Invariant Hand Biometrics Feature Extraction

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Abstract. Hand biometrics relies strongly on a proper hand segmentation and a feature extraction method to obtain accurate results in individual identification. Former operations must be carried out involving as less user collaboration as possible, in order to avoid intrusive or invasive actions on individuals.

This document presents an approach for hand segmentation and feature extraction on scenarios where users can place the hand on a flat surface freely, without no constraint on hand openness, rotation and pressure.

The performance of the algorithm highlights the fact that in less than 4 seconds, the method can detect properly finger tips and valleys with a global accuracy of 97% on a database of 300 users, achieving the second position in the International Hand Geometric Competition HGC 2011.

Keywords: Hand segmentation, invariant feature extraction, mathematical morphology, biometrics, hand geometry.

1 Introduction

In recent years, hand-based biometric systems are evolving from constrained, contact-based approaches [4,16] to completely non-collaborative, unconstrained and contact-less scenarios, where almost no collaboration from user is required.

The main aim of this trend is focus on providing hand biometrics with more comfortability and usability characteristics, increasing the acceptabiblity of final user.

However, as system development attempts to adapt hand biometrics to daily non-collaborative, non-intrusive and non-invasive scenarios, the operations of segmentation and feature extraction increases their current strain.

Therefore, this document presents a segmentation algorithm and feature extraction method to provide accurate results for hand biometrics in a scenario with a flat surface where hand is placed, but with a considerable margin of freedom, providing samples with a wide range of rotation and hand openness.

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The evaluation of the proposed method considers a publicly available database, leading to accurate results, which made this algorithm to achieve the second position in International Hand Geometric Points Detection Competition HGC2011 [12].

The layout of the paper is as follows: First of all, previous approaches are studied under the literature review (Section 2). Afterwards, both the segmentation method (Section 3) and the feature extraction strategy (Section 4) are described, together with the corresponding results (Section 5). Finally, conclusions an future work are presented in Section 6.

2 Literature Review

Several approaches have been proposed to solve the problem of hand segmentation. As an overview, segmentation methods are more complicated, as the background increases in difficulty. Early works attempted to isolate hand from background, given a monochromatic or apriori known background [11,16]. However, more challenging backgrounds were demanded when hand biometrics required no constraint on background, providing solutions for contact-less approaches [3,8,13,5].

At present, hand biometrics are oriented to mobile applications in order to provide more security to mobile devices [15,1]. Therefore, more complicated algorithms are proposed given both the complexity of the segmentation aim and that mobile devices are increasing their capability to carry out complex operation. These algorithm are based on multi-aggregation strategies [14,2]. Moreover, the inclusion of small objects like rings, bracelets and watches has received also attention in previous work [18,14].

In addition to this, a wide range of methods are proposed to detect tips and valleys, in order to provide a starting point for a posterior feature extraction procedure. Most common approaches consider to work on the hand contour [8,10] extracting maximum and minimum values from several transformation on such a contour. In contrast, other methods proposed to separate fingers separately [18] but not to detect tips or valleys. Instead, this finger isolation is proposed to correct the effect of rings on fingers.

However, these approaches frequently lack of precision in peg-free or contactless environments, since hand can be rotated or presented with different poses, having effect on hand contour. Furthermore, hand contour works properly as long as fingers are separated one from each other, otherwise, the contour-based approach provides imprecise and fuzzy results [6,7,19].

Therefore, there exist justification to explore new approaches on both segmentation and finger tip and valley detection, with the aim of extending feature extraction to more challenging and non-collaborative acquisition environments.

3 Segmentation

Before extracting features it is required to isolate hand completely from background. In this case, hands were obtained with a scanner, so that background is under control, although there exist difficulty in segmentation due to the flat surface to be streamed up.

The proposed segmentation algorithm is based on multiscale aggregation [2,14]. Concretely, the method considers image I as a graph $G = (V, E, W)$, where nodes $v_i \in V$ correspond to pixels in image; edges $e_{i,j} \in E$ represent the union between two nodes v_i and v_j; weights $w_{i,j} \in W$ describe the similarity between two nodes v_i and v_j associated by an edge $e_{i,j}$.

The main contribution of this algorithm is to describe each node as a similarity function based on a specific neighbourhood. In other words, each node v_i is described as a function ϕ_{v_i}, assuming a normal distribution $\mathcal{N}(\mu, \sigma)$ in terms of intensities within the 4-neighbour structure. Parameters μ and σ make reference to the average and standard deviation of the intensity in the proposed neighbour structure.

Therefore, the weight $w_{i,j}$ is defined in terms of functions ϕ_{v_i} and ϕ_{v_j} as in Equation 1:

$$w_{i,j} = \int_{\alpha} \sqrt{\phi_{v_i} \phi_{v_j}} d\alpha \tag{1}$$

where α represents the color space. In this case, this color space corresponds to CIELAB, concretely the a layer.

The method carries out the following procedure until only two segment remains:

- Obtain set graph G for image I
- Order pair of nodes according to weights W
- Aggregate nodes in descendent order, based on previous ordering in W
- Calculate function ϕ for each aggregated segment.
- Provide neighbour structure applying Delaunay triangulation

Finally, this method comes out with precise and accurate results for hand segmentation [14], in comoparison to other more demanding approaches [11,17].

4 Feature Extraction

This section describe an approach to detect properly tips and valleys given a hand image. This approach is opposite to those provided within the literature, not being entirely based on hand contour [16,8]. Therefore, the section will be divided into two parts describing both tips and valleys detection. In addition, the proposed scheme is able to classify fingers and thus associate each tip to their corresponding finger.

4.1 Finger Classification

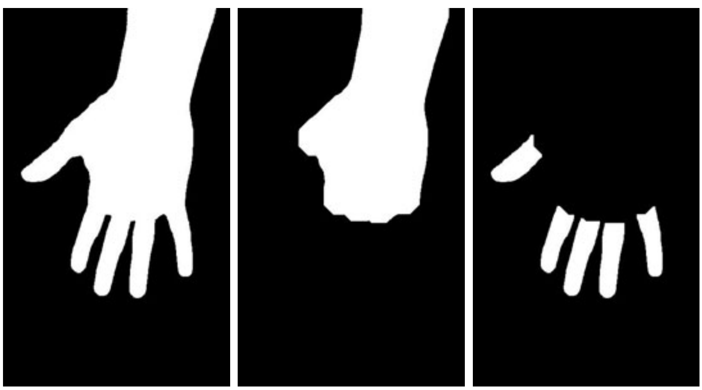
First of all, fingers are splitted from the segmented hand in order to facilitate their classification. Let H be the result provided by segmentation procedure. Applying an opening morphological operator [9] with a disk structural element of size 40 will cause fingers to dissapear, remaining only the part corresponding to palm. This image is named H_p, since it represent those pixels corresponding to palm. Although this operation is very severe, it allows conserve those region blobs which are very dense in terms of pixels, being suitable for deleting prominent blobs like fingers from hand.

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

$$H_f = H \cdot \bar{H}_p \tag{2}$$

being $\cdot$ an operator indicating a logical AND operation between H and the complementary of H_p.

Figure 1 provides a visual example of the fingers isolation method.



(a) (b) (c)

Fig. 1. 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

Afterwards, five blobs are contained in H_f (Figure 1)one of each corresponding to each finger. In case more than five blobs are obtained, an opening morphological operator based on a small disk structural element (size 5) will erase those small and undesired region blobs, with lack of interest for a finger classification.

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

The blob which verifies to have the lowest values in both criteria is the little finger. The next finger with lower area is thumb, and ring, middle and indez are classified according to the distance between their centroids to previous calculated fingers. In other words, that blob whose centroid is closer to little is classified as ring finger, for instance.

4.2 Tip Detection

Having the finger blobs calculated, tip detection consists of calculating the finger extrema. In other words, obtain the furthest pixel in each blob in relation to a reference point, which coincides with the hand centroid, due to their geometric properties of being located in the middle of the palm.

The furthest pixel position is obtained then in relation to hand centroid and based on euclidean distance between two different pixels within image.

Since there are five fingers, this method would lead to five tips.

4.3 Valley Detection

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

Then, the former valleys are calculated according to Equation 3

$$v_k = argmin(||\zeta - h_c||) \tag{3}$$

Finally, index-thumb valley is calculated as the point which provides the biggest area between candidates in $c(t_i, t_t)$, t_t and t_i.

Notice that valley detection is a considerable challenging task, given that some fingers could be together one to each other, difficulting the valley point calculation.

4.4 Left/Right Hand Classification

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

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

This left/right classification can be used to ensure the correct identification of little and thumb, given that images in the training and testing databases correspond to right hands.

5 Results

The results provided under this section regards the evaluation in terms of accuracy of the tip and valley detection. The requirements of the algorithm were to detect properly points (tips and valleys) in comparison to a ground-truth set of points. The result tolerance should be less than 20 pixels, being in that case well detected, otherwise uncorrectly detected.

Figure 2 is provided to show the histogram of scores for the training database, which contained a total of 300 hand images [12]. Scores represent the distance between groud-truth (provided within the training database) and the proposed algorithm result.

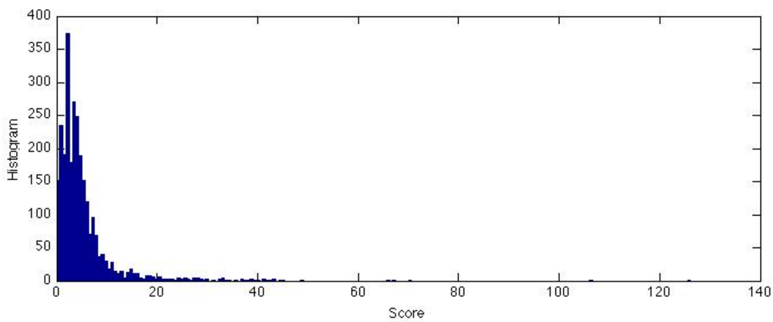


Fig. 2. Histogram of scores for the training datase (300 images)

Most values are lower than the threshold provided by the 20 pixels. In fact, the score average value is 5.13±6.66, with a median of 3.61, which is considerably far from the provided threshold.

Most errors (55.5% of total errors) were due to the index-thumb valley, which authors found very difficult to detect. In addition, the majority of errors were based on an uncorrect valley detection (96.3% of total errors). In total, the algorithm detect unproperly 81 of 2700 points (3%) of the training database.

Finally, the time performance of this approach is described in Table 1. Time results have been measured based on a MATLAB implementation to be run in a PC computer @2.4 GHz Intel Core 2 Duo with 4GB 1067 MHz DDR3 of memory.

Table 1. Time performance of the different operations from segmentation to tip and valley detection. Times are measured in seconds.

Operation	Time (seconds)
Segmentation	0.23±0.02
Fingers Extraction	1.59±0.02
Fingers Classification	< 0.1
Tip Detection	0.20±0.01
Valley Detection	1.07±0.01

Furthermore, points are calculated in less than 4 seconds, given previous implementation and the computer.

6 Conclusions

A hand tip and valley detector algorithm has been presented within this paper. The method is able to locate these points independently from orientation, hand openness and hand colour.

The acquisitions were collected with a scanner, providing the same background for each hand image, being a proper approach to segment image from background a method based on adaptive threshold, combining both low computational cost and efficiency in segmentation.

In addition, a classification is provided to associate each tip to their corresponding finger, so that a posterior left-right classification can be done. This is essential in applications where users can provide any of both hand, and the system must distinguish between them.

Tip and valley detection is described based on mathematical morphology and simple geometrical operations. The results (a score average value of 5.13 ± 6.66 and a success rate of 97%) highlight the fact that the overall method (segmentation and feature extraction) is able to detect properly and precisely the required points. However, more efforts are required in valley detection, since they cause the 96% of the total errors. Moreover, its low computational cost makes this algorithm remarkably suitable and appropriate for contact-less hand biometric applications. In addition, this algorithm achieved the second position in International Hand Geometric Points Detection Competition HGC2011 [12].

Finally, as future work, authors would like to explore the applications of the proposed feature extraction to a biometric system, and evaluate to what extent the proposed method improves the current feature extraction approaches in the literature.

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