Multi-Modal Biometrics Involving the Human Ear

Christopher Middendorff, Kevin W. Bowyer, Ping Yan
University of Notre Dame
Notre Dame, IN
{cmidden1, kwb, pyan}@cse.nd.edu

Abstract

Due to its semi-rigid shape and robustness against change over time, the ear has become an increasingly popular biometric feature. It has been shown that combining individual biometric methods into multi-biometric systems improves recognition. What features should be used, how they should be captured, what algorithms should be used, and how they should be combined are all open questions. In this paper, we discuss several existing methods of combination and the recognition rates of each.

1. Introduction

Ears have gained attention in biometrics due to the robustness of the ear shape. The shape does not change due to emotion as the face does, and the ear is relatively constant over most of a person's life [6, 7].

Pun and Moon [7] give an overview of ear biometrics. They cite the ear's smaller size and more uniform color as desirable traits for pattern recognition. Other characteristics are that it is less invasive than iris or fingerprint recognition and more reliable than voice. They state that the principal methods of ear biometrics are PCA [2], force field transformation [4], local surface patch comparisons using range data [1], Voronoi diagram matching, neural networks, and genetic algorithms. Other methods include geometric feature extraction [3] and for 3D data, ICP [9].

2. Multi-biometric approaches

The aim of multi-biometrics is to improve quality of recognition over an individual method by combining the results of multiple features, sensors, or algorithms. Multi-biometric methods fall into several categories. One is *multi-algorithm, mono-modal*, which employs multiple algorithms on a single input, e.g. performing color and edge algorithms on a single ear image to achieve recognition. Another is *single-algorithm, multi-modal*, which uses a single method on multiple input, e.g. using face and ear images as inputs to PCA as shown in Figure 1, or using several images from the same sensor for comparison. The last is *multi-algorithm, multi-modal*, which uses different approaches on different data, e.g. using PCA on 2D images and ICP on 3D images.

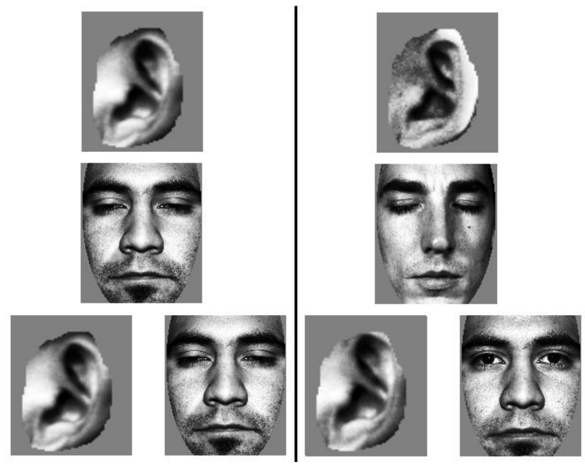

Figure 1: An example of a scenario where individual recognition methods failed, but succeeded when combined (image to appear in [5])

Fusion of multi-biometrics is usually performed at the level of their scores, after results of the individual tests are returned but before the ranking is assigned. One example of such simple fusion is *sum*, where the score from each test is combined, and the sum is ranked. A generalization of this is the *weighted sum*. This is useful if one metric is inherently more reliable than the other, or if it is possible to experimentally determine which metric is stronger in a given case.

Another is *interval*, using the intuition that the higher the difference between the rank-one and rank-two matches, the higher-quality the match (since the greater difference implies less ambiguity between the matches). The intervals between the rank-one and rank-two matches are divided into N bins. For each bin, $P(\textit{correct} \mid \textit{interval})$ is calculated.

When matching is performed, the interval for each metric is compared against the bins, and $P(\textit{correct} \mid \textit{interval})$ is used as the weight for that metric.

Moreno et al. [6] present a neural network approach to combine three different identifiers: ear feature points, ear morphology, and compression networks. They use several combination methods (majority vote combination, Borda combination, Bayesian combination, and weighted Bayesian combination) and find that multi-algorithm performed equivalent to their best individual method (compression network), which had a 93% identification rate.

Chang et al. [2] explored the benefits of combining face and ear biometrics, using PCA for recognition. These experiments were executed under three conditions: day variance (88 subjects), lighting variance (111 subjects), and pose variance (101 subjects). When combined, performance improved significantly for the day variation experiment, from 70.5% rank-one recognition for face and 71.6% rank-one recognition for ear to 90% when the two metrics were combined. A significant improvement is also achieved in the lighting variation experiment. Face recognition in this experiment was 64.9%, and ear recognition was 68.5%. The combined rank-one recognition rate was 87.4%.

Yan and Bowyer [9] explored multi-modal, multi-algorithm and multi-instance biometrics, combining 2D intensity data with 3D range data. Using PCA with the 2D image and ICP with the 3D image and weighting the modalities differently, rank-one recognition of up to 93.1% is achieved on a data set of 202 subjects, and 90.7% on a data set of 302 subjects. Multi-algorithm gave performance up to 90.2%, combining 3D ICP with 3D edge data. Using 3D PCA and ICP gave 87.7% rank-one recognition, and 3D PCA and edge gave a 69.9% recognition rate. Multi-instance biometrics gave improvement over single-gallery, single-probe biometrics as well; In the case of one probe and one gallery, 2D PCA gave 73.4% rank one, 3D ICP gave 81.7% rank one, and combined gave up to 88.2%. In the multi-instance case of two probe and two gallery images, 2D PCA gave 87.5% rank-one recognition and 3D ICP gave 97% rank-one recognition.

Yan [8] extended the ear and face biometric, using 3D face and ear images. Experiments were performed with 174 subjects in the dataset, each with two ear shapes and two face shapes. Rank-one recognition for face was 93.1%, and rank-one recognition for ear was 97.7%. For sum and interval fusion rules, 100% rank-one recognition was achieved.

3. Conclusions

The literature has shown that the use of multi-modal biometrics can improve performance of a recognition system. However, there is no consensus on what features should be used, how they should be acquired, or even how they should be combined. Studies have shown increased performance through combining face and ear biometrics [2], through combining 2D and 3D sensing of the ear, and through combining results from multiple images of the same feature taken with the same sensor [9]. When designing a multi-modal biometric system, one must consider the type of data to be acquired (e.g.. 2D or 3D), the type of recognition algorithm performed on each data element (PCA or ICP), the output of that algorithm (the distance or error metric), the type of fusion to be performed to combine them and the level at which it should be performed.

4. Acknowledgments

Biometrics research at the University of Notre Dame is supported by the National Science Foundation under grant CNS01-30839, by the Central Intelligence Agency, by the US Department of Justice/ National Institute for Justice under grants 2005-DD-CX-K078 and 2006-IJ-CX-K041, by the National Geo-spatial Intelligence Agency, and by UNISYS Corp.

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