Failure to Enroll Rate), caused by the inability to acquire features due to serious infringement or congenital physical anomalies. Especially public access control and forensic applications demand biometric systems with high *universality*, being able to tolerate e.g. *polydactyly* (supernumerary fingers) or *dermatopathia pigmentosa* (a disease causing a lack of fingerprints). Multibiometric systems typically increase universality by using more than one independent modality for verification or identification. To give a concrete example: we have tested a person unable to enroll in a commercial fingerprint system on our multibiometric system. None of the individual minutiae-based matchers (see Fig. 1) was able to classify all genuine authentication attempts of this user as genuine (the best index-finger matcher rejected a single attempt, the worst performing little finger even rejected 7 out of 10 using learned thresholds resulting in almost equal false match rate, FMR, and false non-match rate, FNMR). A combination of scores with Eigenfingers, as proposed in this work, resulted in no classification errors for this user. The existence of inherently low quality fingerprint images (e.g. for manual workers or elderly people) as a significant drawback for the fingerprint modality and the proposal of multibiometrics in order to overcome these limitations is also highlighted in [5]. But in most multibiometric system configurations, this higher accuracy comes at the cost of lower user throughput. Representative mean transaction times for Hand, Fingerprint, Face, Iris, Vein and Voice can be found in [6] and are in the order of 10-20 seconds per modality. Acquisition in serial order accumulates these costs, which can be avoided, when multiple instances of single biometrics can be acquired from a single input source simultaneously. Our proposed Fingerprint- and Eigenfinger-based biometric system illustrated in Fig. 2 exploits exactly this advantage and extracts localized features from a high-resolution scan of the entire hand. While originally designed to combine also hand geometry and palmprint features, we have decided to exclude these features from our system and to concentrate on Minutiae and Eigenfinger features in this work. This decision is based on the following considerations: (a) Minutiae and Eigenfingers provide most accurate results at acceptable processing time requirements; (b) the addition of other hand geometry or palmprint-based features results in little improvements, and; (c) this work focuses on an estimation of the best-performing score combination rule in cross-feature and intra-feature score combinations. Due to the absence of public databases providing high-resolution (at least 250-500 dpi are necessary for minutiae extraction according to [3]) full-hand scans, we have acquired custom databases following a strict test protocol. Image samples of acquired hands are depicted in Fig. 3.

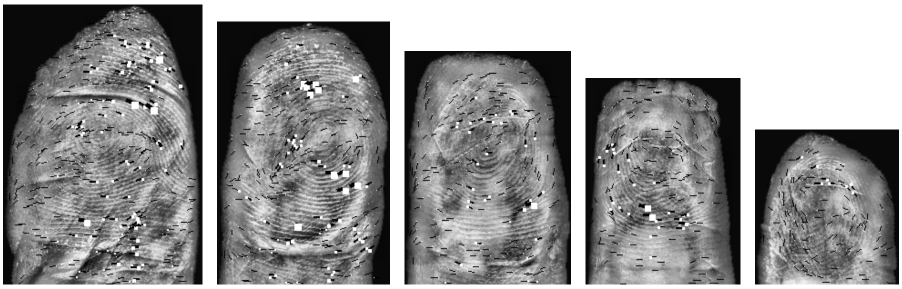

Figure 1 Detected minutiae (thicker lines correspond to higher minutiae quality) in fingerprints (acquired by an optical flatbed scanner) of a user unable to enroll in a commercial fingerprint system.

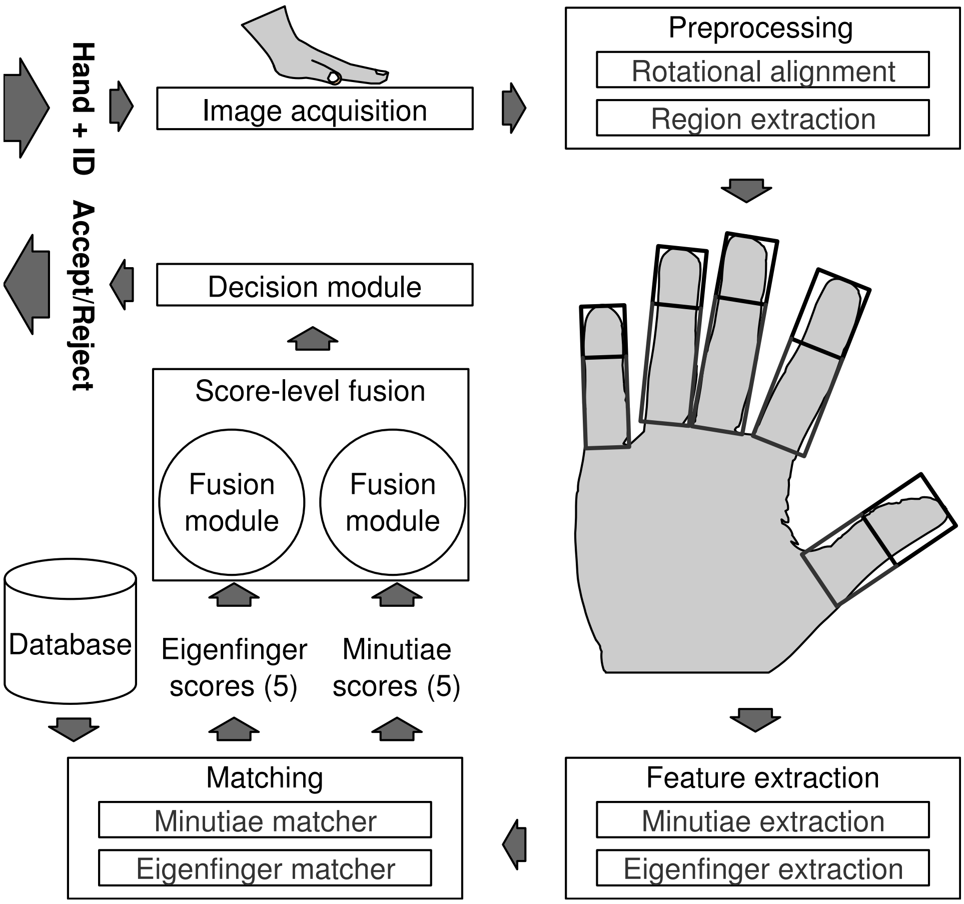

Figure 2 Architecture of the proposed system.

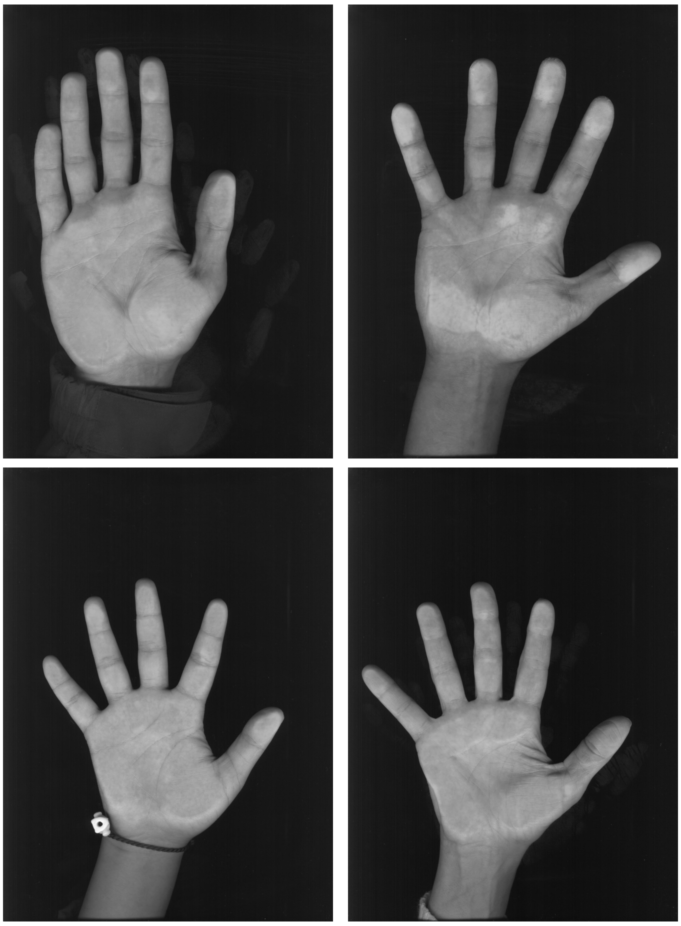

Figure 3 Sample acquired hands

While numerous different classifier combination techniques exist (see e.g. [1, 7] for overviews), score-level fusion is preferred over feature extraction level or abstract level fusion in most practical implementations. Score-level fusion integrates well in biometric systems, since: (a) it can be encapsulated in a separate fusion module between matching and decision subsystems leaving single feature extractors and matchers unchanged; (b) the type of information fused is known to be weakly dependent and still contains rich discriminative information; (c) there is a set of fast combination rules, which can be executed on normalized scores of individual matchers. We do not intend to introduce yet another novel fusion method, but we aim at providing an assessment of well-known score combination methods to evaluate (a) the amount of improvement when multiple instances of the same biometric (Fingerprint and Eigenfinger) are combined, compared to just single instances; (b) total joint performance of all individual classifiers and; (c) the process of estimating optimal modality-specific weights highlighting the problem of overfitting.

Multibiometric fusion is able to address the problem of enrollment errors and insufficient accuracy, but this comes at the cost of further processing overhead. Especially traditional parallel fusion in identification mode, where the biometric sample is compared with each gallery image for each employed feature, lacks good scalability with respect to database size. When serialized in a single-processor environment, the total processing time increases linear in the number of users with a potentially large factor of employed matchers. One idea to address this problem are hierarchical fusion schemes [8, 9] which follow the idea of bringing the final matching decision forward in the chain of matchers and facilitate coarse-to-fine matching. We highlight this problem for Minutiae and Eigenfinger matchers and examine processing requirements of individual matchers. Furthermore we introduce a framework of serial combinations enabling the application of arbitrary combination rules by introducing an additional information flow between levels (accumulating matching information). By examining serial fusion in two different configurations we will illustrate that (a) serial classifiers can decrease processing time significantly and at the same time retain high accuracy of parallel configurations, and; (b) configurations where faster distance-based classifiers reject a majority of bad matches before computationally more demanding best-alignment based matchers contribute to the final decision are more accurate and faster than the best single matcher.

1.2 Related work

Recent biometric systems [10–14] have also identified advantages of single-sensor approaches and proposed a couple of multibiometric solutions based on score-level fusion: [10] obtained a perfect classification in verification mode by combining multi-instance fingerprints of 50 people (600 images) from multispectral palmar scans of the human hand using the simple Sum method for biometric fusion (following a proposal by [11], who use randomly paired samples in their study). [12] combined Eigenfingers (and Eigenpalm) scores using a weighted sum of scores yielding also no errors on a dataset of 110 users (550 images) and 0.72% total error rate in identification mode. By combining linear discriminant analysis (LDA) appearance-based features from palmprint, digitprints and fingerprint regions as well as 14 geometrical measures, [13] achieved an equal error rate (EER) of 0.0005% on a dataset of 100 people (2000 images). [14] evaluate Principal Component Analysis (PCA), Most Discriminant Features (MDF) and Regularized Direct LDA (RD-LDA) feature extraction on palmar images, with RD-LDA performing best (100% correct identification for 920 tests compared to 99.35% for the best single feature Palmprint). In contrast to [10] our system does not make use of a specialized sensor. We extract features from a palmar image of the human hand, acquired by a commercially available flatbed scanner using a configuration similar to [13]. Due to the high availability of document scanners (see, e.g. [15]), the presented method is a low-cost alternative enabling a wide range of possible applications. Unlike [13], who down-scale ROIs (fingerprint regions are resized to 64×64 patches) within the 600 dpi high-resolution image for LDA feature extraction, we make full use of our 500 dpi input image and perform minutiae detection on fingerprints after local contrast enhancement, which is able to increase performance significantly [16]. In contrast to observations in [13, 16] we emphasize on both cross-feature fusion and intra-feature comparisons between matchers of the same biometric feature in this work and identify the best suitable fusion rule for each of configuration experimentally. Compared to [11], fingerprint images are not paired with hand images, but all features are extracted out of a single high-resolution scan. While a tradeoff between sensor quality and recognition accuracy is obvious, we will show that a combination of two highly accurate hand-based features, namely Eigenfinger and Minutiae, produces acceptable results also with standard hardware available for large markets. However, if specialized sensors, such as in [10], are replaced by commercially available hardware, genuine and imposter score distributions of single matchers are expected to overlap to a larger extent, thus the selection of the best suitable fusion method is an important issue. Results in the past have shown, that (a) the combination of only two multi-instance WSQ-compressed fingerprints acquired by FBI-compliant fingerprint scanners may reduce FAR by 48-90% at fixed 0.01% FRR [17]; (b) the performance of combination techniques largely depends on the modeling of the underlying distributions [17]; (c) sum- and product-based fusion methods provide accurate results [10, 13, 18]; (d) for the Sum rule a generalization to a Weighted sum rule improves performance results compared to an unweighted Sum rule in case of combining matchers with different strengths [3, 13, 19]. Motivated by these results, we investigate the performance of weighted versions of standard combination techniques estimating the performance improvement of this generalization. We aim at providing an answer to the question whether the behavior described in (d) may also be observed for other methods. While surveys identifying the most suitable fusion rule for Fingerprint have been conducted ([20] identify the superiority of Product over Sum, Max, and Min, [17] report best performance for Product of Likelihood Ratios among Logistic Regression, Product of FARs, Max of FAR, Min of FAR, Sum of raw scores, Sum of Z-normalized scores and Best Linear), our focus here lies on the comparison of fusion behavior between intra-feature multiple-instance fusion (following similar distributions), and cross-feature fusion (combining Eigenfinger and Minutiae from different fingers). As the outcome on best fusion rule performance may be affected by the choice of normalization techniques [13], we explicitly refer to Min-Max normalization in our evaluation due to its widespread use and simple implementation. Furthermore, we address the problem of general reproducibility of experiments by employing not only one but two different databases. Extending closed-set results in parallel configuration for hand-based identification reported in [13, 14] we present results for serial combinations illustrating the tradeoff between matching time and accuracy.

1.3 Organization

This paper is organized as follows. Section 2 motivates and clarifies design issues for preprocessing and feature extraction stages of the implemented single-sensor multiple-instance Fingerprint and Eigenfinger recognition system. Employed score fusion methods are discussed in Sect. 3. Section 4 focuses on aspects of computational demand and discusses in this context the usage of serial classifier combinations instead of classically employed parallel ones. Experimental setup and results for different score fusion techniques are introduced and analyzed in Sect. 5. Conclusions are outlined briefly in Sect. 6.

2 Image processing and feature extraction

The architecture of the proposed system illustrated in Fig. 2 follows common multibiometric systems [11, 12] and consists of separate modules for the *image acquisition, preprocessing, feature extraction, matching, score level fusion* and *decision* tasks. In contrast to the employed setup in [13] we do also process the thumb region, which provides even better results than the little finger for the Minutiae feature. This section presents processing stages prior to score level fusion. The first discussed preprocessing module operates on gray-scale image data acquired by a flatbed scanner. We employ a HP Scanjet 3500c flatbed scanner introduced in 2002 in a low-cost market segment supporting an area of 216×297

millimeters to acquire a palmar scan of the human hand. An analysis of resolution-duration tradeoff at 100 dpi (the resolution at which Eigenfingers are processed in our system), 300 dpi (low-resolution fingerprint sensors) and 500 dpi (as recommended by the FBI for fingerprint scanners [3]) resulted in average total acquisition times of 15, 25 and 95 seconds respectively for this model and 14, 20 and 43 seconds for a newer HP G3010 model in grey-scale mode. Color information further degraded scan speed by 20-40% (G3010) and 70-100% (3500c).

2.1 Preprocessing

The task of the preprocessing module is to provide each feature extractor with a normalized hand, i.e. it provides (a) a rotation invariant representation of the full palmar hand image with masked background, and; (b) hand contour information with localized landmarks (finger peaks and valleys). Figure 4 lists all employed processing steps using Java-like pseudo-code: First, function `CropInputImage` performs segmentation by means of Fast Otsu's thresholding [21] on the gaussian blurred input image to identify the region of interest containing the hand. After masking background pixels (functions `HandMask` and `Multiply`), rotational alignment is achieved iteratively by employing moment-based best-ellipse fitting [22] (functions `CalculateCenterOfMass` and `CalculateRotation`) and removing visible arm parts at each iteration (function `IterativeArmRemoval`) using a top-down scanning algorithm based on thresholding of vertical slices. However, the final rotational alignment is estimated from the contour (`CalculateHandSilhouette`) aligning the hand at the finger valley between ring and middle finger (`GetMiddleRingFingerValley`) and using the least-squares approximated outer palm boundary for global rotation (`GetPalmBoundaryLineRotation`). In contrast to existing systems operating on palmar hand scans acquired by optical scanners [13, 23], which also employ global thresholding and extract the positions of landmarks (peaks and valleys) by finding maxima and minima of the hand contour, we found that their position is not stable under varying spreadings of fingers, contour artifacts caused by jewelery and insufficient scanning depth. This problem has been solved by refining initial contour candidates, intersecting the major axis of the best-fitting ellipse for each individual finger with the contour (for peaks) and intersecting the bisector of approximated adjacent finger boundaries with the contour (for valleys) [16].

At the end of the preprocessing stage, still regions of interest have to be identified for each feature extractor. Therefore, the next step matches individual fingers (defined as the binary large objects spanned by the contour polygon between two consecutive inter-finger valleys) with best-fitting ellipses. For each finger, two regions are extracted as rectangular bounding boxes aligned with respect to the major axis of each finger's best-fitting ellipse: a fingerprint region corresponding to the upper $\frac{1}{3}$ part of the finger (and $\frac{1}{2}$ for the thumb, respectively) and a finger region clipped at the adjacent valley with closer distance to the finger tip. Finger regions are down-scaled and aligned to a 128×384 canvas for index, middle and ring finger and 128×256 for thumb and little finger. Finally, contrast-limited histogram equalization is applied for quality enhancement.

```
void NormalizeHand(Bitmap hand)
{
   final int max_iterations = 3;
   Bitmap tmp, bin;
   ContourInfo cinfo;
   Point center;
   float rotation;

   tmp = CropInputImage(hand);
   bin = HandMask(tmp);
   hand = Multiply(tmp,bin); // cropped and segmented hand
   tmp = bin; // start to find arm parts in binary image
   for (int i = 1; i < max_iterations; i++){
      center = CalculateCenterOfMass(tmp);
      rotation = CalculateRotation(tmp,center);
      tmp = Rotate(center,rotation,tmp);
      tmp = IterativeArmRemoval(center,rotation,tmp,bin);
   } // within tmp all arm parts are removed
   cinfo = CalculateHandSilhouette(tmp);
   center = GetMiddleRingFingerValley(cinfo);
   rotation = GetPalmBoundaryLineRotation(cinfo,center);
   tmp = Rotate(center,rotation,tmp); // tmp is normalized
   tmp = IterativeArmRemoval(center,rotation,tmp,bin);
   cinfo = CalculateHandSilhouette(tmp);
   AlignHandImage(hand,cinfo,center,rotation);
   AlignHandContour(cinfo); // hand and contour are aligned
   Save(hand);
   Save(cinfo); // normalized image and contour are stored
}
```

Figure 4 Pseudo-code representation of the Normalization procedure.

2.2 Feature extraction and matching

The feature extraction module maps each region sample to a feature vector representation. Ideally, each feature vector is a very compact representation of the input sample supporting good classification of authentication attempts into *genuines* (both feature vectors share the same identity) and *imposters* (they do not share the same identity). The first employed feature targets fingerprints and extracts information (i.e. ridge ending and bifurcation points) from the ridge structure, i.e. the outermost structural part of the epidermis, which can successfully be extracted from palmar scans, given a sufficiently high resolution. However, even in our medium-sized database a couple of users with weakly expressed ridge structure are present, as can be seen from Fig. 5. Using not only a single, but all fingers and combining results with Eigenfinger results will be shown to reduce errors, which would otherwise lead to a misclassification (or reject due to insufficient quality). Using NIST's Minutiae extraction tool *mindtct* [24] we extract position, orientation, quality and type (bifurcation or termination) of Minutiae points from the 5 fingerprint regions.

Matching of templates is executed pairwise and a matching score is generated for each comparison. For Minutiae matching NIST's *bozorth3* [24] matcher has been chosen, which generates a similarity score based on the number of found corresponding minutiae pairs.

Each of the 5 finger regions of thumb, index, middle, ring and little finger is subjected to Eigenfinger processing, a popular technique from face recognition [25]. After normalizing

Figure 5 Good quality (left) and bad quality (right) fingerprints after enhancement.

each finger with respect to a mean image of the particular finger type, the resulting image is projected into a subspace (so-called *Eigenspace*) obtained by estimating the 25 most significant eigenvectors of the covariance matrix of a set of also 25 training images. Its projection coefficients represent the projected finger image in an optimal way (see Fig. 6) with respect to the given feature vector size (the subspace minimizes reconstruction errors [12]) and are used as feature vector. According to [14], who give test results estimating the optimum number of PCA coefficients with respect to EER performance of similar test data, 20 coefficients already provide high classification accuracy (an optimum was found for 100 PCA coefficients providing 0.5% EER compared to 0.53% for 20 coefficients). In contrast to [12, 13] our digitprint algorithm is sensitive to both texture and shape, since we do not restrict each finger to its textural strip. However, as can be seen from the example given in Fig. 6, the method is sensitive to normalization errors: falsely detected finger valleys may result in a larger finger region and thus differing projection coefficients, which naturally also model finger length and shape. Again, a combination with Minutiae results helps to minimize false decisions based on single bad results.

For matching, the Eigenspace-based algorithm employs a manhattan-distance-based classifier and converts distance measures into similarity scores by subtracting the distance from an empirically found maximum. For each feature we apply min-max normalization in order to obtain similarity scores within the interval $[0, 1]$.

3 Fusion and decision

The employed fusion approaches may be classified as transformation-based fusion at the confidence and rank levels [1] using the combination schemes Max, Median, Min, Product, and Sum for verification mode and Score sum, Borda count for identification mode. We evaluate both Minutiae and Eigenfinger score fusion individually as well as the combination of all 10 scores within the scope of a multiple-matcher scenario based on whole-hand images

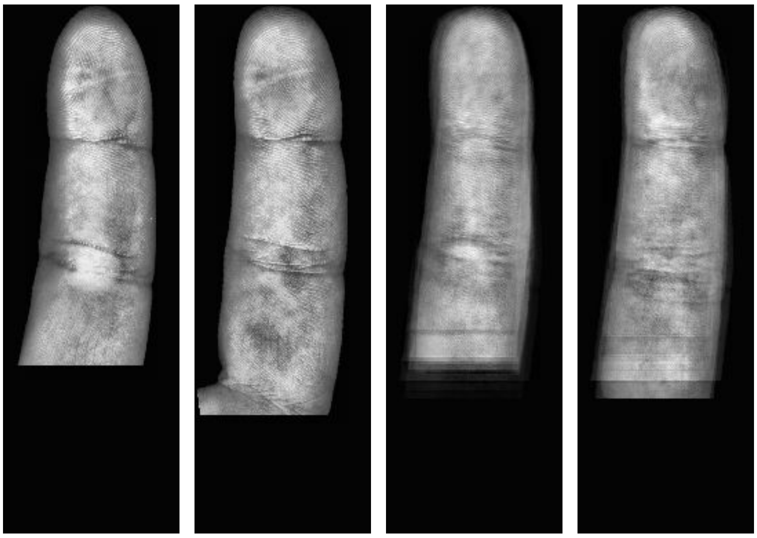

Figure 6 Low-scored intra-personal Eigenfinger authentication attempt (left: originals, right: feature vector projections)

as proposed by [11].

3.1 Fusion in Verification mode

In score-level fusion architectures operating in verification mode, the task of the fusion module is to consolidate a vector $S = (s_1, s_2, \ldots, s_m)$ of matching scores retrieved by m different matchers. According to [26] there are two different approaches for post-classification techniques, namely (a) the classification approach using e.g. Support Vector Machines or k-NN to assign a class $\omega \in \{\omega_1, \ldots, \omega_n\}$ to the input score vector (in case of verification we have $n = 2, \omega_1 = genuine$ and $\omega_2 = impostor$), and (b) the combination approach where individual matching scores are mapped to a single scalar value $s = f(S)$. This work examines the behavior of combination methods, which are applied as functions on normalized scores. Therefore, scores of individual matchers s_i are initially transformed into scores s'_i within a homogeneous domain (similarity scores) and range (the unit interval $[0, 1]$) using *min-max* normalization [1]:

$$s'_i = \frac{s_i - s_i^{\min}}{s_i^{\max} - s_i^{\min}} \tag{1}$$

where s_i^{min} and s_i^{max} are originally the minimum and maximum score values for each matcher estimated from a test set. This simple normalization technique has proven successful in practice (see [10, 26], for example). In order to eliminate its sensitivity to single outliers, we have used the 0.001- and 0.999-quantile values, respectively, and all exceeding values have been replaced by the nearest scalar in $[0, 1]$.

[7] provide a theoretical framework using Bayesian statistics to formulate decision rules for each combination technique. We follow the approaches in [20, 26], who introduce fusion rules as simple mapping functions and use thresholding for the decision task. We focus on

these rules, since they (a) are frequently employed [1, 13], (b) make little assumptions about the type of underlying data. Furthermore we employ generalized versions using weights $w_i \in [0,1], 1 \leq i \leq m$ for each matcher accounting different strengths. For the Sum method, weights are required to satisfy: $w_1 + w_2 + \ldots + w_m = 1$. Neutral weights for the unweighted versions are $w_i = 1\ \forall i\ with\ 1 \leq i \leq m$ for Max, Median, Min, Product and $w_i = \frac{1}{m}\ \forall i\ with\ 1 \leq i \leq m$ for the Sum score combination technique.

- *(Weighted) Max*: this method is tolerant to single bad quality results, e.g. single bad fingerprint matching scores.

$$s = \max_{i=1}^{m} w_i \cdot s'_i; \tag{2}$$

- *(Weighted) Median*: whereas the max score is sensitive to single good matching results, the median tries to suppress outlying results of single matchers.

$$s = \operatorname*{median}_{i=1}^{m} w_i \cdot s'_i; \tag{3}$$

- *(Weighted) Min*: this combination technique is based on an approximation of the product score (see [1]).

$$s = \min_{i=1}^{m} w_i \cdot s'_i; \tag{4}$$

- *(Weighted) Product*: the most sensitive combination to single classifiers returning small scores is the product method. It is statistically based on a direct assumption of independence of single matchers [7].

$$s = \prod_{i=1}^{m} {s'_i}^{w_i}; \tag{5}$$

- *(Weighted) Sum*: The sum or mean of scores covered by this combination technique, is frequently employed in the domain of whole-hand multibiometric systems [10, 12].

$$s = \sum_{i=1}^{m} w_i \cdot s'_i; \tag{6}$$

The determination of weights for the employed score combination techniques is a crucial issue for the performance of the presented score level fusion techniques. One approach to this problem is learning-based estimation: for user-specific weights, [26] proposed to minimize the total error rate for a given test dataset for each user by exhaustive search with a fixed step size over the total range. For globally determined weights, a technique frequently adopted (e.g. in [12] for the combination of Eigenfinger and Eigenpalms or [19] for the combination of face and iris scores) is to reflect unimodal performance. We have applied the exhaustive search approach for weights estimation, but in contrast to [26] weights are determined globally and not individually for each user. In order to reflect the behavior of weighted score combinations on unseen data, a separate test set B is evaluated using all parameters estimated from set A.

3.2 Fusion in Identification mode

Depending on the type of matcher output in identification mode, we investigate two types of identification fusion (see also [27]):

1. **Measurement fusion** being the task of finding a map M,

$$M : \mathbb{D}_1{}^t \times \mathbb{D}_2{}^t \times \ldots \times \mathbb{D}_m{}^t \rightarrow [0,1]^t, \tag{7}$$

where $\mathbb{D}_i{}^t$ is the set of t-dimensional measurement vectors S_i with $S_i[j]$ indicating the degree that the sample image and the j-th gallery image share the same identity according to the i-th feature and $[0,1]^t$ is the domain of normalized similarities for the combined feature. As a representative of this type of fusion we have selected the Score Sum method (see [1]), which is related to the Sum rule and averages (min-max normalized, i.e. $\forall i : \mathbb{D}_i = [0,1]$) scores of matchers, i.e. the common score vector is defined as:

$$S_{\mathrm{SS}} := \frac{1}{m} \sum_{i=1}^{m} S_i. \tag{8}$$

2. **Rank fusion** as a map R,

$$R : \mathbb{N}^{t^m} \rightarrow \mathbb{N}^t, \tag{9}$$

combining rank index vectors $I_i \in \mathbb{N}^t$ of each feature i where $I_i[j] = k$ indicates, that the k-th gallery image is ranked at j-th position. We identify the rank vector R_i in this case as the vector satisfying $\forall j, x \text{ } with \text{ } 1 \leq j, x \leq t : I_i[j] = x \Leftrightarrow R_i[x] = j$. We have selected Borda count (see [1]) as a representative for this type of fusion. This voting-based rank fusion method sums up individual rankings resulting in a consolidated rank index vector I_{BC}. Let $\mathcal{S}_t$ be the set of all permutations of $\{1, \ldots, t\}$, then:

$$I_{\mathrm{BC}} \in \mathcal{S}_t : \forall k, l \text{ } with \text{ } 1 \leq k < l \leq t \Rightarrow \sum_{i=1}^{m} R_i[I_{\mathrm{BC}}[k]] \leq \sum_{i=1}^{m} R_i[I_{\mathrm{BC}}[l]], \tag{10}$$

3.3 Decision module

In verification mode, each score combination technique is designed to return a single similarity measure, which is compared to a threshold. Depending on the outcome of this comparison the authentication attempt is either classified as genuine or impostor. For closed set identification, the rank-1 entry of the corresponding rank index vector, i.e. $I[1]$ is returned in case of rank fusion and the template index j with the highest score $S[j]$ is returned as result in case of measurement fusion.

4 Real-time issues

For biometric systems in online verification or identification scenarios, not only high accuracy is of importance, but also timely response to authentication requests. The first problem to be solved is low user throughput at the image acquisition step. Since image acquisition speed largely depends on the employed resolution, a resolution-duration tradeoff of the employed scanning device has been discussed in Sect. 2. A more severe task to be solved is scalability in identification mode with respect to large system databases. Traditional parallel approaches require a matching of the probe image with all enrolled gallery images. This results in $m \cdot t$ matches, where m is the number of employed matchers and t is the number of gallery images. Thus, additional modalities can increase processing time drastically when serialized in single-processor environments. This problem has been identified in [8] and addressed by the introduction of hierarchical multifeature coding: features are processed in serial order and reduce the set of possible candidates at each level. Using this technique, [8] could reduce processing time requirements of their palmprint identification system from 6.7 seconds to 2.8 seconds. This idea is also used in face detection [9] in order to iteratively reject large numbers of non-faces. We seize this suggestion and extend these models by an incremental computation of the traditional combination rule. We therefore introduce two concepts in order to be able to compute outlined combination rules in Sect 3.2 incrementally:

1. **Sequential order of matchers**: Each biometric matcher does not make use of the full gallery D, but a subset thereof, specified by a characteristic function c_i. For technical purposes, we set

$$\forall j \text{ with } c_i(j) = 0 : R_i[j] = \infty \text{ (BordaCount) and } S_i[j] = 0 \text{ (ScoreSum)}, \quad (11)$$

respectively. Let R be the rank vector of the chosen combination rule using the first i matchers and let $d[i]$ be the desired output dimension, then:

$$\forall j\ c_i(j) := \begin{cases} 1 & \textit{if } i = 1 \vee (i > 1 \wedge c_{i-1}(j) = 1 \wedge R[j] \leq d[i-1]), \\ 0 & \textit{otherwise}. \end{cases} \quad (12)$$

2. **Fixed output dimensionalities**: we define output dimensionalities $d[i], 1 \leq d[i] \leq t$ satisfying $\forall i : i > 1 \Rightarrow d[i] < d[i-1]$, which restrict teach matcher's output in the chain. Finally, the resulting score or index vector is a transformed version of the outcome of the combination technique using all m matchers accounting the final dimensionality reduction to $d[m]$ ranks. The combination method for serial classifiers is applied m times (after each matcher) instead of just once for parallel combination.

While for dimensionality reductions by a constant factor a still the number of matches increases linear with additional users (approximately $t \cdot \sum_{i=0}^{m} a^{-i}$ instead of $t \cdot m$ comparisons for t users and m matchers), this approach bears two advantages: (a) new matchers cause little overhead in terms of processing time; (b) typical asymmetry of matching time requirements can be exploited to reduce total processing time. Matching algorithms may coarsely be divided into two types, (a) distance-based algorithms, which compute simple (Euclidian, Manhattan or HD-based) distances between feature vectors at matching stage, and; (b) best-alignment based algorithms, which employ more sophisticated matching between templates in order to tolerate, e.g., rotation or translation. Whereas the employed Eigenfingers feature is a representative of the first type, matching of corresponding minutiae sets requires an estimation of the best alignment and therefore belongs to the second type. Using serial configurations as outlined above, a (possibly dynamic, dependent on the number of members) set of fast matchers can reduce the set of candidate matches up to a point where more costly, but accurate matchers are involved in the matching process.

5 Experiments

Our assessment of the introduced single-sensor multi-instance Fingerprint and Eigenfinger-based biometric system targets the following issues:

- **Question 1**: *Which unimodal performance with respect to accuracy and processing time of individual fingers can be achieved in both verification and identification mode?*

- **Question 2**: *Does fusion rule performance depend on the type of input data (intra-feature or cross-feature fusion)?*

- **Question 3**: *Do weighted versions of the simple fusion methods show significantly better performance than their unweighted counterparts?*

- **Question 4**: *Which performance with respect to processing time and accuracy can be expected if serial instead of parallel combinations are employed in identification mode?*

As the main performance indicator, the equal error rate (EER), defined as the error where false match rate (FMR) and false non-match rate (FNMR) are equal, has been selected for verification mode assessments. We also give zero false match rates (ZeroFMR, the lowest FNMR for zero false matches) and zero false non-match rates (ZeroFNMR, the lowest FMR for zero false non-matches) for the assessment of high-security and high-convenience scenarios, respectively. Single matchers are also depicted in form of a receiver operating characteristics (ROC) curve plotting pairs of FMR and FNMR values for a given threshold. For weight optimization, we use the area under the ROC curve (AUC) measure in order to favor *flatter* ROC curves. Identification mode results are compared using the Rank-1 Recognition rate.

5.1 Setup

Due to the absence of large-scale publicly available hand databases supporting the required resolution and permitting the parallel extraction of multiple modalities out of a single scan of the human hand, two custom test sets A and B of right hands in 500 dpi and 8-bit gray-scale mode have been acquired at our university. All 443 samples of 86 volunteers (82.4% male, approximately 5 samples per person) in database A and 63 hand images of 31 users (57.1% male, approximately 2 samples per person) in database B were captured in a controlled environment with the HP Scanjet 3500c sensor placed in a box with a round hole at one end for hand insertion (in order to minimize environmental light). Users were advised to touch the sensor, spread their fingers and try not to move during acquisition, but they were free to choose an arbitrary placement on the sensor. The acquisition protocol allowed watches and rings. None of the captured 4250×5850-sized images were excluded from the dataset, even if instructions were violated, resulting in a total failure to acquire (FTA) rate of 0.9% for set A. No failures were reported for set B. For closed set identification test set A is sub-divided into 4 different enrollment sets using each a different sample per class as enrollment template.

5.2 Results

In order to estimate the performance improvement of presented (weighted) score-level fusion techniques, we first assessed Question 1 targeting the accuracy of unimodal Minutiae and Eigenfinger matchers on individual fingers using all possible combinations of samples in set A (909 genuine and 95232 imposter comparisons). Figure 7 depicts all results in form of ROC curves and Table 1 lists performance measures targeting both accuracy and processing time.

An EER-ranking of individual fingers resulted in: index (1.29%), middle, ring, thumb and last, little finger (8.94%). When compared with evaluations based on separate thumb scans in [17] (which report the highest FRR-accuracy at 0.01% FAR for this finger), it is interesting to see, that the thumb's performance is inferior in systems operating on plantar scans of the entire hand (such as in [10] where its ROC curve is classified least accurate and even worse than for the little finger, possibly caused by missing finger alignment). Another difference to [10, 17] is the good performance of the index compared to middle and ring finger, which obviously reflects our system design cropping fingerprint regions depending on the finger length with respect to the adjacent finger valleys. Thus, we conclude that the size of the finger region is a crucial factor for individual performance. The best found ZeroFMR was 6.16% (index) and the best ZeroFNMR was 48.09% (middle). For the Eigenfinger algorithm, the middle finger performed best in terms of EER (2.53%), followed by ring, little, index and thumb (15.00%). [12] reported the same ranking behavior. Furthermore, we did not observe a different ranking behavior when using minimum half total error rate (MinHTER, the minimum of the $\frac{1}{2}$-weighted sum of FMR and FNMR at a given threshold) as comparator for both Minutiae and Eigenfingers. The best ZeroFMR is provided by the middle finger (58.09%), the ring finger is best-suited for convenience scenarios with 21.33% ZeroFNMR. When looking at closed-set identification performance Rank-1 Recognition rates in the order of $85.6 - 99.1\%$ for Minutiae and $56.7 - 91.6\%$ for Eigenfingers could be achieved for a medium-sized gallery (86 classes). Compared to [14] identification performance for Eigenfingers is lower (they report Rank-1 Recognition rates in the range of $94.9 - 97.1\%$ for their PCA-based digitprint feature) which may be caused by the small number of training samples for eigenspace computation and PCA-coefficients (25 instead of 100) in this work. Regarding processing time performance it becomes evident, that Minutiae matching is more time consuming (average matching times of approx. $29 - 59$ $milliseconds$ (ms) per comparison, resulting in total average processing times in a range of $2478 - 5225$ ms per identification request) than Eigenfinger processing (features could create a ranking vector in almost less than 1 ms). More accurate Minutiae-based matchers are observed to exhibit longer average processing times than less accurate ones. This is obviously caused by the fact that larger minutiae sets require more processing time in order to find an optimal alignment, but on the positive side make false positive matches unlikely to occur.

Regarding Question 2 we assessed performance of unweighted fusion methods, listed in Table 2. For intra-feature comparisons on set A all combination methods except the Min method resulted in better EER results than the best unimodal matcher. EER could be reduced by $50 - 84\%$ in case of Minutiae scores and $10 - 43\%$ in case of Eigenfinger scores for Max, Median, Prod and Sum combinations. For these methods also ZeroFMR (improvements by 89% in case of Minutiae and 72% for Eigenfinger) and ZeroFNMR (improvements by 93% in case of Minutiae and 52% for Eigenfinger) are generally lower than for each unimodal matcher. Similar results are obtained when comparing rules using MinHTER. Presumably,

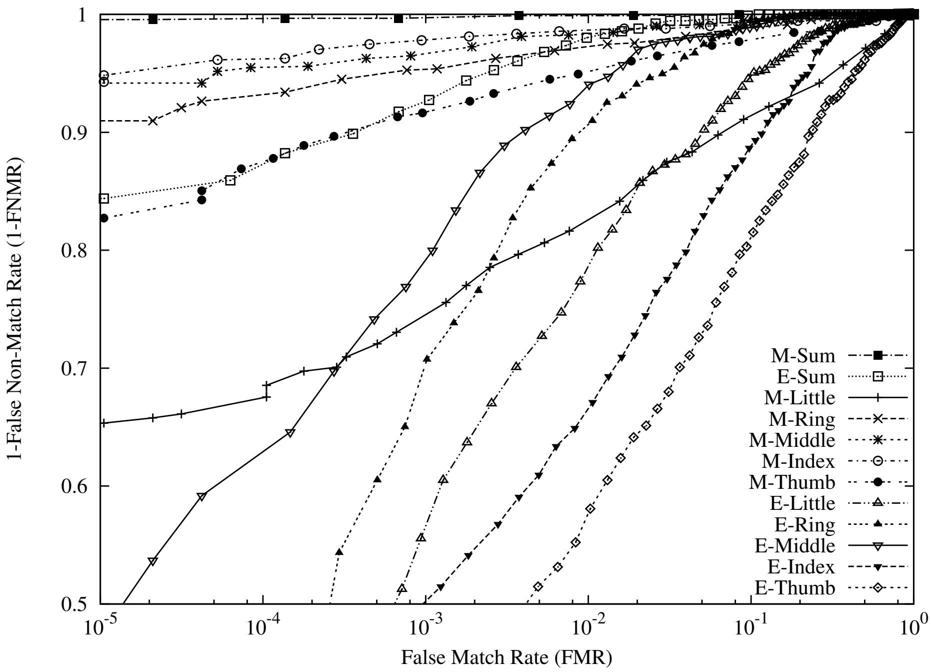

Figure 7 ROC for single Minutiae and Eigenfinger matchers as well as the Sum combination method.

Table 1 Unimodal verification performance by means of EER, ZeroFMR, ZeroFNMR (in percent) and Average Matching Time (in milliseconds) on set A, as well as closed-set identification performance in terms of Rank-1 Recognition Rate (in percent) and Average Processing Time (in milliseconds).

	Minutiae scores					Eigenfinger scores				
	Little	Ring	Mid.	Index	Thu.	Little	Ring	Mid.	Index	Thu.
EER	8.94	2.30	1.50	1.29	3.33	7.31	3.80	2.53	10.66	15.00
ZeroFMR	36.30	10.45	6.93	6.16	17.93	85.48	80.75	58.09	76.90	85.14
ZeroFNMR	93.51	72.18	48.09	98.88	99.65	75.81	21.33	21.86	75.25	90.73
MatTime	28.63	48.62	58.59	58.79	47.14	0.003	0.006	0.005	0.007	0.015
Rank-1	85.6	98.0	98.8	99.1	96.7	76.4	89.7	91.6	68.1	56.7
ProcTime	2478	4205	5111	5225	4090	< 1	< 1	< 1	< 1	< 1

the best score combination technique turned out to be the Sum of min-max-normalized scores in both Minutiae and Eigenfinger scenarios exhibiting a flatter ROC curve than each unimodal matcher, see Fig. 7. An evaluation on set B resulted in a similar behavior, however for Minutiae more than one method yields perfect separation. The Min method turned out to be unusable in both Minutiae and Eigenfinger recognition scenarios since almost all performance measures degrade. This result supports theoretical and practical considerations in [7], who show that the statistically motivated Sum rule outperforms the other Min, Max, Product and Median rules in case of combining different estimates of the same posterior probabilities. [13] employ fusion of LDA-based fingerprint, digitprint and palmprint features examining (among others) Max, Min, Prod and Sum rules (on min-max normalized scores) and report $13 - 99.8\%$ reduction in EER as well as a different ranking behavior (Product, Sum, Min, Max in the order of accuracy). Comparing their results with our experiments we conclude, that Min and Max as well as the relative performance differences between Product and Sum depend on the type of underlying score distributions. However, Product and Sum are almost always among the two best untrained rules, which is consistent with results in [13] also for different normalization techniques. For cross-feature combination of all Minutiae and Eigenfinger scores, the best performance of unweighted methods with respect to EER is delivered by the Product score combination (0.08%), closely followed by Sum (0.11%) and yielding a total improvement of 94% compared to the best individual matcher and 62% compared to the best unweighted combination method on Minutiae scores only. While the Sum method proved to be the best alternative in case of combining solely Minutiae or Eigenfinger scores, the Product combination exhibited better results in the cross-feature (heterogeneous multiple-matcher and multiple-instance combination of Minutiae and Eigenfinger scores) case with also low ZeroFMR (0.55%) and ZeroFNMR (0.14%) values. Min and Max methods delivered unsatisfactory results, see Table 3. A reason for this behavior becomes visible, if genuine- and imposter-score distributions for Minutiae and Eigenfinger are inspected (see Fig. 8 for distributions for the best-performing Minutiae and Eigenfinger instances). The imposter-score distribution for Minutiae-based matchers exhibits low mean and rather small variance. Thus, the Min method is oversensitive to Minutiae scores, while Max tends to ignore Minutiae scores resulting in unsatisfactory results.

Table 2 Fusion results of unweighted and weighted combination methods by means of EER, ZeroFMR and ZeroFNMR values (in percent) for Minutiae scores and Eigenfinger scores on sets A and B.

	Fusion of Minutiae scores						Fusion of Eigenfinger scores					
	EER		*ZeroFMR*		*ZeroFNMR*		*EER*		*ZeroFMR*		*ZeroFNMR*	
	A	B	A	B	A	B	A	B	A	B	A	B
Max	0.22	0.00	2.64	0.00	45.04	0.00	2.27	1.58	56.00	26.47	10.26	1.72
Median	0.65	0.05	1.65	2.94	20.35	0.05	1.88	2.70	37.07	20.59	26.63	3.18
Min	3.20	2.42	11.44	11.76	100	4.69	6.45	2.94	41.47	32.35	67.99	19.39
Product	0.31	0.00	0.88	0.00	3.21	0.00	1.88	2.69	18.92	17.65	19.03	3.07
Sum	0.21	0.00	0.66	0.00	13.80	0.00	1.45	1.48	16.28	17.65	10.45	1.82
W-Max	0.31	0.15	2.20	2.94	7.50	0.16	1.79	1.14	60.51	32.35	12.45	1.25
W-Median	0.37	0.15	1.76	5.88	1.65	0.16	1.49	0.31	33.11	23.53	5.82	0.31
W-Min	1.29	2.94	5.28	5.88	42.11	20.74	2.38	2.94	67.22	35.29	10.80	4.59
W-Product	0.16	0.00	0.88	0.00	1.69	0.00	1.31	0.45	14.19	17.65	4.24	0.47
W-Sum	0.11	0.00	0.55	0.00	2.97	0.00	1.20	0.41	17.38	17.65	5.25	0.42

Table 3 Fusion results (EER, ZeroFMR and ZeroFNMR in percent) on set A, if all 10 Minutiae and Eigenfinger scores are combined.

	EER	*ZeroFMR*	*ZeroFNMR*
Max	2.02	41.91	10.26
Median	0.22	2.53	4.72
Min	3.63	11.44	100
Product	0.08	0.55	0.14
Sum	0.11	1.21	1.97

In order to obtain answers to Question 3, we evaluated weighted versions of the presented combination techniques. Set A has been employed to compute optimal weights with respect to the AUC performance measure using an exhaustive discrete search in $[0, 1]$ for a given step size. This step size has been selected as $\frac{1}{10}$ in case of Max, Min, Median and Product combination, and $\frac{1}{20}$ for Sum (using only weights summing up to 1). From the results in Table 2 we can see, that it is an oversimplification to say that weighted combination

Table 4 Parallel versus serial combination performance (Rank-1 Recognition Rate in percent and Average Processing Time in milliseconds) for closed-set identification mode combining Minutiae-Index, Minutiae-Middle, Eigenfinger-Middle, Eigenfinger-Ring.

	Parallel combination		Serial combination (configurations 1 and 2)			
	BordaCount	ScoreSum	BordaCount1	BordaCount2	ScoreSum1	ScoreSum2
Rank-1	99.7	99.9	99.2	99.4	99.9	99.8
ProcTime	10338	10338	2561	8110	2550	8109

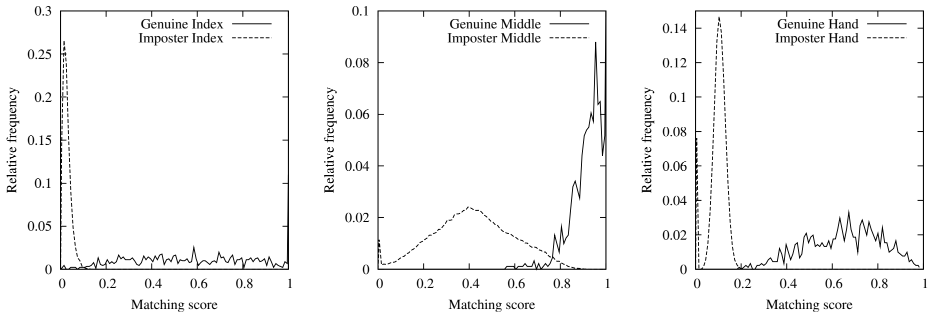

Figure 8 Genuine and imposter score distributions for Minutiae-Index (left), Eigenfinger-Middle (middle) and Product (right).

schemes result in generally higher accuracy, since (a) by optimizing the AUC performance EER, ZeroFMR or ZeroFNMR may increase and (b) even better performance on training data (set A) can not automatically be extended to unseen objects (set B). This behavior can also observed when MinHTER is used for optimization - resulting in an even worse degradation of ZeroFMR and ZeroFNMR values - and may be caused by the problem of overfitting. Thus, regarding Question 3, solely Weighted Product and Sum combination yielded higher accuracy for almost all reported rates or retained perfect separation in both training set A and test set B. Generally, on the training set A weights could improve EER performance of unweighted combination methods by up to 63%.

Finally, Question 4 is targeted by an identification experiment comparing parallel and serial combinations of the 2 most accurate matchers for both Minutiae and Eigenfinger features. In our serial configuration setup we conservatively defined a class reduction factor of two, i.e. $d[0] = \frac{t}{2}, d[i+1] := \frac{d[i]}{2}$, and examined two natural choices for the order of matchers:

- **Configuration 1**: this configuration selects fast classifiers at lower ranks followed by more costly features, i.e. the order is *Eigenfinger-Middle, Eigenfinger-Ring, Minutiae-Index, Minutiae-Middle*.
- **Configuration 2**: by selecting matchers in the order of accuracy we try to avoid an early exclusion of the genuine identity: *Minutiae-Index, Minutiae-Middle, Eigenfinger-Middle, Eigenfinger-Ring*.

Results for parallel and serial combinations are outlined in Table 4. Presumably, in both configurations serial classifiers can almost retain high accuracy of parallel approaches (BordaCount reports slightly worse accuracy with $99.2 - 99.4\%$ instead of 99.7%, serial ScoreSum combinations perform almost equally well with $99.8 - 99.9\%$). But significant savings of processing time are feasible for serial configurations (up to a factor of 4 using the fast configuration, and at least by over 20% using the conservative configuration) reducing total matching time from over 10338 ms to 2550 ms. Generally, ScoreSum combination performs better than BordaCount, which is not surprising, as it retains more discriminative information. Finally, we applied an exhaustive search for an optimum configuration of matchers (using a separate randomized training database and restricting the search to the 4 preselected matchers) with respect to a cost function with weights $\omega_1 = 1, \omega_2 = 10^{-5}$ on Rank-1 Recognition and Average processing Time. The best serial combination turned out to be ScoreSum considering only three of the four matchers (*Eigenfinger-Middle, Eigenfinger-Ring, Minutiae-Index*) with rather fast reduction of dimensions 9, 4, 1 yielding a total accuracy of 98.7% at 616 ms (99.7% at 591 ms on training set).

6 Conclusions

We have introduced a multi-instance Fingerprint and Eigenfinger-based biometric system and verified by experiment, that a combination of matching scores can increase performance significantly, and thus tolerate the application of common flatbed scanners for Fingerprint and Eigenfinger processing. As a by-product of this evaluation, we have examined the performance of (weighted) score combination methods based on min-max-normalized scores in the given context of cross-feature and intra-feature multiple-instance fusion. Simple Sum turned out to be best-suited for the separate combination of Minutiae and Eigenfinger scores with a total EER of 0.21% for Minutiae and 1.45% for Eigenfinger using a medium-sized dataset. Product combination delivered lowest error rates of 0.08% EER, 0.55% ZeroFMR and 0.14% ZeroFNMR in the total combination scenario. Weights obtained by exhaustive search could not be successfully applied to unseen objects for Max, Median, and Min. Solely Weighted sum or product yields constantly better results also on unseen objects. Serial classifiers turned out to decrease processing time significantly compared to parallel approaches and to retain high accuracy of their parallel counterparts. Serial Score Sum with a performance of 99.9% correct identifications at an average total processing time of 2550 ms (compared to 10338 ms for Parallel Score Sum) reported even lower processing time requirements than the most accurate single matcher (Minutiae-Middle with 98.8% at 5111 ms). Further work will concentrate on larger datasets, parameter choice for serial classification and different approaches to weights estimation.

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