

Article

Unconstrained and Contactless Hand Geometry Biometrics

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1 **Abstract:** This paper presents a hand biometric system for contact-less, platform-free sce-
2 narios, proposing innovative methods in feature extraction, template creation and template
3 matching. The evaluation of the proposed method considers both the use of three contact-less
4 publicly available hand databases, and the comparison of the performance to two competi-
5 tive pattern recognition techniques existing in literature: namely Support Vector Machines
6 (SVM) and k -Nearest Neighbour (k -NN). Results highlight the fact that the proposed method
7 outcomes existing approaches in literature in terms of computational cost, accuracy in human
8 identification, number of extracted features and number of samples for template creation.
9 The proposed method is a suitable solution for human identification in contact-less scenarios
10 based on hand biometrics, providing a feasible solution to devices with limited hardware
11 requirements like mobile devices.

12 **Keywords:** Contactless Hand Biometrics, Invariant Feature Extraction, Security, Pattern
13 Recognition, Image Processing, Hand Geometry, Unconstrained Biometrics

14 1. Introduction

15 At present, trends in biometrics are inclined to provided human identification and verification without
16 requiring any contact with acquisition devices. The point of aiming contact-less approaches for biomet-
17 rics regards the upward concerns with hygiene and final user acceptability.

18 Concretely, hand biometrics usually have made use of a flat platform to place the hand, facilitating not
19 only the acquisition procedure but also the segmentation and posterior feature extraction. Consequently,
20 hand biometrics is evolving to contact-less, platform-free scenarios where hand images are acquired in
21 free air, increasing the user acceptability and usability.

22 However, this fact provokes an additional effort in segmentation, feature extraction, template creation
23 and template matching, since these scenarios imply more variation in terms of distance to camera, hand
24 rotation, hand pose and unconstrained environmental conditions. In other words, the biometric system
25 must be invariant to all these former changes.

26 The presented method proposes a hand geometry biometric system oriented to contact-less scenar-
27 ios. The main contribution of this paper is threefold: firstly, a feature extraction method is proposed,
28 providing invariant hand measurements to previous changes; second contribution consists of providing
29 a template creation based on hand geometric distances, requiring information from only one individual,
30 without considering data from the rest of individuals within the database; finally, a proposal for template
31 matching is proposed, minimizing the intra-class similarity and maximizing the inter-class likeliness.

32 The proposed method is evaluated using three publicly available contact-less, platform-free databases.
33 In addition, the results obtained with these databases will be compared to the results provided by two
34 competitive pattern recognition techniques, namely Support Vector Machines (SVM) and k -Nearest
35 Neighbour, often employed within the literature.

36 Finally, the layout of this paper remains as follows: First of all, a literature review is carried out in
37 Section 2. Secondly, the feature extraction method is described in Section 3.2, together with a description
38 of the database involved in the evaluation (Section 4). Afterwards, the comparative evaluation and the
39 corresponding results are presented in Section 5. Finally, conclusions and future work are introduced in
40 Section 6.

41 2. Literature Review

42 Hand biometric systems have evolved from early approaches which considered flat-surface and pegs
43 to guide the placement of the user's hand [1–3], to completely platform-free, non-contact techniques
44 where user collaboration is almost not required [4–7]. This development can be classified into three
45 categories according to the image acquisition criteria [8]:

- 46 • Constrained and contact based. Systems requiring a flat platform and pegs or pins to restrict hand
47 degree of freedom [2,3].
- 48 • Unconstrained and contact based. Peg-free scenarios, although still requiring a platform to place
49 the hand, like a scanner [6,9].
- 50 • Unconstrained and contact-free. Platform-free and contact-less scenarios where neither pegs nor
51 platform are required for hand image acquisition [5,10].

52 In fact, at present, contact-less hand biometrics approaches are increasingly being considered because
53 of their properties in user acceptability, hand distortion avoidance and hygienic concerns [11,12], and
54 their promising capability to be extended and applied to daily devices with less requirements in terms of
55 image quality acquisition or speed processor [9,10,13].

56 In addition, hand biometrics gather a wide variety of distinctive aspects and parameters to identify
57 individuals, considering whether fingers [7,14,15], hand geometric features [2,3,6,15,16], hand contour
58 [2,10,17], hand texture and palmprint [8,18] or some fusion of these former characteristics [7,14,19].

59 More specifically, geometrical features have received notorious attention and research efforts, in com-
60 parison to other hand parameters. Methods based on this strategy (like widths, angles and lengths) re-
61 duce the information given in a hand sample to a N -dimensional vector, proposing any metric distance
62 for computing the similarity between two samples [20].

63 In opposition to this method, several schemes are proposed in literature applying different proba-
64 bilistic and machine learning techniques to classify properly user hand samples. The most common
65 techniques are k -Nearest Neighbours [21], Gaussian Mixture Models [3,22], naïve Bayes [21] or Sup-
66 port Vector Machines [9,18,21], which is certainly the most extended technique in hand biometrics due
67 to their performance in template classification.

68 Nonetheless, these latter strategies present several drawbacks in comparison with distance-based ap-
69 proaches in terms of computational cost and efficiency, since probabilistic-based strategies require other
70 user samples to conform an individual template. In other words, systems based on a classifier approach
71 are trained for each of the enrolled persons, requiring samples from other enrolled individuals for a sep-
72 arate classification. This fact may become a computational challenge, for large-population systems [20].
73 However, in terms of individual identification performance, they certainly succeed in relation to current
74 distance-based methods.

75 An overview on recent hand biometrics systems is presented in Table 1. This table presents the
76 relation between the features required for identification, the method proposed, the population involved
77 together with the results obtained, in terms of Equal Error Rate (EER).

78 As hand biometrics tends to contact-less scenarios, hand image pre-processing increases in difficulty
79 and laboriousness, since less constraints are required concerning background, i.e. the part behind the
80 hand.

81 Several approaches in literature tackle with this problem by providing non-contact, platform-free
82 scenarios but with constrained background, usually employing a monochromatic color, easily distinctive
83 from hand texture [23]. More realistic environments propose a color-based segmentation, detecting hand-
84 like pixels either based on probabilistic [16] or clustering methods [18,24]. Although, the constraints on
85 background are less restrictive in this case, the performance of this segmentation procedure still lacks in
86 accuracy.

87 However, a feasible solution for this latter scenario is based on an acquisition involving short distance
88 to sensor. This approach considers the use of infrared illumination [9,18], due to the fact that infrared
89 light only lighten close-to-camera regions, avoiding further regions (background) to be illuminated and
90 therefore not acquired by the infrared camera.

91 Most recent trends in hand segmentation consider no constraint on background, proposing more ef-
92 ficient approaches based on multiscale aggregation, providing promising results in real scenarios [24].
93 This scenario is clearly oriented to the application of hand biometrics in mobile devices.

94 Moreover, hand biometrics also consider different acquisition modalities, namely 3D data acquisition
95 [14,25], infrared cameras [9,18], scanners [6] or low-resolution acquisition devices [10,13].

Table 1. Literature review on most recent works related to contact-less hand biometrics based on hand geometry. This table presents the relation between the features required for identification, the method proposed, the population involved together with the results obtained, in terms of Equal Error Rate (EER).

Year	Ref.	Features	Method	Population Size	EER (%)
2007	[5]	5-35 distances	Projective invariants	23	2.11
	[21]	23 distances	Entropy Discretization and SVM	100	5
	[4]	15 hand distances	SVM	18	8
	[26]	5 distances	AAM	18	5
2008	[18]	30-40 finger widths	SVM	20-30	4.2-6.3
	[27]	15 graph distances	DBNN	250	0.89
	[16]	Palmprint	Gabor Filters and SVM	49	1.7
2009	[7]	Zernike Descriptors	Fusion SVDD	86	1.5
	[14]	2D and 3D features	Savitzky-Golay filters	177	2.6
	[10]	Contour	DTW alignment	45	3.7
	[28]	40 distances	SVM	260	0.0035-5.7
2010	[15]	30 distances and angles	Correlation	50	4.2
	[25]	2D and 3D palmprint and geometry	Surface Code	114	0.71

96 Best results in Table 1 are achieved by Rahman et al. [27] and Kanhangad et al. [25]. The former
 97 work consists of applying Distance Based Nearest Neighbour (DBNN) and Graph Theory to both feature
 98 extraction and feature comparison. In contrast, the latter work presents a new approach to achieve
 99 significantly improved performance even in the presence of large hand pose variations, by estimating the
 100 orientation of the hands in 3D space and then attempting to normalize the pose of the simultaneously
 101 acquired 3D and 2D hand images.

102 As a conclusion, contact-less hand biometrics is receiving an increasing attention in recent years, and
 103 many aspects remain unresolved such as invariant feature extraction or hand template creation.

104 3. Methodology

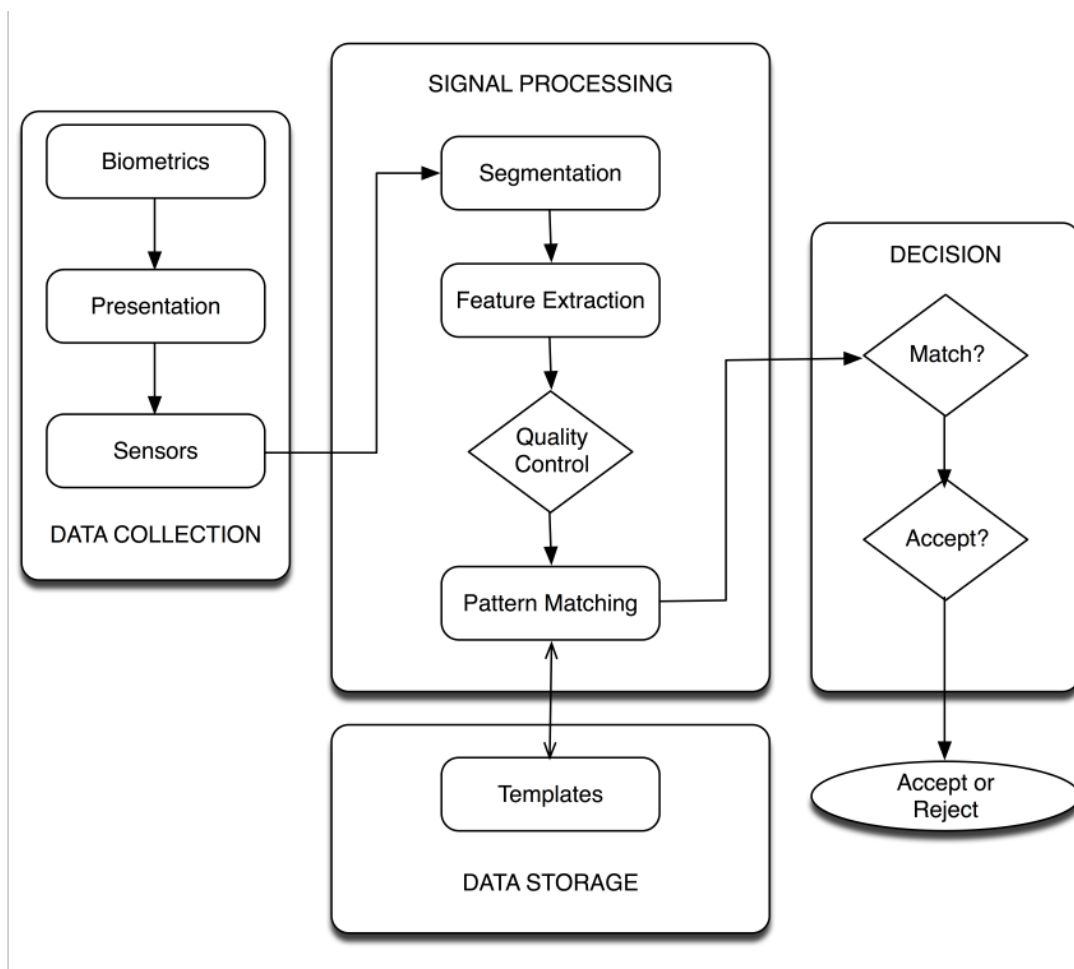
105 A general biometric system involves the following steps, presented in Figure 1:

- 106 • Data Collection module is dedicated to acquired data from the biometric sensor.
- 107 • Signal Processing module involves both the pre-processing step to provide a precise segmentation
 108 and the creation of the template.

- 109 • Data Storage module stores the template, protected to ensure the biometric information is not
110 compromised.
- 111 • Decision module provides the resolution on the identity of an individual given the template and
112 the data collected previously.

113 The contribution of this paper is focused on the Signal Processing module and Decision module,
114 defining geometric features invariant to changes like distance to camera, hand rotation or hand pose,
115 together with the creation of a template requiring data from one single individual instead of using data
116 from the whole biometric database. Concerning the Decision module, this paper proposes a template
117 matching method, which outperforms competitive pattern recognition techniques like k -NN and SVM
118 (Section 5).

Figure 1. Diagram of a general biometric system.



119 3.1. Hand image acquisition and pre-processing

120 Contact-less biometrics impose on users almost no constraints in terms of distance to camera, hand
121 orientation and so forth, implying a demanding pre-processing stage in terms of segmentation and con-
122 tour extraction accuracy. This step is essential for a posterior precise feature extraction, and the whole

123 hand biometric system relies strongly on this prior procedure. In addition, the proposed hand image
 124 acquisition contains no specific constraints on the characteristics of the camera

125 The pre-processing proposed is independent from the database, in other words, there are no specific
 126 strategies for every database. In addition, the pre-processing method contains several steps, briefly
 127 described as follows:

- 128 • Segmentation, which consists of isolating hand from background precisely.
- 129 • Finger classification, carried out after segmentation process, it consists of identifying each finger
 130 (index, middle, ring or little) correctly with independence of previous possible changes (rotation,
 131 hand orientation, pose and distance to camera).
- 132 • Valleys and tips detection, essential in order to provide accurate mark points from which features
 133 can be extracted.
- 134 • Left-Right hand classification, based on the fact that an individual can provide any hand, and the
 135 system must firstly classify the hand. Notice that without this method, fingers from left hand could
 136 be compared to fingers from right hand, resulting in errors in identification.

137 After introducing the main parts of the pre-processing stage, each step is explained more in detail.

138 Firstly, concerning segmentation, a method based on gaussian multiscale aggregation [24,29] was se-
 139 lected based on their properties of linearity with the number of pixels and segmentation accuracy. The
 140 proposal of this method is justified since the biometric evaluation will consider three different databases
 141 with different backgrounds and image specifications, and the multiscale aggregation strategy can provide
 142 an accurate segmentation for each database, independently on their acquisition characteristics (illumina-
 143 tion condition, backgrounds, color or grayscale image and so forth).

144 This method provides a binary image as a result of the segmentation procedure, indicating which
 145 pixels correspond to hand, and which pixels to background. This binary image will be used for contour
 146 and feature extraction in Section 3.2. A deep understanding and explanation of this method is far beyond
 147 the scope of this paper.

148 Afterwards, fingers are split from the segmented hand in order to facilitate their classification. Math-
 149 ematically, let H be the result provided by segmentation procedure (Figure 2(a)). Applying an opening
 150 morphological operator [30] with a disk structural element of size 40 will cause fingers to disappear,
 151 remaining only the part corresponding to palm. This image is named H_p (Figure 2(b)), since it represent
 152 those pixels corresponding to palm. Although this operation is very severe, it allows conserving those
 153 region blobs which are very dense in terms of pixels, being suitable for deleting prominent blobs like
 154 fingers from hand [7].

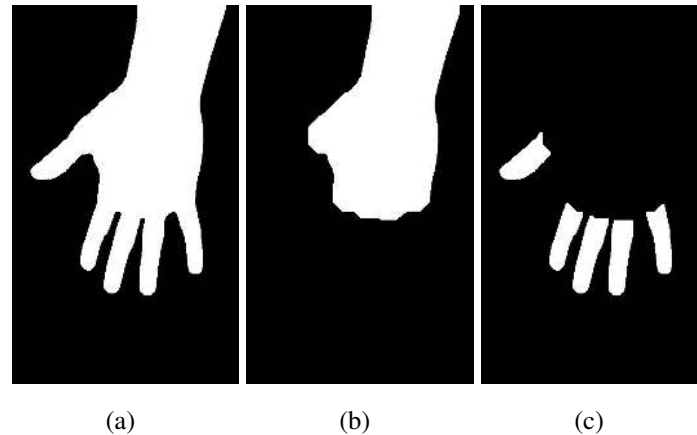
155 Given H and H_p , it is straightforward to calculate H_f which represents the region blobs corresponding
 156 to fingers (five fingers, Figure 2(c)), by the following relation (Equation 1)

$$H_f = H \cdot \bar{H}_p \quad (1)$$

157 being \cdot an operator indicating a logical AND operation between H and the complementary of H_p .
 158 In case, image H_f contained some spurious blobs, they are erased by selecting the five most prominent
 159 blobs in image.

160 Figure 2 provides a visual example of the fingers isolation method.

Figure 2. Fingers isolation steps: (a) represents the original segmented image, H ; (b) the result after applying morphological operator (opening, disk 40), H_p ; (c) H_f represents fingers after subtracting H_p to H .



161 Afterwards, five blobs are contained in H_f (Figure 2) one of each corresponding to each finger. In case
 162 more than five blobs are obtained, an opening morphological operator based on a small disk structural
 163 element (size 5) will erase those small and undesired region blobs, with lack of interest for a finger
 164 classification.

165 In order to distinguish among fingers, all of them are classified according to two criteria: the ratio
 166 between blob length and width (eccentricity) and area (number of pixels within blob).

167 The blob which verifies to have the lowest values in both criteria is the little finger. The next finger
 168 with lower area is thumb, and ring, middle and index are classified according to the distance between
 169 their centroids to previous calculated fingers. In other words, that blob whose centroid is closer to little
 170 is classified as ring finger, for instance. A similar criteria was proposed by [6].

171 Having the finger blobs calculated, tip detection consists of calculating the finger extrema of each
 172 blob. In other words, obtain the furthest pixel in each blob in relation to a reference point. In this paper,
 173 such point coincides with the each finger centroid, due to their geometric properties of being located in
 174 the middle of each finger. Others points could be the hand centroid [10], or minimum/maximum points
 175 in contour curve [20].

176 Finally, since there are five fingers blobs, this method leads to five tips.

177 In contrast to tip detection, obtaining valleys requires more effort. Let c be the hand contour obtained
 178 from the edge blob in H . Let t_k be the finger tip corresponding to finger k , with $k = \{t, i, m, r, l\}$
 179 meaning thumb, index, middle, ring and little respectively. In addition, $\zeta_k = c(t_k, t_{k+1})$ is the edge
 180 portion from tip t_k and t_{k+1} . Valley points verify to be the closest point to hand centroid h_c . However,
 181 only little-ring, ring-middle and middle-index valleys support this criterion. The valley corresponding to
 182 index-thumb will be treated separately.

183 Then, the former valleys are calculated according to Equation 2

$$v_k = \arg \min_k (|\zeta_k - h_c|) \quad (2)$$

184 Notice that valley detection is a considerable challenging task, given that some fingers could be to-
185 gether one to each other, making difficult the valley point calculation.

186 Finally, last step consists of classifying the hand as left or right for a proper posterior feature compar-
187 ison, with the aim of avoiding features from the same finger but from different hands.

188 Thus, hand can be classified as right or left by using three points: t_t , t_l and h_c . Two vectors are
189 considered, joining h_c to each point tip t_t and t_l , which are represented by v_T and v_L respectively. These
190 former vectors are on the same plane, so that their cross-vector product will be normal to that plane.

191 There exist a direct relation between right-left hand classification and vector $v_T \times v_L$. The sign of the
192 z component of $v_T \times v_L$ is associated with right hand, in case the sign is positive and left hand, otherwise.

193 In addition, this image pre-processing achieved second position in the Hand Geometric Points Detec-
194 tion International Competition HGC2011 [31].

195 3.2. Feature Extraction

196 The proposed method extracts features by dividing the finger from the basis to the tip in m parts.
197 Each of these former parts measures the width of fingers, based on the euclidean distance between two
198 pixels. Afterwards, for each finger, the m components are reduced to n elements, with $n < m$, so that
199 each n component contains the average of $\lfloor \frac{m}{n} \rfloor$ values, gathering mean value, μ and standard deviation
200 σ . In other words, template is extracted based on an average of a finger measures set, being more reliable
201 and precise than one single measure. This approach provides a novelty if compared to previous works in
202 literature, where more simple measures were considered [2,3,21].

203 Thus, the template can be mathematically described as follows. Let $F = \{f_i, f_m, f_r, f_l\}$ be the set of
204 possible fingers, namely index, middle, ring and little, respectively.

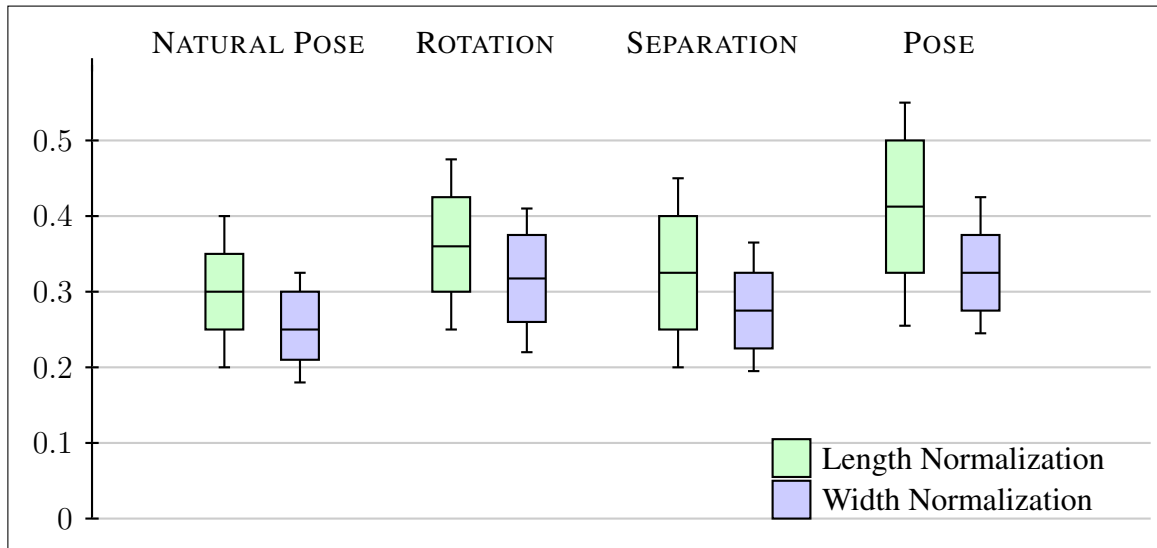
205 Each finger f_k is divided into m parts from basis to top, resulting in the set of widths $\Omega_{f_k} =$
206 $\{\omega_1, \dots, \omega_m\}$. From set Ω , the template is represented by $\Delta_{f_k} = \frac{1}{\delta_{f_k}} \left\{ \delta_1^{f_k}, \dots, \delta_n^{f_k} \right\}$, where each $\delta_t^{f_k}$
207 is defined as the average value of at least $\lfloor \frac{m}{n} \rfloor$ components in Ω_{f_k} . Notice that this division could imply
208 that last element δ_n could be the average of more than $\lfloor \frac{m}{n} \rfloor$ components in order to ensure that every
209 element in Ω_{f_k} is considered to create Δ_{f_k} . In addition, $\bar{\delta}_{f_k}$ represent the width arithmetic average,
210 providing the normalization for vector Δ_{f_k} .

211 Therefore, each hand sample is represented by a $M = 4 \times n$ components vector $\Delta = \{\Delta_{f_k}\}$ with
212 $k \in \{i, m, r, l\}$, where the initials stand for index, middle, ring and little finger. Thumb is not considered
213 due to its great variability in terms of movement, flexibility and orientation [18].

214 The width average normalization proposed for each Δ_{f_k} attempts to provide independence on several
215 acquisition changes like hand rotation, distance to camera and invariance to small differences in pose. In
216 contrast to the normalization provided in the literature based on finger length [3,18,20], a normalization
217 oriented to average width contains the same properties in terms of invariability against distance to camera
218 and rotation, but with the benefit of providing also independence on pose position respect to camera.

219 In order to evaluate the performance of both normalization strategies, four scenarios are proposed
220 with different changes in acquisition. First, features are extracted from samples in natural pose, as
221 stated in Section 3.1. Second scenario considers in-plane rotation changes, within the acquisition plane.
222 Third scenario states different separation distance between hand and camera, and finally, changes in pose
223 orientation. These changes cover all possible degrees of freedom in hand contact-less approaches.

Figure 3. Mean and standard deviation of the difference between hand templates in different evaluation conditions (natural pose, changes in rotation, separation between hand and camera and pose orientation). The normalization based on average width provides less variation intra-class in every aspect than the finger length normalization.



224 Figure 3 represents the intra-class variation between features of same individuals in terms of euclidean
 225 distance, in four different scenarios, for both normalization approaches: length (represented in green)
 226 and average width (represented in clear blue). Average value and standard deviation of the variation of
 227 extracted features in previous four scenarios are gathered, supporting the affirmation that average width
 228 normalization provides more invariant features to previous changes.

229 3.3. Template Definition

230 This section describes the creation of the hand template considering only samples (hand feature vec-
 231 tors) from a single individual, in contrast to most extended approaches in literature which propose the
 232 use of samples of all enrolled individuals on the system to create individual templates [20].

233 Let W be a $N \times M$ matrix containing N rows vectors of M components (columns) representing the
 234 N required samples to conform the template.

235 This matrix W is created for each individual, and it is represented by $W = \{W_1, \dots, W_N\}$, where
 236 each W_i is a row vector containing a total of M components, coinciding with the number of distances
 237 contained in each extracted vector from a hand acquisition.

238 Let \widetilde{W} be a $\binom{N}{2} \times M$ matrix, representing the absolute euclidean difference between every pair of
 239 row vectors in W . In other words, $\widetilde{W} = \{|W_1 - W_2|, |W_1 - W_3|, \dots, |W_{N-1} - W_N|\}$, gathering a total
 240 of $\binom{N}{2}$ possible pairs. Matrix \widetilde{W} represents to some extent the variation between hand acquisitions for
 241 each template position.

242 In fact, matrices W and \widetilde{W} lead to the definition of two parameters, which are μ^W and $\sigma^{\widetilde{W}}$, namely
 243 the average of extracted features and the standard deviation of the difference variation. These latter
 244 parameters attempt to collect the behaviour of all the vectors contained in W and the similarity between

245 previous vectors, provided by the vector pairwise likelihood. Based on these characteristics, these vector
246 parameters are essential to create the template.

247 More in detail, operators μ and σ are functions applied to matrices, defined as follows in Equations 3
248 and 4 respectively, $\forall p, q \in \mathbb{N}$, assuming, for generalization sake, that matrix contains real values (\mathbb{R}).

$$\begin{aligned} \mu: M_{p \times q}(\mathbb{R}) &\rightarrow M_{1 \times q}(\mathbb{R}) \\ M &\mapsto \mu^M = \left\{ \frac{1}{p} \sum_{k=1}^p M_{k,j} \right\}_{\forall j \in \{1, \dots, q\}} \end{aligned} \quad (3)$$

$$\begin{aligned} \sigma: M_{p \times q}(\mathbb{R}) &\rightarrow M_{1 \times q}(\mathbb{R}) \\ M &\mapsto \sigma^M = \left\{ \sqrt{\frac{1}{p} \sum_{k=1}^p \left(M_{k,j} - \frac{1}{q} \sum_{i=1}^q M_{i,j} \right)^2} \right\}_{\forall j \in \{1, \dots, q\}} \end{aligned} \quad (4)$$

249 In addition, the template will consider also those $k < M$ components which remain less invariant
250 along different samples, i.e., template will discard those components whose variability is dissimilar to
251 some extent. This criterion is gather by vector $\pi_{1 \times M}$ defined as

$$\pi_i = \begin{cases} 1, & \text{if } \sigma_i^{\widetilde{W}} \leq \mu^{\sigma^{\widetilde{W}}} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

252 where $\sigma_i^{\widetilde{W}}$ corresponds to the i th component of vector $\sigma^{\widetilde{W}}$, and $\mu^{\sigma^{\widetilde{W}}}$ is the average of vector $\sigma^{\widetilde{W}}$ as
253 defined in Equation 3.

254 Therefore, π contains a '1' value in those positions where the feature variability is under the average
255 of the variability, indicating which distances remain more invariant over acquisition.

256 Finally, based on this vector π , a last parameter is defined, which will be useful when comparing a
257 sample (original or impostor) to a provided template. This parameter is represented by γ , and it is defined
258 as the average value of the first standardized moments applied to non-null positions in π . In other words,

$$\gamma = \frac{1}{M} \left(\frac{\mu^{\widetilde{W}}}{\sigma^{\widetilde{W}}} \pi^T \right) = \frac{1}{M} \sum_{i=1}^M \frac{\mu_i^{\widetilde{W}} \pi_i}{\sigma_i^{\widetilde{W}}} \quad (6)$$

259 where π^T makes reference to the transposition of matrix π . Furthermore, parameter γ can be regarded
260 as the inverse of the coefficient of variation [30], providing a dimensionless number to compare samples
261 with widely different means.

262 Finally, the hand template associated to a specific user is defined as $\mathcal{H} = (\mu^W, \sigma^{\widetilde{W}}, \pi, \gamma)$.

263 3.4. Matching based on the hand distances template

264 Provided the template \mathcal{H} , which collects global information from samples of a same individual, it
265 is mandatory the definition of a likelihood function able to indicate to what extent an acquire sample
266 (impostor or genuine) is similar to previous template \mathcal{H} .

267 Thus, given a hand feature vector $h_{1 \times M}$ of M components (as defined in Section 3.2), the likelihood
 268 function is defined as the similarity probability $p(h|\mathcal{H})$ given by the following relation (Equation 7):

$$p(h|\mathcal{H}) = \frac{1}{M} e^{-\alpha H H^T} \quad (7)$$

269 defining H as

$$H = \frac{1}{\gamma} \left(\frac{h - \mu^W}{\sigma^{\widehat{W}}} \circ \pi \right) = \frac{1}{\gamma} \left(\sum_{i=1}^M \pi_i \frac{h_i - \mu_i^W}{\sigma_i^{\widehat{W}}} \right) \quad (8)$$

270 where operator $A \circ B = [a_{ij}b_{ij}]_{\forall i,j}$ is defined as the Hadamard product, an entrywise multiplication
 271 for any two matrices $A, B \in M_{p \times q}(\mathbb{R})$, $\forall p, q \in \mathbb{N}$. Furthermore, parameter α is a global value set
 272 experimentally to $\alpha = 0.01$ for the whole biometric system.

273 This probability $p(h|\mathcal{H})$ is within the interval $[0, 1]$, indicating that sample h belongs to user with
 274 template \mathcal{H} as $p(h|\mathcal{H}) \rightarrow 1$, and vice versa.

275 Therefore, the biometric verification based on this approach can be carried out by stating a threshold
 276 $th \in [0, 1]$, so that an individual (with template \mathcal{H}_k) accesses the system providing a sample h_k , then the
 277 user is correctly verified (authenticated) if $p(h_k|\mathcal{H}_k) \geq th$. Otherwise, the user is rejected.

278 Similarly, the identification is considered by considering same previous threshold th , so that, provided
 279 a sample of a user, h_k , the system must decide whom the sample belongs to, or, whether the user is not
 280 enrolled in the system. In other words, if $\arg(\max_i p(h_k|\mathcal{H}_i) \geq th)$ determines that $i = k$ then the sample
 281 h_k is properly identified, otherwise the user is not enrolled in the system.

282 Some approaches in literature fail in associating sample h_k with a non-existing profile, since they
 283 provide the most likelihood an similar class, even if the sample provided by h_k corresponds to a non-
 284 registered individual [20].

285 As a matter of fact, a trade-off must be achieved for th for the sake of an accurate performance in
 286 terms of false rejection and false acceptance [1].

287 This effect will be discussed under the result section (Section 5).

288 4. Databases

289 The proposed scheme in Sections 3.2 and 3.3 are evaluated considering three public databases.

290 The first database contains hand acquisitions of 120 different individuals of an age range from 16 to
 291 60 years old, gathering males and females in similar proportion.

292 With the aim of a contact-less approach in hand biometrics, hand images were acquired without
 293 placing the hand on any flat surface neither requiring any removal of rings, bracelets or watches. Instead,
 294 the individual was required to open his/her hand naturally, so the mobile device (an HTC) could take a
 295 photo of the hand at 10-15 cm of distance with the palm facing the camera.

296 This acquisition procedure implies no severe constraints on neither illumination nor distance to mobile
 297 camera, being every acquisition carried out under natural light. In addition, it is a database with a huge
 298 variability in terms of size, skin color, orientation, hand openness and illumination conditions. In order to
 299 ensure a proper feature extraction, independently on segmentation, acquisitions were taken on a defined
 300 blue-coloured background, so that segmentation can be easily performed, focusing on hands. Both

301 hands were taken, in a total of two sessions: During the first session, 10 acquisitions from both hands
302 are collected; second session is carried out after 10-15 minutes, collecting again 10 images per hand.
303 The image size provided by the device is 640x340 pixels. This first database is publicly available at
304 *www.gb2s.es*. This database will be referred in this paper as GB2S database.

305 Second database is named 'IIT Delhi Palmprint Image Database version 1.0' [32], and it is a palmprint
306 image database consisting of a hand images collection from the students and staff at IIT Delhi, New
307 Delhi, India. This database has been acquired in the IIT Delhi campus during July 2006 - Jun 2007
308 using a simple and touchless imaging setup. All the images are collected in the indoor environment
309 and employ circular fluorescent illumination around the camera lens. The currently available database
310 is from 235 users, all the images are in bitmap format. All the subjects in the database are in the age
311 group 12-57 years. Seven images from each subject, from each of the left and right hand, are acquired in
312 varying hand pose variations. Each of the subject is provided with live feedback to present his/her hand
313 in the imaging region. The resolution of these images is 800x600 pixels. This database will be referred
314 in this paper as IITDelhi database.

315 Third database acquisition setup is inherently simple and does not employ any special illumination
316 nor does it make use of any pegs to cause any inconvenience to users. The Olympus C-3020 digital
317 camera (1280 x 960 pixels) was used to acquire both images from 287 individuals, with ten samples per
318 user. The users were only requested to make sure that their fingers do not touch each other and most of
319 their hand (back side) touches the imaging table. A further explanation of this database can be found in
320 [33]. This database will be referred in this paper as UST database.

321 As a conclusion, these databases contain different acquisition procedures (population size, distance
322 to camera, different illumination, hand rotation and the like) being a suitable evaluation frame for testing
323 the proposed method.

324 5. Results

325 A complete evaluation of a biometric system must entail different aspects such as performance/identification
326 accuracy, trade-off between false match rate and false non-match rate and dependency on the number of
327 training samples and features. Given the variety of aspects to evaluate, this section is divided into the
328 following parts:

- 329 ● Evaluation criteria for biometric systems
- 330 ● Comparative evaluation to SVM and k -NN employing the proposed databases
- 331 ● Study of performance dependency on the number of training samples
- 332 ● Study of performance dependency on the number of features
- 333 ● Study of the improvement provided by the feature extraction method

334 In addition, temporal aspects and computational cost evaluation will be carried out within each of the
335 previous presented sections, provided the following computer specifications: a PC computer @2.4 GHz
336 Intel Core 2 Duo with 4GB 1067 MHz DDR3 of memory, considering that the proposed method was
337 completely implemented in MATLAB.

Table 2. FTE and FTA rates for each database. These values will be considered during the calculation of FAR, FRR and EER rates in the evaluation.

	GB2S	IITDelhi	UST
FTE (%)	0	0.5	0
FTA (%)	0.4	0.7	0.2

338 5.1. Evaluation Criteria for Biometric Systems

339 There exist several types of testing for a biometric system considering a wide variety of aspects such as
 340 reliability, availability and maintainability; security, including vulnerability; conformance; safety; human
 341 factors, including user acceptance; relation between cost and benefit or privacy regulation compliance.
 342 The purpose of this section is to conduct a technical performance testing in terms of error rates. More in
 343 detail, the proposed assessment involves a technology evaluation, defined as an offline evaluation of one
 344 or more algorithms for the same biometric modality using a pre-existing or specially collected corpus of
 345 samples.

346 The evaluation criteria are defined by the following rates [12,34]:

- 347 • False-Non Match Rate (FNMR): Proportion of genuine attempt samples falsely declared not to
 348 match the template of the same characteristic from the same user supplying the sample.
- 349 • False Match Rate (FMR): Proportion of zero-effort impostor attempt samples falsely declared to
 350 match the compared non-self template.
- 351 • Failure-to-enroll rate (FTE): Proportion of the population for whom the system fails to complete
 352 the enrollment process.
- 353 • Failure-to-acquire (FTA): Proportion of verification or identification attempts for which the system
 354 fails to capture or locate and image or signal of sufficient quality.
- 355 • False Reject Rate (FRR): Proportion of verification transactions with truthful claims of identity
 356 that are incorrectly denied. Moreover, FRR is defined as follows: $FRR = FTA + FNMR \times (1 - FTA)$
- 357 • False Accept Rate (FAR): Proportion of verification transactions with wrongful claims of identity
 358 that are incorrectly confirmed. Furthermore, FAR is calculated as follows: $FAR = FMR \times (1 - FTA)$
- 359 • Equal Error Rate (EER): Rate at which both FAR and FRR coincides. In general, a system with
 360 the lowest EER is most accurate.

361 Table 2 contains the FTE and FTA rates for the three proposed databases: GB2S, IITDelhi and UST.
 362 These values will be taken into account in order to obtain FAR, FRR and EER rates in each evaluation
 363 scenario, as defined previously.

364 The behaviour of these latter parameters will be used for the evaluation across different databases,
 365 methods and dependency with variable parameters presented in Section 3.

Table 3. Equal Error Rate for each database and method. The results obtained with GB2S database are worst in comparison to the other databases since GB2S database present more variability in terms of hand rotation, distance to camera and environmental conditions. These results were obtained considering 4 samples for training, and 20 features per finger, i.e. $M = 80$.

	GB2S	IITDelhi	UST
k -NN	4.3 ± 0.2	3.9 ± 0.2	3 ± 0.1
SVM	3.1 ± 0.1	2.4 ± 0.1	2.1 ± 0.2
Proposed	2.5 ± 0.2	2 ± 0.2	1.4 ± 0.1

366 5.2. Comparative evaluation to SVM and k -NN employing the proposed databases

367 The proposed method will be compared in terms of technical evaluation [35] to two competitive pat-
 368 tern recognition techniques, namely Support Vector Machines (SVM) and k -Nearest Neighbour (k -NN)
 369 [21]. Although a wide explanation of these approaches is beyond the scope of this paper, some con-
 370 cerns must be taken into account with reference to the manner both approaches carry out classification.
 371 Both SVM and k -NN create a template based on information from other individuals, in contrast to the
 372 proposed template method, where only samples from a single individual are required to conform the
 373 template.

374 In addition, there exist another difference concerning the similarity score provided by these methods.

375 As stated in previous Sections 3.3 and 3.2, the similarity score measures the similitude between a
 376 template and a collected sample. The similarity score in the SVM is considered as the distance to the
 377 corresponding hyperplane associated to the most likely class. Likewise, the similarity score in the k -NN
 378 is the minimum distance associated to an element within the corresponding class. In these experiments,
 379 k coincides with 3, providing a major voting selecting of the corresponding class, and SVM employs
 380 linear kernel functions. This SVM and k -NN configurations are justified since it is the most suitable
 381 value compromising both identification performance and computational cost.

382 Table 3 presents the Equal Error Rates obtained for each method (k -NN, SVM and proposed) in
 383 relation to the three employed databases in the evaluation (GB2S, IITDelhi and UST).

384 This table shows that SVM overcomes k -NN in terms of EER but the proposed algorithm improves
 385 the results obtained by both pattern recognition technique. The results obtained with the GB2S database
 386 are higher than those obtained with the other databases, since GB2S database contains more variability
 387 in terms of hand rotation, pose, distance to camera and environmental conditions (e.g., illumination).

388 Furthermore, performances of each method are provided by means of ROC (Receiver Operating
 389 Curve) curves [5,32], indicating the behaviour of the overall system. Concretely, Figure 4 presents the
 390 results of the three methods (proposed, k -NN and SVM) for the database GB2S. In addition, Figure 5
 391 presents the results of the three methods (proposed, k -NN and SVM) for the databases IITDelhi (Figure
 392 5 (a)) and UST (Figure 5 (b)).

393 Both Figures 4 and 5 illustrate that the proposed method improves the performance obtained by the
 394 other two methods along three contact-less databases.

Figure 4. ROC curves for the proposed method in comparison to k -NN and SVM, using GB2S database. These results were obtained considering 4 samples for training, and 20 features per finger ($M = 80$).

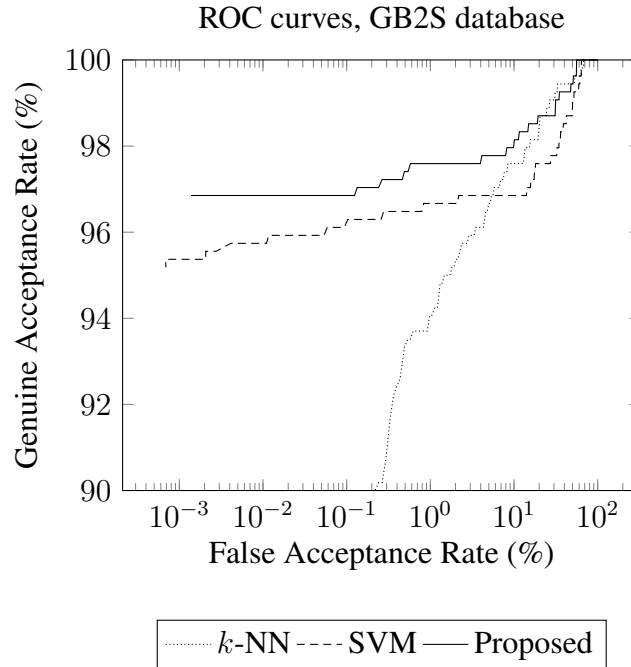
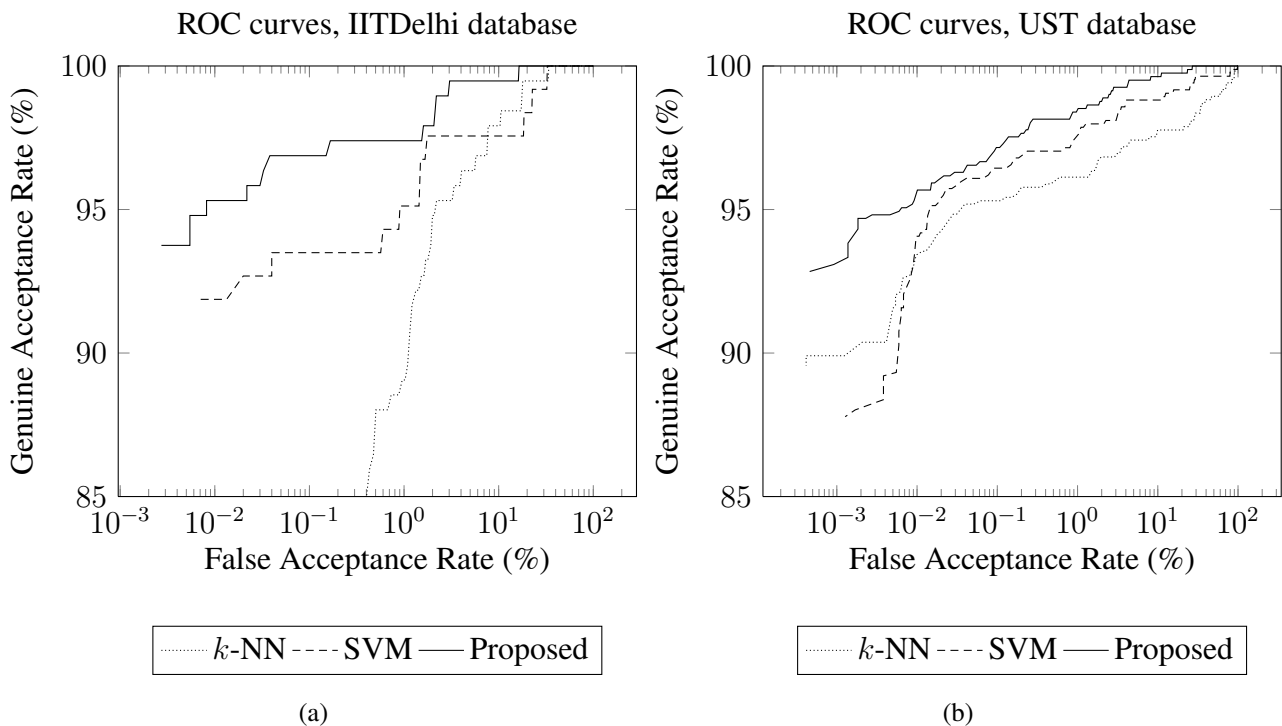


Figure 5. ROC curves for the proposed method in comparison to k -NN and SVM, using IITDelhi (a) and UST (b) databases. These results were obtained considering 4 samples for training, and 20 features per finger ($M = 80$).



395 5.3. Study of performance dependency on the number of training samples

396 Biometric systems provide more precise results when more samples during the enrollment are ac-
397 quired. The number of these samples coincides with the number of samples used to train the biometric
398 system. Therefore, the study of the dependency between the performance of the whole system and the
399 number of training samples is essential since an increment of the training samples will lead to an incre-
400 ment in performance, at expense of a diminution on the user acceptance and comfortability [11,12,35].

401 The performance of a biometric system is measured in terms of Equal Error Rate (EER) as defined in
402 Section 5.1. The results are presented in Figure 6 (a), where the variation of EER is presented along the
403 number of training samples for each database. Due to the different number of samples per individual (7
404 for IITDelhi, 10 for UST and 20 for GB2S), the maximum number of training samples for IITDelhi is 6
405 and for UST is 9. In addition, Figure 6 was obtained fixing the number of extracted features to 20 per
406 finger, i.e. $M = 80$.

407 However, an increase in the number of training samples to create the template results in an increment
408 of the time. Figure 7 (a) provides the relation between time and number of training samples to extract
409 the template. The proposed approach needs much less time to create the template since only considers
410 samples from a single user, in contrast to SVM or k -NN where the template must consider samples from
411 other users. Similarly, the values presented in Figure 7 were obtained fixing the number of extracted
412 features to 20 per finger.

413 5.4. Study of performance dependency on the number of features

414 Together with the number of training samples, the number of features (distances) extracted from each
415 hand is strongly related to the overall system performance. An increment on the number of features
416 results in an increment of the performance, as well as in an increment of the computational cost.

417 Figure 6 (b) contains the performance dependency on the number of features of the proposed method
418 for the three databases: GB2S, IITDelhi and UST. This evaluation compares the evolution of the Equal
419 Error Rate (EER) in relation to the number of features extracted for each hand.

420 In contrast, the computational cost increases substantially in relation to the number of features. More
421 in detail, the computational cost contains both the time required to train the biometric system and the time
422 needed to carry out the comparison. The latter time is negligible provided the computer specifications
423 where experiments are carried out, since comparing a M -dimensional vector with the three approaches
424 requires almost no time in comparison to other steps such as segmentation, feature extraction or the
425 training of the biometric system.

426 In contrast, the number of features increases the processing time during the training. Figure 7 (b)
427 gathers the behaviour of the training time for the three systems (template-based, SVM and k -NN), in
428 relation to the number of extracted features.

429 The results obtain in both Figures 6 (b) and 7 (b) were obtained fixing the number of training samples
430 to 4, and considering only the GB2S database, assuming that similar results will be obtained for the other
431 two databases.

Figure 6. Comparative Equal Error Rate (EER) variation in relation to number of training samples to create the template and the number of features per finger, for the three databases: IITDelhi, UST and GB2S.

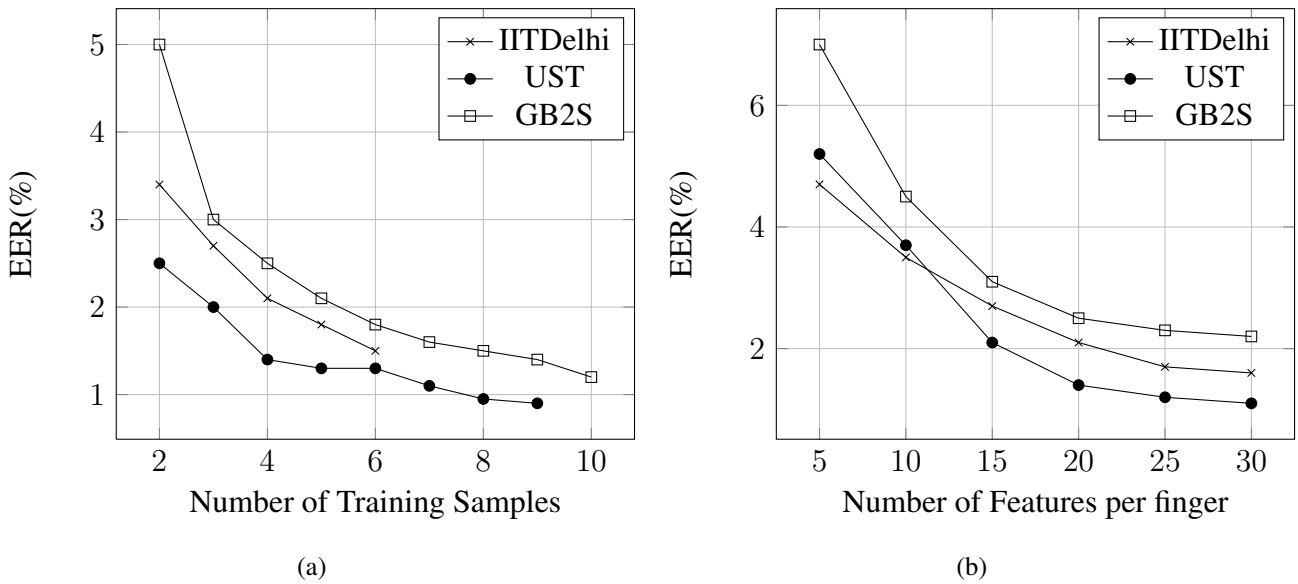


Figure 7. Comparative time variation in relation to number of training samples to create the template and the number of features per finger, for the proposed method, SVM and k -NN. Time is measured in seconds.

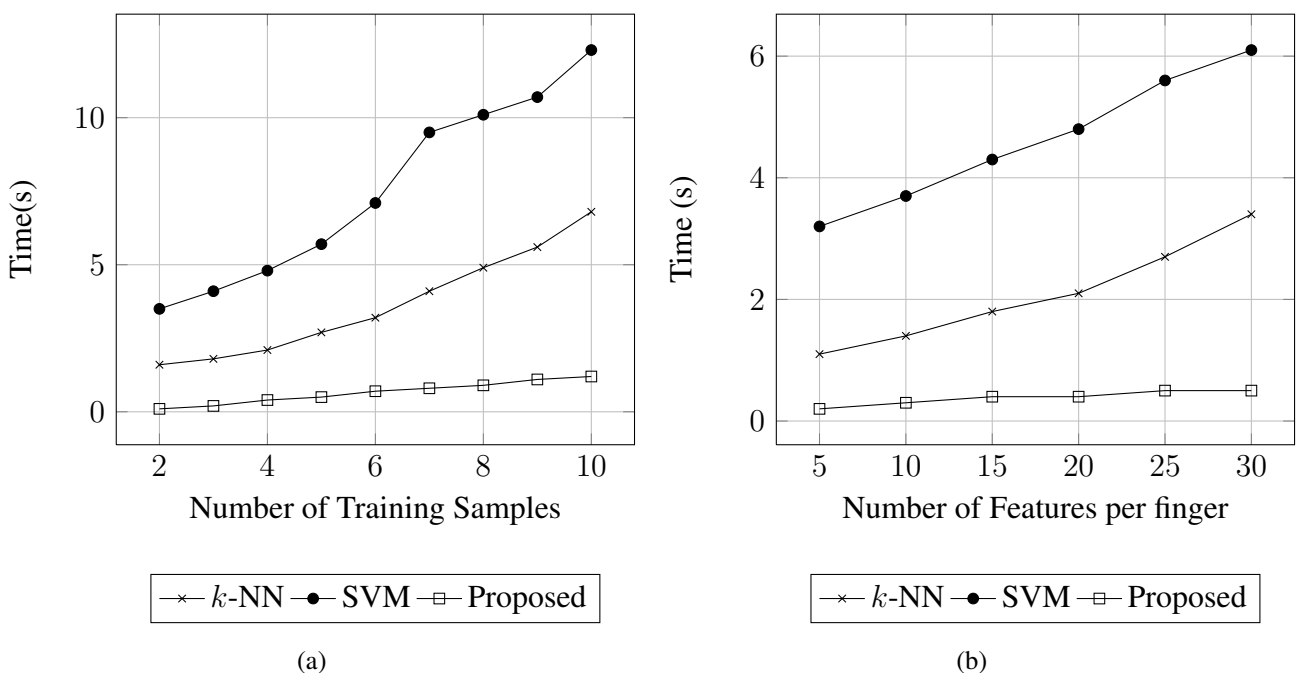


Table 4. Comparative study of the improvement achieved by the proposed feature extraction method for each pattern recognition method (proposed, k -NN and SVM). The improvement achieved by the proposed method is remarkable. These results were obtained considering 4 samples for training, and 20 features per finger, i.e. $M = 80$.

	Standard Method [2,3]	Proposed Method
k -NN	7.1 ± 0.2	4.3 ± 0.2
SVM	6.3 ± 0.2	3.1 ± 0.1
Proposed	4.8 ± 0.1	2.5 ± 0.2

432 5.5. Study of the improvement provided by the feature extraction method

433 Apart from template creation, another innovative contribution of this paper consists of providing a
434 feature extraction as described in Section 3.2.

435 Table 4 gathers the results obtained applying the proposed method and standard width feature extrac-
436 tion [2,3]. It shows that the use of this feature extraction method decreases the EER for each pattern
437 recognition method, obtaining a remarkable improvement compared to standard extraction methods.

438 In addition, results presented in Table 4 where obtained by using the GB2S database. It is not difficult
439 to assume that the feature extraction method conserves its properties, regardless the database.

440 Finally, the number of training samples was 4 and the number of feature extracted was also 20 per
441 finger, as in all the evaluation scenarios.

442 6. Conclusions and Future Work

443 This paper has presented a biometric system based on hand geometry oriented to contact-less and
444 platform-free scenarios. The contribution of this paper consisted of three innovative aspects: the pro-
445 posal of a feature extraction method, invariant to distance to camera, hand rotation, hand pose and
446 environmental conditions; the creation of a template involving only data (features) from one single indi-
447 vidual; and a template matching able to minimize the intra-class similarity variation and maximize the
448 inter-class likeliness.

449 The evaluation was carried out with three publicly available contact-less, platform-free databases,
450 comparing the results obtained to two competitive pattern recognition techniques, namely Support Vector
451 Machines (SVM) and k -Nearest Neighbour (k -NN), widely employed within the literature.

452 The results obtained show that the feature extraction method is able to provide invariant to changes
453 features. In fact, the proposed method has achieved the second position in the Hand Geometric Points
454 Detection International Competition HGC2011.

455 The template proposal only considers features from an individual. In other words, the template does
456 not require information from the individuals contained on the rest of the database. This template creation
457 not only reduces the computational cost of the enrollment procedure but also it allows biometric systems
458 of one single individual, oriented to applications in mobile devices, for instance.

459 In fact, the use of both the feature extraction method and the template creation decreases remarkably
460 the Equal Error Rate of the system, regardless the database involved. In addition, the feature extraction

461 method improves the performance of the three compared approaches: the proposed method, SVM and
462 k -NN. A further comparison to other existing feature extraction methods remains as future work.

463 Finally, the template matching proposed outperforms the presented pattern recognition techniques SVM
464 and k -NN in terms of identification and verification performance. This template matching only consid-
465 ers those positions within the template with less intra-class variation, instead of comparing the whole
466 template.

467 In general, the low computational cost required with this approach, together with the accurate per-
468 formance in human identification makes of this proposed method a suitable scheme for devices with
469 low hardware requirements, and its unconstrained and contact-less acquisition procedure can extend the
470 applicability of this proposed system to a wide number of scenarios. In addition, there is no constraint
471 on the quality of the camera during the acquisition, since one of the databases was obtained with a mobile
472 phone.

473 Considering future work, an implementation of this method in mobiles remains as future work to-
474 gether with its corresponding evaluation in real environments. Furthermore, more contact-less databases
475 will be regarded for evaluation, together with the exploitation of both hands in a fusion scheme to im-
476 prove identification and verification. Finally, an in depth evaluation of the effect of acquisition changes
477 (distance-to-camera, hand rotation and openness variations) in identification performance will be consid-
478 ered.

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