Towards hand biometrics in mobile devices

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Abstract: The increasing demand of security oriented to mobile applications has raised the attention to biometrics, as a proper and suitable solution for providing secure environment to mobile devices.

With this aim, this document presents a biometric system based on hand geometry oriented to mobile devices, involving a high degree of freedom in terms of illumination, hand rotation and distance to camera. The user takes a picture of their own hand in the free space, without requiring any flat surface to locate the hand, and without removals of rings, bracelets or watches.

The proposed biometric system relies on an accurate segmentation procedure, able to isolate hands from any background; a feature extraction, invariant to orientation, illumination, distance to camera and background; and a user classification, based on k-Nearest Neighbor approach, able to provide an accurate results on individual identification. Previous schemes combine simplicity, low computational cost and efficiency, so that their implementation in mobile devices is feasible. The proposed method has been evaluated with two own databases collected with a HTC mobile. First database contains 120 individuals, with 20 acquisitions of both hands. Second database is a synthetic database, containing 408000 images of hand samples in different backgrounds: tiles, grass, water, sand, soil and the like.

The system is able to identify individuals properly with False Reject Rate of 5.78% and False Acceptance Rate of 0.089%, using 60 features (15 features per finger).

1   Introduction

This paper presents a method to identify individuals based on hand geometry features by using mobile devices, not only during the acquisition procedure but also when carrying out the individual identification.

Hand biometrics applied to mobile devices allow a contact-less approach for this biometric technique without requiring any additional hardware or sensor, combining the strengths of

hand biometrics in terms of identification with the extended use of mobile devices.

The proposed biometric technique is performed by acquiring a hand picture of the user with a mobile devices, having the palm up facing the camera. In other words, the idea consists that user could take a picture of his/her own hand with the mobile phone. The challenge of this biometric technique lies in the variability existing in changes like camera distance, orientation and hand openness.

The segmentation algorithm implies slight constraints on backgrounds where hand acquisitions can take place, and the features conforming template are invariant to previous changes.

In addition, the k Nearest Neighbor classification algorithm is suitable for mobile implementation combining simplicity and high rates in identification performance. The system accuracy has been evaluated with two own public databases: first database, of 120 individuals, contains 20 samples of both hands per user and is oriented to assess system behaviour in relation to individual identification accuracy; second database, with 408000 pictures of hand with different backgrounds (grass, tiles, parquet, wood and the like) is aimed to evaluation system performance in terms of segmentation.

2 Literature Review

The idea of extracting unique information from hand with the aim of personal identification was early already proposed [SRSAGM00]. In fact, the quantity of works presented under the topic of hand biometrics makes intractable to provide a fair overview within this document [FS09]. Therefore, the main interest of this literature review gets down to contact-less approaches, where hand is not located on a flat surface [FS09].

Most common scenarios consider image acquisition on free-space with visible light requiring few constraints on the background with standard CCD cameras. In contrast, in order to avoid background effects on segmentation, infrared illumination was proposed as a suitable solution to meet this goal [MFAT08], achieving better results when compared to visible light.

With regard to mobile devices, biometrics attempt to respond to the huge and increasing demand in security applications oriented to mobile devices covering from daily scenarios [LGYC10] to government environments [ADA10].

Finally, some works have assessed to what extent hand biometrics are accepted by individuals [KEGD07], concluding that users react very positively to hand biometric sensors. Moreover, none of the individuals thought the device could invade their personal activity, preferring this biometric technique to the existing card-based access system.

3 Segmentation by means of Gaussian Multiscale Aggregation

The proposed method is based on multiscale aggregation [MnAdSSC10], considering an image I as a graph $G = (V, E, W)$ were V represents nodes in graph corresponding to pixels in image, E stands for the edges connecting pairs of previous nodes V and W the weight of previous edges, measuring the similarity between two nodes (pixels) in V.

The similarity between nodes in first scale will be set based on their neighbourhood of each pixel, which is a 4-neighbourhood structure for the first scale. These two parameters are collected into a single function $\phi_{v_i}^{[s]}(\mu_{v_i}^{[s]}, \sigma_{v_i}^{[s]})$ representing the degree of being similar to node v_i, where s represents the scale. For simplicity sake, $\phi_{v_i}^{[s]}(\mu_{v_i}^{[s]}, \sigma_{v_i}^{[s]}) = \phi_{v_i}^{[s]}$, to avoid and excessive complicated notation.

Thus, the similarity between two neighbour nodes v_i and v_j at scale s is defined as in Equation 1.

$$w_{ij}^{[s]} = \int \phi_{v_i}^{[s]} \phi_{v_j}^{[s]} d\zeta \tag{1}$$

where ζ makes reference to the complete color space. The more similarity between membership functions, the higher weight $w_{ij}^{[s]}$. Moreover, functions $\phi_{v_i[s]}$ are normalized by definition so that $\int \phi_{v_i}^{[s]} d\zeta = 1$, for every scale s. Notice that w_{ij} is only calculated for neighbour pixels, according to the neighbourhood provided by each scale s.

This method iterates along all weights sorted in W so that every node is associated with a subgraph. Next step consists on extracting the new membership functions for each subgraph, based on the functions associated with the nodes within such a subgraph.

For a given subgraph in the subsequent scale, $G_k^{[s+1]}$, the membership function is defined as follows in Equation 2.

$$\phi_{G_k}^{[s+1]} = \frac{\bigcup_j^N \phi_{G_j}^{[s]}}{\int \bigcup_j^N \phi_{G_j}^{[s]} d\zeta} \tag{2}$$

where N represents the number of nodes gathered by subgraph $G_k^{[s+1]}$. Notice $\phi_{G_k}^{[s+1]}$ is normalized according to definition, so that $\int \phi_{G_k}^{[s+1]} d\zeta = 1$.

However, a new structure must be provided efficiently to these scattered nodes, since the initial structure of 4-neighbourhood grid is lost with this aggregation method. Moreover, in addition to function $\phi_{v_j}^{[s]}$, every node v_j is provided with their location within image I in terms of vertical and horizontal cartesian coordinates. When obtaining $G_k^{[s+1]}$, the centroid of those gathered nodes is calculated, so that each subgraph on subsequent scales have a position within image. This centroid, ξ, allows to provide a structure in subsequent scales by means of Delaunay triangularization [dBvKOS08].

This operation represents the final step in the loop, since at this moment, there exist a new subgraph $G^{[s+1]} = \bigcup_k G_k^{[s+1]}$ at scale $s + 1$ where each $G_k^{[s+1]}$ represents a node, and

edges $E^{[s+1]}$ are provided by Delaunay triangulation, and weights $W^{[s+1]}$ are obtained based on Equations 1 and 2.

The whole loop is repeated until only two subgraphs remain, as stated at the begining of this section ($G = G_h \cup G_b$).

The computational cost of this algorithm is quasi-linear with the number of pixels, since each scale gathers nodes in the sense that nodes in subsequent scales are reduced by (in practice) a three times factor. Therefore, the total time is comparable to two times the processing time to aggregate first scale.

4 Feature Extraction

Hand image acquisition with a mobile devices implies a wide variability in terms of hand rotation, distance to camera and pose orientation. During the acquisition procedure, users are said to take their hand picture, with the mobile camera facing completely the hand, avoiding changes in pose orientation. However, users are free to choose distance to camera and hand rotation. Therefore, features extracted from segmentation must be invariant to these former changes in order to ensure a proper accuracy in terms of identification.

Let S be the segmentation result provided by previous Section 3. First of all, the algorithm separates fingers from palm, given that the whole information of posterior features will be extracted from fingers only by carrying out a morphological opening with a disk structural element of size 40, so that fingers are completely erased from the original image, being the palm mostly conserved. At this point, those with lower area are selected as candidate to be whether thumb or little, being the criteria to distinguished between then the ratio between length and width. To put it another way, the algorithm associates thumb to the dickest and smallest finger.

Having detected little and thumb, the classification of the rest fingers is straightforward.

Due to the acquisition procedure, fingers could point at any direction and could have difference lengths and widths even among intra-class samples because of the distance to camera variability.

Therefore, normalization must be considered to ensure invariance to these former changes. Concretely, the presented approach proposes a normalization scheme based on finger length, dividing each extracted feature by their corresponding finger length. Mathematically, let $F = \{f_i, f_m, f_r, f_l\}$ be the set of possible fingers, namely index, middle, ring and little, respectively. Then, finger lengths are represented by the set $\Lambda = \{\lambda_{f_i}, \lambda_{f_m}, \lambda_{f_r}, \lambda_{f_l}\}$. Lengths are measured in terms of euclidean distance between the corresponding tip point to the bases of the finger.

In addition, thumb finger is not considered on the template, due to their noticeable movement freedom within hand plane.

Concerning width features, a different approach to literature is proposed considering average values to describe every feature. In other words, m distances are taken along the finger,

measuring the existent width between finger sides. Afterwards, these former measures are splitted into n (with $n < m$) sets, containing the average values of the corresponding $\lfloor \frac{m}{n} \rfloor$ parts gathered by each set. For each set, average μ and standard deviation σ is calculated.

Furthermore, each n component is normalized according to the corresponding finger length, based on former discussion about normalization.

In other words, each finger f_k is divided into m parts from basis to top, resulting in the set of widths $\Omega_{f_k} = \{\omega_1, \ldots, \omega_m\}$. Considering set Ω, the template is represented by $\Delta_{f_k} = \left\{ \frac{\delta_1^{f_k}}{\lambda_{f_k}}, \ldots, \frac{\delta_n^{f_k}}{\lambda_{f_k}} \right\}$, where each $\delta_t^{f_k}$ is defined as the average value of at least $\lfloor \frac{m}{n} \rfloor$ components in Ω_{f_k}.

Final step in biometrics systems design regards template comparison, which means to decide whether two provided templates belong to a same individual.

A suitable solution is k Nearest Neighbor as a simple, effective and nonparametric classification method, which has been extensively used in a wide number of biometric applications [LCW09]. In addition, their computational cost is adequate for mobile applications, and the results (Section 6) justify this selection. The specific parameters are $k = 3$ (the number of nearest neighbors used in the classification) and the euclidean distance as metric.

5   Databases

The proposed biometric technique is oriented to mobile applications and therefore, the algorithm must be tested with images acquired from a mobile device. Two databases are collected: First database assesses (train, validate and test) the whole system in terms of identification efficiency. Second was created synthetically based on first database to evaluate only the performance of segmentation, with the aim of evaluating the proposed algorithms in different environments and scenarios. These databases are both available at *http://www.gb2s.es*.

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

Second database represents the tool to evaluate segmentation, assessing to what extent the segmentation algorithm can satisfactory isolates hand from background on real scenarios. Different backgrounds are considered in an attempt to cover all possible real scenarios, containing textures from carpets, fabric, glass, grass, mud, different objects, paper, parquet, pavement, plastic, skin and fur, sky, soil, stones, tiles, tree, walls and wood. Five different images from every texture were considered to ensure more realistic environments. All previous texture backgrounds were taken from *http://mayang.com/textures/*. This database contains a total of 408000 images.

Tabelle 1: Segmentation evaluation by means of factor F in a synthetic database with 17 different background textures.

Texture	$F(\%)$	Texture	$F(\%)$	Texture	$F(\%)$
Carpets	92.3±0.2	Paper	91.3±0.2	Stones	91.4±0.1
Fabric	89.1±0.1	Parquet	88.4±0.3	Tiles	90.3±0.2
Glass	94.3±0.1	Pavement	89.1±0.2	Tree	96.3±0.2
Grass	93.7±0.1	Skin and Fur	95.7±0.2	Wall	94.2±0.1
Mud	89.8±0.1	Sky	96.4±0.2	Wood	93.8±0.1
Objects	92.1±0.2	Soil	89.4±0.1		

6 Results

The scope of this paper describes hand segmentation on mobile devices from hand acquisition with the camera embedded on a mobile phone to the individual classification indicating whom the hand image belongs to. A global evaluation must consider complete assessment of each steps in hand biometrics.

In order to evaluate segmentation performance, a supervised evaluation method was considered. This method compares the result provided by the segmentation method with a ground-truth image. Furthermore, in order to measure to what extent the result is similar to ground-truth, factor F [AGBB07] is proposed, providing a suitable manner to assess segmentation and accuracy.

The former factor F is defined as $F = \frac{2RP}{R+P}$ where R stands for Recall and P for Precision. The results of factor F obtained for second database are presented in Table 1.

There exist two parameters which affect the performance in terms of identification and verification: the number of features extracted per finger and the number of samples to train the classifier based on k-NN.

In addition, the criteria to evaluate is defined by the following rates [KEGD07]: False-Non Match Rate (FNMR), False Match Rate (FMR), Failure-to-enroll rate (FTE), Failure-to-acquire (FTA), False Reject Rate (FRR), False Accept Rate (FAR).

Best value is obtained with $N = 12$ and $\Delta_{n=15}$ which implies 12 samples for training and a total of 60 features per hand (15×4). However, competitive results can be obtained by reducing both values. It is remarkable, the low value of FMR in every configuration, which means that the proportion of users that are accepted wrongly is almost negligible, ensuring that only enrolled users can access the system.

In addition, the value for FRR and FAR can be obtained for the best system. This values coincides with FRR = 5.98% and FAR = 0.089%.

The proposed system has been implemented on two different arquitectures: a MATLAB implementation (running in a PC Computer @2.4GHz) and a JAVA-Android implementation oriented to an HTC Desire @1GHz and 576 MB RAM. Due to the obvious differences in hardware, the implementation was tackled differently in each situation.

Tabelle 2: Temporal performance of both implementation measured in seconds.

Operation	PC @2.4GHz (seconds)	HTC @1GHz (seconds)
Acquisition	< 0.1	< 0.1
Segmentation	0.7±0.08	1.5±0.2
Feature Extraction	0.4±0.1	0.8±0.2
Matching	0.1±0.01	0.4±0.05

In order to compare both implementations, Table 2 is provided. Despite of the difference in the hardware, the HTC implementation is able to provide individual identification in less than 3 seconds, which is a reasonable time performance for a mobile application.

7 Conclusions

A biometric system based on hand geometry recognition oriented to mobile devices is proposed within this document.

Users can take a picture of their hands by holding the mobile phone with the remaining hand, providing a high degree of freedom in terms of rotation and distance to camera. Therefore, this biometric technique solves the identification problem in a more challenging environment, given that there are few limitations and constraints on the background which is behind the hand.

The idea is to provide a non-invasive and comfortable biometric technique on mobile devices to final users.

The segmentation algorithm is based on multiscale aggregation, by using L*a*b* color space, very suitable for mobile applications due to their combination of computational cost and efficiency.

The template which describes univocally the individuals is based on N samples extracted from the user, obtaining best results when $N = 12$ samples are required. Furthermore, the classification is based on a k-Nearest Neighbor approach which provides the biometric system with competitive identification rates (FRR = 5.78% and FAR = 0.089%), with low computational cost, for a mobile implementation.

Concerning future work, authors would like to explore the variation of FAR and FRR rates under different backgrounds, the effect of blur and the inclusion/removal of rings in identification performance and the improvement of the segmentation algorithm, so that better results could be obtained, reducing the Failure-to-acquire (FTA) rate. In addition, an evaluation in terms of user acceptability is also considered as future work.

Literatur

[ADA10]   T. Alhussain, S. Drew und O. Alfarraj. Biometric authentication for mobile govern-
               ment security. In *Intelligent Computing and Intelligent Systems (ICIS), 2010 IEEE
               International Conference on*, Jgg. 2, Seiten 114–118, 2010. ID: 1.

[AGBB07]   S. Alpert, M. Galun, R. Basri und A. Brandt. Image Segmentation by Probabilistic
               Bottom-Up Aggregation and Cue Integration. In *IEEE Conference on Computer
               Vision and Pattern Recognition, 2007. CVPR '07.*, Seiten 1–8, june 2007.

[dBvKOS08]   Mark de Berg, Marc van Kreveld, Mark Overmars und Otfried Schwarzkopf. *Com-
               putational Geometry: Algorithms and Applications*. Springer, 3rd. Auflage, April
               2008.

[FS09]   Leong Lai Fong und Woo Chaw Seng. A Comparison Study on Hand Recogniti-
               on Approaches. In *Soft Computing and Pattern Recognition, 2009. SOCPAR '09.
               International Conference of*, Seiten 364–368, 2009. ID: 1.

[KE06]   E. Kukula und S. Elliott. Implementation of hand geometry: an analysis of user
               perspectives and system performance. *Aerospace and Electronic Systems Magazine,
               IEEE*, 21(3):3–9, march 2006.

[KEGD07]   E.P. Kukula, S.J. Elliott, B.P. Gresock und N.W. Dunning. Defining Habituation
               using Hand Geometry. In *Automatic Identification Advanced Technologies, 2007
               IEEE Workshop on*, Seiten 242–246, 7-8 2007.

[LCW09]   Haitao Liu, Yang Cao und Zengfu Wang. A novel algorithm of gait recognition. In
               *Wireless Communications and Signal Processing, 2009. WCSP 2009. International
               Conference on*, Seiten 1–5, 2009. ID: 1.

[LGYC10]   Huiqi Lu, S. Gheitanchi, R. Young und C. Chatwin. A symbian based mobile user
               authorization system using mobile networks. In *Wireless Advanced (WiAD), 2010
               6th Conference on*, Seiten 1–5, 2010. ID: 1.

[MFAT08]   A. Morales, M.A. Ferrer, J.B. Alonso und C.M. Travieso. Comparing infrared and
               visible illumination for contactless hand based biometric scheme. In *Security Tech-
               nology, 2008. ICCST 2008. 42nd Annual IEEE International Carnahan Conference
               on*, Seiten 191 –197, 2008.

[MnAdSSC10]   Ángel García-Casarrubios Muñoz, Carmen Sánchez Ávila, Alberto de Santos Sierra
               und Javier Guerra Casanova. A mobile-oriented hand segmentation algorithm based
               on fuzzy multiscale aggregation. In *Proceedings of the 6th international conference
               on Advances in visual computing - Volume Part I*, ISVC'10, Seiten 479–488, Berlin,
               Heidelberg, 2010. Springer-Verlag.

[SRSAGM00]   R. Sanchez-Reillo, C. Sanchez-Avila und A. Gonzalez-Marcos. Biometric iden-
               tification through hand geometry measurements. *Pattern Analysis and Machine
               Intelligence, IEEE Transactions on*, 22(10):1168–1171, oct 2000.