Empirical Evaluation of Ear Biometrics

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1 Introduction

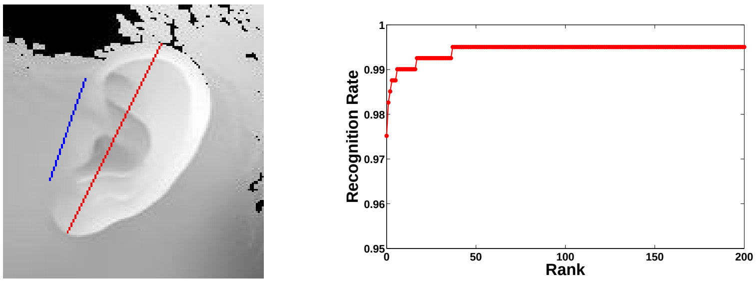
The work presented in this paper is unique in several points with respect to prior work. We report results from the largest experimental dataset to date, in terms of number of persons or number of images or number of algorithms considered. Ours is the first work to consider ICP-based recognition on a large dataset with 404 subjects. Also because we use a large experimental dataset, we are able to explore how the different algorithms scale with dataset size.

Moreno et al. [4] experiment with three neural net approaches to recognition from 2D intensity images of the ear. Their testing uses a gallery of 28 persons plus another 20 persons not in the gallery. They find a recognition rate of 93% for the best of the three approaches. method. Yuizono [8] implemented a recognition system for 2D intensity images of the ear using genetic search. In the experiment they had 660 images from 110 persons, with 6 images per person. They reported that the recognition rate for the registered persons was approximately 100%. Bhanu and Chen presented a 3D ear recognition method using a local surface shape descriptor [2]. With twenty range images from 10 individuals (2 images each) are used in the experiments and a 100% recognition rate is achieved for their dataset. In [3], Chen and Bhanu use two-step ICP on a dataset of 30 subjects with 3D ear images. They claimed that this method yielded 2 incorrect matches out of 30 pairs of ears.

All the images used in this paper were acquired at the University of Notre Dame between October 7, 2003 and December 10, 2004. In each acquisition session, the subject sat approximately 1.5 meters away from the sensor, with the left side of the face facing the Minolta Vivid 910 range scanner. One 640x480 3D scan and one 640 x 480 color image are obtained nearly simultaneously.

2 Algorithms

In our previous work, we examined three algorithms. They are PCA-based, edge-based and ICP-based approaches [6]. The ICP-based approach yields the best performance. Besl and McKay's classic ICP algorithm has been implemented [1]. Given a set of source points P and a set of model points X, the goal of ICP is to find the rigid transformation T that best aligns P with X. Beginning with a starting estimate of the registration T_0, the algorithm iteratively calculates a sequence of transformations T_i until the registration converges.



(a) Two-Line Landmark (b) CMC Curves on 404 Subjects

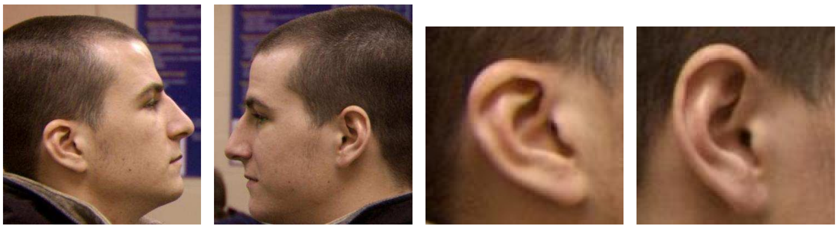
Figure 1. ICP-Based Approach

The earliest good image for each of 404 persons was enrolled in the gallery. The latest good image of each person was used as the probe for that person. The ICP-based approach does not require such extensive normalization. We use a two-line landmark to crop the ear, shown in Figure 1(a). One line is along the border between the ear and the face, and the other is from the top of the ear to the bottom.

Various refinements to the ICP algorithm were considered, several of which were incorporated into an improved algorithm. The amount of the ear shape used in the gallery and probe representations was adjusted to reduce interference from the background. A step to remove outlier point matches was added to reduce the effects of incorrect correspondences. Our improved algorithm produces substantially better results. Using a 404-person dataset, with a single 3D ear scan as the gallery enrollment for a person, and a single 3D ear scan as the probe for a person, the new algorithm achieves 97.5% rank-one recognition [7]. The CMC curve of the ICP approach on the 404-person dtaset is demonstrated in Figure 1(b).

3 Ear Symmetry Experiment

So far the ear data used in our experiments is of good quality, and the gallery and probe images are basically straight-on ear images, of the same ear, on different days. We called this "controlled conditions". It would be very interesting to look at the experimental results from less controlled conditions.



(a) Right Ear (b) Left Ear (c) Right ear) (d) Mirrored Left ear

Figure 2. Image acquired for Ear Symmetric experiments

One less controlled approach is matching a mirrored left or right ear, which means that for one subject we enroll his right ear and try to recognize using his left ear. This approach assumes bilateral symmetry of the ear. Two different angles of view have been examined. They are 30 degree off the center and 45 degree off the center. The initial data processing includes landmark ground truth and ear extraction, which are the same as we described in previous sections. The right ear of the subject is used as the gallery, and the left ear is used as the probe, see Figure 2. For this initial experiment, both ear images are taken on the same day. The performance achieves 90.9% when we used 88 subjects dataset and 30 degrees off the center for both of ears, and 89.1% when we used 119 subjects dataset and 45 degress off the center for both of ears. By analyzing the results, we found that most people's left and right ears are at least close to bilaterally symmetric. But some people's left and right ears have different shapes. Figure 2 shows an example of this. Thus it seems that symmetry-based ear recognition cannot be expected to be as accurate, since the assumption of bilateral symmetry of ear shape is not always

4 Summary And Discussion

We present results of the largest experimental investigation of ear biometrics to date. ICP matching of the 3D data, achieving 97.5% on a 404-person dataset. ICP-based matching not only achieves the best performance, but also shows good scalability with size of dataset. The data set used represents over 400 persons, each with images acquired on two different dates. In order to test the robustness and variability of ear biometrics, ear symmetry is also investigated. In our experiments around 90% of people's right ear and left ear are symmetric. Several topics for additional work seem important and promising. One is to consider methods of improving the computation time required by ICP matching. Another is to further investigate the scalability of 3D ear recognition performance with increased data set size. A third topic is to investigate possible performance improvement by combining 2D and 3D recognition for a multi-modal result [5].

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