THREE-DIMENSIONAL FACE AND FINGER BIOMETRICS

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ABSTRACT

The use of dense range scans of the face to supplement or supplant visible-light images in face recognition systems has been a subject of recent interest in the biometrics community. This paper summarizes recent research activities designed to assess the potential of a high-resolution 3D face scan as a viable biometric, using a large database of such scans. We show that 3D faces offer potential for this application but also exhibit challenges that must be addressed before systems based on 3D face can be fielded. We also describe preliminary results from a study of 3D hand shape biometrics employing curvature classification of the finger skin surface.

1. INTRODUCTION

Research on 3D face recognition started over a decade ago; yet, to date the number of research articles and commercial products describing or performing face recognition in 3D has been fairly small. Cartoux *et al.* [1] matched face profiles obtained from a bilateral symmetry plane's intersection with the face. Lee and Milios [2] matched extended Gaussian images generated from a curvature-based segmentation of the 3D face image to match probe and gallery faces. Gordon [3] registered face images using a curvature-based segmentation and matches faces by computing volume differences between the probe and gallery images. More recently, Achermann *et al.* [4] applied PCA and HMM techniques developed for 2D images to range data. Beumier and Acheroy [5] fused 2D and 3D matching scores. Bronstein *et al.* [6] employed isometric transformations and canonical images to handle variations in face shape due to facial expression.

Commercial vendors are now offering 3D face recognition systems with integrated sensors. Geometrix [7] offers a stereo face sensor and a recent conference demonstration paper by Medioni *et al.* [8] describes an alignment-based recognition technique employing the well-known ICP registration procedure. A4Vision [9] offers a structured light system and a matching engine. Given the market potential of robust biometric systems, commercial interest in 3D biometrics seems likely to remain high.

Another area of biometric research that has seen some recent interest is hand shape. Jain and students [10,11] have developed and investigated 2D hand geometry biometrics that compute features from the silhouette of the hand. There has been almost no work on 3D biometrics of the hand. Lay [12] projected a grating pattern on the back surface of the hand and captured the pattern distorted by hand shape, and attempted to match binarized versions of these distorted grids.

One key to establishing the performance of biometric systems is thorough testing on realistic data sets of size sufficient to bolster performance claims. Open data sets are very valuable when comparing different systems, although commercial products sometimes are tuned to a particular sensor and might not be expected to perform well when presented with other types of data.

In this paper, we address the recognition of subjects from 3D range scans of the face or the top of the hand. We summarize our recent published work on 3D face matching using PCA. These results confirm good performance overall, but pronounced sensitivity to facial expression change. To our knowledge, this is the first paper to investigate and test 3D shape biometrics of the hand. We describe preprocessing, feature extraction, and curvature-based matching procedures for 3D hand scans, and demonstrate degradation in performance when probe and matching gallery images are obtained on different days. All data collected in this research study is either already available or will be made available as part of a large biometric data repository containing over 100,000 images of various types[1].

2. 3D DATA ACQUISITION AND PROCESSING

The "workhorse" 3D sensor in our laboratory is the Minolta Vivid 900/910 sensor. This laser scanner, acquired in 2001 and upgraded in 2003, obtains a 640x480 range image and a registered color image in about 8 seconds. Our database contains over 4,000 3D face images collected starting in Spring 2002 and continuing to the present. Experiments reported in this paper use subsets of this collection.

The acquisition of 3D face and hand images is part of a larger data collection effort underway since 2002. At present, we have 300 experimental subjects active in the project, with about 160 in common from week to week (this yields a large amount of repeat data). In addition to 3D face and hand scans, approximately 80,000 high-resolution color face images, 15,000 infrared face images, and additional small collections of ear images have been collected. In addition, ac-

[1] http://www.nd.edu/~cvrl

quisition of iris images began in 2004 and approximately 2,400 are collected each week (six images from each eye).

Each 3D face image undergoes some processing prior to use in recognition experiments. As acquired, the set of range pixels is not registered to a face-centered coordinate system. We normalize these images by placing the nose tip at the origin and forcing the corners of the eyes to lie on a horizontal line at the same depth as the center of the chin. These normalization steps are depicted in Figure 1.

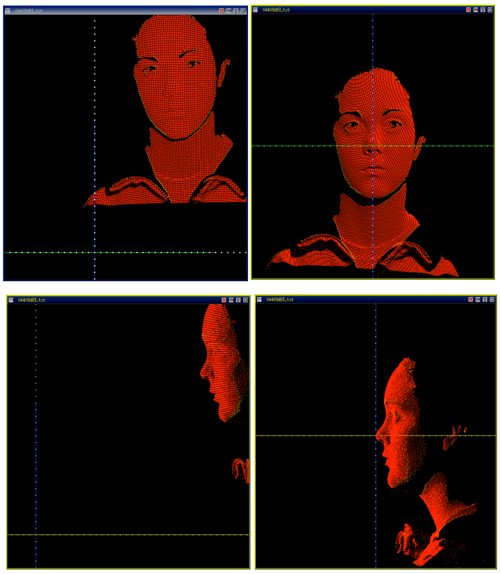

Figure 1. 3D face image normalization. Left: before normalization. Right: after normalization.

3. 3D FACE RECOGNITION USING PCA

Chang *et al.* [13] report on PCA-based recognition experiments performed using 3D and 2D images from 200 persons. One experiment uses a single set of later images for each person as the probes, and another experiment uses a larger set of 676 probes taken in multiple acquisitions over a longer elapsed time. We employ the Colorado State University face recognition evaluation software distribution [14] in our experiments using PCA. Some eigenspace pruning was done to remove low-discrimination basis vectors with highest variation and lowest variation. Figure 2 shows a cumulative match characteristic plot for the individual modes and a system that fuses modes at the metric level. Results in both experiments were approximately 99% rank-one recognition for multi-modal 3D+2D, 94% for 3D alone and 89% for 2D alone. This work represents the largest experimental study yet reported in the literature either for 3D face alone or for multi-modal 2D+3D, in terms of the number of subjects, the number of gallery and probe images, and the time lapse between gallery and probe image acquisition.

Our experiments with PCA based face recognition revealed strong sensitivity to facial expression change between the gallery (enrolled) image and the probe image to be recognized. Figure 3 contains intensity and range images of a subject under three facial expressions. Figure 4 shows the

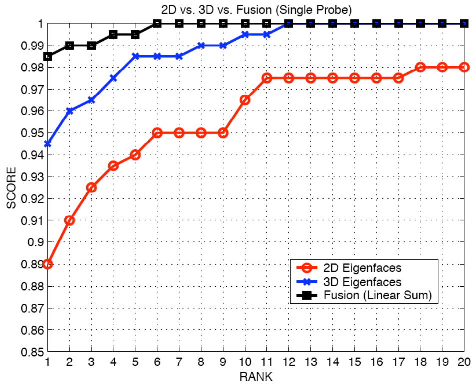

Figure 2. Performance of PCA-based 2D, 3D, and fused 2D/3D face matcher.

results of a comparative study pitting PCA-based 2D and 3D face recognizers against one another in the presence of elapsed time between probe and gallery and also expression change. We see that expression change causes a more significant drop in 3D system performance than in 2D system performance. A robust facial recognition system should be able to accommodate variation in expression.

Handling change in facial expression would seem to require at least some level of part-whole model of the face, and possibly also of the range of possible non-rigid motion of the face. This is a topic of our current research. We believe that facial alignment with a variant of the ICP algorithm and a facial segmentation based on curvature may offer some robustness to expression change.

Figure 3. Intensity and range images of three facial expressions.

4. HAND SHAPE BIOMETRICS

As noted above, there have been relatively few articles in the published literature relating to hand shape as a biometric, and those papers that do exist focus on silhouette features and silhouette matching. We have been examining the 3D shape of the hand as a potential biometric and report some initial results here.

Figure 5 shows range and registered color images of a hand captured by the Minolta 900/910 range sensor in our

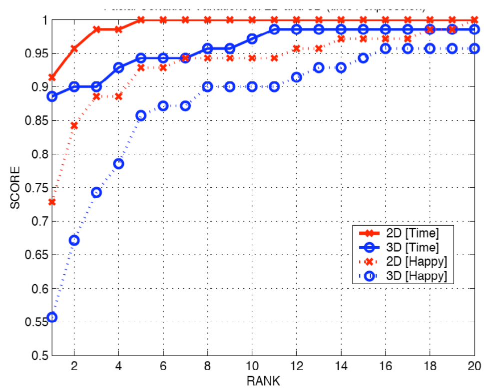

Figure 4. Performance of PCA-based 2D and 3D face recognition: elapsed time and expression change effects.

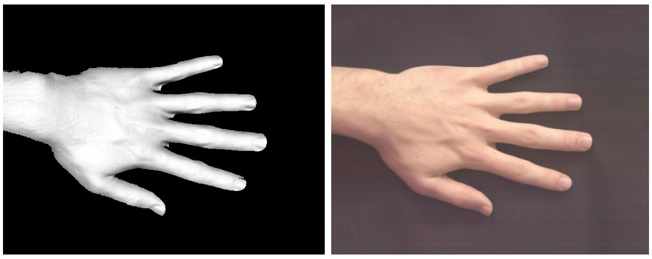

Figure 5. Range and color images of a hand.

laboratory. We have 132 experimental subjects for whom five range images of the hand are available (two images the first week and three images the second week). Experimental conditions require careful positioning of the hand and accommodation of the large variability in hand size from person to person. One barrier to widespread acceptance of 3D hand shape biometrics may be the lack of scanners specialized to the hand.

Range images of the hand are processed and segmented into individual finger images by silhouette processing. Indentations in the silhouette identify valleys between fingers, and their positions along the silhouette contour are used as segment boundaries; thus, the fingers can be extracted and processed individually. We currently extract the index, middle and ring fingers, denoted α, β, and γ, generating masks as shown in Figure 6. The mask and the corresponding range pixels are rotated so that the major axis of the mask is coincident with the horizontal axis in the output finger range images. This alignment step suppresses finger pose variations.

Range pixels on the finger surface are classified using the shape index classifications proposed by Koenderink [16]. These were adapted to free-form surface representation and global object recognition by Dorai and Jain [17]. The shape index SI is a scalar computed from principal curvatures and intervals in the shape index value correspond to shape classes such as ridge, valley, and plane. Figure 7 shows shape index images for the aligned fingers in Figure 6. These classification maps tend to capture local finger features such as creases and looser skin over the knuckles, as well as the ridge near the nail bed. Clearly, a dense range map is necessary for

Figure 6. Index (α), middle (β), and ring (γ) finger masks extracted from a range image.

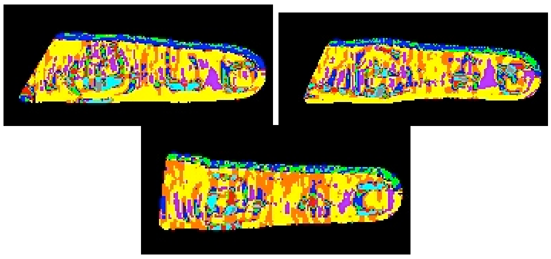

Figure 7. Shape classification maps for aligned finger images.

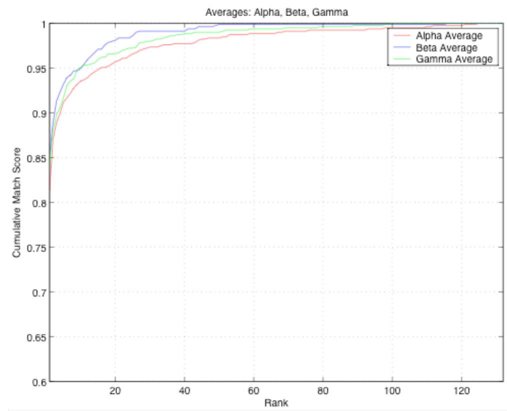

Figure 8. Cumulative Match Characteristic for finger matching experiments.

this representation to be useful; at a coarser scale the finger is reasonably well approximated by a cylinder and the distinctive local shape features would be lost.

At present, we employ a very simple finger matching technique. Since we know the finger type (α, β, or γ), we match probe finger shape class images with gallery finger classification images of the same type. A simple correlation score is computed:

$$S(f_1, f_2) = \frac{1}{N} \sum_{(i,j) valid} I(f_1(i,j) - f_2(i,j)),$$

where *f1* and *f2* are the two finger images with *N* valid mask pixels in common between them, and *I()* is the indicator function that returns unity if its argument is zero and zero otherwise. Thus, this score is the total fraction of valid shape pixels that agree in classification.

Figure 8 shows CMC plots depicting recognition accuracy averaged across fourteen experiments involving different probe and gallery image sets. Each line on the plot indicates one of the three fingers. These experimental results are surprisingly good considering the simplicity of the matcher.

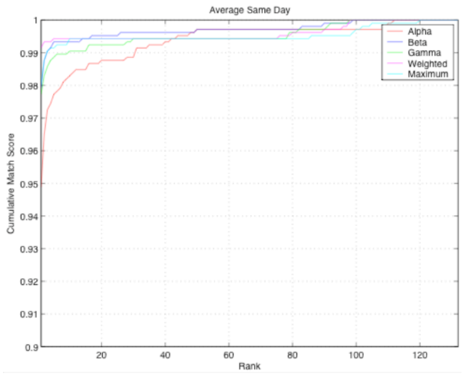

Figure 9. CMC plot for same-day matching experiments.

Figures 9 and 10 reveal a performance drop with elapsed time between probe and gallery acquisition. Figure 9 shows averaged CMC plots for probes and galleries acquired on the same day. In addition to plots for individual finger performance, performance curves for metric-level fusion using a "max" rule (highest-confidence finger match is used) and an "average" rule (the average score is computed over all three fingers) are shown. Figure 10 is a corresponding plot for probes and galleries acquired one week apart. From these plots, we see a notable drop in performance associated with elapsed time. We are investigating this effect.

5. CONCLUSIONS

In this paper, we have described two classes of 3D biometrics: face (which has a decade of history and now is appearing in fielded systems) and finger (which, to our knowledge, has not been examined as a potential biometric heretofore). Our initial experiments with both suggest that their viability but also highlight potential performance problems. Future work will address these problems through careful testing on the largest database of 3D biometric data available, as well as development of new and improved algorithms for matching.

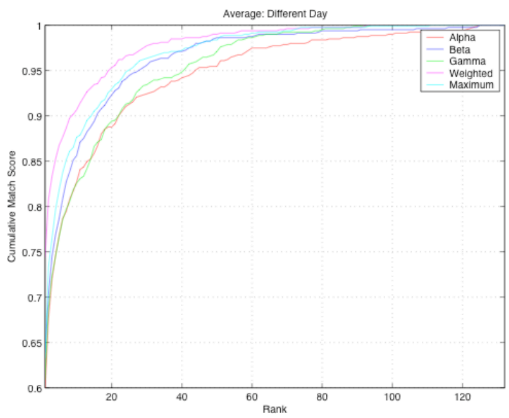

Figure 10. CMC plot for different-day matching experiments.

6. ACKNOWLEDGEMENTS

This research was supported by the US Office of Naval Research under grant N00014-02-1-0410 and by the US National Science Foundation under grant EIA-0130839. DW is supported by a GEM Fellowship administered by the University of Notre Dame.

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