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### A contactless identification system based on hand shape features

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#### Abstract

This paper aims at studying the viability of setting up a contactless identification system based on hand features, with the objective of integrating this functionality as part of different services for smart spaces. The final identification solution will rely on a commercial 3D sensor (i.e. Leap Motion) for palm feature capture. To evaluate the significance of different hand features and the performance of different classification algorithms, 21 users have contributed to build a testing dataset. For each user, the morphology of each of his/her hands is gathered from 52 features, which include bones length and width, palm characteristics and relative distance relationships among fingers, palm center and wrist. In order to get consistent samples and guarantee the best performance for the device, the data collection system includes sweet spot control; this functionality guides the users to place the hand in the best position and orientation with respect to the device. The selected classification strategies - nearest neighbor, supported vector machine, multilayer perceptron, logistic regression and tree algorithms - have been evaluated through available Weka implementations. We have found that relative distances sketching the hand pose are more significant than pure morphological features. On this feature set, the highest correct classifier provide a CCI rate above 90%. Results also show how these algorithms perform when the number of users in the database change and their sensitivity to the number of training samples. Among the considered algorithms, there are different alternatives that are accurate enough for non-critical, immediate response applications.

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Peer-review under responsibility of the Conference Program Chairs *Keywords:* Biometry, hand-shape based identification, classification, smart spaces.

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#### 1. Introduction

The increasing availability of low-cost technology that makes possible to interpret in-air gestures, such as compact devices including depth sensors, facilitate the creation of different concepts of interaction. Although these devices are often designed to interface with laptops or applications, they have a great potential as tools to be integrated in our daily life environments for non-critical applications. In particular, algorithms for gesture recognition are usually categorized as user-independent or user-dependent, depending on their need for previous training. User-dependent ones usually provide a better accuracy<sup>1</sup>, even if the additional training effort may reduce the system usability perception. Our previous works in this area have led us to search for a confortable identification mechanism, compatible with infrastructure devices enabling gesture recognition and delivering user identification without the need to equip the user with any extra device (e.g. wearable accelerometers).

The objective of this work is then to explore the possibilities of delivering a functional identification method based on contactless hand shape analysis on a Leap Motion sensor. Although this sensor is being widely used for interaction, to the best of our knowledge there are not empirical studies in the identification issue. The paper is oriented to compare the performance of different classification algorithms regarding accuracy, training needs and scalability. To introduce this comparison, Section 2 provides a review of previous research on shape hand-based identification. Section 3 defines the identification strategy itself, starting by the hand features to be used. Within this Section, it is also described the classification algorithms and the sweet pose tool used to gather the testing dataset. On this dataset, Section 4 presents a performance comparison that analyzes the information within the selected hand features; it also evaluates specific implementations of the algorithms, taking into consideration their accuracy, time to build the model, need for training and scalability. Finally, Section 5 discusses on results and further work.

#### 2. Related work

Shape-based hand recognition is one of the first live biometrics-based recognition systems. The first systematic system to capture hand and finger images is dated in 1858<sup>2</sup>. In the mid 1960's, Robert Miller invented a mechanical hand geometry identification device<sup>3</sup>. The first commercial device (Identimate)<sup>4</sup> used mechanically scanned photocells to measure the finger length, the endpoint contours and the skin translucency. This device was in use from 1970's to 1987. In 1986, Recognition System presented the ID3D HandKey<sup>4</sup>, the first device using low-cost digital imaging sensors. Currently, the increasing number of commercial systems and patents demonstrates the effectiveness of this biometric approach, with many approaches proposed and evaluated (e.g. Kong et al.<sup>5</sup> and Duta<sup>6</sup> provides complete surveys).

Many hand-based biometric schemes work obtaining geometric measures of the hand and then extracting a set of features from these geometric measures. The main hand recognition approaches are based on hand geometry, hand contour and palm print. The hand geometry systems use only hand geometric features, for instance, finger lengths, finger widths, palm areas, measure ratios, etc. These methods reduce the information given in a hand sample to a *N*-dimensional vector that is used to implement a matching algorithm based in a metric distance. Other alternative schemes are proposed in literature applying different probabilistic and machine learning techniques, like *k*-Nearest Neighbours<sup>7</sup>, Gaussian Mixture Models<sup>8</sup>, or Support Vector Machines<sup>7,9,10,11</sup>. For instance, in Morales et al.<sup>12</sup>, 40 features obtained from finger widths for 3 finger are used to train a supported vector machine (SVM). Adán et al.<sup>13</sup> use a hand natural reference system in order to make the system robust against different hand poses, and the classification is based in a time averaged feature vector. This system is based on a webcam. Sánchez-Reillo et al.<sup>14</sup> use 25 features, such as finger widths, finger and palm heights, finger deviations and angles of the interfinger valleys with respect to the horizontal, modeling them using Gaussian mixtures. Jain et al.<sup>15</sup> use an imaging scheme to select 16 features, such as the length and width of the fingers, the aspect ratio of the palm to the fingers, and the thickness of the hand. Öden et al.<sup>16</sup> use geometric features and finger shapes. The finger shapes are modeled using fourth degree polynomials. They obtain 16 features that are compared using the Mahalanobis distance.

Hand contour based systems use the hand silhouette to perform the matching. Yoruk et al.<sup>17</sup> use 2048 points of contour coordinates to construct a raw feature vector and independent component analysis features are used in the identification and verification tasks. Woodard et al.<sup>18</sup> use shape indices based on 3D shape curvature and a match score based in correlation coefficients between shape descriptors. Finally, palm print systems use the palm silhouette

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