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Feature Selection for Sensor Interoperability: A Case Study in Fingerprint Segmentation

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***Abstract*—The need for sensor interoperability has increased tremendously in many fingerprint large-scale application areas such as e-commerce, welfare-disbursement and e-education. However, the problem of feature selection for sensor interoperability has received limited attention in the literature. In this paper, the relationships among person, sensor and feature are discussed. Especially, a feature selection method for sensor interoperability is proposed. Some experimental results of feature selection for sensor interoperability in fingerprint segmentation are presented as a case study. Experiments show that the various features exhibit different sensor interoperability on different sensors.**

***Keywords*—sensor interoperability, feature selection, fingerprint, segmentation**

I. Introduction

Sensor interoperability refers to the ability of a biometric system to adapt to the raw data obtained from a variety of sensors [1]. Nowadays, most biometric systems are designed on a hypothesis that the data used in enrollment and verification stages have to be obtained from sensors with the same type [2]. Usually the classifiers are trained on data originated using a certain sensor alone thereby restricting their ability to act on data from other kind of sensors [3]. This limitation baffles the use of multiple sensors with different characteristics in a single biometric system [4].

There are three important roles in a biometric system: (a) *person* who uses the system; (b) *sensor* which acquires biometric data; (c) *feature* which represents the biometric trait. A typical biometric system consists of three modules: (a) *sensor module* which acquires the raw biometric data of a person; (b) *feature extraction module* which extracts a feature set from the acquired data; (c) *matching module* in which the extracted feature set is compared against the templates residing in the database through the generation of matching scores and decision, as shown in figure 1.

Several approaches to sensor interoperability are known. In [1], the problem of sensor interoperability is discussed and the impact of changing sensors on the matching performance of a fingerprint system is presented as a case study. In [4], an enrolment strategy using signatures from the two Tablet PCs is proposed. In [5], fingerprint sensor interoperability is studied using a multi-sensor database acquired with three different fingerprint sensors. In [6], a fingerprint scaling scheme using the average inter-ridge distance is presented to deal with the variability due to differences in resolution. In [7] and [8], a nonlinear calibration scheme based on the Thin-Plate Spline (TPS) model is used to register a pair of fingerprint sensors.

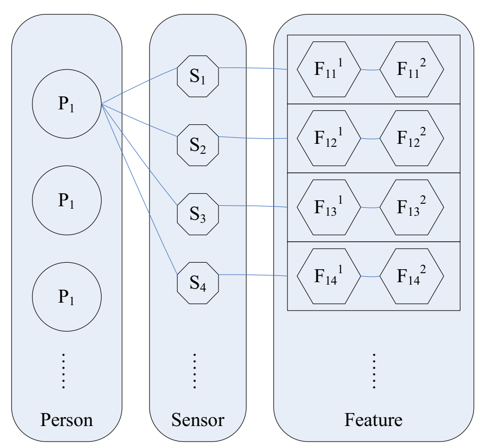

Figure 1. Three roles and three modules in a biometric system

These techniques, however, are all working on improving performance from system modules. The roles, especially the relationships of these roles, are not received adequate attention. Feature is an important issue for biometric sensor interoperability. To the best of our knowledge, no systematic

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study has been conducted to ascertain its effect on biometric systems.

There are two gaps in sensor interoperability community, i.e., sensory gap and semantic gap. This situation is very similar with image retrieval community [9]. The sensory gap is the gap between the user's finger and the information in a (computational) description, e.g. an image. This gap makes recognition from image content challenging due to limitations in recording [10]. The semantic gap is the lack of coincidence between the feature that one can extract from the visual data and the information that the same data has. A few works try to solve this problem [11].

In this paper, we discuss the feature selection for sensor interoperability using a case study in fingerprint segmentation.

The remainder of the paper is organized as follows. Section 2 presents the feature selection for sensor interoperability in fingerprint segmentation as a case study. Section 3 describes experiment procedures and presents some experimental results. Section 4 gives summary and some future works about this presented method.

II. Fingerprint Segmentation: A Case Study

The goal of fingerprint segmentation is to separate the fingerprint foreground area from the background area [12]. The current approaches for fingerprint segmentation can be classified into the following two categories: block-wise based and pixel-wise based methods [13]. In this paper, we study the pixel-wise based method. There are three features often used in fingerprint segmentation: *Coherence, Mean* and *Variance* [14].

In a window W around a pixel, the coherence is defined as:

$$Coh = \frac{\left|\sum_W \left(G_{s,x}, G_{s,y}\right)\right|}{\sum_W \left|\left(G_{s,x}, G_{s,y}\right)\right|} = \frac{\sqrt{\left(G_{xx} - G_{yy}\right)^2 + 4G_{xy}^2}}{G_{xx} + G_{yy}} \quad (1)$$

Where $\left(G_{s,x}, G_{s,y}\right)$ is the squared gradient, $G_{xx} = \sum_W G_x^2$, $G_{yy} = \sum_W G_y^2$, $G_{xy} = \sum_W G_x G_y$ and $\left(G_x, G_y\right)$ is the local gradient. More information on the coherence can be found in [15].

The average gray value measures how gray the pixel is. Using I as the intensity of the image, the local mean for each pixel is given by:

$$Mean = \sum_W I \quad (2)$$

The variance measures the gray variance around the local area. The variance is for each pixel given by:

$$Var = \sum_W \left(I - Mean\right)^2 \quad (3)$$

The Coherence, Mean and Variance feature values are normalized in the [0, 1] range.

In this paper, the sensor interoperability of Coherence, Mean and Variance will be discussed as a case study.

A. Single Sensor

Suppose the *ith* person is represented as P_i, and the *jth* sensor is represented as S_j. The *kth* impression's feature set of the same finger of P_i oriented from S_j can be represented as

$$F_{ij}^k = \left\{F_{ij}^{kl} \mid l = 1, 2, \ldots, m\right\} \quad (4)$$

where l is the number of the pixels in the impression.

We assume there is some a priori probability $P(F_{ij}^k)$, and the probability density is $p(F_{ij}^k)$. Suppose the experimental probability is $\widehat{p\left(F_{ij}^k\right)}$, and the mean value of probability is $\overline{p\left(F_{ij}^k\right)}$, we can evaluate the feature stability related with person and sensor through

$$Stability\left(*\right) = \frac{1}{k}\sum_{j=1}^{k}\sqrt{\sum_{i=1}^{c} X_i\left(\widehat{p_i\left(F_*^j\right)} - \overline{p_i\left(F_*^j\right)}\right)^2} \quad (5)$$

where k is number of the impression and * means the relationship of roles. We take c hits on $\widehat{p\left(F_{ij}^k\right)}$ and $\overline{p\left(F_{ij}^k\right)}$ equably, and in this case c is 100.

For example, we assume there are 8 impressions of an individual oriented from the same sensor. The probability of foreground pixel's mean feature of every impression can be illustrated by figure 2. The feature stability gives a measure how well the feature is distributing on the same sensor and individual. In this case, the stability value is 4.48%.

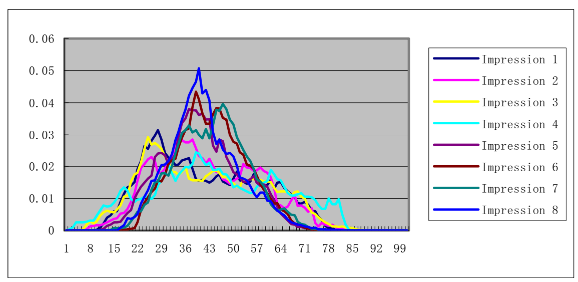


Figure 2. The probability of foreground pixel of 8 impressions

B. Multi-sensors

Consider first the single sensor foreground-background segmentation, and suppose the dichotomizer has divided the space into two regions R_1 and R_2 in a possibly nonoptional way. There are two ways in which a classification error can occur.

$p\left(\hat{\omega}_1 \mid \omega_0\right)$: The probability that a foreground pixel is classified as background.

$p\left(\hat{\omega}_0 \mid \omega_1\right)$: The probability that a background pixel is classified as foreground.

where w_0 and w_1 represent the classes of foreground pixel and background pixel, respectively,

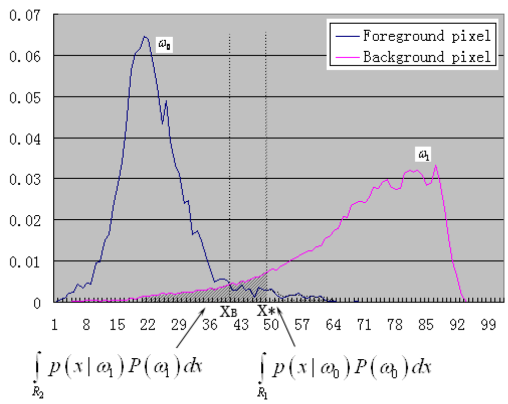


Figure 3. Error probabilities of single sensor

Because these events are mutually exclusive and exhaustive, the probability of error is

$$P(error) = \int_{R_1} p(x|\omega_0)P(\omega_0)dx + \int_{R_2} p(x|\omega_1)P(\omega_1)dx \quad (6)$$

The Bayes classifier maximizes this probability by choosing the regions so that the integrand is maximal for all x; no other partitioning can yield a smaller probability of error. So we will discuss the situation using the Bayes classifier, as shown in figure 3.

Because the decision point x^* is chosen arbitrarily for the figure, the probability of error is not as small as it might be. In particular, a part of error can be eliminated if the decision boundary is moved to x_B.

In the multi-sensor case, the situation will be more complicate. The probability of error will be

$$P(error) = \sum_{i=1}^{c}\sum_{\substack{j=1 \\ j\neq i}}^{c}\left[P\left(x\in R_j|\omega_i\right)\right]P(\omega_i) \quad (7)$$

In this paper, we will discuss the 2-sensor case to illustrate the problem.

Clearly, as shown in figure 4,

$$\begin{aligned} P(error) &= \frac{1}{2}\sum_{i=1}^{6}P(x\in R_i) \\ &= \frac{1}{2}\left(P_1(error) + P_2(error) + \sum_{i=5}^{6}P(x\in R_i)\right) \end{aligned} \quad (8)$$

The $P_1(error)$ and $P_2(error)$ depend neither on how the feature space is partitioned into decision regions nor on the form of the underlying distributions. So,

$$P^*(x) = P(x\in R_5) + P(x\in R_6) \quad (9)$$

We argue that $P^*(x)$ is the first key descriptor to measure the decline of performance when we use multi-sensor.

On the other hand, the difference of $P_1(error)$ and $P_2(error)$ reflects the performance gap on the feature, so it is the second key descriptor.

$$P^- = \left|P_1(error) - P_2(error)\right| \quad (10)$$

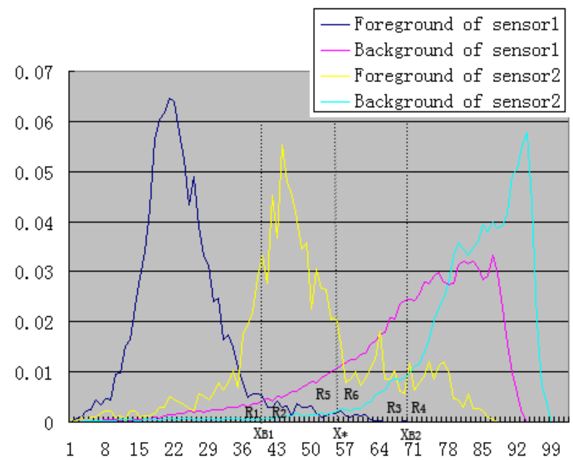


Figure 4. Error probabilities of multi-sensor

C. Feature selection for sensor interoperability

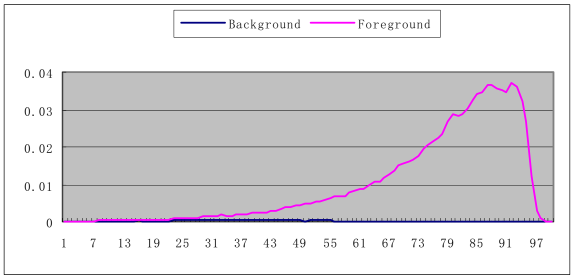
We argue that problem of sensor interoperability originates from two factors. The first one is the inherent performances gap between two sensors e.g. $P^-(x)$. The second one is the drop of performance caused by coordinating two sensors e.g. $P^*(x)$.

Consider the case where the probabilities of feature F using two sensors, *S1* and *S2*, are known. For simplicity we assume that we can compute the $P^*(x)$ and $P^-(x)$. For a given threshold t, there are three situations:

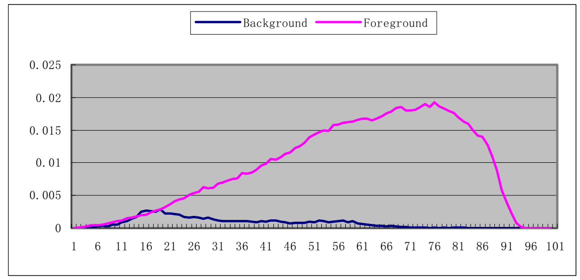
- $P^*(x)$ and $P^-(x)$ are smaller than t. It means there is no significant difference in performance when different sensors are used during the training and testing phases of a fingerprint recognition system. In this situation, we call F is *sensor interoperable* on S_1 and S_2.
- Although $P^*(x)$ is larger than t, if we move the probability curve to a certain position, $P^*(x)$ could be smaller than t. It means we can use different sensors in the system, but we need to use adaptive or unsupervised parameters during the training and testing phases. In this situation, we call F is *limited sensor interoperable* on S_1 and S_2.
- $P^*(x)$ or $P^-(x)$ cannot be smaller than t in any situation. It means an important drop of performance will happen. In this situation, we call F is *sensor non-interoperable* on S_1 and S_2.

III. Experiments

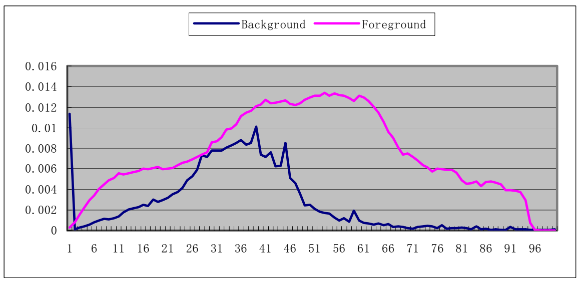
We take some experiments on the feature selection for sensor interoperability. The fingerprint database used in our experiments is FVC2000 DB1-3 Set B [16]. It consists of fingerprint impressions obtained from 10 non-habituated, cooperative subjects. Every subject was asked to provide 8 impressions of the same finger. Table 1 summarizes the global features of the three databases.



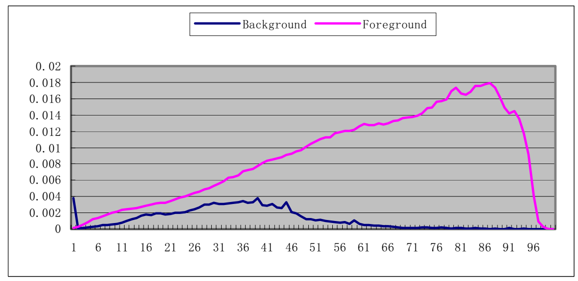
(a) Coherence of DB1



(b) Coherence of DB2

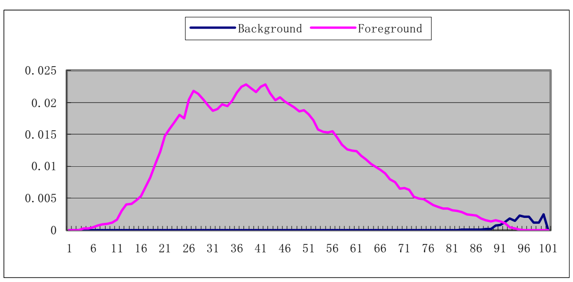


(c) Coherence of DB3

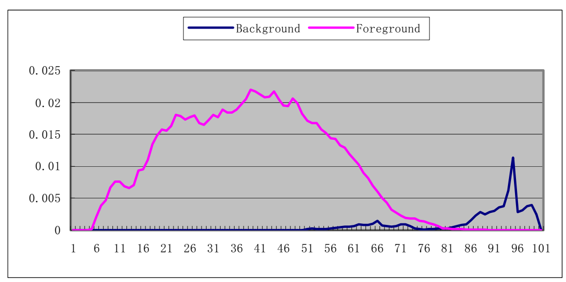


(d) Coherence of all DB

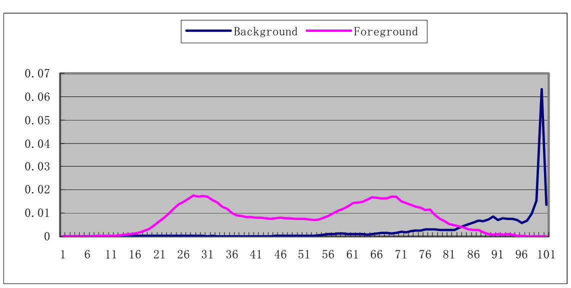
Figure 5. The statistical model of probability distribution for Coherence



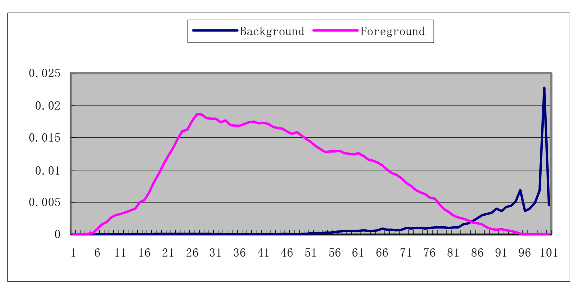
(a) Mean of DB1



(b) Mean of DB2



(c) Mean of DB3



(d) Mean of all DB

Figure 6. The statistical model of probability distribution for Mean

Table 1: The three FVC2000 Databases

	Sensor Type	Image Size	Resolution
DB1	Optical Sensor	300*300	500dpi
DB2	Capacitive Sensor	256*364	500dpi
DB3	Optical Sensor	448*478	500dpi

The three different databases were collected by using the following sensors/technologies:

(a) DB1: Secure Desktop Scanner by KeyTronic
(b) DB2: TouchChip by ST Microelectronics
(c) DB3: DFR-90 by Identicator Technology

A. *The feature stability*

At first, we test the feature stability of the same person's 8 impressions on the same sensor. The results are shown in table 2. We can see clearly that the "Secure Desktop Scanner" by KeyTronic used in DB1 is the most stable sensor, and Coherence is the most stable feature in this case.

Table 2: The feature stability of the same person

	Coherence	Mean	Variance
DB1	3.37	4.19	3.84
DB2	5.68	8.29	7.94
DB3	3.96	7.90	4.05

The second test aim at revealing the feature stability of different persons on the same sensor. The results show that the "Secure Desktop Scanner" still is the most stable sensor, and the stabilities are keeping in falling down, as shown in table 3.

Table 3: The feature stability of the different persons

	Coherence	Mean	Variance
DB1	6.05	6.38	6.29
DB2	6.09	6.56	8.38
DB3	11.55	12.89	10.21

We also tested the feature stability of different person using different sensors. The results show that the DB1 and DB2 are the most stable sensor pares.

Table 4: The feature stability of the different sensors

	Coherence	Mean	Variance
DB1+DB2	6.83	6.94	5.24
DB2+DB3	7.53	7.53	11.47
DB1+DB3	10.17	10.17	12.75

B. *Feature selection for sensor interoperability*

In order to evaluate the feature selection for sensor interoperability, several procedures have been done in our experiments. First, we segmented each images in FVC2000 DB1-3 Set B by hand and marked the foreground/background label on every pixels. Then, we build up the statistical model of probability distribution for Coherence, Mean and Variance as shown in figure 5-7. Finally, the relationship between features and sensors can be exacted as illustrated by table 5.

Table 5: The relationship between features and sensors

	Coherence	Mean	Variance
DB1+DB2	limited	limited	interoperable
DB2+DB3	limited	non	interoperable
DB1+DB3	limited	non	interoperable
DB1+DB2+DB3	limited	non	interoperable

In order to evaluate the relationship, we carried out the experiments with methods of Bazen [14] on the FVC2000 DB1-3. The parameters we used in the system are fixed value. The results show that the Variance is the best feature when the system uses three different sensors, and the Mean is worst, as shown in table 6.

Table 6: Error probabilities of segmentation

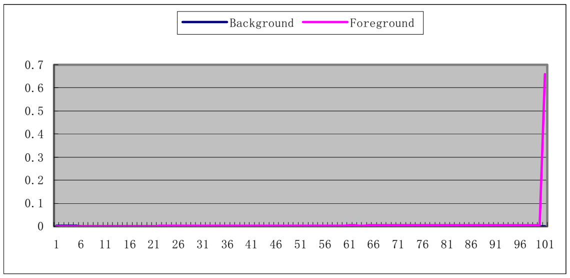
	Coherence	Mean	Variance
Threshold	0.45	0.85	0.45
DB1	26.5%	5.8%	7.1%
DB2	17.2%	12.0%	2.0%
DB3	22.7%	26.3%	4.4%

IV. SUMMARY AND FUTURE WORK

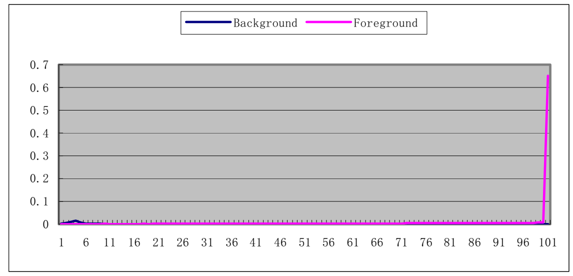
The need for sensor interoperability is pronounced because of the widespread deployment of biometrics systems in various applications and the request of users. Feature selection is an important issue for biometric sensor interoperability. To our best knowledge, no systematic study has been conducted to ascertain its effect on biometric systems.

In this paper, the relationships among person, sensor and feature are discussed. Two factors, i.e., the inherent performances gap and the drop of performance caused by coordinating two sensors, can be regarded as reasons of sensor interoperability problem. We discuss the feature selection for sensor interoperability using a case study in fingerprint segmentation. We have illustrated the impact of feature selection on the sensor interoperability of a biometrics system. Experiments show that the various features exhibit different sensor interoperability on different sensors.

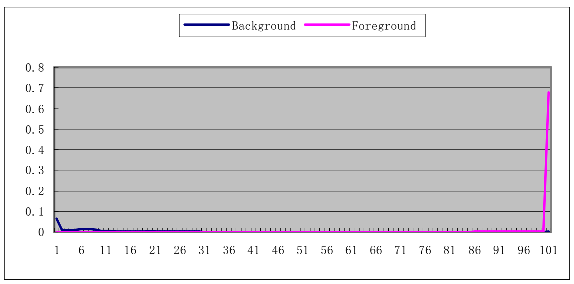
Currently, three features in fingerprint segmentation are studied. Applying our method to other features or biometrics technologies is an interesting future issue.



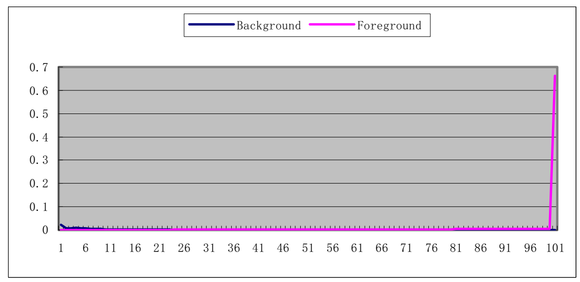
(a) Variance of DB1



(b) Variance of DB2



(c) Variance of DB3



(d) Variance of all DB

Figure 7. The statistical model of probability distribution for Variance

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