Biometrics Research at University of South Florida, Tampa

The ability of being to identify humans from a distance in a passive manner has obvious applications in surveillance and threat assessment. However, there are other possible innovative uses, such as in smart rooms, designing identity-aware electronic devices, and next generation computer games and virtual environments. In this general context, our biometrics effort, which spans nearly eight years, covers a broad swath of issues and activities that can categorized into three major chunks.

1. **Biometric Performance Evaluation and Testing**

   We have extensive experience in this area. USF has established a 1.4 Tera-bytes of multi-modal image data over a common set of subjects, including analog and digital color face images taken indoors, digital color face images taken outdoors, digital color images of the ear, digital video sequences of human gait taken indoors and outdoors, IR face images, **and Cyberware 3-D scans** of the face. USF established the **HumanID Gait Challenge problem** (http://www.GaitChallenge.org), which is the now the de facto standard to measure progress and to characterize the properties of gait recognition. This data was used in the DARPA HumanID program to benchmark progress and in the Face Recognition Vendor Technology (FRVT) Evaluations by NIST. USF has also **established multi-modal (face, fingerprint, and voice)**, near distance datasets that span both indoor and outdoor conditions over six months.

   USF established a framework for the **Performance Evaluation of Video Analysis and Content Extraction** (VACE) Algorithms for text, face, hand, person and vehicle detection, tracking and recognition, event detection, recognition and understanding in the context of meetings, broadcast news, UAV and outdoor surveillance. This framework was used by the Advanced Research and Development Activity (renamed IARPA recently) to benchmark progress. The project is one of the first of its kinds in conducting a full-fledged formal evaluation of computer vision algorithms in a wide range of video domains.

(a) (b) (c) (d) (e)

Modalities that can be used to recognize or identify a person from a distance include (a) ear shape, (b) gait or walking style, (c) body shape, (e) face, and voice. We are investigating all these modalities at USF. We are also looking at privacy and security issues related to these modalities. For instance, we have designed algorithms that can reconstruct face template just from similarity score, exposing a serious vulnerability of face recognition algorithms (See (d) above).

2. **Biometric Algorithms and Their Fusion:**

USF has designed, developed, and refined individual biometrics related algorithms **in face, gait, ear, and voice**. USF has designed a number of algorithms in gait recognition, based on spatio-temporal correlation, silhouette averaging, and dynamics normalizing. The silhouette averaging algorithm is the fastest gait recognition algorithm to date and performance that is at least as good as the gait recognition benchmark in the DARPA program; this is important for real-time implementations. The Dynamics Normalized Gait Recognition approach, whose performance on the HumanID Gait Challenge dataset is shown, is the *best* performing gait recognition algorithm to date. USF has **demonstrated the superior performance of this recognition approach also on UMD and CMU datasets**.

Being able to **recognize a person or a group of persons** that pose a threat to a convoy or secure site or a **secure border from as far as possible (50m to 300m) is an essential tool for force and homeland protection**. To this end, need to be able to (a) detect persons at a distance, determine sex, age, and race, based on physical characteristics such as body shape, height, and body shape, and (b) recognize and classify activity type of a person or a group of persons as being threatening or non-threatening. We recommend the development **of multimodal surveillance techniques** based on **video and audio** to better understand human intent and activities. For the 50m to 300m range, face, gait (walking style), voice, ear, and their combination will be considered. For distances greater than 300 m, biometric models will be limited to gait and voice, although gait could be demonstrated with several types of sensors.

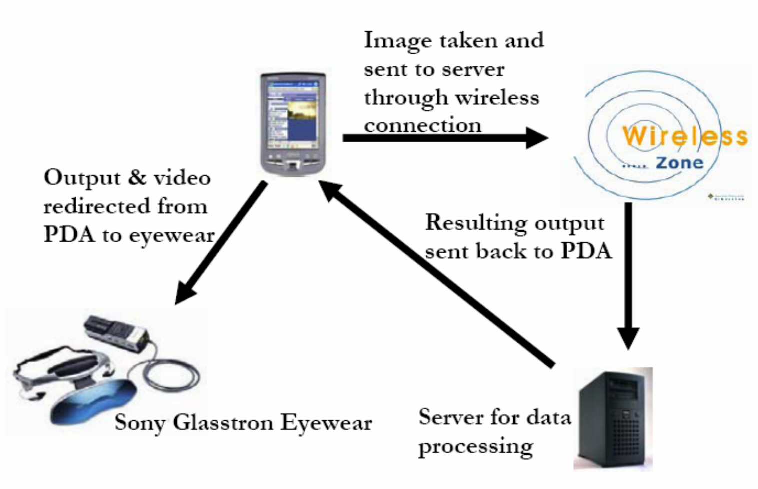
We have been conducting extensive research in the combination of **multiple biometric modalities such as combination of ear and face, face and gait, and face and voice**. Our experiments all use real multiple biometric data from the same subject pool and are focused toward outdoor situations. We explored the possibility of using both face and gait in enhancing human recognition at a distance performance in outdoor conditions.

Table 1: Feasibility of different biometrics modalities at different distances

Biometric Modality	Contact	Far (> 50m)	Remote (300 m)
Fingerprint	Yes	No	No
Face	Yes	Yes	Potentially, not portable Requires high zoom lens
Iris	Yes	Potentially, zoom lens, Cooperative subjects	No
Voice	Yes	Yes	Yes, requires antennae
Gait	No	Yes	Yes
Ears	Yes	Potentially, zoom lens	No

3. **Biometric Systems: Architectures, Security and Privacy**

We have experimented with the design of PDA-based, portable, face recognition system that captures a face, sends it to a server for authentication, which reports back to the PDA identification results. Such portable solutions could be useful in many civilian and military related situations.



PDA based mobile architecture for face biometrics that we have implemented and demonstrated.

We are also looking into security and privacy related issues. We have formulated a novel scheme to reconstruct face images from match scores, exposing a potential source for **security breach in the face recognition systems**. We used an affine transformation to approximate the behavior of the face recognition system using an independent set of face templates termed as break-in set. Selected subsets of templates in the break-in set were then matched only once with the enrolled templates of the targeted subject. Given the distances of the targeted subject's template, we embedded that template in the learned affine space and inverted the modeling affine transformation to arrive at the original template. A cursory look at match scores from a biometric system may not appear to be a weak link in terms of security and privacy issues; however, with our proposed we revealed that even **match scores carry sufficient information for reverse engineering of the original templates** and should be protected in the same way as the original templates.

In the identification scenario one has to perform one to many matches to identify a new face image (query) among a set of gallery images. In such scenarios, the query image needs to be compared to all the images in gallery. Consequently, the response time for a single query image is directly proportional to the gallery size. The entire process is computationally expensive for large gallery sets. One possible approach to avoid such expensive computation and to provide faster response time is to index or bin the gallery set. In case of well developed biometrics such as fingerprints, a binning process based on ridge patterns such as whorl loop and arches is used for indexing. **We have developed a general theory, based on linear subspace approximations, for constructing algorithm-specific indexing schemes for any biometric.**

Journal Publications in Biometrics

1. P. K. Mohanty, S. Sarkar, P. Jonathon Phillips, R. Kasturi, "Subspace Approximation of Face Recognition Algorithms: An Empirical Study," *IEEE Transactions on Information Forensics & Security*, accepted July 2008.
2. P. Mohanty, S. Sarkar, R. Kasturi, "From Scores to Face Template: A Model-based Approach," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 12, Dec. 2007.
3. H. Vajaria, T. Islam, P. Mohanty, S. Sarkar, R. Sankar, R. Kasturi, "Evaluation and analysis of a face and voice outdoor multi-biometric system," *Pattern Recognition Letters*, vol. 28, no. 12, pp. 1572– 1580, Sept. 2007.
4. Z. Liu and S. Sarkar, "Outdoor recognition at a distance by fusing gait and face," *Image and Vision Computing*, vol. 25, no. 6, pp. 817—832, June 2007.
5. Z. Liu and S. Sarkar, "Improved Gait Recognition by Gait Dynamics Normalization," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 6, pp. 863–876, June 2006.
6. S. Sarkar, P. Jonathon Phillips, Z. Liu, I. Robledo, P. Grother, K. Bowyer, "The Human ID Gait Challenge Problem: Data Sets, Performance, and Analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 2, pp. 162–177, Feb. 2005. (118 Google Scholar, 30 citations)
7. I. Robledo and S. Sarkar, "Statistical motion model based on the change of feature relationships: human gait-based recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 10, pp. 1323–1328, Oct 2003
8. K. Chang, K. W. Bowyer, S. Sarkar, and B. Victor, "Comparison and Combination of Ear and Face Images In Appearance-Based Biometrics," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 9, pp. 1160–1165, Sept. 2003. (89 Google Scholar, 29 ISI citations)

Conference, Workshop Publications in Biometrics

9. H. Vajaria, S. Sarkar, and R. Kasturi, "Clip Retrieval Using Multi-Modal Biometrics in Meeting Archives," *International Conference on Pattern Recognition*, accepted 2008.
10. V. Manohar, D. Goldgof, S. Sarkar, and Y. Zhang, "Facial Strain Pattern as a Soft Forensic Evidence," *IEEE Workshop on Applications of Computer Vision*, pp. 42–48, 2007.
11. P. Mohanty, S. Sarkar, R. Kasturi, "Privacy & Security Issues Related to Match Scores," *IEEE Workshop on Biometric Privacy and Security*, pp. 162–162, June 2006.
12. P. Mohanty, S. Sarkar, R. Kasturi, "Designing Affine Transformations based Face Recognition Algorithms," *IEEE Workshop on Face Recognition Grand Challenge*, vol. 3, pp. 173, 2005.
13. P. Mohanty, S. Sarkar, R. Kasturi, "A Non-Iterative Approach to Reconstruct Face Templates from Match Scores," *International Conference on Pattern Recognition*, vol.4, no.pp. 598-601, 2006
14. Y. Zhang, D. Goldgof, and S. Sarkar, "Elastic Face, An Anatomy-based Biometrics Beyond Visible Cue," *International Conference on Pattern Recognition*, Aug. 2004.
15. Z. Liu, L. Malave and S. Sarkar, "Studies on Silhouette Quality and Gait Recognition," *IEEE Conference on Computer Vision and Pattern Recognition*, vol. 2, pp. 704–711, June 2004.

16. Z. Liu and S. Sarkar, "Simplest Representation Yet for Gait Recognition: Averaged Silhouette," *International Conference on Pattern Recognition*, Aug. 2004.

17. P. J. Phillips, S. Sarkar, I. Robledo, P. Grother, and K. Bowyer, "The Gait Idenfication Challenge Problem: Data Sets and Baseline Algorithm," *International Conference on Pattern Recognition*, vol. 1, pp. 385–388, Aug 2002. (87 Google Scholar citations)

18. B. Victor, K. Bowyer, and S. Sarkar, "An Evaluation of face and ear Biometrics," *International Conference on Pattern Recognition*, vol. 1, pp. 429–432, Aug 2002.

19. P. J. Phillips, S. Sarkar, I. Robledo, P. Grother, and K. W. Bowyer, "Baseline Results for the Challenge Problem of Human ID Using Gait Analysis," *International Conference on Automatic Face and Gesture Recognition*, pp. 137–142, May 2002. (65 Google Scholar citations)

Computing Facilities

At USF, we have access to significant amount of computing, storage facilities, and distribution bandwidth to accomplish data intensive tasks. The available computing equipment falls into several categories. We have a 64-node Beowulf cluster with each node having 2GB of memory. There are a 9TB and 7TB RAIDs available. A shared 8 processor Sunfire with 32GB of memory and 1.8 terabytes of disk is an available compute server. There are 2 Beowulf clusters of 49 and 42 processors of Pentium 4, 2+Ghz machines available for University-wide use. They can be used for distributed/parallel computing experiments. They have 2-4GB of memory per processor. In addition, there are currently several Sunblade 100s, a Linux/Windows PC and 4 Linux machines (2 Ghz/2GB), 1 Linux machine (3 Ghz) with 4GB of memory are also available. A Sunfire 280 with 1G of memory is available for file serving and computation. There are also numerous PCs running Windows and Linux OS.