Developing a Contactless Palmprint Authentication System by Introducing a Novel ROI Extraction Method

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Abstract

In this paper, we propose a novel contactless palmprint authentication system where the system uses a CCD camera to capture the user's hand at a distance without any restrictions and touching the device. Furthermore, a novel and high performance region of interest (ROI) extraction method which makes use of nonlinear regression and palm model to extract the ROIs with high success is proposed. Comparative results indicate that the proposed ROI extraction method gives superior performance as compared to the previously proposed point-based approaches. To show the performance of the proposed system, a novel contactless database has also been created. This database includes images captured from the users who present their hands with various hand positions and orientations in cluttered backgrounds. Furthermore, experiments show that the proposed system has achieved a recognition rate of 99.488% and Equal Error Rate of 0.277% on the contactless database of 145 people containing 1752 hand images.

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1. Introduction

The recent research attention focused on the improvement of palmprint recognition systems can be ascribed to its commercialization potentials in real-world biometric applications. As a result, most of the end-users of this technology seek to deploy secure, accurate, hygienic biometric identification solutions. A contactless palmprint acquisition device can be the ultimate solution to alleviate such hygiene concerns. For this reason, the trend has been toward the contactless acquisition devices and developing robust approaches for contactless hand-based biometrics [1][2][3][4].

This paper presents a novel contactless palmprint recognition system with a novel region of interest (ROI) extraction method. The users present their hands without touching any guidance peripheral. Furthermore, there is no limitation about the scene behind the users' hand.

1.1. Related Works

In the literature, the first contactless palmprint image acquisition and recognition system was developed by Han et al. in 2007. This system [5] consists of a standard PC and an image capturing device that captures two images for each hand by two cameras. One of them is a NIR (Near Infrared) camera that captures NIR images with NIR lighting to segment hand regions under unconstrained scenes by hardware. The other one is a CMOS web camera used for capturing color hand images. In this system, users have to

22 open their hands and place them toward the camera at a distance from 35
23 cm to 50 cm.

24 Michael et al. developed 3 different contactless palmprint recognition
25 systems[6][3][7]. Their first developed system [6] involves a web camera,
26 a fluorescent light and an enclosure. The segmentation of the hands was
27 achieved by a simple algorithm (skin-color thresholding). In [3] where a
28 multi-modal palmprint and knuckle print system was presented, the lighting
29 source was replaced by a bulb emitted yellowish light. They also included a
30 dimmer to adjust the brightness of the light bulb. The third system [7] uses
31 additionally two biometric models: hand vein and hand geometry. To obtain
32 the vein images the system involves a second camera, infrared (IR) filter, a
33 number of infrared LEDs, and a diffuser paper.

34 In the recent work [8], Sato et al. have been proposed to normalize the
35 deformation arising from the different hand postures, for reliable palm image
36 matching. Their contactless system consists of a diffraction grating laser
37 and a high-speed camera. The geometric correction of the image has been
38 achieved by the measured 3D points with the use of diffraction grating laser
39 and grid pattern.

40 Other recent studies also include the mobile contactless biometrics [1]
41 and the simultaneous use of 3D and 2D hand information in the contactless
42 systems [2]. Although the mobile contactless palmprint systems allow ease
43 of use, their recognition performances are not satisfactory at present. On the
44 contrary, the proposed system in [2] gives superior recognition performance
45 in unrestricted schemes as compared to the mobile contactless systems, but
46 the cost and computation complexity of the system are very high, and the

47 3D digitizer can be affected by the ambient noise.

48 One of the important considerations in the contactless setting is how the
49 palm can be segmented from hands that have pose and orientation variations
50 within unrestricted background. Some of the recently proposed contact-
51 less palmprint systems [1][6] use monotone backgrounds for palm capturing
52 to eliminate the complex segmentation problems. The works performed by
53 [3][6], for instance, use skin color based segmentation and variations. But,
54 this approach gives poor segmentation results for the images which have
55 skin-colored backgrounds.

56 Because the use of pixel-based techniques leads to errors and in some sce-
57 narios they are not adequate for correct segmentation, Doublet et al. [9] pro-
58 posed to improve the skin color modeling approach with active shape model
59 (ASM). In our earlier work [10], we have proposed to use Active Appearance
60 Model for palm segmentation within unrestricted backgrounds which is also
61 used in this study. This method makes use of a combined statistical model
62 of shape and texture together to segment the palm images.

63 ROI extraction is one of the most important and influential steps for the
64 palmprint recognition/verification which is not emphasized as required in the
65 papers although it can directly affect the results. Almost all the methods
66 presented in the literature have extracted the ROIs with point wise manner
67 by using the valley points of the gaps between the fingers [11][12]. The
68 major steps of the most common method proposed by Zhang et al. [11] are
69 as follows: (i) Convert the grayscale image to a binary image. (ii) Obtain the
70 boundaries of the gaps between the fingers. (iii) Calculate the tangent of the
71 upper and lower gaps, which represents the y axis. (iv) Draw a line (x axis)

72 passing through the midpoint of two valley points which is perpendicular to
73 these points. (v) Extract a fixed size region based on the coordinate system.

74 In [12], Connie et al. proposed to utilize from the gap between middle
75 and ring finger. They drew two lines passing through the valley points of the
76 gaps and assigned the two corner points of the square region as the midpoint
77 of the index finger and little finger on these lines. Similarly, Badrinath and
78 Gupta [13] developed a new method inspired by the works of Connie et al.
79 and Zhang et al.. This method uses the tangent of the two gaps (reference
80 line) between the fingers. And the two corner points of the square region are
81 assigned as the midpoints of the fingers on the lines drawn at specific angle
82 with respect to the reference line.

83 The researchers in [6] have introduced an enhancement to ROI extraction
84 which utilizes from the pixel neighborhoods. According to this approach, a
85 pixel can be considered as a valley point if some of the neighboring points lie
86 in the non-hand region while the most of the neighbors are the points of the
87 hand region. In the work presented by Leng et al. [14], the regions of valleys
88 were determined after some morphological operations. And centroids of the
89 regions of the candidate valley points that satisfies all conditions (4, 8 and
90 16 point check) were chosen as the final valley points. In another paper [15],
91 the valley points of the gaps between fingers were selected by the modified
92 Harris Corner Detection algorithm.

93 Unlike the others, Li et al. [16] presented a ROI alignment refinement
94 method based on the principal lines to improve the verification accuracy.
95 They applied the iterative closest point method to estimate the transforma-
96 tion parameters of the images. The transformation was performed and the

97 new aligned ROI was then produced.

98 In the literature, there are many types of palmprint recognition algo-
99 rithms: Local feature-based [11], holistic-based [17], and hybrid [18]. Local
100 feature-based approaches extract local features from palmprint images and
101 use a matcher to compare them [11][4][19]. Holistic-based approaches extract
102 the features by regarding a palmprint image as a whole image, or a high di-
103 mensional vector. Appearance-based methods also called subspace methods
104 [17][20] are involved in this group. In many subspace methods, the feature
105 extraction methods (such as PCA, LDA or LPP) are combined with the spec-
106 tral representations. The Gabor feature based Kernel Fisher Discriminant
107 Analysis which gives superior results than other feature extraction methods
108 has been proposed in our recent study [21]. Hybrid methods [18], which
109 utilize from more than one feature extraction approaches were proposed to
110 improve the recognition accuracies [22].

111 1.2. Contributions of this paper

112 We have endeavored to develop a novel contactless palmprint recognition
113 system. Our contactless system consist of a CCD camera, a DC auto iris
114 lens, LED light sources, a standard PC, a touch screen and an enclosure to
115 acquire palmprint images, as shown in Fig. 1. The main contributions are:

- 116 • A novel contactless device for high quality palmprint image acquisition
117 in real environment is developed. The trade-off between quality and
118 flexibility (free hand placement in unrestricted environment) is opti-
119 mized for high recognition results.
- 120 • As a novelty, the usage of fitted palm model and nonlinear regression

(Least Squares Support Vector Regression) to extract the region of interests (ROI) of the palms is proposed. This model-based approach provides reliable ROI extraction that is robust to the small segmentation errors. Whereas point wise approaches are substantially affected from these errors.

- One of the most important stages in developing a contactless palmprint recognition system is to accurately segment freely positioned hands under unconstrained scenes. For that consideration, it is proposed to use Active Appearance Model [23] method for palm segmentation. In this study, the AAM method is configured specifically to achieve palm segmentation accurately for the contactless palmprint authentication system.
- A novel database for contactless system is constituted by collecting 1752 images from 145 different subjects who present their hands in various directions, positions under unrestricted environment.

2. Materials and Methods

2.1. Contactless Palm Image Acquisition System

In this work, our earlier restricted palmprint identity verification system [21] has been further developed to achieve an unrestricted contactless palmprint verification system. External view of the system is shown in Fig. 1. This system involves a standard PC with Intel Core2 Quad CPU, 4GB RAM and 500GB HD to execute authentication program written in C++ programming language.

Figure 1: External view of our palm image acquisition system and a hand presented to the system.

144 The capturing device is a low-cost CCD camera with DC auto iris lens
 145 which has 28mm focal length, maximum aperture of $f/2.8$ and wide angle of
 146 vision for viewing hand region completely. Shutter speed, focal aperture and
 147 focus adjustments of the camera have been made for the best image quality.
 148 Although the images taken with a low f-number gives focused hand images
 149 at a distance and out of focused background (leads to better segmentation),
 150 it is not suitable for the contactless biometric systems. The reason is that
 151 the distance between the hand and camera can be varied in different ses-
 152 sions which results in unfocused palm images. Furthermore, faster shutter
 153 speed can provide sharpened images for shaken hands, but it needs more
 154 illumination which removes the details of the palm texture.

155 To reveal the details in the palm image and to reduce the negative effect
 156 of the ambient lighting variations, LED-based light sources were located at
 157 a specific location and with a certain angle (as shown in Fig. 1). Further-

158 more, the intensity of the LED light was adjusted to an optimal value. The
159 bottom light source was located to remove the side effects of the 3D posture
160 variations, and the upper light source was located at the right side of the
161 enclosure with 45 degrees to make the wrinkles and ridges visible.

162 The subjects interact with the system by using a touch screen. In this
163 way, the verification errors caused by the erroneous usage of the system are
164 decreased. The camera and the light sources are controlled by an electronic
165 interface which communicates with PC via a serial port interface. The upper
166 surface shape of the enclosure is formed as a trapezoid hole due to the con-
167 cordance with the hand shape. Furthermore, wooden plates on two sides of
168 the enclosure were added for ensuring the proper presentation of the hands
169 to the system. Users' hands do not touch these wooden plates. They are in-
170 cluded to the system in order to guide users to present their palms correctly
171 with appropriate hand-camera distances. Thus, the probable presentation
172 errors which lead to unfocused palmprint images can be prevented as much
173 as possible.

174 The acquisition of the palm image is realized in such a way that the user
175 presents his/her hand about 20 cm above the CCD camera. There is no other
176 restriction to the users and to the background scenes.

177 *2.2. Hand Segmentation*

178 In our study, the segmentation of the hand was realized by an advanced
179 model based segmentation method named as AAM method. The construc-
180 tion of the appearance model was done by using our earlier proposed palm
181 model with 25 landmark points [10].

182 *2.2.1. Active Appearance Model (AAM)*

183 The AAM method [23] consists of two stages; model construction and
 184 model search. In both stages the shape vector, $\mathbf{s}$, is represented by the
 185 coordinates of the ℓ landmark points, $\mathbf{s} = (x_1, y_1, \dots, x_\ell, y_\ell)^T$. Then, a shape
 186 variation, modeled based on PCA, is defined by a linear combination of a
 187 mean shape, $\bar{\mathbf{s}}$, and n shape base vectors, $\mathbf{P}_s$:

$$\mathbf{s} = \bar{\mathbf{s}} + \mathbf{P}_s \mathbf{b}_s \quad (1)$$

188 where $\mathbf{b}_s$ is the shape parameter vector that controls the synthesized
 189 shape. After the mean shape is calculated, the training textures are warped
 190 onto the mean shape, $\bar{\mathbf{s}}$, in order to obtain shape free textures. Then, the
 191 texture model is given by:

$$\mathbf{g} = \bar{\mathbf{g}} + \mathbf{P}_g \mathbf{b}_g \quad (2)$$

192 where $\mathbf{g}$ is the synthesized shape free texture, $\bar{\mathbf{g}}$ is the mean texture vector,
 193 $\mathbf{P}_g$ is the eigenvector of texture and $\mathbf{b}_g$ is the texture parameter vector. Com-
 194 bined appearance model parameters are obtained by concatenating weighted
 195 shape parameters and texture parameters.

196 In the model search, the texture error (E) between the model texture
 197 (g_m) and the image texture (g_s) is evaluated with the Euclidean distance
 198 and minimized by tuning the model and pose parameters. The optimization
 199 of the model is realized by assuming a linear relationship between parameter
 200 changes, $\delta \mathbf{c}$, and pixel differences, $\delta \mathbf{g}$, for facilitation of the computation.

$$\delta \mathbf{c} = \mathbf{A} \delta \mathbf{g} \quad (3)$$

201 where the matrix $\mathbf{A}$ is estimated by the regression at the training stage.
 202 For large models, regression has been replaced by estimating the Jacobian,
 203 $\partial(\delta\mathbf{g})/\partial\mathbf{c}$, over the training set. This gives better results and far less com-
 204 putation overhead. More details on the AAM method can be found in [23].

205 2.2.2. Palm Modeling

206 In the palm modeling, 25 anatomical landmark points (as shown in Fig. 2),
 207 corresponding to the borders of the shape, are manually selected, as in [10].
 208 Ten of them describe the end points of the palm model and can be located
 209 by sliding their positions forward or backward along the border of the hand
 210 shape. This flexibility make the presentation of the whole fingers or up-
 211 per/lower palm arcs unnecessary (presenting approximately 50% of the upper
 212 and lower palm arcs is sufficient).

213 The rest 15 landmark points are also used to model the gaps between the
 214 fingers, the upper and lower palm arcs. Each gap in the model is represented
 215 by three points (valley, left and right corner points).

216 2.2.3. Implementation of the AAM

217 In our studies, to implement the AAM method, we used the open source
 218 AAM API library [24], coded in C++ programming language by M. Stegmann.
 219 Use of this library, allows the users to change many parameters of the im-
 220 proved version of the AAM method. The applied parameter adjustments
 221 determined as optimum are listed below:

- 222 • In the model construction stage, the eigenvectors which are associated
 223 with the smallest eigenvalues were truncated (98% of the sum of the
 224 eigenvalues were involved).

- 225 • The optimization of the model was realized by estimating the Jacobian
226 over the training set.
- 227 • The initialization of the model search was performed by scanning a 5×5
228 mesh on the test image for all model parameters. Likewise, orientation
229 and scale of the models were set to the optimal values (5 scalings (0.75,
230 0.85, 1.0, 1.15, 1.25) and 5 orientations (-20, -10, 0, 10, 20)).
- 231 • The model was fitted in a two-stage procedure. In the first stage,
232 the optimum 15 models which have the minimum model reconstruc-
233 tion errors were determined and saved. In the second stage, fine grain
234 search was performed in these 15 models only. The fine grain search
235 was achieved by pattern search approximation. The numbers of the
236 iterations were selected as 15 and 25 for the first and second stages,
237 respectively. The convergence level was set to 0.00001.
- 238 • Damping factors [25] were used to improve the fitting performance and
239 determined as 1.0, 0.5, 0.25, 0.12, 1.25, 1.5.

240 *2.3. Region of Interest Extraction*

241 After palm image has been segmented, palmprint region, called Region of
242 Interest (ROI), is extracted for subsequent processes. This region generally
243 has a squared shape and involves sufficient information to represent the palm.

244 A novel regression-based approach is proposed for the extraction of ROI
245 which utilizes the hand shape model. Almost all the other approaches in the
246 literature are pixel-based, and hence a possible inaccurate selection of the
247 hand valley points will lead to vast erroneous extraction of ROI. The model-

248 based approach proposed in this study prevents the weakness of the pixel-
249 based approaches by using the palm model as a whole in the regression. The
250 major performance difference between the model and pixel-based approaches
251 arises from the accurate determination of the hand orientation.

252 Although the proposed approach is suitable for model-based methods, it
253 can be easily adapted to the traditional segmentation methods by determin-
254 ing landmark points.

255 The four major steps in the extraction of the ROI are:

256 **Step 1.** In our method, the orientation of each palm is characterized by
257 the slope (m) of a line ($y=mx+n$) which shows the main direction of the palm.
258 As a first step, a training set that contains hand images is constituted from
259 different shaped hands. Then the slope of each palm in this set is manually
260 determined by a supervisor and enrolled into a palm slope database. These
261 slopes are used to estimate the orientation of each palm as a function of
262 landmark points in the following steps.

263 **Step 2.** The orientation of each palm is associated with the positions
264 of the landmark points which constitute the palm model, and trained with
265 a nonlinear regression method. Thus, the small errors at the determination
266 of the landmark points do not affect the palm orientation. In our study, we
267 have used Least Squares Support Vector Regression (LS-SVR) [26] method
268 with RBF kernel. This method is selected due to the following reasons:
269 low computational cost, performance, and enabling non-linearity for complex
270 structures. The method is given by the following optimization problem:

$$\min_{w,b,e} J_P(\mathbf{w}, e) = \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{\gamma}{2} \sum_{i=1}^N e_i^2 \quad (4)$$

$$\text{subject to } y_i = \mathbf{w}^T \varphi(\mathbf{s}_i) + b + e_i, i = 1, \dots, N \quad (5)$$

where y_i and $\mathbf{s}_i$ are considered as the orientation of a palm (m), and a vector formed by the positions of the landmark points ($\mathbf{s}_i = [P1_x, P1_y, P2_x, P2_y, \dots, P25_x, P25_y]$, respectively. $\varphi(\cdot) : \mathbb{R}^n \rightarrow \mathbb{R}^{n_h}$ is a mapping to a high dimensional feature space. e_k and b are the error and bias terms in the formulation. N is the number of samples and γ represents the error tolerance. This optimization problem means that the distances between the separating hyperplane and the training samples are precisely "1" unit (with the allowed error which is adjusted by the squared loss function).

The kernel form of the above problem is obtained by constructing the Lagrangian, eliminating $\mathbf{w}$, e , and applying kernel trick. The final formula is represented by the linear Karush-Kuhn-Tucker system:

$$\begin{bmatrix} 0 & \mathbf{1}_v^t \\ \mathbf{1}_v & \mathbf{K} + \gamma^{-1} \mathbf{I}_N \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \mathbf{y} \end{bmatrix} \quad (6)$$

where $\mathbf{I}_N \in \mathbb{R}^{N \times N}$ is an identity matrix, $\mathbf{K}$ is the kernel matrix, and $\mathbf{y} = [y_1; \dots; y_N]$, $\mathbf{1}_v = [1; \dots; 1]$, $\alpha = [\alpha_1; \dots; \alpha_N]$.

Step 3. For the test sample, a palm direction (see Fig. 2) which is searched for the ROI extraction is then estimated by using the palm model at the regression. This is achieved by the following formula in LS-SVR:

$$y(s) = \sum_{i=1}^N \alpha_i k(\mathbf{s}, \mathbf{s}_i) + b \quad (7)$$

287 where k is the kernel function, and s is the test sample.

288 **Step 4.** The upper and lower lines are then obtained as parallel lines to
289 the palm direction and passing tangentially to the curves of the upper and
290 lower palm arcs (see Fig. 2). The width of the palm can be determined by
291 measuring the distance between these two lines. A line which is perpendicular
292 to the upper and lower lines and tangent to one of the gaps between the
293 fingers that does not intersect with the other gaps at two points is defined
294 as a reference line. This line can be visualized as the innermost gap between
295 the fingers. The distance between the upper and lower lines, L , is then used
296 to extract the ROI of the palm, and is shown in Fig. 2. To form the ROI, the
297 upper, lower and reference lines have to be shifted toward the center of palm
298 by $0.07L$, $0.07L$ and $0.02L$, respectively. The resultant square shaped ROI
299 with edge length $0.86L$ is formed between the intersections of these lines.
300 The shifting amount and the size of the ROI are determined empirically with
301 the aim of reducing the negative effects caused by the various hand postures.
302 This approach also ascertains to retain the maximum palmprint information.
303 The position of the lines and the extracted ROI are shown in Fig. 2.

304 Finally, since the ROI sizes can be varied due to the distance between the
305 hand and the camera, the extracted ROI images are resized to a 128×128
306 pixel resolution. Furthermore, the hands can be also in different sizes.

307 2.4. Palm Feature Extraction

308 In our earlier work [21], The Gabor-based kernel Fisher discriminant anal-
309 ysis method for online palmprint verification system has been employed to
310 control the entries of the PC laboratory of our department since October
311 2009 [27] with a great success. In this paper, this method is implemented

Figure 2: Illustration of the proposed Region of Interest (ROI) extraction method.

to achieve contactless palmprint recognition/verification experiments. The method consists of two stages: Gabor wavelet feature representation of the palmprint images, and Kernel Fisher Discriminants for meaningful feature extraction (which has more discriminative power).

2.4.1. Gabor Wavelet Feature Representation

In Gabor wavelets, basis function is Gabor kernel which is Gaussian modulated by a complex sinusoidal:

$$g(x, y) = \left(\frac{1}{2\pi\sigma_x\sigma_y} \right) \exp \left[-\frac{1}{2} \left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) + 2\pi j W x \right] \quad (8)$$

where σ_x and σ_y are the horizontal and vertical standard deviations of Gaussian envelope, and W is central frequency. Gabor wavelets can be ob-

321 tained with dilations and rotations of the Gabor kernel.

322 Because Gabor functions form a non-orthogonal basis set, filtered images
 323 has redundant information. Manjunath and Ma [28] developed a strategy
 324 to reduce this redundancy. In our experiments, to reduce the computational
 325 cost, this scheme was used with five different scales and four orientations of
 326 Gabor wavelets. Parameters of the Gabor function were selected as in [21].

327 2.4.2. Kernel Fisher Discriminants (KFD)

328 Fisher Linear Discriminants (FLD) aims at finding the best separation
 329 hyperplane via maximizing the between-class variances (S_B) and minimizing
 330 the within-class variances (S_W). Nonlinear version of FLD, called KFD,
 331 can be implemented in a similar manner by adding the kernel trick [29].
 332 Alternatively, Mika et al. [30] proposed to use convex quadratic programming
 333 (optimization) problem for large number of samples:

$$\min_{\alpha, b, \xi} \|\xi\|^2 + CP(\alpha) \quad (9)$$

334 subject to:

$$\mathbf{K}\alpha + \mathbf{1}b = \mathbf{y} + \xi \quad (10)$$

$$\mathbf{1}_i^T \xi = 0, i = 1, 2 \quad (11)$$

335 for $\alpha, \xi \in \mathbb{R}^\ell$, and $b, C \in \mathbb{R}$, $C \geq 0$. Besides, define $\mathbf{1} \in \mathbb{R}^\ell$ as the
 336 vector of all ones. Here, $\mathbf{K}$ is the kernel matrix, b is the bias term, C and P
 337 are regularization function and the regularization parameter. The term $\|\xi\|^2$
 338 minimizes the variance of the error. The first constraint pulls the outputs of
 339 the each sample to its class and the second ensures that the average outputs

for each class is the label. Then, the KFD features for the test sample $\mathbf{x}$ is computed by:

$$(\mathbf{w} \cdot \Phi(\mathbf{x})) = \sum_{i=1}^{\ell} \alpha_i k(\mathbf{x}_i, \mathbf{x}) \quad (12)$$

where $k()$ is the kernel function and ℓ is the number of training samples.

The KFD explained above can be easily extended to multi-class problem with the output coding techniques. In our experiments we used RBF kernel and one-versus-all (1vsA) output coding techniques due to the achieved superior performance compared to other approaches.

2.5. Matching and Classification

In this study, Weighted Euclidean Distance (WED) [31] has been selected for the similarity measurement which gives superior results than other metrics (such as Euclidean, Manhattan and cosine). It is defined as follows:

$$d_k = \left(\sum_{i=1}^d \frac{(f(i) - f_k(i))^2}{(s_i)^2} \right)^{1/2} \quad (13)$$

where f and f_k are the feature vectors of the test sample and k -th training sample, respectively; s_i is the standard deviation of the i -th feature; and d denotes the feature length of the samples.

Nearest Neighbor (NN) classifier, which provides high performance with less computation overhead, was used to perform the classification of the test patterns.

357 **3. Experiments**

358 *3.1. Databases*

359 The performance of the proposed approach is evaluated on two different
360 contactless palmprint databases. One of them (KTU-Contactless Palm DB)
361 is a new and realistic database which is constituted by the images captured
362 from the proposed contactless palmprint authentication system. Another one
363 is the most publicly used contactless palm DB: IIT Delhi Palmprint Image
364 Database version 1.0 (briefly IITD database) [32].

365 *3.1.1. KTU-Contactless Palm DB*

366 In this work, a contactless palm database ¹ has been constituted for the
367 performance measurement of the proposed system. By the novel palm image
368 acquisition system totally 1752 images of size 768×576 were collected for the
369 palm database. These images belong to the right hand of the 145 individuals,
370 of whom 105 are male and the rest are female. The minimum, maximum and
371 average number of images per palm are 6, 30 and 12, respectively.

372 To evaluate the performance of the proposed method more realistic, and
373 to simulate the various difficulties that can be encountered, the hand images
374 in the database were collected by performing various scenarios. They are: (1)
375 The environment brightness was changed by decreasing/increasing the light
376 intensity in the room to reveal the invariability on the external brightness.
377 Some hand image samples with the estimated palm model for this type of
378 scenario are shown in Fig. 3.i,k. (2) The users are asked to present their
379 hands toward the capturing device by changing the hand-camera distance to

¹The details can be found in “<http://ceng2.ktu.edu.tr/cvpr/contactlessPalmDB.htm>”

380 construct a database with different shaped hand images. They are also asked
 381 to present their hands in various pose and translations (strongly bending
 382 their hands downward, changing the space between the fingers, excessively
 383 moving their hands in the forward/backward, and the left/right directions,
 384 different hand rotations to right and left sides). Some of the hand images
 385 in our database and their segmentation results (palm models) are also given
 386 in Fig. 3.a, c, e-g, i, k-l. (3) The objects which have similar textures and
 387 colors such as faces, other hands and complex textured objects were also
 388 added to the background to evaluate the robustness of the algorithms on
 389 the complex backgrounds. The sample images and their palm models are
 390 shown in Fig. 3.b, d, j. In the meantime, we captured the images at different
 391 times during the day so as to acquire natural differences on the external
 392 lighting conditions. Furthermore, the users did not remove the rings or other
 393 ornaments from their fingers while the hand images were taken (see Fig. 3.j).
 394 The KTU-Contactless Palm DB also includes hand images which have partly
 395 viewed palms or occlusions to the palmprint regions.

396 *3.1.2. IITD Database*

397 This publicly available contactless palm image database [32] consists of
 398 the hand images collected from the students and staff at IIT Delhi, India. The
 399 images in the database (with pixel resolutions of 800×600 pixels) have been
 400 acquired in the Biometrics Research Laboratory during January 2006 - July
 401 2007 using a very simple contactless imaging setup. This database divided
 402 into two sub-data sets: left and right hand image data sets. The left hand
 403 image data set consists of 1393 palm images from 234 individuals, while the
 404 right hand image data set consists of 1376 palm images from 233 individuals.

Figure 3: Segmentation results for twelve samples of KTU-Contactless Palm DB with different scenarios. There is a hand (a), face (b) or a book (c) at the background; the hand is moved excessively to right (d) / forward (e) / backward (f), rotated to the left direction (g) or strongly bent downward (h); the fingers are downwardly-inclined (i), spaces between them are reduced (f) or increased (j); thumb finger is out of the scene (k); the ring is not removed from a finger (c); a light source is present on the scene (l).

405 The minimum number of images for each hand is 5. The images are grabbed
 406 in a semi-closed enclosure and so there is no background complexity as in our

407 database. Additionally, the images of this database are not taken in different
408 environment brightnesses, and the spaces between the fingers are not changed
409 excessively. However, the hand images have different pose variations arisen
410 from the contact-free structure of the system.

411 *3.2. Experimental Results and Discussions*

412 In the experiments, for the model construction in AAM, a training set
413 with 73 images was constituted. The images in the training set were selected
414 due to the representation ability of the variations on the shape and texture
415 of the palm images. Furthermore, the number of the samples in the train-
416 ing set is determined according to the trade-off between the computational
417 complexity arising from large data sets and incompatibility occurred from
418 small data sets [25]. The ROI selection results of the proposed method are
419 given visually with the sample images in a comparative manner. In addition
420 to these results, recognition rate, ROC graph and Equal Error Rate (EER)
421 values were computed to quantify the performance of the recognition and
422 verification systems.

423 *3.2.1. Experiments on KTU-Contactless Palm DB*

424 In this section, the ROI images extracted by the proposed method were
425 analyzed in comparison with the images of a point-based method [12] intro-
426 duced by Connie et al. The most commonly used ROI extraction method
427 [11], described by Zhang et al., was not taken into account in the compar-
428 isons. Because, there is an uncertainty in the determination of the ROI size
429 (the extracted ROIs have a fixed size which are suitable for their palm im-
430 ages only), and the location of a ROI is determined with the visible part of

431 the palm (extracting the central part as ROI) which can lead to mislead-
432 ing results. Therefore, another commonly used method, which is similar to
433 the Zhang et al.'s method, was selected for the comparisons. In [12], the
434 midpoints on the index and little fingers are used to locate the ROI of the
435 palm. The midpoints are also estimated by using the gaps between the fin-
436 gers and the contour of the hand shape. Henceforth, we called this technique
437 as classical ROI. To obtain the ROIs with this approach, the gaps between
438 the fingers and the contour of the hand shape were extracted from the fitted
439 palm model.

440 Generally, it has been observed from the visual comparisons that the pro-
441 posed method provides more accurate selection of the ROIs as compared to
442 the classical method. Sample palmprint images extracted by these methods
443 are given in Fig. 4.

444 In Fig. 4, for each item, the images in the left and right are extracted
445 with the classical and proposed ROI extraction methods, respectively. The
446 samples which are linked with the arrows are obtained from the same user
447 with different hand postures. Although the selection of the ROIs are trans-
448 lated and scaled with the use of the classical method, the proposed method
449 results are not affected with different postures. Besides, the valley point near
450 the thumb finger can be seen and the ROI can be misplaced substantially in
451 some images for the classical ROI approach.

452 There are two main reasons for the general performance improvement
453 obtained by the proposed ROI extraction approach. First of them is the
454 removal of the occurred errors due to the faulty detection of the valley points
455 of the gaps between the fingers. These errors are the common problems for

Figure 4: A visual comparison of the ROI images extracted from two different methods. It shows that there are some problems for the classical method: The images are translated, scaled (a), and rotated (b); wrinkles of the thumb finger is seen (c), and the ROI is misplaced (d).

456 the point-based approaches which are very sensitive to valley point selection.
 457 Incorrect valley point selection may cause such methods to obtain rotated,
 458 translated and scaled ROI images. In the proposed method, orientation

459 of the hand and ROI are evaluated with regressing all landmark points in
 460 the training set, which are annotated by a supervisor. Furthermore, the
 461 major changes occurred from small errors can be tolerated by a regularization
 462 coefficient in LS-SVR. Therefore, the results are not greatly affected by the
 463 errors originated from faulty landmark point selection in our method. The
 464 second reason that affects the performance negatively is the existence of the
 465 wrinkles in the palmprint region which are caused by decreasing the distance
 466 between the thumb and the index finger. This negative effect is observed
 467 in a more pronounced manner in classical ROI methods as compared to
 468 the proposed method since the ROI is extracted more closely to the thumb
 469 finger. Besides, in some hand shapes, the valley point between the thumb
 470 and index finger appears on the ROIs extracted by the classical approach.
 471 In our approach, the position of the ROI (the distances to the edges of the
 472 palm) is empirically determined to prevent such errors. These problems are
 473 illustrated in Fig. 4.

474 To draw attention on the importance of the ROI extraction techniques
 475 with quantitative results, the recognition and verification experiments were
 476 performed in a comparative manner. In the experiments, the first four sam-
 477 ples for each palm belonging to an individual are selected for training set,
 478 and the rest are selected for the test set. The results, extracted by using
 479 both ROI approaches, are summarized in Table 1.

480 In the recognition experiments the proposed ROI extraction method gives
 481 better results as compared to the classical ROI extraction method. We have
 482 observed a performance improvement of 0.854% as compared to the method
 483 given in [12] and we have achieved an overall recognition rate of 99.488%.

Table 1: Recognition and verification results (%) of the Gabor-based KFD method on KTU-Contactless Palm DB by using the classical and the proposed methods.

	Classical ROI	Proposed ROI
Recognition Rate	98.634	99.488
GAR (when FAR=1E-4%)	92.726	97.056
EER	0.621	0.277

484 The achieved 99.488% recognition rate means that only 6 images were clas-
485 sified incorrectly when the palmprints were extracted by using the proposed
486 ROI method.

487 Verification results of the system were obtained by matching each test
488 sample with all of the training samples. Correct and incorrect matchings are
489 defined by whether two samples are from the same palm or not, respectively.
490 The total number of matchings is 679,760. The correct matching number is
491 4,688, and the incorrect matching number is 675,072. The false acceptance
492 rate (FAR) and false reject rate (FRR) curves are estimated by correct and
493 incorrect matchings and illustrated for the proposed ROI extraction method
494 in Fig. 5.

495 From the FAR-FRR graph, it can be seen that, FAR and FRR curves are
496 separated from each other sufficiently and EER of the unrestricted contactless
497 palmprint verification system is considerably low (only 0.277%) with the
498 proposed method. The classical ROI extraction method leads to more than
499 twice verification errors.

500 The performance of a biometric system is mostly illustrated by the ROC
501 curve, which is frequently used in the assessment of genuine acceptance rate

Figure 5: Logarithmic FAR-FRR graph for the proposed method on KTU-Contactless Palm DB.

502 against false acceptance rate. The ROC curves for the proposed ROI and
 503 classical ROI extraction methods are shown comparatively in Fig. 6.

Figure 6: Comparative ROC curves for different ROI extraction methods on KTU-Contactless Palm DB.

504 It is clear from the ROC curves that our ROI extraction approach gives
 505 superior GAR results than the point-based approach in all of the FAR values.
 506 For the false acceptance rate of 1E-4%, 97.056% genuine acceptance rate is

507 achieved with the proposed method, while with the use of classical ROI
 508 method only 92.726% GAR can be achieved.

509 As another experiment, to evaluate the developed contactless system's
 510 general performance and reveal the effect of the increase in the number of
 511 the training samples on the recognition/verification performance, we used
 512 the first 2, 3, 4 and 5 samples for each subject as training samples. The
 513 recognition rates and Equal Error Rates of the system are listed in Table 2.

Table 2: Recognition and verification results (%) of the proposed method on KTU-Contactless Palm DB, with increasing number of training samples.

# of training samples per subject	2	3	4	5
Recognition Rate (%)	97.606	98.709	99.488	99.708
EER (%)	0.855	0.487	0.277	0.117

514 Table 2 shows that, for the increasing number of the training samples, the
 515 Recognition Rate (RR) and EER are logarithmically increased and decreased,
 516 respectively. Besides, the performance of the five training samples per palm
 517 is higher than others, in which 99.708% RR and 0.117% EER are achieved.
 518 However, it is known from the practical experience that, the users are mostly
 519 unwilling to present their hands repeatedly. Therefore, the use of a few
 520 number of training samples can be preferred in a real life application. If
 521 the system was trained with only two samples per palm, the results were
 522 obtained as: 97.606% RR and 0.855% EER. In our studies given above, four
 523 training samples scheme was preferred for the optimality and practicability.
 524 This scheme also used in the performance comparisons with the literature.

3.2.2. Experiments on IITD DB

The performance of the proposed ROI extraction method is also evaluated on the public IIT Delhi Palmprint Image Database version 1.0 [32] through the recognition and verification experiments. For the training of AAM model, 73 sample hand images are selected. These samples are also used for training the direction of the palm. In the experiments three samples for each palm were selected for the training set, and the rest were chosen for the test set due to the limitations on the samples per individual. The verification and recognition results are summarized in Table 3 for the left and right hand data sets separately.

Table 3: Recognition and verification results (%) of the Gabor-based KFD method on IITD DB by using the classical and the proposed methods.

Data set	Criterion	Classical ROI	Proposed ROI
left hand	Recognition Rate	98.842	99.421
	GAR (when FAR=1E-3%)	85.112	92.708
	EER	0.145	0.033
right hand	Recognition Rate	98.523	99.409
	GAR (when FAR=1E-3%)	91.581	95.900
	EER	0.267	0.149

The recognition results of the left and right hand data sets are very close to each other and better for the proposed ROI extraction method than the classical method. While the recognition rates of the proposed method are approximately 99.4% for both data sets, the recognition rate of the classical method for the left and right hand data sets are 98.8% and 98.5%, respec-

540 tively. This means that the proposed method gives a higher recognition rate
541 of 0.579% than the classical method in the worst case.

542 Verification results also support the superiority of the proposed method.
543 In the experiments, for the left and right hand data sets, the correct matching
544 numbers are 2,073 and 2,031; and the incorrect matching numbers are 483,009
545 and 471,192, respectively. The obtained EERs by the proposed method are
546 much lower than the EERs of the classical method. The proposed methods
547 reduces the errors by 75% as compared to the classical method for the left
548 hand data set and by about 50% for the right hand data set. The ROC
549 curves for the proposed ROI and classical ROI extraction methods on IITD
550 DB are shown comparatively in Fig. 7.

551 The ROC curves show that the proposed ROI extraction method gives
552 superior ROC curves than the classical point-based method. For the left
553 hand data set, with the false acceptance rate of 1E-3%, 95.900% genuine
554 acceptance rate is achieved by the proposed method, while with the use of
555 classical ROI method only 91.581% GAR can be achieved. This distinction
556 can be more visible for the right hand data set (92.708% - 85.112%). All of the
557 recognition/verification results achieved on the IITD DBs are consistent with
558 the results achieved on the KTU-Contactless Palm DB: the proposed method
559 gives higher GAR values for the all FAR values in the ROC curves, it reduces
560 the errors (EERs) by 50% minimally, and it has 99.4% recognition rates for
561 both databases. The EER values of the proposed method are 0.277% and
562 0.149% for the KTU and IITD DBs, respectively. And it gives 0.854% and
563 0.579% higher recognition rates for the KTU and IITD DBs, respectively.
564 Hereby, it is confirmed that the proposed method gives better recognition

(a)

(b)

Figure 7: Comparative ROC curves for different ROI extraction methods on IITD DB (a) for the left hand data set (b) for the right hand data set.

565 and verification results than the classical point-based approaches.

566 3.3. Comparisons

567 In this section, a comparison on the recognition/verification accuracies
 568 has been given for our contactless palmprint system and the other recently

569 proposed contactless palmprint systems. Quantitative performance results
 570 of the contactless recognition/verification systems were given in Table 4 with
 571 the number of images, number of training samples per subjects and number
 572 of individuals which the experiments performed on. Although some of the
 573 contactless systems include other biometrics or multi-spectral structures ²
 574 we only consider 2-D palmprint parts of them. In the comparisons, the pa-
 575 pers utilized CASIA palmprint database were not taken into account despite
 576 they have lower performances (for example in [34] the EER is 0.9%). Be-
 577 cause, CASIA database consists of images acquired from a peg-free but not
 578 a contact-free device.

579 Most of the papers in the literature have usually presented either veri-
 580 fication or recognition results of their systems. However, in our work both
 581 experiments were performed. Hence, we have selected high quality five stud-
 582 ies for the verification and three studies for the recognition comparisons,
 583 which were recently published.

584 From the comparisons in Table 4, it can be seen that our contactless palm
 585 database is one of the biggest database in the literature. Most of the con-
 586 tactless palm databases (5 of 8 analyzed databases) have a smaller number
 587 of samples and individuals than our database has (e.g. in [38] there are only
 588 49 individuals and 490 samples). Furthermore, in [33] the database involves
 589 right and left hand images, and so it provides a significant advantage for
 590 the verification of the palmprints. From the database comparisons we can
 591 say that, the results of the experiments in this paper are more reliable and

²for example in [33] the 3-D and 2-D palmprint features, in [3] palmprint and knuckle-
 print biometrics were combined

Table 4: Comparison of the proposed and other contactless palmprint recognition/verification systems.

	Proposed Method	In [35] 2014	In [4] 2011	In [33] 2011	In [2] 2011	In [3] 2010	In [36] 2011	In [37] 2009	In [38] 2007
EER (%)	0.277	0.43	0.57	1.22	1.10	1.97	-	-	-
RR (%)	99.488	-	-	-	-	-	98.92	97.55	98.5
# of individuals	145	235	110	177	114	100	233	130	49
# of samples	1752	1400	1540	3540	570	1000	1376	1170	490
# of training samples per subject	4	LOO	LOO	5	LOO	LOO	LOO	3	7

592 realistic than the others. Furthermore, the complexities of the images in
593 the databases are satisfactory from the point of representing the real-world
594 conditions. Some of the studies emphasized on the cluttered backgrounds
595 (e.g. in [3] and [38]) and the others emphasized on the pose, translation and
596 scale variations in semi-closed background (e.g. in [35] and [2]) to simulate
597 the difficulties on the real-world conditions. Our database also includes im-
598 ages which were collected with pose, translation and rotation variations on
599 different cluttered backgrounds.

600 In the proposed work, Gabor wavelets based Kernel Fisher Discriminant
601 Analysis was performed to extract the palmprint features. Most of the palm-
602 rint verification studies such as [33], [3], [2] and [36] used the coding ap-

603 proaches for the same purpose. In [38], a novel robust decomposition method
 604 was suggested. Poinot et al. [37] utilized the Gabor filter and binarization
 605 to extract the features. Unlike the others, in [4] and [35], SIFT-based local
 606 descriptors were used as the palmprint features. For the matching and clas-
 607 sification, Weighted Euclidean Distance and Nearest Neighbor methods were
 608 used in our work, respectively. On the other hand, all of the papers, men-
 609 tioned above, used the Hamming distance for matching (in [35] and [4] also
 610 Euclidean distance were used for SIFT feature matching). The classifications
 611 of the palms in the recognition experiments were achieved by Support Vector
 612 Machines in [38], Rank-Level Fusion in [36], and Nearest Neighbor in [37].

613 The number of training samples per subject is an important criterion for
 614 the subspace methods in which the features are extracted from these training
 615 samples. However, for the other methods (e.g. coding-based methods, SIFT-
 616 based methods), the training set / test set separation is not essential. In
 617 these methods, since it does not influence the extracted features directly, each
 618 sample can be matched with all the other samples in the data set, and this
 619 leads to greater number of matchings. In other words, a sample is matched
 620 to all the remaining samples of that subject repeatedly for all of the test
 621 samples to generate genuine match scores. So, we refer to this approach as
 622 "leave-one-out (LOO)". The works in [2], [3], [4], [35] and [36] used LOO, and
 623 can not be compared with the proposed method in this respect. Although,
 624 Kanhangad et al. used competitive coding in [33], they separate the samples
 625 to training set / test set and used five samples for training set. The other
 626 works ([37] and [38]) which are selected for recognition comparisons used
 627 three and seven samples for training, respectively. When compared with the

628 results of the proposed method for three training samples per subject it can
629 be seen that, Poinot et al. [37] gives a lower performance.

630 Table 4 also shows that, the performance of the proposed contactless
631 palmprint authentication system is encouraging and superior to the others
632 (0.277% EER and 99.488% RR). The number of verification errors occurred
633 in [3] is higher by a factor of seven as compared to the proposed system.
634 Besides, the system which has the highest verification performance in the
635 literature [35] gives 50% more errors as compared to the proposed method.
636 Furthermore, in some papers it is stated that the matching was performed
637 in a leave-one-out manner, and the images in their databases were not sep-
638 arated as training and test sets. This selection scheme on the database can
639 affect their results positively. Similarly, the highest recognition rate given in
640 the papers referenced above is 0.568% lower than the proposed system. In
641 other words, the number of errors given in those papers are higher than the
642 errors occurred in this study at least by a factor of two for the recognition
643 experiments.

644 Another comparison can be made by discussing the results for the IITD
645 touchless palmprint database. In [35], 0.43% and 0.49% EER, in [4] 0.20%
646 and 0.21% EER were achieved for the left and right palm data sets, respec-
647 tively. However, with the proposed method superior results can be achieved
648 as highlighted by the EER results of 0.033% and 0.149% for the left and right
649 palm data sets. Also, the recognition rate given in [36] (97.55%) for the right
650 palm data set is lower than the recognition rate of the proposed method for
651 this data set (99.41%).

652 Consequently, it has been revealed that the robustness of the evaluated

653 system is very competitive and promising as a whole with all of its parts
654 including image acquisition device, segmentation, ROI extraction and recog-
655 nition. This observation is confirmed by extensive evaluation studies carried
656 on an unrestricted contactless palmprint database.

657 4. Conclusion

658 This paper presents a novel contactless palmprint image capturing and
659 recognition system. In this system, the users were asked to introduce their
660 hands above the CCD camera with various hand pose and orientations under
661 unconstrained environment. Due to the presence of these challenges where
662 the pixel-based segmentation methods can not give acceptable results, we
663 utilized AAM-based palm modeling to accurately segment the palms.

664 For the extraction of a central area from a palm image (called ROI), a
665 novel ROI extraction approach which utilizes the palm model and nonlinear
666 regression has been proposed. Because it removes weaknesses of the other
667 approaches, a great deal of improvement has been achieved by the usage of
668 this method. The performance of the method was evaluated with recognition
669 rate, equal error rate, and ROC graph. The possible reasons of the success
670 are also illustrated with ROI image samples.

671 In our contactless palmprint database, that contains 1752 images col-
672 lected from 145 subjects, we have achieved high genuine acceptance rate
673 (97.056% GAR) at low false acceptance (0.0001% FAR) rate, 0.277% EER,
674 and 99.488% recognition rate, which are clearly encouraging for the contact-
675 less palmprint system under unconstrained scenes. This high performance
676 is also supported by the results of the recognition/verification tests on the

677 public IIT Delhi Palmprint Image Database. In future works, the proposed
678 system should be transformed to an online contactless palmprint identifica-
679 tion system and more users should be included into the database to test its
680 feasibility in large organizations.

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Contactless Palmprint Authentication System Design

A Novel Model-Based ROI Extraction Method

AAM-Based Robust Palm Segmentation

Contactless Palmprint DB: pose variations, cluttered backgrounds
1752 images, 145 subjects

Encouraging results:
0.277% EER, 99.488% RR