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# A Score-Level Fusion Method with Prior Knowledge for Fingerprint Matching

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## Abstract

*Fingerprint matching is one of the most widely used biometrics for personal identification. However, the performance of fingerprint identification system is insufficient for many applications. Lots of methods were proposed to improve system performance by introducing more information into matching process. In this paper, we introduced a new kind of information named prior knowledge and proposed a score-level fusion method with prior knowledge for fingerprint matching. The trend and discrimination of scores are used as prior knowledge with sigmoid function to search the optimal fusion parameters. Experimental results show that the proposed prior knowledge is useful for fingerprint matching and the score-level fusion algorithm is effective to improve system performance and comparative to the best ones in FVC2004.*

## 1. Introduction

Fingerprints are graphical patterns of ridges and valleys on the skin surface of fingertips [8]. Due to its uniqueness, a fingerprint is considered to be one of the most reliable biometrics for personal verification. Fingerprint recognition has been studied for many years and lots of algorithms have been proposed to improve the performance of fingerprint identification system. Minutiae are believed to be the most popular and powerful features for fingerprint matching. However, since the existence of translation, rotation and especially distortion between two impressions, minutiae usually cannot be accurately aligned. Thus many assistant features, such as ridge features [2, 1], local minutiae structures [3] and local orientation features [9], have been proposed to solve this problem.

Despite these assistant features, the accuracy of state-of-the-art fingerprint-matching systems is still not comparable to human fingerprint experts in many situations [6]. Low image quality, high distortion and limited feature extraction accuracy are some important reasons. Recently, some researchers try to match fingerprints using multimodal methods, including multiple features [4, 7], multiple fingers [10] and multiple impressions [11] *et al*. Those multimodal methods are proved effective for system accuracy improvement.

All of these methods, assistant features or multimode fingerprint, aimed at improving system performance by introducing more useful information. In this work, we introduced a new kind of information named prior knowledge and proposed a score-level fusion method with prior knowledge for fingerprint matching. The trend and discrimination of each score were used as the prior knowledge with sigmoid function to search the optimal fusion parameters. While prior knowledge is not limited to be the trend and discrimination of scores but can be any information of the scores themselves that can be extracted and is useful for the final matching.

The rest of this paper is organized as follows. The next section explains the proposed prior knowledge. Section 3 presents the details of proposed score-level fusion method. The experimental results are shown in section 4 and conclusions are drawn in section 5.

## 2. Prior knowledge for fingerprint matching

After pre-alignment, several similarity scores can be obtained, *e.g.*, minutiae similarity, orientation image difference. Without loss of generality, we assume three kinds of scores $A$, $B$ and $C$ all range from -1 to 1 and are with the following attributes separately:

$A$ - scores that with larger values indicating greater possibility of match (*e.g.*, minutiae similarity).

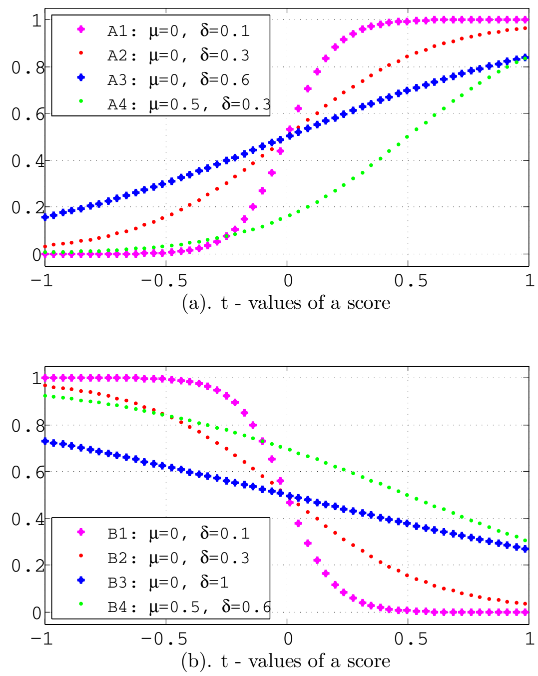


**Figure 1. Sigmoid curves with different $\mu$ and $\delta$: (a) for the scores belonging to kind $A$, (b) for the scores belonging to kind $B$.**

$B$ - scores that with smaller values indicating greater possibility of match (*e.g.*, orientation image difference).

$C$ - any other scores not belong to $A$ and $B$, *e.g.*, those nearer to a certain value between -1 and 1, indicating greater possibility of match.

Considering a similarity score belonging to kind $A$, the relationship between its value and its contribution to the final matching score can be represented by one of the curves in Figure 1(a). The curves are with the same trend that they rise with the increase of the scores' value, which accords with the attribute of scores in $A$. But they are with different rise rate and different value range, which means different scores can have different discrimination for the final match. For example, the purple curve of score $A1$ ranges from 0 to 1, and its rise range is mostly between -0.4 and 0.4. Thus the maximum possible contribution of $A1$ to the final matching score is 1, and only when value from -0.4 to 0.4, $A1$ has the ability to distinguish good match from bad match. Among these four scores in Figure 1(a), $A2$ with the red curve should be the one who has the highest discrimination, because its curve has both the maximum value range (0,1) and the maximum rise range (-1,1).

Note that the curves are not linear, but rise sharply in the middle and slowly in the two sides, which means that the values nearby the middle will be distinguished more delicately. This accords with the phenomenon that scores occur more often in the vicinity of the middle value where need to be distinguished more carefully. Figure 1(b) is for scores belonging to kind $B$, which is similar with $A$ except the reverse trend.

For a score of kind $C$, the relationship between its value and its contribution to the final matching score can be represented by some other curves after fully analysis. In this paper, our study focus on scores of $A$ and $B$. Those of $C$ will be studied in future.

Actually, curves in Figure 1 are the sigmoid curves defined in Eq.(1) and Eq.(2) with different $\mu$ and $\delta$ ($\delta > 0$), which mean different middle values and rise rates separately and determine the discrimination of curves.

$$f_1(t) = \frac{1}{1+e^{\frac{\mu-t}{\delta}}} \tag{1}$$

$$f_2(t) = \frac{1}{1+e^{\frac{t-\mu}{\delta}}} \tag{2}$$

For simplicity, we use symbol $x$ to represent a score belong to $A$ or $B$, and use $Sig(x)$ to represent the relationship between the value of $x$ and its contribution to the final matching score, thus Eq.(1) and (2) can overwrite as Eq.(3).

$$Sig(x) = \begin{cases} f_1(x) & \text{for } t \text{ belonging to } A \\ f_2(x) & \text{for } t \text{ belonging to } B \end{cases} \tag{3}$$

## 3. Score-level fusion with prior knowledge

As mentioned in section 2, the parameters $\mu$ and $\delta$ determine the discrimination of sigmoid curves. In this section, we propose a GA-based method to obtain appropriate or optimal values of $\mu$ and $\delta$ for each similarity score, and illuminate our score-level fusion algorithm.

### 3.1 Fusion for a final score

Before fusion, a normalization process is needed because different scores have different value ranges. we use Eq.4 to normalize these scores.

$$\overline{x} = \frac{x - nx}{mx - nx} \times 2 - 1 \tag{4}$$

where $\overline{x}$ is the normalization result of score $x$, $mx$ and $nx$ are the maximal value and minimal value of this score separately. A training data set is needed to acquire the value of each $mx$ and $nx$. After this normalization process, all values of scores will be between -1 and 1, thus meet the requirements of Eq.(3).

With a combination rule for scores fusion, the final matching score can be obtained.

### 3.2 Training for optimal fusion parameters

To obtain optimal parameters $\mu$ and $\delta$ for each score, a training process is needed. We use a genetic algorithm (GA) to train these optimal parameters. Figure 2 demonstrates the training stage of the proposed fusion algorithm in detail.

### 3.3 Test stage of the proposed algorithm

After the training stage in 3.2, we get the optimal fusion parameters $r_o = \{(\mu_k, \delta_k), k = 1, 2, ..., m_f\}$. In test stage, the scores for fusion are firstly extracted, then normalized and fused using the combination rule, thus the final matching score can be concluded.

## 4 Experimental results

We use 7 common used fingerprint similarity scores as follows to fusion for expriments:

1. The number of matched minutiae ($minuNum$).
2. The matching ratio of minutiae ($minuRatio$).
3. The average similarity of matched minutiae ($minuSimi$).
4. The matching score ($pScore$) after pre-alignment.
5. The average difference of minutiae pairs distances ($biLength$).
6. The ridge similarity ($ridgeSimi$).
7. The mean difference of aligned orientation images ($oriImage$).

The pre-alignment algorithm used for experiments is same with Ref. [3]. Definition and computation of these 7 scores can be found in Ref. [1, 4]. Among these 7 scores, 1,2,3,4 and 6 belong to kind $A$, others belongs to kind $B$.

Here we give the parameters used in training stage: the number of scores ($m_f = 7$), the number of individuals in a generation ($pSize = 50$), the maximum number of generations ($maxG = 300$), the probability of crossover ($crosPr = 0.6$) and the probability of mutation ($mutPr = 0.2$).

We conducted experiments on FVC2004DB1 [5]. Set B is used for training to figure out the maximal value $mx$ and minimal value $nx$ of each score and the optimal fusion parameters $r_o$; set A is used for testing. EERs of the 7 scores and fusion EER on are listed in Table 1. The last value in the table is EER of our fusion method with prior knowledge and is much lower than other EERs, which confirms that our method is effective for fusion.

**Table 1. EERs of each score and fusion.**

| Scores | EER(%) | Scores | EER(%) |
|---|---|---|---|
| $minuNum$ | 10.93 | $biLength$ | 32.51 |
| $minuRatio$ | 15.56 | $ridSimi$ | 16.46 |
| $minuSimi$ | 4.180 | $oriImage$ | 14.98 |
| $pScore$ | 3.858 | fusion(PK) | 2.82 |

**Table 2. EERs on FVC2004DB1**

| Alg. | EER(%) | FVC2004 | EER(%) |
|---|---|---|---|
| CN | 3.85 | P047 | 1.97 |
| SV [4] | 3.41 | P101 | 2.72 |
| GW | 3.51 | P097 | 3.38 |
| PK | 2.82 | | |

To evaluate the performance of the proposed algorithm, we compared four algorithms on FVC2004DB1. Algorithm CN uses the conventional minutiae matching rate to calculate final matching score. Algorithm SV is a state-of-art fingerprint fusion algorithm combined descriptor and SVC-based scoring proposed in Ref. [4]. Algorithm GW uses GA to training weights of scores for fusion, which is similar with the proposed algorithm but without prior knowledge. And algorithm PK is our score fusion method with prior knowledge. We use minimizing EER as objective function of GA and addition as combination rule. To valid the proposed algorithm, we also compare our algorithm with the best three ones (*i.e.*, P047, P101, P097)in FVC2004.

The ROC curves of the four algorithms are plotted in Figure 3. The EER of all above algorithms are reported in Tables 2. From ROC curves, we can see that algorithm PK obtains the best results, which indicate our algorithm is effective to improve the performance of fingerprint identification system. The EERs in Tables 2 show the proposed fusion algorithm is comparative to the best ones in FVC2004.

From Figure 3 and Tables 2, we can see our algorithm PK obtain better performance than GW. As GW is similar with PK but without prior knowledge, it can prove that the proposed prior knowledge is useful for score fusion and fingerprint matching.

Experiments are conducted on a PC with Intel Core i5@3.20GHz. The average time consumption of each individual is about 15 ms in training. Thus the whole time for training is 4 min. The time consumption on fusion for each test is less than 4 ms.

## 5 Conclusion and future work

The proposed prior knowledge and score-level fusion method combine the trend and discrimination of scores with sigmoid function. Experimental results show that the proposed prior knowledge is useful and the

**Algorithm:** GA-based training stage of the proposed score-level fusion algorithm with prior knowledge.

**Input:** Two set of scores by genuine match and imposter: $G = \{g_{ik}, i = 1, 2, ..., m_g, k = 1, 2, ..., m_f\}$ and $H = \{h_{jk}, j = 1, 2, ..., m_h, k = 1, 2, ..., m_f\}$, where $g_{ik}$ and $h_{jk}$ are the values of score $k$ in $i^{th}$ genuine match and $j^{th}$ imposter. $m_f$, $m_g$ and $m_h$ are the numbers of scores, genuine match and imposter.

**Output:** The optimal fusion parameters after training: $r_o = \{(\mu_k, \delta_k), k = 1, 2, ..., m_f\}_o$, where $\mu_k$ and $\delta_k$ are the sigmoid parameters of score $k$ for fusion.

**Initialization**:

$pSize$ — Number of individuals in a generation
$maxG$ — Maximum number of generations

$R = \{r_q, q = 1, 2, ..., pSize\}$ — Initial population, where $r_q = \{(\mu_k, \delta_k), k = 1, 2, ..., m_f\}_q$ is the $q^{th}$ randomly generated individual of $R$, $-2 \le \mu_k \le 2$ and $0 < \delta_k < 1$.

$cntG = 1$ — Generation count
$curGen = R$ — Current generation

**Step 1.** Calculate value (*e.g.*, EER) of each individual in $curGen$.

**Step 2.** Evaluate the fitness of each individual based on their values and find the best-fit individual $r_t$. $r_o = r_t$.

**Step 3. Repeat the following until** $cntG \ge maxG$

**1.** Select $pSize$ individuals from $curGen$ using roulette-wheel selection based on their fitness.

**2.** Generate new $pSize$ individuals through crossover and mutation operations.

**3.** Replace individuals in $curGen$ with the new $pSize$ individuals. $cntG = cntG + 1$.

**4.** Calculate the value of each individual in $curGen$.

**5.** Evaluate the fitness of each individual based on their values and find the best-fit individual $r_t$.

**6.** If $r_t > r_o$, then $r_o = r_t$.

**Figure 2. GA-based training stage of the proposed fusion algorithm.**

score-level fusion algorithm is effective to improve system performance and comparative to the best ones in FVC2004.

The prior knowledge is not limited to be the trend and discrimination of scores but can be any information related to the scores themselves which can be extracted from training process and is useful for the final matching. The models to imitate the contribution of scores is not limited to be sigmoid function either. Better models and more useful prior knowledge will be studied in future.

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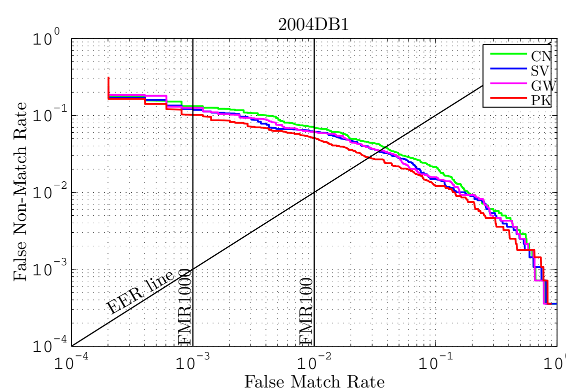


**Figure 3. ROC curves of algorithms.**