

# Predicting fingerprint biometrics performance from a small gallery

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## Abstract

Predicting the performance of a biometrics is an important problem in a real-world application. In this paper, we present a binomial model to predict both the fingerprint verification and identification performance. The match and non-match scores are computed, using the number of corresponding triangles as the match metric, between the query and gallery fingerprints. The triangles are formed using the minutiae features. The match score and non-match score in a binomial prediction model are used to predict the performance on large (relative to the size of the gallery) populations from a small gallery. We apply the model to the entire NIST-4 database and show the results for both the fingerprint verification and the identification.

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*Keywords:* Fingerprint verification; Fingerprint identification; Performance prediction; Binomial model

## 1. Introduction

In order to ensure a high confidence in security, biometrics such as fingerprint, palm, face, gait, signature, and speech is used. Among these biometric traits, fingerprints have been used for a long time because of their uniqueness and immutability. In fingerprint recognition systems endpoints and bifurcations, named minutiae, are commonly used as features. Depending on application there are two kinds of fingerprint recognition systems: verification systems and identification systems (Maltoni et al., 2003). A verification system generally stores users' fingerprints as sets of minutiae in the database. At some future time, it compares a person's fingerprint with her/his own minutiae set to verify if this person is indeed who she/he claims to be. This is a one-to-one matching problem. The system can accept or reject this person according to the verification result. An identification system is more complex, where, for a query fingerprint, the system searches the entire data-

base to find out if there are any fingerprint minutiae sets saved in the database that can match it. It conducts one-to-many matching (Maltoni et al., 2003). There are two kinds of identification systems: the closed-set identification and the open-set identification (ISO/IEC19795-1, 2006). The closed-set identification is the identification for which all potential users are enrolled in the system. The open-set identification is the identification for which some potential users are not enrolled in the system. The verification and the closed-set identification are special cases of the open-set identification. In this paper, we provide the prediction model for the open-set identification system performance.

How a fingerprint recognition technique works for a large population is often asked in a practical application. In this paper, we develop a binomial model to predict a large population performance based on a small gallery. We first calculate the number of corresponding triangles (formed using noncolinear minutiae features) between each fingerprint in a probe set (search fingerprints) with every fingerprint in the gallery (file fingerprints). The features of a triangle used for matching include the minimum angle,

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median angle, triangle handedness, triangle direction, maximum side, minutiae density, and ridge counts. Then, we use the number of corresponding triangles to estimate distributions of the match and non-match scores. After this, we use the *cumulative match characteristic* (CMC) curve to rank all these scores. The CMC curve shows different probabilities of recognizing a fingerprint depending upon how similar the minutiae set for this query fingerprint is in comparison with the other fingerprints in the gallery. Finally, we use a binomial distribution model to compute the probability that the match score is within rank  $r$ . We verify this model on the *NIST Special Database 4* (NIST-4) which is the rolled fingerprint database.

This paper is organized as follows. In Section 2 we present the related work and contributions. The details of the fingerprint identification and verification techniques and the prediction model are given in Section 3. In Section 4, prediction performance for both the verification and the identification on the NIST-4 database are described. Finally, in Section 5 conclusions are provided.

## 2. Related work and contributions

Prediction models are mostly based on the analysis of the feature space or the match score and non-match score (Bhanu et al., 2004). Pankanti et al. (2002) measure the amount of information needed to establish the correspondence between two fingerprints. They present a fingerprint individuality model which derives an expression to estimate the probability of false match based on the minutiae features between two fingerprints. Tan and Bhanu (2003) present a two-point model and a three-point model to estimate the error rate for the minutiae based fingerprint recognition. Their approach not only measures the position and orientation of the minutiae but also the relations between different minutiae to find the probability of the correspondence between two fingerprints. They allow the overlap of the uncertainty area of any two minutiae. Johnson et al. (2003a) build a mathematical model that is based on the feature space to predict the gait identification performance. The Mahalanobis distance and the  $L_2$  norm are used to compute the similarity within the feature space. They make an assumption about the probability density function that the population variation is much larger than the individual variation. For the NIST-4 fingerprint database, the features (Bhanu and Tan, 2002) that we use do not satisfy this assumption. Thus, their approach is not applicable.

Wayman (1999) and Daugman (2003) develop a binomial model that uses the non-match score distribution. This model underestimates the recognition performance for large galleries. Phillips et al. (2003) develop a moment model, which uses both the match score and non-match score distributions. Since all the match score and the non-match score are sampled independently, the probability of error is increased and the prediction result underestimates the identification performance. Johnson et al. (2003b) improve the moment model by using multiple

non-match score sets. They average the match scores on the whole gallery. For each match score, they count the number of times that a non-match score is larger than the match score, leading to an error. In this paper, they assume that the distribution of the match score is uniform. Grother and Phillips (2004) introduce the joint density function of the match and non-match scores to estimate the face identification performance. Since the joint density is generally impractical to estimate, they assume that the match score and the non-match score are independent and their distributions are the same for a large population.

Tabassi et al. (2004) and Wein and Baveja (2005) use the fingerprint image quality to predict the performance. They define the quality as an indication of the degree of separation between the match score and non-match score distributions. The farther these two distributions separate the better the system performs.

In this paper, we use a binomial model that is similar to Grother and Phillips (2004). However, as compared to Grother and Phillips (2004) we set the threshold  $t = 12$  instead of  $t = -\infty$  for the closed-set and open-set identification. Moreover, we use our prediction model to estimate the fingerprint verification and identification performance for large populations. We first estimate the match score and non-match score distributions and then compute the probability that the non-match score is larger than the match score. In the open-set identification the match score that is larger than a threshold is required for the correct match. The use of this threshold in our model is an improvement over the work done by (Bhanu et al., 2004).

The contributions of this paper are as follows:

- (1) We present a binomial model to predict a large population performance based on a small gallery. Using the match score and non-match score obtained from the small gallery, we estimate distributions of the match score and the non-match score. We use these distributions in the prediction model that follows the binomial distribution to predict the performance on a large population.
- (2) The approach is tested on the entire NIST-4 data set of 2000 fingerprint pairs.

## 3. Technical approach

Fingerprint identification problem can be regarded as the verification performed for the probe image with every gallery image in the database. Additionally, the indexing followed by the verification can solve this problem (Bhanu and Tan, 2002). By using indexing, we can significantly reduce the number of candidate hypotheses to be considered by the verification algorithm, which selects the best hypothesis (Tan and Bhanu, 2002). Here, we have two sets of data: the gallery and the probe set. The gallery is a set of fingerprint minutiae saved in the database. For each fingerprint, there is one set of minutiae saved in the gallery. The

probe is a set of query fingerprints. Since our prediction model can be applied to other biometrics, we use the terms gallery and probe set instead of the file and search terms which have been historically used in fingerprint systems. The recognition performance needs to be estimated on a large population  $N$  which is the unknown data set. Based on the given gallery and probe set, we would like to estimate the fingerprint recognition performance on a large population.

The fingerprint matching algorithm that we use is based on the representation of fingerprint minutiae by triangles (Tan and Bhanu, 2002). We extract minutiae for every fingerprint. Then, we randomly choose any three noncolinear minutiae to form a triangle. Thus, one fingerprint can get hundreds of triangles. The features that we use to find the corresponding triangles in two fingerprints are: minimum angle  $\alpha_{\min}$ , median angle  $\alpha_{\text{med}}$ , triangle handedness  $\phi$ , triangle direction  $\eta$ , maximum side  $\lambda$ , minutiae density  $\chi$ , and ridge counts  $\xi$ . The details about these features of a triangle are given in Section 3.2.

Since we use triangles as the basic representation of a fingerprint, we provide more information about this representation. In Germain et al. (1997), authors use triangles and combine the indexing and the verification together by recognizing the top (ranked 1) hypothesis. They use the length of each side of a triangle, the ridge count between a pair of minutiae, and angles of minutiae orientation as their features. These features have some problems: the minutiae orientation changes greatly under the distortion, the length changes are not insignificant under the distortion and the uncertainty of the minutiae location is not considered (Tan and Bhanu, 2002). Tan and Bhanu (2002) improve this approach by choosing more robust features and performing the indexing and the verification separately. So their approach has two main differences with (Germain et al., 1997). The first one is that in the indexing step they get top  $T$  hypotheses and then use the verification process to verify these hypotheses. The second one is that they use different features as mentioned in the above. These features can tolerate reasonable amount of distortions, like translation, rotation, scale, shear, local perturbation, occlusion, and clutter (Bhanu and Tan, 2002). These features have been found to be effective for the fingerprint indexing and verification (Bhanu and Tan, 2002; Tan and Bhanu, 2002).

There are two steps in the identification process: indexing and verification. Fig. 1 is the outline of the fingerprint identification system.

### 3.1. Prediction model

Assume that sizes of the probe set and the gallery are all  $n$ . For each fingerprint in the probe set, we compute the number of corresponding triangles with every fingerprint in the gallery. Then, we compute the number of corresponding triangles as the similarity score between a pair of fingerprint images. If this pair of fingerprint images

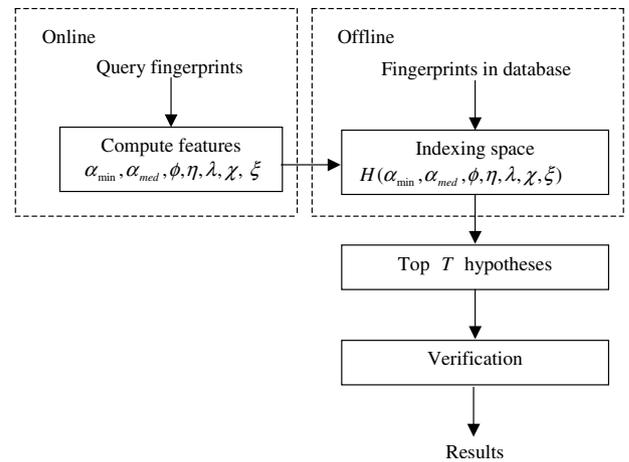


Fig. 1. Fingerprint identification system.

are the prints of the same finger, then the similarity score is called the match score. Otherwise, the similarity score is called the non-match score. If we have enough match and non-match scores, then we can estimate the *probability density functions* (PDFs) of these two distributions. Assume  $ms(x)$  and  $ns(x)$  represent the distribution of the match score and the non-match score respectively. If the match score is higher, then the fingerprints are more similar. The error occurs when any given match score is smaller than any of the non-match scores. The probability that the non-match score is greater than or equal to the match score  $x$  is  $NS(x)$  where,

$$NS(x) = \int_x^{\infty} ns(t) dt \quad (1)$$

Then, the probability that the non-match score is smaller than the match score is  $1 - NS(x)$ .

We rank all the match score and the non-match score in descending order. The probability that the match score is at rank  $r$ , is given by the binomial probability distribution,

$$C_{r-1}^{N-1} (1 - NS(x))^{N-r} (NS(x))^{r-1} \quad (2)$$

Since the match is known to occur we use  $C_{r-1}^{N-1}$  instead of  $C_r^N$ . Integrating over all the match scores, the probability that the rank of the match score is  $r$  can be written as,

$$\int_{-\infty}^{\infty} C_{r-1}^{N-1} (1 - NS(x))^{N-r} (NS(x))^{r-1} ms(x) dx \quad (3)$$

In theory, the match scores can be any value within  $(-\infty, \infty)$ . Thus, the probability that the match scores are within rank  $r$  is

$$P(N, r) = \sum_{i=1}^r \int_{-\infty}^{\infty} C_{i-1}^{N-1} (1 - NS(x))^{N-i} (NS(x))^{i-1} ms(x) dx \quad (4)$$

Considering the correct match happens above a threshold  $t$ , the probability that the match score is within rank  $r$  becomes

$$P(N, r, t) = \sum_{i=1}^r \int_t^\infty C_{i-1}^{N-1} (1 - NS(x))^{N-i} (NS(x))^{i-1} ms(x) dx \quad (5)$$

If we consider the rank is at 1, then the prediction model without the threshold  $t$  becomes

$$P(N, 1) = \int_{-\infty}^\infty (1 - NS(x))^{N-1} ms(x) dx \quad (6)$$

The prediction model with the threshold  $t$  can be written as

$$P(N, 1, t) = \int_t^\infty (1 - NS(x))^{N-1} ms(x) dx \quad (7)$$

Here, we made a simplifying assumption that the match scores and the non-match scores are independent and their distributions are the same as that of large populations. In the above equations  $N$  is the size of a large population and we need to estimate the performance on this population. We use a small size gallery to estimate distributions of  $ms(x)$  and  $ns(x)$ .

### 3.2. Fingerprint indexing

We randomly choose any three noncolinear minutiae to form a triangle. The following features form the indexing space  $H(\alpha_{\min}, \alpha_{\text{med}}, \phi, \eta, \lambda, \chi, \xi)$ :

- **Angles**  $\alpha_{\min}$  and  $\alpha_{\text{med}}$ . Assume  $\alpha_i$  are three angles in a triplet, where  $i = 1, 2, 3$ .

$$\alpha_{\min} = \min\{\alpha_i\}, \quad \alpha_{\max} = \max\{\alpha_i\},$$

$$\alpha_{\text{med}} = 180^\circ - \alpha_{\min} - \alpha_{\max}.$$

- **Triangle handedness**  $\phi$ . Let  $Z_i = x_i + jy_i$  be the complex number corresponding to the location  $(x_i, y_i)$  of point  $P_i, i = 1, 2, 3$ . Define  $Z_{21} = Z_2 - Z_1$ ,  $Z_{32} = Z_3 - Z_2$ , and  $Z_{13} = Z_1 - Z_3$ . Let triangle handedness  $\phi = \text{sign}(Z_{21} \times Z_{32})$ . Points  $P_1, P_2$ , and  $P_3$  are noncolinear points, so  $\phi = 1$  or  $-1$ .

- **Triangle direction**  $\eta$ . We search the minutiae in the image from top to bottom and left to right. If the minutiae is the start point, then  $v = 1$ , otherwise  $v = 0$ . Let  $\eta = 4v_1 + 2v_2 + v_3$ , where  $v_i$  is  $v$  value of point  $P_i, i = 1, 2, 3$  and  $0 \leq \eta \leq 7$ .
- **Maximum side**  $\lambda$ . Let  $\lambda = \max\{L_i\}$ , where  $L_1 = |Z_{21}|$ ,  $L_2 = |Z_{32}|$ , and  $L_3 = |Z_{13}|$ .
- **Minutiae density**  $\chi$ . In a local area ( $32 \times 32$  pixels) centered at the minutiae  $P_i$ . If there exists  $\chi_i$  minutiae, then the minutiae density for  $P_i$  is  $\chi_i$ . Minutiae density  $\chi$  is a vector consisting of all  $\chi_i$ .
- **Ridge counts**  $\xi$ . Let  $\xi_1, \xi_2$ , and  $\xi_3$  be the ridge counts of sides  $P_1P_2, P_2P_3$ , and  $P_3P_1$  respectively. Then,  $\xi$  is a vector consisting of all  $\xi_i$ .

During the offline step, we compute these features for each fingerprint in the gallery and set up the indexing space  $H(\alpha_{\min}, \alpha_{\text{med}}, \phi, \eta, \lambda, \chi, \xi)$ . During the online step, we compute these features for each query fingerprint and compare them with the features represented by the indexing space  $H$ . If the error between them is small enough then we “think” that the query fingerprint is probably the same as the “stored” fingerprints that have similar features. Fig. 2 is an example of two corresponding triangles in a pair of fingerprints. In the impression #1, we randomly pick three noncolinear minutiae A, B, and C to form a triangle  $\Delta ABC$ . The features in this triangle are  $\{\alpha_{\min} = 30^\circ, \alpha_{\text{med}} = 65^\circ, \phi = 1, \eta = 6, \lambda = |AC|, \chi = \{0, 0, 0\}, \xi = \{6, 5, 12\}\}$ . Meanwhile, three noncolinear minutiae a, b, and c in the impression #2 form  $\Delta abc$ . Its features are  $\{\alpha_{\min} = 31^\circ, \alpha_{\text{med}} = 63^\circ, \phi = 1, \eta = 6, \lambda = |ac|, \chi = \{0, 2, 0\}, \xi = \{6, 5, 12\}\}$ . If the error between these two triangles are within the error tolerance (Tan and Bhanu, 2002), we “think” they are corresponding triangles. The output of this process is a list of hypotheses, which is sorted in descending order of the number of potential corresponding triangles. Top  $T$  hypotheses are the input to the verification process.

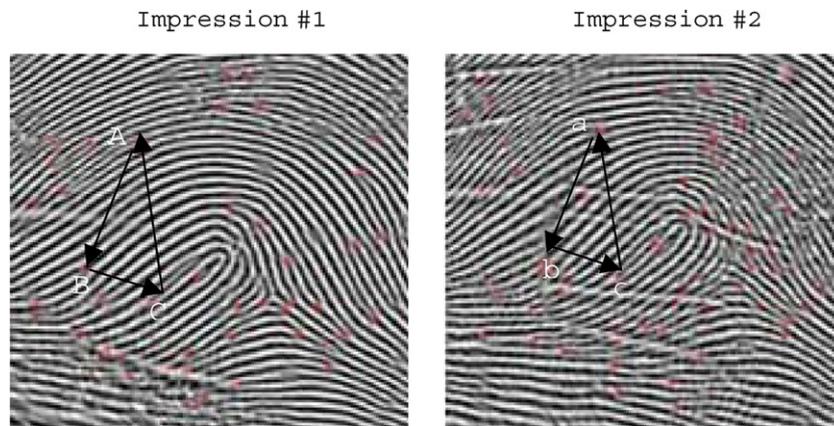


Fig. 2. An example of two corresponding triangles in a pair of fingerprints.

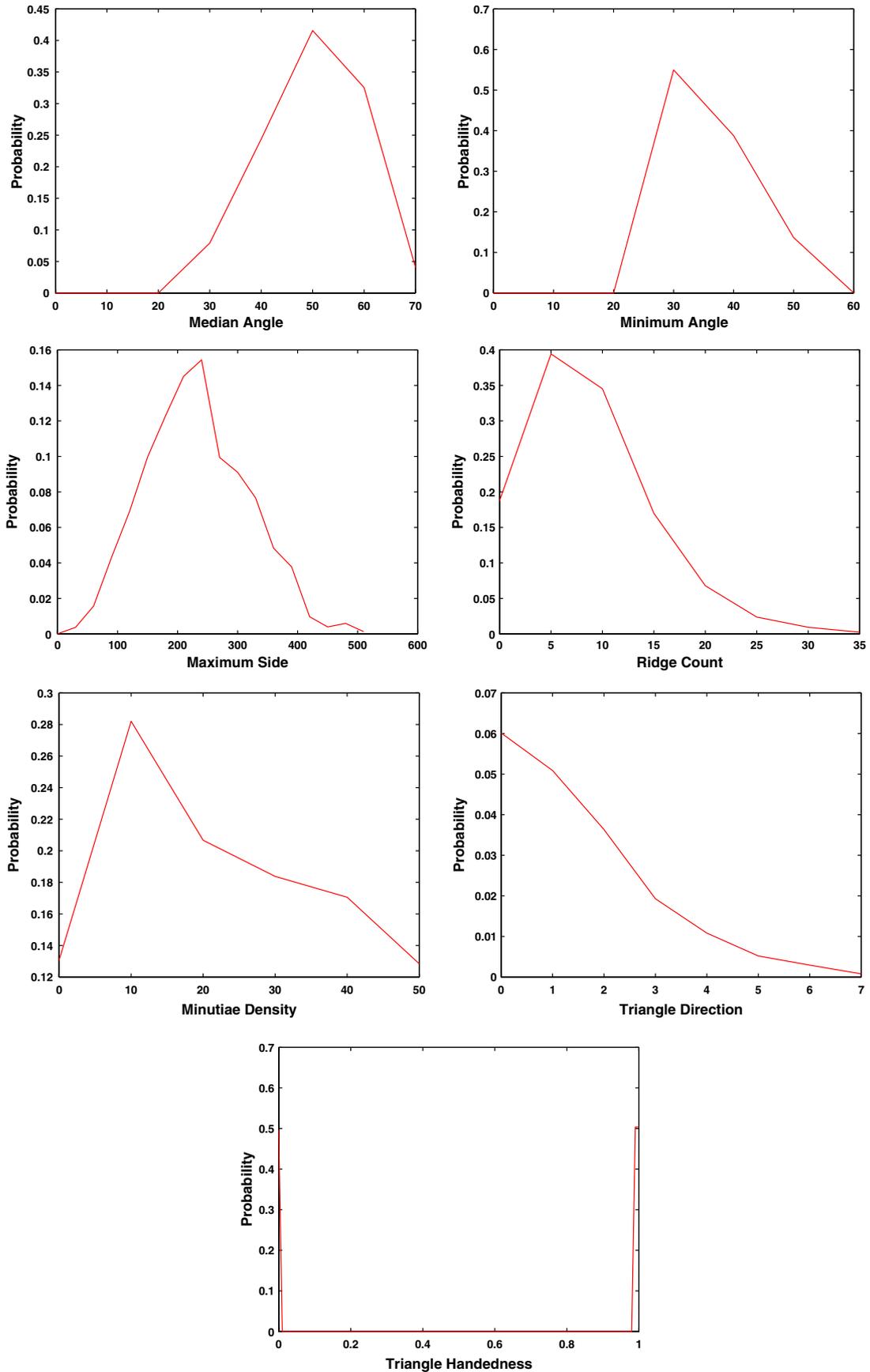


Fig. 3. Fingerprint features distributions: median angle  $\alpha_{med}$  (in degree), minimum angle  $\alpha_{min}$  (in degree), maximum side  $\lambda$  (in pixel), ridge count  $\zeta$  (a number), minutiae density  $\chi$  (a number), triangle direction  $\eta$  (a number), and triangle handedness  $\phi$  (a number).

### 3.3. Fingerprint verification

Suppose there are  $M$  and  $Q$  minutiae in the gallery and query fingerprints respectively.  $\Delta_m$  and  $\Delta_q$  are potential corresponding triangles. We assume  $F(s, \theta, t_x, t_y)$  is the transformation between the query and gallery fingerprints, where  $s$  is a scale parameter,  $\theta$  is a rotation parameter,  $t_x$  and  $t_y$  are translation parameters. If these parameters are within limits (Tan and Bhanu, 2002), then we apply this transformation as the transformation between potential corresponding triangles  $\Delta_m$  and  $\Delta_q$ . The details of how to estimate the transformation parameters are explained in (Tan and Bhanu, 2002). Based on the transformation  $F(s, \theta, t_x, t_y)$ , we compute the distance

$$d = \arg \min_i \left\{ \left\| F \left( \begin{bmatrix} x_{j,1} \\ x_{j,2} \end{bmatrix} \right) - \begin{bmatrix} y_{i,1} \\ y_{i,2} \end{bmatrix} \right\| \right\} \quad (8)$$

where  $(x_{j,1}, x_{j,2})$  and  $(y_{i,1}, y_{i,2})$  are two sets of minutiae in the gallery and query fingerprints,  $j = 1, 2, \dots, M$  and  $i = 1, 2, \dots, Q$ . If  $d$  is smaller than a threshold, then we can say that  $(x_{j,1}, x_{j,2})$  and  $(y_{i,1}, y_{i,2})$  are the corresponding points. If the number of corresponding points is larger than a minimum acceptable number, then we define  $\Delta_m$  and  $\Delta_q$  as the corresponding triangle pair (Tan and Bhanu, 2002).

## 4. Experimental results

All the fingerprints that we use in the experiments are from the NIST-4 database. It consists of 2000 pairs of fingerprints. Each of the fingerprints is labelled with ‘f’ or ‘s’ that represents different impressions of a fingerprint followed by an ID number. Since fingerprints in the NIST-4 are collected by an ink-based method, many fingerprints are of poor quality and some of them even contain characters and handwritten text. The size of a fingerprint image is  $480 \times 512$  pixels and the resolution is 500 DPI. If we randomly choose a fingerprint from the NIST-4, there are  $\sim 78$  minutiae features and  $\sim 8862$  qualified triangles. The distribution for features of triangles is shown in Fig. 3. As mentioned in Section 3.1, we consider the prediction of the verification rate and the identification rate at rank  $l$  against the database of various sizes for the galleries of two specific sizes.

A sample of four pairs of fingerprints is shown in Fig. 4. The matching results are shown in Table 1. The values on the diagonal are match scores, off diagonal values are non-match scores. For the correct recognition, match scores should be greater than non-match scores. For the fingerprint  $s0026\_03$ , the match score is 0, while the non-match score between  $s0026\_03$  and  $f0006\_09$  is 3, obviously this is not correct. In Fig. 4 note that the quality of  $s0026\_03$  is not good. It could not find any corresponding triangle with  $f0026\_03$ , while it has 3 corresponding triangles with  $f0006\_09$ .

From this database we choose all of the 2000 ‘f’ images as our gallery and 2000 ‘s’ images as our probe set. Match-

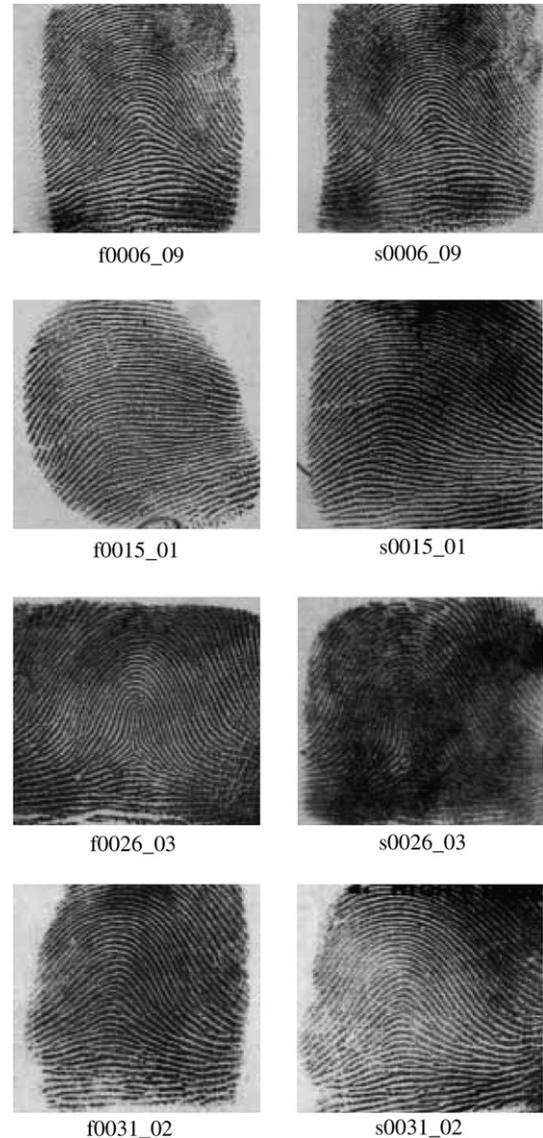


Fig. 4. Sample images from the NIST-4.

Table 1

Match score and non-match score for sample test images matched with database images

Test	Database			
	f0006_09	f0015_01	f0026_03	f0031_02
s0006_09	719	0	0	4
s0015_01	0	106	0	0
s0026_03	3	0	0	0
s0031_02	0	0	0	810

ing all these fingerprint pairs we get 2000 match scores and approximately 4 million non-match scores. For the identification, we verify the top 25 hypotheses from the indexing results. The actual performance for these fingerprints is shown in Fig. 5. Using these 2000 match scores and a subset of non-match scores (randomly selected 2000 from  $\sim 4$  million possibilities), we compute the distributions of the

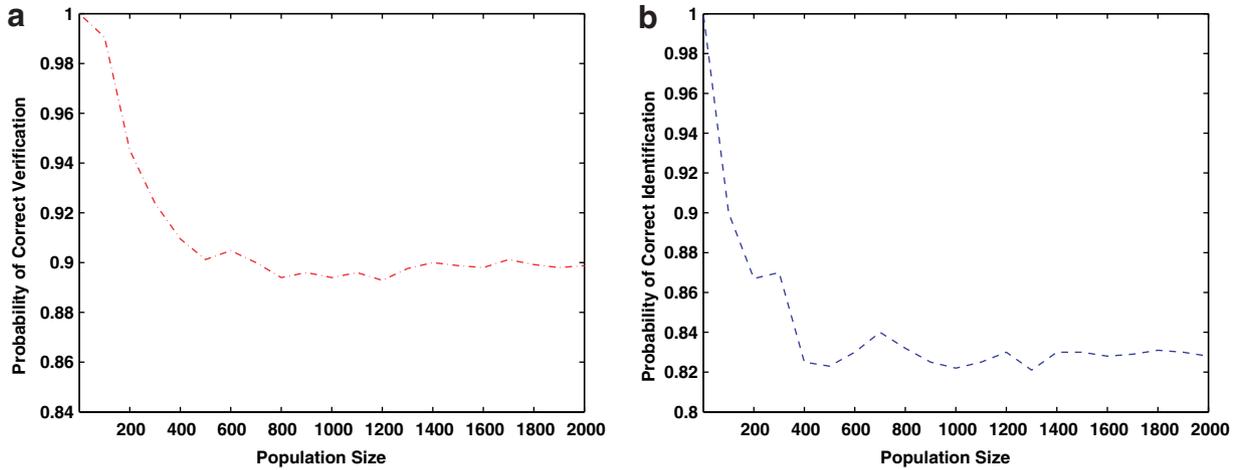


Fig. 5. Actual performances for the NIST-4 fingerprint database. (a) Verification performance and (b) identification performance.

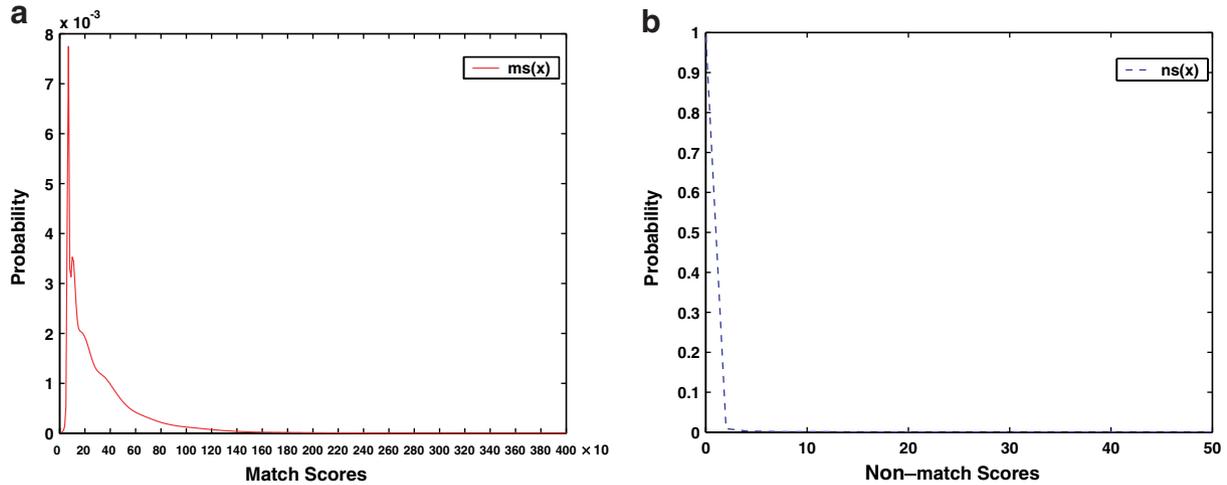


Fig. 6. Similarity score distributions. (a) Match score distribution and (b) non-match score distribution.

match score and the non-match score. Fig. 6 shows the distributions of the match score and the non-match score.

Next, we use small galleries to predict the fingerprint verification and identification performance for a large population.

- *Fingerprint verification:* In the verification, if the match score is less than a threshold then we believe the fingerprint pair does not match. From Fig. 6 we know that 99.95% non-match scores are less than 12, so we choose the threshold  $t = 12$ . This threshold is applied in the prediction model  $P(N, 1, t)$ . In order to show the effect of this threshold we provide both the prediction results  $P(N, 1, t)$  and  $P(N, 1)$ .

We randomly choose a small number of fingerprints  $n = 50$  or  $70$  from the NIST-4 to be the small gallery to predict the fingerprint verification performance for a large population. We repeat the experiment 10 times and average the results to obtain the predicted

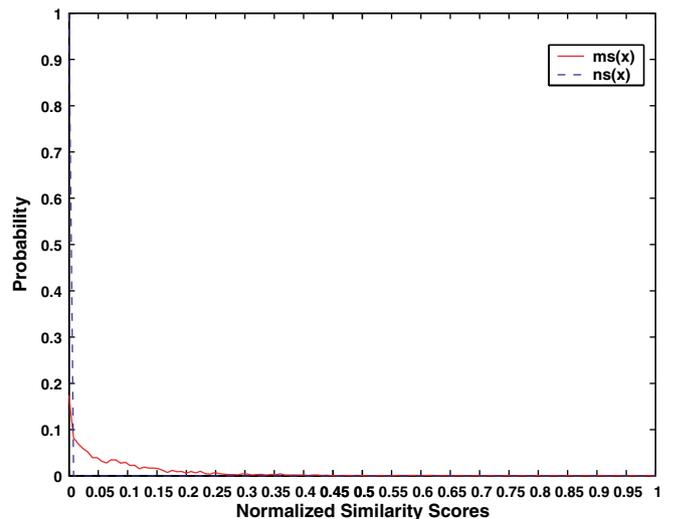


Fig. 7. Similarity score distributions for small gallery when  $n = 50$ .

performance. The size of the probe set is the same as the size of the small gallery. We use the verification technique to compute the match score and non-match score. Fig. 7 shows the distributions of the match and non-match scores when  $n = 50$ .

Fig. 8 shows the absolute error between the experimental and predicted verification performance by model  $P(N, 1)$  and  $P(N, 1, t)$ , respectively. When we do the verification the threshold for the correct match is  $t = 12$ . So the prediction result, when we set  $t = 12$ , is better than in the case when  $t = -\infty$ . We can see that the 70-person model provides better performance than the 50-person model.

- *Fingerprint identification*: Like the verification process, we randomly choose a small number of fingerprints  $n = 70$  or  $120$  from the NIST-4 as our small gallery to predict the identification performance. For the fingerprint identification problem, the output of the indexing step is the top  $T$  hypotheses. Here  $T = 25$ . After the verification, if the match score ranks top 1 and is greater

than 12, then we regard this as the correct match. We obtain distributions of the match score and the non-match score in this process. Then, we apply the prediction models  $P(N, 1)$  and  $P(N, 1, t)$  to predict its performance for a large population. We repeat the experiment 10 times and average the results to obtain the predicted performance. Fig. 9 shows the absolute error between the experimental and predicted identification performance made by these two models. In this model, we assume that the match score and non-match score distributions of a large population are the same as the distributions which we get from the small galleries. From Fig. 9 we note that the 120-person model provides a better prediction than the 70-person model.

- *Discussion*: In the experiments different sizes of small galleries are used to estimate the fingerprint verification and identification performance on a database of large sample images. From Figs. 8 and 9 we can make the following four observations: (a) The larger the size of the small gallery the better is the prediction performance.

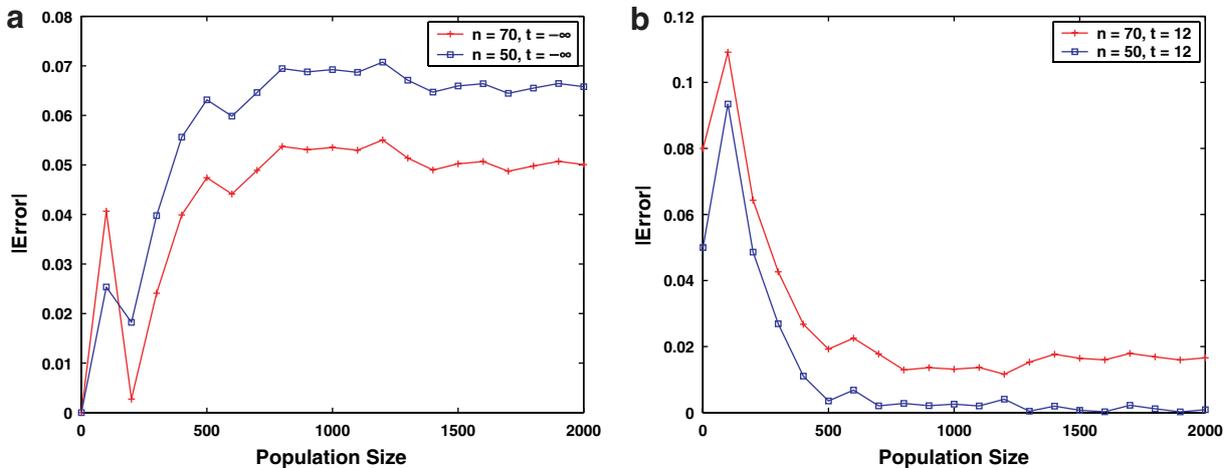


Fig. 8. Absolute error between the experimental and predicted verification performance. (a) By model  $P(N, 1)$  and (b) by model  $P(N, 1, t)$ .

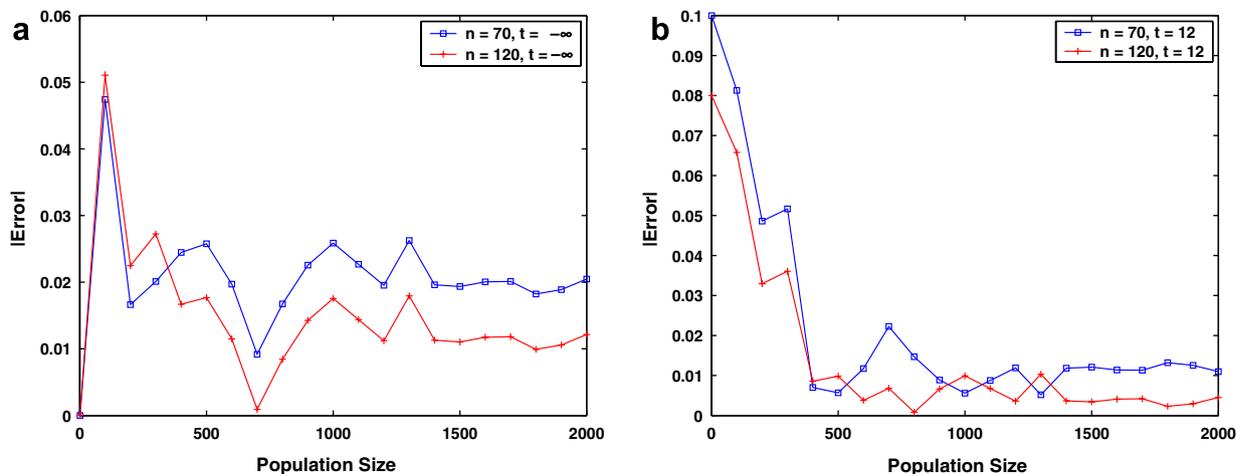


Fig. 9. Absolute error between the experimental and predicted identification performance. (a) By model  $P(N, 1)$  and (b) By model  $P(N, 1, t)$ .

(b) The error contributed by the prediction model  $P(N, 1, t)$  is much smaller than the error contributed by  $P(N, 1)$ . Note that we do the verification and identification with the threshold for the correct match to be  $t = 12$  as discussed earlier in this section. (c) For a given small gallery size, the error between the actual performance and the prediction, beyond a certain size of the population, reduces with the increase in the population size. The behavior of plots for small size populations is related with the accuracy of the assumption that the match score and the non-match score obtained from the gallery are the true representation of the scores on a large population. (d) The smaller error with the increase in the size of the population for the larger gallery size is evident since the match and non-match score distributions are now more accurate.

## 5. Conclusions

In this paper, we developed a model to predict both the fingerprint verification and the fingerprint identification performance. We used a fingerprint verification and identification algorithm to find the match and non-match scores. Then we used these scores in a binomial prediction model. We evaluated the model on the NIST-4 fingerprint database. The assumptions we made for this model are: (a) the match score and the non-match score are independent (b) all the fingerprints in the gallery have similar distributions. Based on the results presented in this paper we find that our prediction model is a valuable attempt for the fingerprint performance prediction rather than having no prediction at all. In the future, we will investigate the problem of how to find the optimal small gallery size for prediction (Wang and Bhanu, 2005) and will conduct experiments on larger data sets than used in this paper. Note that our model can be applied to other kinds of biometrics and object recognition systems (Wang et al., 2005).

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