1. Introduction
Ease-of-use is critical to widespread use of biometrics. While many people are interested in developing multi-biometric systems, the ease of use of the multi-biometric will be driven by the most difficult to use biometric. Face is a highly desirable biometric for multi-biometric fusion since it can also be used by humans for verification and because it is the only biometric that can be acquired at a reasonable distance. For multi-biometric systems it would be ideal to have a second biometric that can be acquired in the same image and used to improve the recognition or identification accuracy. But no such “compatible” biometric has been available until now. This paper presents such a biometric – projective invariant hand-geometry.

We review a new non-contact non-intrusive hand geometry personal identification technique. The hand feature vector is constructed using projective invariant features. This paper extends previous work where we introduced the concept of projective invariant of hand. The noise immunity and the discriminability possessed by hand feature vectors using different types of projective invariant are studied. The hand identification function can be accomplished by a single view of the hand independent of the viewing angles, and is ideal for fusion with face-based recognition. A standard digital camera is used to capture the hand images in a non-contact and non-intrusive manner what makes it ideal for eventual fusion with face, though we focus on just the hand-based features in this presentation. Twelve feature points extracted from the finger creases model each hand. A projective permutation invariant (PPI) hand feature vector is created based on the 12-feature point hand model. Full details of the work discussed herein are presented in [1].

2. Review of prior work
Jain et. Al. [2] developed a hand geometry verification system based on a 16-dimensional hand feature vector consisting of various sizes of fingers and the palm. With the use of five pegs to guide the placement of a user’s hand on a flat surface, an 8% EER was reported. Jain et. al. [3] also developed a system aligning hand contours and measuring the Mean Alignment Error to determine the distinction between two hands. They used the similar five-peg device. Wong et al [4] presented a peg-free hand geometry system by using a flatbed optical scanner for hand image capturing. Significant geometrical landmarks of a hand were extracted to align the hands to a certain direction. Then the hand sizes and the shape of the fingertips regions were measured. They achieved 88.9% genuine acceptance rate and 2.2% false acceptance rate (FAR) by a 30-dimensional hand feature vector. All these systems discussed above still require contact-based imaging devices significantly reducing their ease of use and limiting their value for multi-biometric fusion.

In [5], we presented a projective invariant hand-geometry approach based on 16 features and cross-ratios computed from subsets of 5 points. Different ordering of five points results in different 2D cross ratios. By fixing one of the five points as the intersection point, different cross ratios can be categorized into five groups. Each group corresponds to one intersection point and has the permutation of the remaining 4 points. The 24 permutations in each group yield only six different cross ratios [6]. The permutation invariant property of these six cross ratios can be expressed. We intend to have a function that includes all six different 2D cross ratios \( \tau_i \) \((i=1, 2, \ldots, 6)\)  with equal contribution, so that the function will have the same value under all possible permutations [6,7,8]. In our research, we consider the first, the second, the third symmetric polynomials, and the second order power sum symmetric polynomial.

3. Hand Modeling
In our work, we use a standard digital camera as the imaging device. We request a user to join his/her fingers closely and keep their hands stretched flat while taking the hand images. Thus the hand plane composed of the fingers and the palm can be modeled as a rigid two-dimensional planar object. We do grant users the flexibility to pose their hands at any orientation as long as the major part of the hand plane is exposed to the camera. Therefore, the images of the hand plane taken from different viewpoints can be regarded as the projections of the original hand plane onto another projective plane. Fig. 1 shows hand images of two individual hands and the features detected therein. By
using a mixture of edge detectors and Hough transforms, three segments of the creases at the finger joints can be detected, and the central point of each segment is automatically extracted as a feature point. Excluding the thumb, the remaining four fingers produce 12 feature points. This 12-point structure is used as our hand model and generates 792 different five-point sets yielding 3,960 dimensions using PPI features. An important question is how sensitive the invariant features are to noise in the detected feature locations. A detected feature point will be located in an uncertainty area centered at the desired position. An ellipse with the major axis perpendicular to the finger seams models this uncertainty area. A hand with 500 noisy samples per feature is shown on the right of Fig 1.

Figure 1. Images of two hands and the detected feature points in them. The right shows a hand with 500 “noisy” samples per feature.

Experimental Results
In our experiments, 52 images from 23 persons are created and used as our real image database. The resolution of each image is 400×400 pixels, while the size of each hand in the image varies slightly. A thousand noisy hand models are generated from each real model by adding Gaussian positional noise to each feature point. We use the normalized Euclidean distance between a vector and its noise-corrupted counterpart to exhibit the noise immunity of the hand feature vector. We have studied the noise immunity of all five types of invariants including cross ratios and four PPIs. For each type of invariants, a real hand model is used as the reference hand model. Then the 1,000 noise corrupted synthetic hand models corresponding to the real hand model are matched with the reference hand model. The distance results are averaged over all 1000 noisy images. The results are shown on the right.

In order to verify the ability of our proposed technique in distinguishing between clients and impostors, we have performed a full matching test on all the 52 real hand images, i.e. 1,326 different pairs. The EER is used to measure the system performance. Some experimental results are presented in Table 1. It shows that $I_d(t)$ obtains the best performance with an EER of 0.0% when the feature vector dimension increases to 18. The cross ratios are seen to be far more noise sensitive. The results show the PPI hand-geometry has potential as a new biometric and may be ideal for fusion with face-based biometrics.

References