A User-Centered Framework for Adaptive Fingerprint Identification

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Abstract. In recent years, law enforcement personnel have been greatly aided by the deployment of automated fingerprint identification systems (AFIS). These "black-box" systems largely operate by matching distinctive features automatically extracted from fingerprint images for their decisions. However, current systems have two major shortcomings. First, the identification result depends solely on the chosen features and the algorithm that matches them. Second, these systems cannot improve their results by benefiting from interactions with expert examiners who often can identify small differences between fingerprints. In this paper, we demonstrate by incorporating *Relevance Feedback* in a fingerprint identification system as an add-on module, a persistent semantic space over the database of fingerprints for an expert user can be incrementally learned. Here, the learning module makes use of a *Dimensionality Reduction* process that returns both a low-dimensional semantic space and an out-of-sample mapping function, achieving a two-fold benefits of data compression and the ability to project novel fingerprints directly onto the semantic space for identification. Experimental results demonstrated the potential of this user-centered framework for adaptive fingerprint identification.

Keywords: User-centered, Biometrics, Fingerprint identification, Adaptive information processing, Relevance feedback, Dimensionality reduction.

1 Introduction

Biometric authentication based on a person's physiological and behavioral traits is gaining acceptance as a method for uniquely verifying one's real identity [1]. Among these biometric traits: fingerprint, face, speech, iris and hand geometry are the most commonly used. Biometric authentication systems have been applied with successes in a number of real world applications in law enforcement, border control, welfare services, etc. An early example of this technology was the Automated Fingerprint Identification System (AFIS).

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However, current systems have two major shortcomings. First, the result of identification depends solely on the features selected and the algorithm that matches them. Second, there is no way of having these systems adapt their outcomes to seasoned examiners, who often can identify minute differences between fingerprints beyond what is capable of by current systems. In other words, most AFIS have a static processing architecture that lacks a functionality to capture and reuse knowledge of expert examiners in constructing the identification outcome. As an illustration, a simplified model of current generation systems is shown in Figure 1.

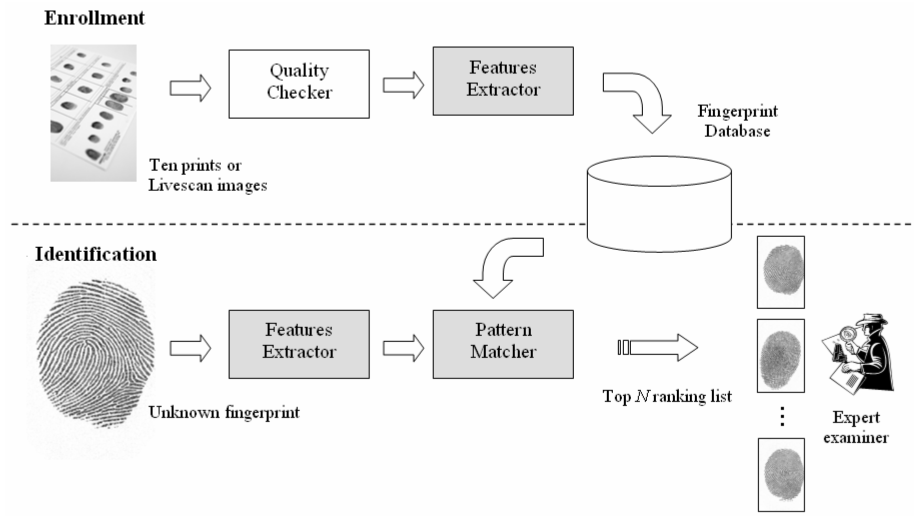

Fig. 1. A simplified model of current Automated Fingerprint Identification System (AFIS)

Due to both the Features Extractor and the Pattern Matcher being fixed, there is no way for improving the identification result even if impressions of the same finger as the unknown fingerprint did not turn up initially in the top N images of the ranking list. The user would be misled in judging that such a finger/identity does not exist in the database based only on the direct outcome of the system. The impact of such problem could potentially be minimized if feedbacks from an expert examiner on the relevance or irrelevance of certain fingerprints were captured, enabling the system to recalculate the ranking list accordingly. Here, we emphasize that the power to accept or reject the outcome of relevance feedback lies with the expert user.

In this paper, we demonstrate by incorporating *Relevance Feedback* in a fingerprint identification system as an add-on module, a persistent semantic space over the database of fingerprints for an expert user can be incrementally learned. Whereas relevance feedback has been extensively researched and applied in document retrieval and more recently in content-based image retrieval [2]; however, not much has been reported on integrating relevance feedback into biometric authentication systems both in research and in practice. One reason could be that in order for biometric authentication to benefit from relevance feedback, a supervised setting is necessary which is not possible in many deployment scenarios. However, in the case of an AFIS, the operating requirement makes it a suitable application for novel integration of relevance feedback and biometric authentication.

The remainder of this paper is organized as follows. In Section 2, an overview of the user-centered framework will be given. In Section 3, the fingerprint features used in this research will be briefly described. In Section 4, the major components of the proposed framework will be explained. In Section 5, experimental evaluation of the user-centered framework will be presented. Lastly, in Section 6, we will conclude and mention future directions.

2 Overview of Proposed Framework

The User-centered framework is made up of three main components including: *Input Space Transformation*, *Relevance Feedback*, and *Semantic Space Learning*. The framework is designed to be loosely rather than tightly coupled with other modules of the host AFIS as shown in Figure 2. As a result, it could be integrated as an add-on module in an existing system with some customizations.

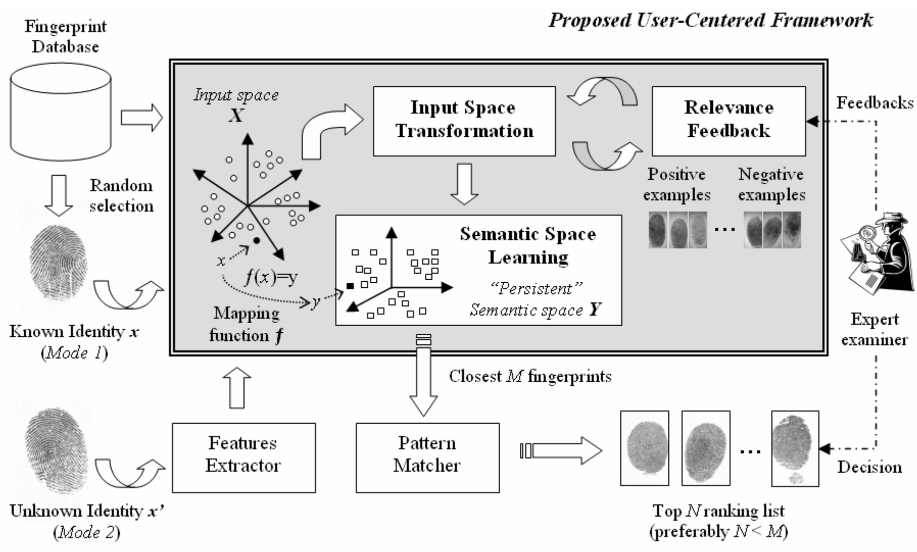

Fig. 2. Relationship of the proposed framework with modules of the host AFIS

Besides these three components, an important element of the learning framework is the input space X from which the persistent semantic space will be learnt. By a sequence of relevance feedback from an expert examiner the state of the input space will be updated. The source of data that forms the basis for constructing the initial input space is the set of extracted features, one for each fingerprint in the database. They are obtained by processing the corresponding fingerprint images by the Features Extractor module of the host system. Inside such module, normally a sequence of image processing steps are performed such as image enhancement, segmentation of fingerprint regions, detection and extraction of fingerprint features, and possibly mapping features to numeric values [3].

The proposed framework provides a novel mechanism by which an examiner can choose to incorporate his or her subjective knowledge into the construction of the persistent semantic space over the fingerprint database. There are four distinct steps in the execution of this mechanism, which are summarized as follows.

First, input to the framework is in the form of a fingerprint x, either by random selection from the database or taken from an unknown identity. These are denoted as Mode 1 and Mode 2 in Figure 2, respectively. Mode 1 is useful if the examiner chooses to incorporate additional knowledge into the formation of his or her persistent semantic space without being presented with an unknown identity. In such case, no features extraction is needed as the fingerprint is drawn from the database. In Mode 2, the examiner is being presented with a fingerprint from an unknown identity. In this case, features of the unknown fingerprint will be extracted by the host system before being passed to the framework.

Second, the examiner interacts with the framework via the *Relevance Feedback* component. Regardless of whether it is operating in Mode 1 or Mode 2, based on the fingerprint selected, the framework returns a subset of fingerprints (excluding x) that are similar based on the nearest neighbor criterion. The examiner selects as positive those fingerprints that are judged similar based on detailed observations. The negative selections are those that are judged dissimilar. Given the positive and negative selections, the corresponding entries in the distance matrix (the representation we used in this work) will be adjusted by the *Input Space Transformation* component, thereby transforming the input space X. The relevance feedback loop repeats until the user decides to exit. The outcome is a distance matrix that has learnt the semantic judgment of the expert examiner.

Third, based on the transformed distance matrix, the *Semantic Space Learning* component will either construct (if for the first time) or update the persistent semantic space of the expert examiner. To accomplish this, we modeled the learning process as a *Dimensionality Reduction* (*DR*) problem in which the input space corresponds to the D-dimensional features space while the semantic space to a lower-dimensional embedding space of dimension d ($d<<D$) [4]. Two advantages can be achieved by this modeling. First, the amount of computation that is required to operate in the high-dimensional features space can be significantly reduced by the data compression gained from *DR*. This makes both the learning and use of the semantic space more efficient. Second, by utilizing a suitable *DR* method that supports additionally an out-of-sample extension [5], a mapping function f that projects an unknown fingerprint onto the semantic space without repeating the learning process can be obtained. These advantages enable the learning framework to achieve the required efficiency.

Fourth, based on the state of the semantic space, a list of M fingerprints that are closest to the input can be identified. In the case of Mode 2 where the main objective is to decide if the unknown fingerprint is similar to any fingerprints stored in the database, this interim list will be passed to the Pattern Matcher module of the host AFIS. By the pattern matching process, a top N ranking list will be returned as the identification result to the expert examiner for his or her acceptance or rejection.

3 Fingerprint Features

Here, we summarize the steps of the features extraction algorithm used in the paper [3]. It employs both global and local ridge characteristics to construct a fixed length vector of size $D = 512$ for every fingerprint called FingerCode. Each FingerCode is comprised of an ordered enumeration of the features extracted from the local ridge characteristics contained in each sub-image or sector specified by a tessellation. As a result, each sector captures the local information and the ordered enumeration of the tessellation captures the invariant global relationships among these local patterns. Finally, Gabor filters are applied to decompose the local discriminatory characteristics in each sector into bi-orthogonal components based on their spatial frequencies. Figure 3 visualizes the process of features extraction carried out by [3].

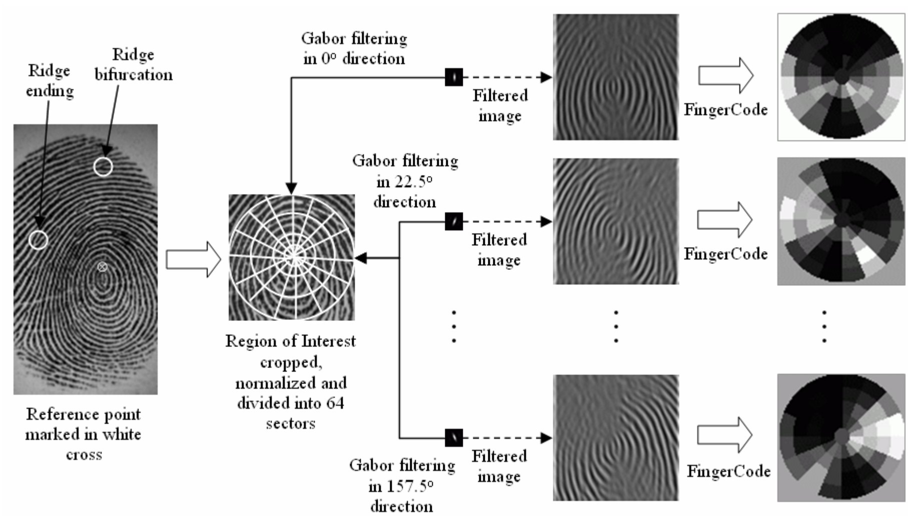

Fig. 3. Fingerprint features are extracted by [3] using a bank of Gabor filters aligned in eight different directions including {0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135°, 157.5°}

4 Framework Components

In this section, each of the three major components of the user-centered framework depicted in Figure 2 will be explained.

4.1 Input Space Transformation

The main function of this component is to transform the topology among objects of the input space X through iteratively updating the distance matrix. The ij-th element of this matrix, denoted M_{ij}, measures the Euclidean distance between the FingerCode vectors of fingerprints i and j in R^D as:

$$M_{ij} = \sqrt{\sum_{k=1}^{D} (i_k - j_k)^2} \tag{1}$$

Based on these pair-wise distances, the semantics of the input space can be encapsulated by the n-by-n real-valued matrix M, where n equals the number of fingerprints that are involved.

The amount of updating is determined by the subjective knowledge input by the expert examiner as captured through the *Relevance Feedback* component, which will be described in Section 4.2. Against an input fingerprint x, after one iteration of relevance feedback a list of *nret* most similar fingerprints in the database is retrieved and shown to the examiner. From the list, the examiner can indicate as positive selections those that he or she considers similar and negative selections those that are dissimilar. The sets of positive and negative selections are denoted by $P = \{p_1, p_2, \ldots, p_i\}$ and $N = \{n_1, n_2, \ldots, n_j\}$ respectively, with $nret = i + j$. In addition, there is an adjustable parameter $\beta \in (0,1]$ that controls the amount of increase or decrease made to the entries of the distance matrix after each iteration. The initial values for *nret* and β used in our experiments were 10 and 0.8, respectively.

Here, it is worthwhile to emphasize that a distance matrix is only one method of encapsulating the semantics of an input space. While it is not a goal in this paper to compare the relative performances of different representations, we note that in recent years a number of research efforts have proposed alternate representations that are more suitable in certain situations. One of these is by using a kernel function as similarity measure, thereby resulting in a kernel Gram matrix that captures the pair-wise similarity between objects in a potentially very high-dimensional features space [6]. Another representation would be the use of a pure metric space where only the pair-wise distances are known, while the geometrical properties of a Euclidean space is not required.

4.2 Relevance Feedback

In the user-centered framework, an expert examiner interacts with the fingerprint identification system via the *Relevance Feedback* component. Relevance feedback, an *adaptive information processing* technique, was first applied in document retrieval in the 1960s. It was later adapted and used in content-based image retrieval (CBIR) that has a strong link to this research. In its most common form, relevance feedback involves polling the user for feedback on the relevancy of the current retrieval results. Based on the feedback, the system learns and improves its performance in the next round, iteratively if necessary.

As described in Section 2, the proposed framework has two modes of operation at present. For the initial formation and subsequent updating of the semantic space, *Mode* 1 is used. In this mode, a fingerprint x in the database can either be picked randomly or chosen by the examiner. Based on fingerprint x, a subset of fingerprints (excluding x) that are similar based on closest distances is returned by the *Input Space Transformation* component. Through the graphical user interface (GUI), the examiner marks as positive selections those fingerprints that are judged similar according to his or her subjective knowledge. The negative selections are those that are judged dissimilar. These feedbacks are passed back to the *Input Space Transformation* component where the corresponding entries in the distance matrix will be decreased or increased accordingly. The relevance feedback loop repeats until the examiner decides to exit the current "learning" session. The outcome is a transformed distance matrix that has incorporated the subjective knowledge of the fingerprint examiner.

Below, we summarize the relevance feedback process by the pseudo code given in Figure 4. The inputs include the *n*-by-*n* distance matrix, the parameter *nret* indicating the number of fingerprints included in the feedback, and β that determines how much the entries of the distance matrix will be increased or decreased.

```
INPUT:      n × n distance matrix, nret, β
OUTPUT:     updated n × n distance matrix

bool exit = FALSE;

while (not exit)
  if (examiner selects an image)
      x = selected image;
  else
     select an image x randomly from the database;
  end

  display the nearest nret images to image x based on smallest distances (excluding x);
  the examiner marks both positive and negative selections;

  for (positive selections i and j)
       update their entries in the distance matrix by M_ji = M_ij = M_ij × β;
  end
  for (positive selection i and negative selection j)
       update their entries in the distance matrix by M_ji = M_ij = M_ij / β;
  end

  if (the examiner is satisfied) exit = TRUE; end
end

return updated distance matrix;
```

Fig. 4. Pseudo code of the relevance feedback process

4.3 Semantic Space Learning

In this research, the "learning" of the persistent semantic space is modeled as a dimensionality reduction process that projects the higher-dimensional features space onto a lower-dimensional semantic space. The two-fold benefits are data compression and a mapping mechanism that can project an unknown fingerprint onto the semantic space without repeating the entire learning process. This is used when the proposed framework is operating under *Mode* 2 in which the fingerprint examiner is being presented a fingerprint of an unknown identity *x*'. Taking its feature vector as input, the framework projects it onto the semantic space by using the learnt mapping function. From this, the closest *m* fingerprints can be identified and passed as input to the Pattern Matcher module of the host system to obtain the top *n* ranking list for the examiner's evaluation.

Whereas traditional linear methods like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) have been used in dimensionality reduction, a number of new techniques have been proposed recently for dealing with the inherent non-linearity that exists in the relational structure among complex objects like those of biometric data [6]. In addition to the lower-dimensional representation for the input data, some of the DR methods can return a direct *out-of-sample* mapping function by which novel input can be projected onto the latent space while others make use of estimation techniques that are more universally applicable.

In this paper, due to our choice of representing the input space as a distance matrix, we have selected two representative methods, namely Multi-Dimensional Scaling (MDS) and Laplacian Eigenmaps (LE), as candidates for the learning of the persistent semantic space because they make use of the distance matrix in their DR process. The former is a global non-linear method while the latter is a local non-linear method, according to the taxonomy given in [4]. However, as both of these methods do not return an out-of-sample mapping function directly, we resort to using an *estimation technique* to achieve the similar objective.

In order to assess the improvement in identification accuracy due to relevance feedback, we will compare the results obtained by MDS and LE (both employing relevance feedback) with PCA and Locality Preserving Projections (LPP) (both not employing relevance feedback) in our empirical experiments. First, the reason for selecting PCA in our comparison is that it is often used as a benchmark while being able to return a linear mapping function for projecting novel input onto the semantic space. Second, the reason for including LPP in our comparison is that while it employs a distance matrix (an extension of LE) in its DR process, it is not required to have the matrix updated. Furthermore, it can return a linear mapping function for out-of-sample extension directly.

5 Experimental Evaluation

To demonstrate the potential of the proposed framework for improving identification accuracy, several experiments were conducted on a subset of the MCYT-Fingerprint-100 (Ministerio de Ciencia y Tecnología, Spanish Ministry of Science and Technology) sub-corpus collected by the Biometric Research Laboratory - ATVS of the Universidad Politecnica de Madrid under the MCYT project [7]. The MCYT-Fingerprint-100 sub-corpus consists of ten prints, each having 12 impressions, of 100 people taken using two different acquisition devices, making a total of 24,000 ($100 \times 10 \times 12 \times 2$) fingerprints.

For our experiments, we randomly chose 50 fingers out of the sub-corpus, resulting in a database of 1,200 ($50 \times 12 \times 2$) fingerprints. In these experiments, 1,100 fingerprints (i.e., 11×2 impressions from each finger) comprised the training set while the remaining 100 fingerprints as the test set. The test fingerprints will be used as query in our experiments. We used three parameters $nc = 50$, $ns = 24$, and $tns = 22$ to denote the number of fingers (or classes), the total number of impressions for each finger, and the number of impressions for each finger in the training set, respectively.

In performing our experiments, we addressed the limitation of not being able to involve actual fingerprint examiners at this stage by developing a software module to simulate the quality of relevance feedback (right versus wrong decisions) that would have been given by either a *normal* or a *strong* expert. To accomplish this, in our simulation we made use of a random number r generated from a normal distribution with mean $\mu = 0$ and standard deviation $\sigma = 1$ that obeys the 68-95-99.7% rule (Figure 5). For each fingerprint that appears in the list of most similar m fingerprints after each iteration of relevance feedback, we decide if the expert would make a right or wrong decision based on the following two simple rules:

$$\text{Normal expert:} \quad |r| \le 1 \quad \text{(right)}, \quad |r| > 1 \quad \text{(wrong)} \tag{2}$$

$$\text{Strong expert:} \quad |r| \le 2 \quad \text{(right)}, \quad |r| > 2 \quad \text{(wrong)} \tag{3}$$

In other words, for similar fingerprints that were wrongly judged as dissimilar, their distances from the novel input will be increased (divide by β) while dissimilar fingerprints that were incorrectly judged as similar will be decreased (multiply by β).

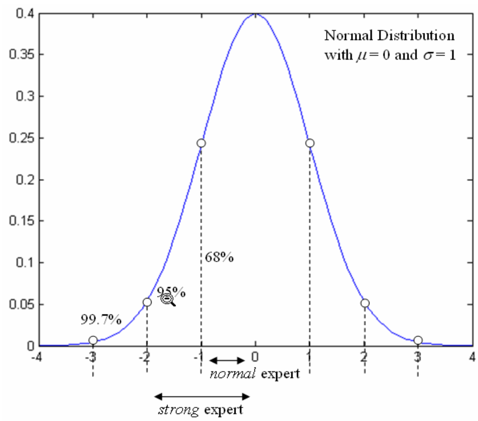

Fig. 5. Simulate *normal* and *strong* experts in the experiments using the 68-95-99.7% rule of normal distribution with mean $\mu = 0$ and standard deviation $\sigma = 1$

Furthermore, to ensure that our experimental results are repeatable, the following three conditions were adhered consistently in our experiments:

1. A sequence of fingerprints (each identified by a unique number in the database) was generated beforehand, and used in the experiments that involve relevance feedback;
2. The dimensionality of the semantic space (d = 6) is estimated by a Maximum Likelihood Estimator based on the training set; and
3. k = 12 as the number of nearest neighbors used in MDS, LE and LPP to construct the neighborhood graph in their DR process.

5.1 Experiment #1

This experiment compares visually the mapping of the set of FingerCode vectors from the input space (D = 512) to the semantic space (d = 6) by different DR methods. In Figure 6, the left column plots the initial semantic space in the first two dimensions for 7 of the 50 fingers used in experiments for sake of illustration. The right column shows the updated semantic space after projecting the test set using OOS extension.

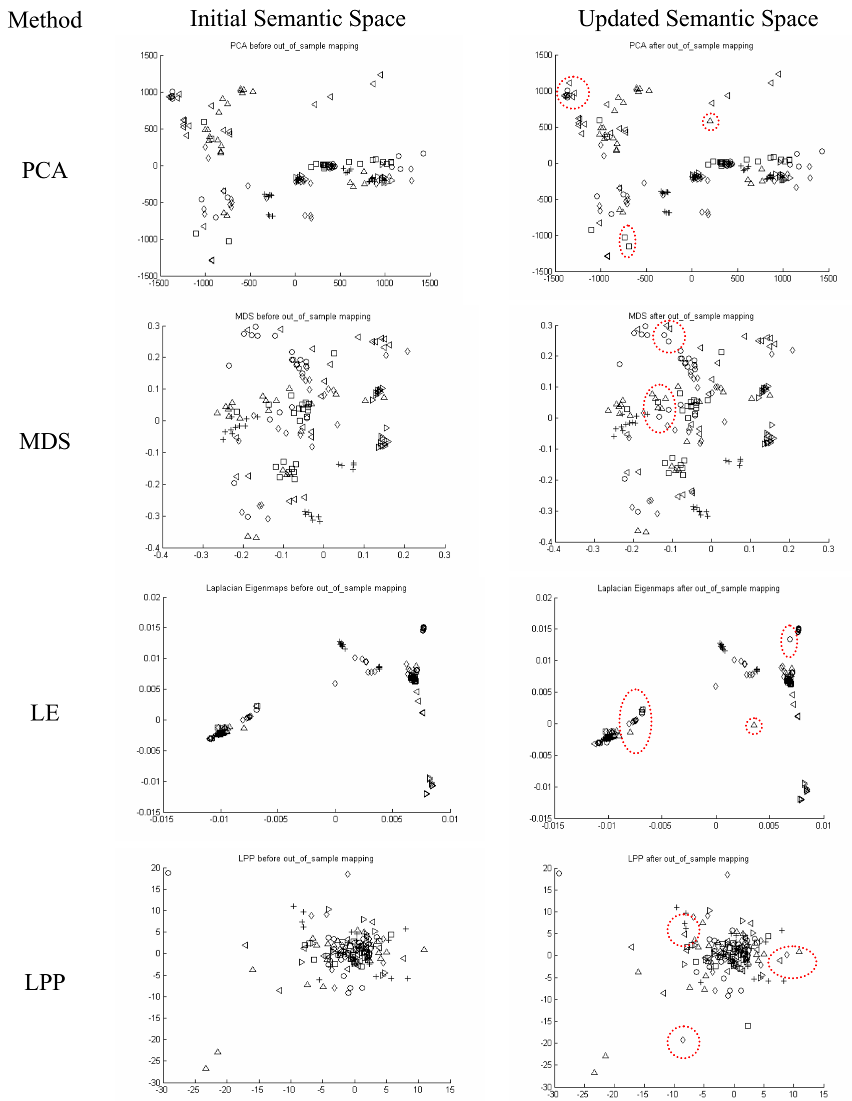

Fig. 6. Left column plots the initial semantic space in the first two dimensions for 7 of the 50 fingers used in experiments for sake of illustration. Right column plots the updated semantic space after projecting the test set (some highlighted in dotted circles) using OOS extension.

5.2 Experiment #2

The second experiment attempts to compare the difference between a *normal* and a *strong* expert by their effects on the identification accuracy measured using the *k*-NN classification errors. The left sub-figure of Figure 7 shows the result by the normal expert while the right sub-figure the result by the strong expert, respectively. In these figures, only MDS and LE that incorporated relevance feedback into their DR process are shown. The baseline refers to the *k*-NN classification errors obtained by using the default Euclidean distance in the initial high-dimensional features space. Note that, a suffix like "rf_10" meant the result obtained after 10 iterations of relevance feedback.

From the plots of Figure 7, it is reasonable to conclude that there is no significant difference in identification accuracy between a normal and a strong expert (as defined earlier in this section) based on our experimental setup. Based on this comparison, we have therefore decided to simulate a normal expert in the final experiment as this would be more representative of the real world situation.

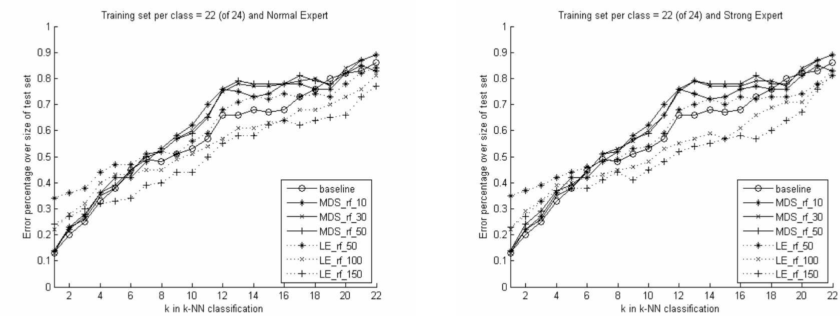

Fig. 7. Comparison of a *normal* expert (left plot) and a *strong* expert (right plot) on their identification accuracy based on *k*-NN classification errors for "relevance feedback" enabled MDS and LE

5.3 Experiment #3

In the final experiment, we compare the identification accuracy obtained by applying PCA, LPP, MDS, and LE. One might recall that both PCA and LPP return a linear mapping for out-of-sample extension directly albeit without incorporating relevance feedback, while both MDS and LE do in this experiment.

In Figure 8, one can observe that PCA performed worse than the baseline for all values of *k* while LPP did significantly worse. For MDS, one can notice that there is no significant improvement in identification accuracy even after going through 30 or 50 iterations of relevance feedback. On the other hand, while LE started out having worse performance than the baseline, PCA and MDS; after 100 iterations of relevance feedback, it has already achieved better accuracy than the baseline for $k > 6$; while after 150 iterations, it has better accuracy for k > 4. A conclusion based on the results of this empirical experiment could be drawn here. That is, certain DR methods like LE is capable of obtaining more improvement in accuracy than others such as MDS, which also exploited relevance feedback.

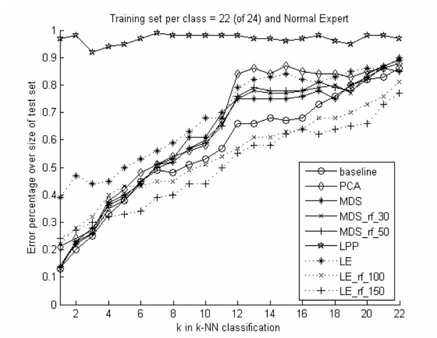

Fig. 8. Comparison of identification accuracy of MDS, LE and their "relevance feedback" enabled extensions with PCA and LPP

6 Conclusions

In this paper, we have introduced a user-centered framework for adaptive fingerprint identification that can be incorporated as an add-on module in a host AFIS. This is achieved by exploiting relevance feedback to capture an expert examiner's subjective knowledge into the formation of a persistent semantic space over the fingerprint database in which the accuracy of identification might be potentially improved.

Several experiments were conducted on a subset of the MCYT-Fingerprint-100 sub-corpus to simulate the performance of the proposed framework. The experimental results demonstrated the framework's potential for adaptive fingerprint identification.

Future works include potential collaboration with Australian Federal Government's CrimTrac Agency in implementing the proposed framework in their AFIS for actual testing and developing approaches for adaptation to larger fingerprint databases.

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