

Hand Biometric Case Study

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This section presents a summary of four papers on hand mobile biometrics. Among the four, only the first one uses a touch method, while the other three use a touchless method. Overall, method and experimental results are compared and tabulated at the end of this section.

The first paper discusses Tartz and Gooding's study [1] on hand biometric authentication method using raw capacitance data on a mobile phone.

The algorithm follows the following sequence: raw capacitance data acquisition, preprocessing, two-step segmentation, feature extraction, matching, and decision-making.

The data are obtained by placing the full four fingers (excluding the thumb) and the top part of the right hand palm for about 3 s on a 7-inch screen mobile phone with a 40×64 resolution display that is connected to a data logger. All noises are normalized and filtered.

Next, the images are segmented. The first segmentation process concerns the finger length features. In this step, the capacitance sensor data are averaged and all the sensor rows are totaled and plotted. With the touch capacitance sensor, any crease in the hand appears as a dip in the curve—the deeper the crease, the sharper the dip. Using this technique, the fingers can be separated from the palm by first looking at the end of the curve and then locating the final sharp drop, which is interpreted as the longest finger. Next is locating an earlier sharp drop in the curve that

lies within certain limit from the final sharp drop. This one is interpreted as the deep crease between the palm and the fingers. Anything between this dip and the final dip are extracted as the finger length features.

The second segmentation extracts finger width features. This step takes only the finger data, sums the capacitance touch sensor columns, and plots the sum result. The dips in the curve are interpreted as separation between the four fingers from which the finger width features are extracted. The extraction results from these two segmentation processes (finger length and finger width) are then used to create finger profiles. These profiles are the features used for matching and decision-making.

This raw capacitance study was done twice. The first study consists of 8000 comparisons taken from 40 subjects (20 males and 20 females) aged 18–58. Out of eight data collection trials, the first three trials are used as the template for matching, while the rest trials are used for authentication attempts. The study yielded a 2.5% equal error rate (EER). Results are calculated using normalized coefficient correlation (NCC) in matching and then varying the threshold value. The second study is a longitudinal study of 6100 comparisons, taken from 10 subjects (five males and five females).

There were also eight data collection trials, but this one is taken over the course of only 1 month. It yielded a 2.3% EER.

While the previous study is using touch for authentication, many studies in hand biometrics opted for a contactless method. Chora and Kozik [2] proposed a contactless mobile hand biometric that is based not only on palm print but also on knuckles features. The palmprint features are extracted using three-valued mask function, while the knuckle features are extracted using Probabilistic Hough Transform (PHT) and Speeded Up Robust Features (SURF). The images are taken using standard mobile cameras.

In palmprint feature extraction, the palmprint images are acquired using mobile phone cameras. The images are preprocessed by detecting the skin color, determining the corners, separating the palm from the background, and marking the most significant points in the palm to obtain the rectangular shape features.

Skin color detection is done by using a specific set of RGB color space to classify a section of an image as skin: $R > 95$, $G > 40$, $B > 20$, $\max(R, G, B) - \min(R, G, B) > 15$, $|R - G| > 15$, $R > G$, $R > B$. Corner or edge determination is done by blurring the image. Separating palm from the background is done through binarizing the image with the value of 1 for the palm and 0 for the background. Although the study extracted both polygonal shape

palm region and rectangular shape, only the rectangular shape is used in the next extraction step.

The rectangular shape region is obtained by locating seven points and four lines on the palm in order to perform palm rotation. Finding this seven points started from first locating a P.0 point representing the longest finger, which is the tip of the middle finger, then locating four more points: one at the joint between the index and middle fingers (denoted as P.1), one at the joint between the middle and ring fingers (denoted as P.2), one at the joint between the index and the thumb (denoted as P.3), and another at the joint between the ring and little fingers (denoted as P.4). The first line L1 is created by connecting P.1 and P.4. Using P.1 as a pivot, two more lines can be generated from L1: (1) L2, by rotating L1 30° counterclockwise and (2) L3, by rotating L1 60° counterclockwise. Another line, L4, is determined by using P.4 as pivot and rotating L1 60° clockwise. The following three points are generated from the intersection of each of these lines with the palm edge: (1) P.7, being the intersection of L2 and the palm edge; (2) P.5, being the intersection of L3 and the palm edge; and (3) P.6, being the intersection of L4 and the palm edge. Connecting these seven points create the polygonal palm region and combining this polygonal shape with L1 allows palmprint rotation. The rectangular palm region can be extracted from this rotation result by once again locating P.1 and P.4.

The next extraction step concerns the mask function generation and size. The mask is in the form a matrix that contains only three values: -1, 0, and 1. Chora and Kozik investigated three methods to select the appropriate mask (randomly, manually, and by implementing “eigen-palms”).

They also investigated three different mask sizes (15×15 , 20×20 , and 45×45) that generate three different resolutions. The results are evaluated based on effectiveness, which is measured by computing the percentage of the lowest equal values of false acceptance ratio (FAR) and false rejection ratio (FRR).

Chora and Kozik's palmprint study used 252 images taken from 84 subjects (three images per subject). Their results showed that the lowest FAR = FRR percent rates are yielded by the eigen-palms mask generation method (FAR = FRR of 2.5%) and the 45×45 mask (FAR = FRR of 1.7%).

To improve performance, Chora and Kozik proposed to combine the palmprint features with the knuckle features, although they did the palmprint and knuckle experiments separately. Their knuckle feature extraction experiment sample images are preprocessed by (1) obtaining the

lines on knuckle skin where the fingers bend and (2) removing the noise using PHT. The classification method had three steps. First, 50 images are selected using basic feature vectors. Second, five images with the lowest distance are selected using PHT feature vectors. Third, one image out of these five is selected using the SURF descriptor. In the case where the SURF descriptor failed to find an image, the first of the five PHT results is used.

For the knuckle identification study, Chora and Kozik used the IIT Delhi Knuckle Database. The database contains 790 images that are taken from 158 subjects aged between 16 and 55. The images are in bitmap format with the resolution of 80×100 pixels.

The experiment yielded an average EER value of 1.02%. The PHT method by itself yields 95.56% accuracy, while the SURF 85.57%. Combined PHT-SURF method, however, yielded better result than PHT-only or SURF-only methods.

Another contactless mobile hand biometric is proposed by Franzgrote et al. [3]. Their method allows mobile palmprint authentication system using hand orientation normalization method and accelerated Competitive Code. Their preprocessing stage mainly concerns region of interest (ROI) extraction, which is achieved by performing hand orientation normalization, valley points determination, and ROI formation. The image resolution started with 640×480 and was later reduced to 100×100 after ROI extraction. The images are taken using a smartphone camera.

The algorithm used is the accelerated version of Competitive Code, which is first proposed by Kong and Zhang [4]. The original Competitive Code consists of two steps: (1) code computation and (2) matching. Franzgrote et al. [3] modified the code computation step by using a different set of Gabor functions described as the following:

$$\Psi(x, y, \theta) = e^{-\frac{x'^2 + y'^2}{2\sigma^2}} \cos\left(2\pi \frac{x'}{\lambda} + \phi\right)$$

$$x' = x \cos \theta + y \sin \theta$$

$$y' = -x \sin \theta + y \cos \theta,$$

where $\sigma = 0.3$, $\lambda = 4$, $\phi = 2$, and $\theta = 0$.

The six two-dimensional Gabor filters (x, y, θ) with orientation θ_p are applied to the ROI $I(x, y)$ to create the following rule for the winner to take all [3]

$$\arg \min_{\theta_p} [I(x, y) * \Psi(x, y, \theta)].$$

In the matching step, Franzgrote et al. computed the angular distance using bitwise operations [3]

$$D(P, Q) = \frac{\sum_{x=1}^n \sum_{y=1}^n \sum_{i=1}^3 P_M(x, y) \wedge Q_M(x, y) \wedge (P_i^b(x, y) \oplus Q_i^b(x, y))}{3 \sum_{x=1}^n \sum_{y=1}^n P_M(x, y) \wedge Q_M(x, y)},$$

where P and Q are competitive codes, n is the size, P_M and Q_M are the binary masks representing nonpalmprint pixels, P_i^b and Q_i^b are the i -th bit plane of P and Q , respectively, \wedge is the bitwise operator “and,” and \oplus is the bitwise operator “exclusive or.” The Competitive Code is then accelerated through comparing only a smaller section, calculating the matching score, and applying it to the whole.

Franzgrote et al. used 600 palmprint images that are taken from 30 subjects; 10 images per hand for each subject. The results show that starting from 0.46 threshold value, the palmprint matching success rate achieved higher percentage and much lower rejection rate. Regarding the computation time of the Competitive Code, the code computation step in the nonaccelerated competitive code is 87 ms, while its accelerated version is 5 ms. Moreover, the code matching step of a regular Competitive Code took 4.258 s to complete, while its accelerated version took only 0.116 s.

Also contributing to contactless mobile hand biometric authentication method is Ota et al. [5]. Their study introduced a variation to the previously discussed method, as they used remote palmprint recognition system. In this method, a mobile phone acts as an end-user system that communicates with a server on which a palmprint authentication algorithm is stored.

The algorithm has two stages as it combines a preprocessing method that includes a technique proposed by Yörük et al. [6] with a palmprint recognition algorithm proposed by Ito et al. [7–12] that is based on

phase-only correlation (POC). The new preprocessing stage comprises six steps with the fifth step using the method proposed by Yörük et al.

The first preprocessing step is image extraction. The process extracted only the right half of the image since key point detection only requires the right half of an image. The image is then reduced to half its size in the second step. The third step converts the previous RGB color space to HUE saturation value (HSV) to allow skin color detection using the following:

$$\begin{cases} 0 \leq H \leq 50 \\ 300 \leq H \leq 360 \end{cases}$$

The resulting image is then converted to binary image using the H channel. The fourth step is the opening process, which consists of the erosion and dilation processes. Each process is executed once using a kernel with a structuring element in a shape of a 3-pixel radius disk. The

fifth step is determining significant points. The algorithm determined significant points located at the joining points between the fingers; one between the index and middle fingers and another between the ring and little fingers. In the sixth step, these significant points are used to form a rectangular shape palmprint region. The image is then normalized and converted to grayscale. The resulting palmprint region is a 160×160 pixel grayscale image.

The next stage in the algorithm, which is the matching stage, consists of two steps. The first matching step maps between images using the POC, generating a 32×32 pixel block and 16 “corresponding points” [5]. The second matching step took this block and the corresponding points to compute the matching score.

In addition to combining two existing methods, Ota et al. proposed a remote system consisting of a mobile phone and a server. The mobile phone is used to take the palm images, convert these images using the above preprocessing method, send and receive data to and from the server, and display results. The server is used to store data, query the database, customize authentication service, compute the matching score, make decision regarding matching result, and send the result back to the mobile phone.

In this study, Ota et al. sampled 12 subjects, taking five pictures of each subject's left palm. Among the 1770 possible combinations for those 60 images, 120 combinations are used as genuine users to test the FRR, while

the 1650 combinations are used as impostor users to test the FAR value.

The results show that the lowest EER is 3.3% at 0.263 threshold value and that best accuracy is achieved when the minimum threshold is set to be greater than 0.182 and the maximum greater than 0.283. In assessing the computation time, Ota et al. found that the algorithm took 0.94 s to complete, while the communication between mobile phone and server took 5.48 s.

Excluding Franzgrote et al. study that presented the results using receiver operating characteristic (ROC) instead of EER, the lowest EER of the three-hand biometric study is 1.02%, which is achieved by Chora and Kozik's knuckle identification study. Although Chora and Kozik did the palmprint and knuckle study separately, each study generated the lowest EER. Considering a slightly lower number of subjects, Tartz and Gooding's results of 2.5% and 2.3% fare well with Chora and Kozik's. The lowest performance is 3.3%, achieved by Ota et al. in their remote palmprint recognition study. Table 14.1 shows how the four studies fare against each other.

TABLE 14.1 Comparison of Studies Done by Tarts and Gooding, Chora and Kozik, Franzgrote et al., and Ota et al.

Publication	Sensor	Subjects/ Database	Technique	Hand	Results (%)
Tartz and Gooding [1]	Mobile phone capacitance	40 subjects (1st) 10 subjects (2nd)	Capacitance	Right	EER = 2.5 (1st) EER = 2.3 (2nd)
Chora and Kozik [2]	Mobile camera	84 subjects	Palm print	Right	EER = 2.5 (eigen-palms) EER = 1.7 (45 × 45 size)
		IIT Delhi Knuckle Database: 158 subjects, bitmap format	Knuckle	Not described	EER = 1.02
Franzgrote et al. [3]	Smartphone camera	30 subjects	Palm print	Both	ROC curve
Ota et al. [5]	Smartphone camera	12 subjects	Palm print	Le	EER = 3.3

EER, equal error rate.

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