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Abstract: In recent years, the tasks of fingerprint examiners have been greatly aided by the development of automatic fingerprint classification systems. These systems operate by matching low-level features automatically extracted from fingerprint images, often represented collectively as numeric vectors, for their decision. However, there are two major shortcomings in current systems. First, the result of classification depends solely on the chosen features and the algorithm that matches them. Second, the systems cannot adapt their results over time through interaction with individual fingerprint examiners who often have different degrees of experiences. In this paper, we demonstrate by incorporating relevance feedback in a fingerprint classification system, a personalized semantic space over the database of fingerprints for each user can be incrementally learned. The fingerprint features that induce the initial features space from which individual semantic spaces are being learned were obtained by multispectral decomposition of fingerprints using a bank of Gabor filters. In this learning framework, the out-of-sample extension of a recently introduced dimensionality reduction method, called Twin Kernel Embedding (TKE), is applied to learn both the semantic space and a mapping function for classifying novel fingerprints. Experimental results confirm this learning framework for examiner-centric fingerprint classification.

A Learning Framework for Examiner-Centric Fingerprint Classification using Spectral Features

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ABSTRACT

In recent years, the tasks of fingerprint examiners have been greatly aided by the development of automatic fingerprint classification systems. These systems operate by matching low-level features automatically extracted from fingerprint images, often represented collectively as numeric vectors, for their decision. However, there are two major shortcomings in current systems. First, the result of classification depends solely on the chosen features and the algorithm that matches them. Second, the systems cannot adapt their results over time through interaction with individual fingerprint examiners who often have different degrees of experiences. In this paper, we demonstrate by incorporating relevance feedback in a fingerprint classification system, a personalized semantic space over the database of fingerprints for each user can be incrementally learned. The fingerprint features that induce the initial features space from which individual semantic spaces are being learned were obtained by multispectral decomposition of fingerprints using a bank of Gabor filters. In this learning framework, the out-of-sample extension of a recently introduced dimensionality reduction method, called *T*win *K*ernel *E*mbedding (TKE), is applied to learn both the semantic space and a mapping function for classifying novel fingerprints. Experimental results confirm this learning framework for examiner-centric fingerprint classification.

Keywords: Fingerprint Classification, spectral features, twin kernel embedding, out-of-sample extension, learning framework, semantic space

1. INTRODUCTION

In recent years, the tasks of fingerprint examiners in law enforcement have been greatly aided by the development of automatic fingerprint classification systems [1]. There are largely two operating scenarios, one for identifying to which fingerprint class a particular fingerprint belongs to, and another for deciding which fingerprints in the database that a novel fingerprint might be similar. These two scenarios are respectively called *discrete* and *continuous* classification in the relevant literature [2].

As an automatic fingerprint classification system is a pattern recognition application, its operation relies on comparing salient features extracted from the fingerprint images, normally forming vectors, for its final decision. With these feature vectors, the fingerprints can be projected as points in a very high dimensional Euclidean space. In the case of discrete classification, due to the existence of only a handful of distinct classes of fingerprints, that include left loop, right loop, whorl, arch and tented arch, in reality the high-dimensional features space could be very sparse. Often the fingerprints are located in clusters in the features space that together form a manifold of a much lower dimension. For the continuous case, ideally fingerprints of the same finger should form compact clusters. However, in reality, the cluster boundaries are not very distinct with much overlapping. This can be caused by a number of reasons like occlusion, scars, etc., leading to high intra-class variations among impressions of the same finger and low inter-class variations among impressions from different fingers. In this paper, we have focused mainly on the *continuous* classification case.

No matter we are dealing with either discrete or continuous classification, there are two major shortcomings with current automatic fingerprint classification systems. First, the result of classification depends solely on the features selected and the algorithm that matches these features. Second, there is no way of having the systems adapt the result to individual fingerprint examiners, who often have different level of experiences, over time. Taking these two problems together, we can say for the same fingerprint, the result of classification (whether discrete or continuous) will be the same regardless of who uses the system and how many times he or she has interacted with it.

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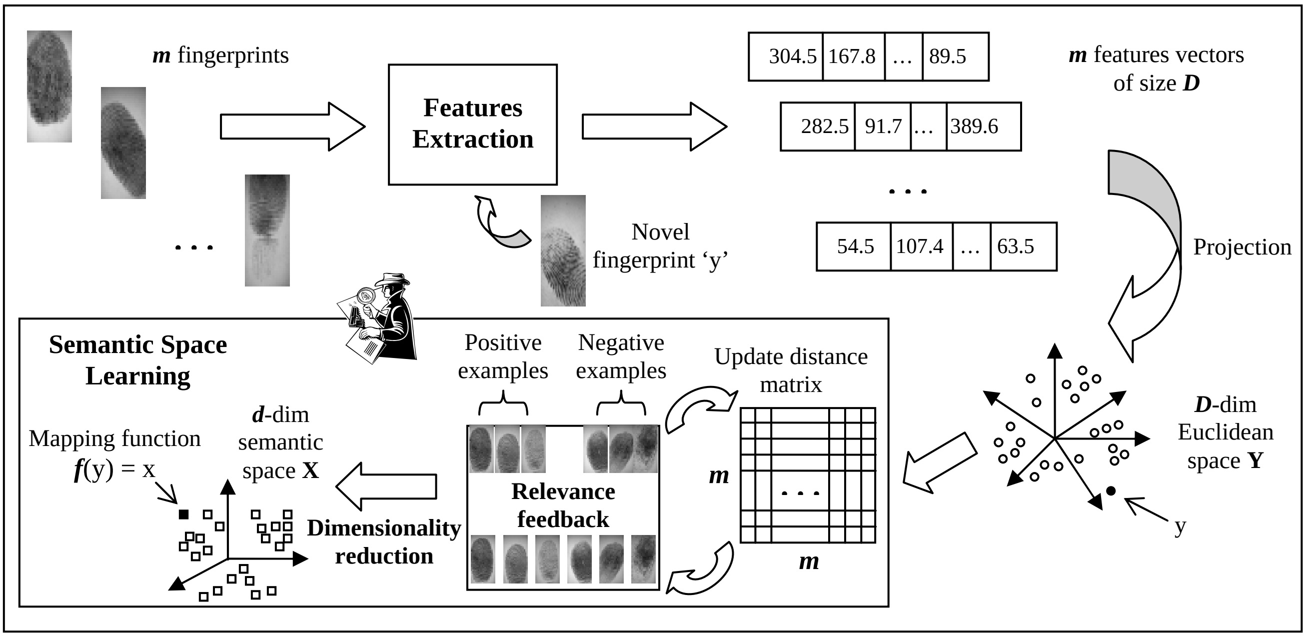


Fig. 1. The Learning Framework showing the major components, *Features Extraction* and *Semantic Space Learning*. Semantic Space Learning is in turn comprised by Relevance feedback and Dimensionality reduction modules.

To address these problems, in this paper we introduce a personalized learning framework that can adapt and improve the classification result for individual fingerprint examiners through repeated interactions with the system. This is achieved by exploiting relevance feedback from a fingerprint examiner by means of choosing both positive and negative examples in an iterative fashion. The outcome is a personalized and persistent semantic space for each fingerprint examiner in which the quality of classification is improved. This idea resembles long-term learning in Content-based Image Retrieval research proposed in [3,4], but differs in both the application and the method of learning. The fingerprint features that induce the original features space from which individual semantic spaces are being learned are obtained by multispectral decomposition of fingerprints (taken as texture images) using a bank of Gabor filters aligned in eight different directions.

In this research, the learning model can be considered as a dimensionality reduction process in which the features space corresponds to the input space while the semantic space to the embedding (or latent) space. From this, we apply the out-of-sample extension of our recently proposed *T*win *K*ernel *E*mbedding (TKE) method to incrementally learn both the semantic space and the mapping function by which novel fingerprints can be classified in the semantic space [5,6]. Experimental evaluation conducted on a subset of the open Fingerprint Verification Competition 2002 (FVC2002) Db2 database reveals the potential of this learning framework for examiner-centric fingerprint classification [7].

The remaining of this paper is organized as follows. In Section 2, a diagram of the learning framework is presented, with major components highlighted and explained. In Section 3, the procedure of extracting spectral features by multispectral decomposition of fingerprints using Gabor filters will be briefly described. In Section 4, the relevance feedback process and the dimensionality reduction algorithm by which the examiner-centric semantic space is learned will be explained. In Section 5, experimental evaluation using a subset of the FVC2002's Db2 database will be presented. Finally, we will conclude and mention future directions in Section 6.

2. OVERVIEW OF LEARNING FRAMEWORK

The proposed learning framework consists of two major components, namely *Features Extraction* and *Semantic Space Learning*. Semantic Space Learning is in turn comprised by the *Relevance feedback* and the *Dimensionality reduction* modules. A diagram illustrating the relationship between these components and modules, together with their input and output, is shown in Figure 1. In the remaining of this section, we will briefly overview the role of each of these main components and modules while leaving further details to their respective sections.

First, the input to the *Features Extraction* component is a set of m fingerprint images that will altogether constitute the database. The size and resolution of these images depend on the particular fingerprint scanner that was used. Within this module, a series of image processing steps are performed, like image enhancement, segmentation of fingerprint regions, detection and extraction of fingerprint features, and mapping features to numeric values. The set of numeric values will be merged to form a vector. Depending on the number of features involved, each of these vectors can be viewed as a point in a high-dimensional Euclidean space of dimension $D \in \Re$. The distance between any pair of fingerprints, i and j, can be measured by the Minkowski distance of order p (i.e., $\|v_i - v_j\|_p$) of the difference vector. Based on these distances, an m by m distance matrix can be obtained.

Second, a fingerprint examiner interacts with the classification system via the *Relevance feedback* module. In the training phase, an image q in the database can either be picked randomly by the system or chosen by the examiner. Based on the image selected, the system returns a subset of images (excluding q) that are similar based on the nearest neighbor criterion. The examiner indicates as positive examples those images that are judged similar based on prior experiences. The negative examples are those that are judged dissimilar. With the positive and negative examples, 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 outcome is a distance matrix that has *learnt* the semantic judgment of the examiner.

Finally, through the *Dimensionality reduction* module, both the d-dimensional ($d << D$) semantic space of the examiner and a mapping function that is capable of embedding a novel fingerprint in the semantic space *directly* can be obtained. Here, the out-of-sample extension of the TKE method is the inference engine behind this DR module. By mapping novel fingerprints directly onto the personalized semantic space, examiner-centric fingerprint classification can be achieved.

3. EXTRACTION OF SPECTRAL FEATURES

A fingerprint reflects the pattern of individual epidermal ridges and furrows that appear on the surface of a finger. Its uniqueness depends upon the overall pattern of ridges and furrows and the local ridge anomalies known as minutiae. Out of more than 150 minutiae that were identified, the ridge endings and ridge bifurcations are the most common (Refer to Figure 2). Normally, the pattern of flow of ridges and furrows on a finger varies continuously so that it can be considered an oriented texture field. Often, textured images (including fingerprints) contain a small range of spatial frequencies. Textures that are mutually distinct differ considerably in their dominant frequencies. By decomposing the texture field into a number of spatial frequency and orientation channels, textured regions possessing different spatial frequency, orientation, or phase can be easily discriminated.

In this research, we made use of a features extraction algorithm proposed in [8]. It employs both global and local ridge characteristics to construct a short and fixed length vector 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. Thus, 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. In summary, this algorithm consists of four processing stages (Refer to Figure 2):

I. locate a reference point in the fingerprint image;

II. extract and tessellate the region of interest into sectors around the reference point;

III. spectral decomposition in eight different directions using a bank of Gabor filters;

IV. compute the FingerCode based on individual sectors in the filtered region of interest.

In the following sub-sections, each of these steps will be briefly explained. Interested readers are referred to the original paper [8] for more details.

3.1 Locate Reference Point

In [8], the reference point (x_r, y_r) is defined as the location of maximum curvature along the concave ridges of the fingerprint image. The method used was based on multiple resolution analysis of the orientation field. For a fingerprint image, the orientation field O is defined as an M by N image where $O(i,j)$ indicates the local ridge orientation at pixel (i,j). Instead of having one value at every pixel, the local ridge orientation is often specified for a block of size w by w.

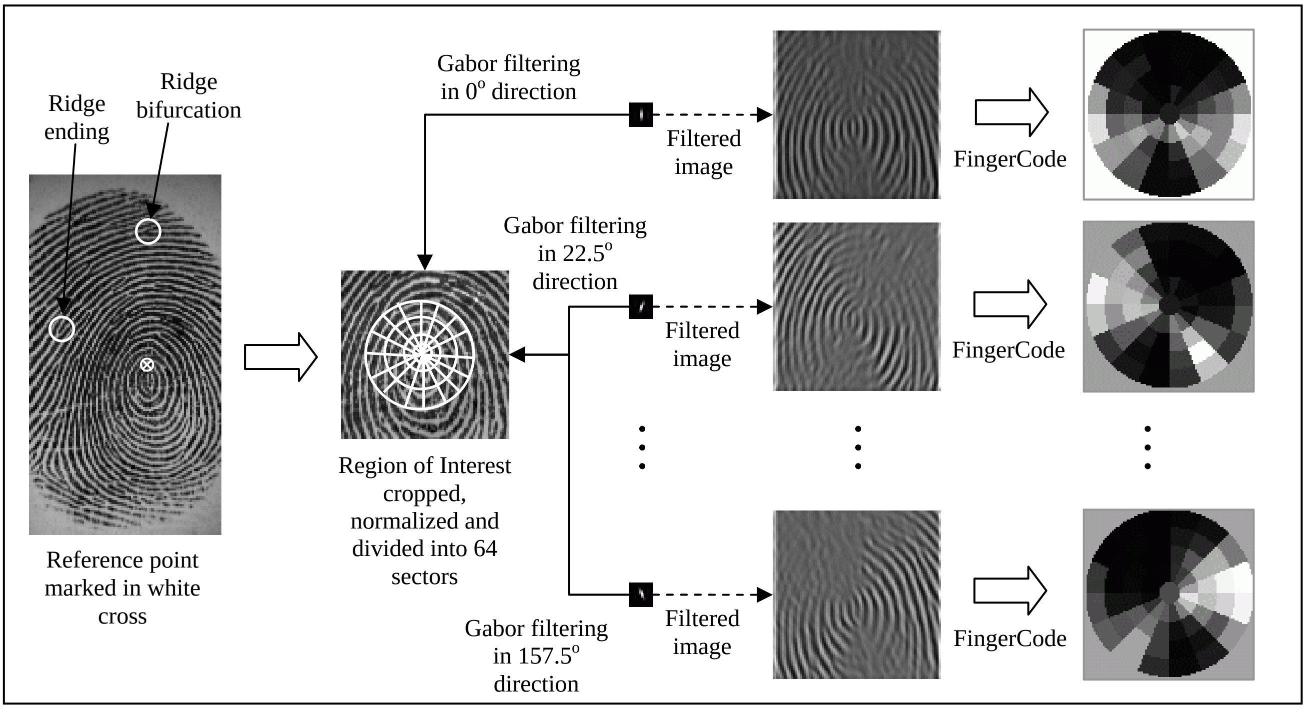


Fig. 2. Extraction of Spectral Features by multispectral decomposition using a bank of Gabor filters aligned in eight different directions including {0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135°, 157.5°}. *All images are shown in half their original sizes.*

There are largely six steps in this processing stage:

i). Estimate the orientation field O using a block of size w by w (w = 15, 10, or 5 pixels could be used).[1]

ii). Construct a smoothed orientation field O' by convolving O with a two-dimensional low-pass filter W with unit integral, whose size is w_Φ by w_Φ as follow:

$$O'(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{\Phi'_y(i,j)}{\Phi'_x(i,j)}\right), \tag{1}$$

where

$$\Phi'_x(i,j) = \sum_{u=-w_\Phi/2}^{w_\Phi/2} \sum_{v=-w_\Phi/2}^{w_\Phi/2} W(u,v)\cdot \cos(2O(i-uw, j-vw)), \tag{2}$$

$$\Phi'_y(i,j) = \sum_{u=-w_\Phi/2}^{w_\Phi/2} \sum_{v=-w_\Phi/2}^{w_\Phi/2} W(u,v)\cdot \sin(2O(i-uw, j-vw)). \tag{3}$$

iii). Using only the sine component of O', construct an image S as:

$$S(i,j) = \sin(O'(i,j)). \tag{4}$$

iv). Next, another image L is constructed from S by taking the difference between the sums of pixel intensities computed in two geometric regions[2] R_1 and R_2 in the neighborhood of each pixel (i,j) as:

$$L(i,j) = \sum_{R_1} S(i,j) - \sum_{R_2} S(i,j). \tag{5}$$

[1] Refer to [8] p.850 for the orientation field estimation algorithm based on least mean square.
[2] Refer to [8] p.851 (Figure 7) for a diagram of these geometric regions.

v). Determine the pixel in L that has the maximum value, and assign its coordinate as the reference point.

vi). Repeat steps 1-5 using a different block size w' by w' ($w' < w$) for a pre-defined number of iterations until a stable reference point is found.

3.2 Extract and Tessellate Region of Interest

Once the reference point (x_r,y_r) on a fingerprint image is located, the region of interest can be extracted and tessellated. In [8], the region of interest is defined as the set of all sectors S_i tessellated in terms of two parameters r and θ as:

$$S_i = \{(x,y) \mid b(T_i+1) \le r < b(T_i+2), \theta_i \le \theta < \theta_{i+1}, 1 \le x \le N, 1 \le y \le M\}, \tag{6}$$

where

$$T_i = i/k, \tag{7}$$

$$\theta_i = (i \bmod k) \times (2\pi/k), \tag{8}$$

$$r = \sqrt{(x-x_r)^2 + (y-y_r)^2}, \tag{9}$$

$$\theta = \tan^{-1}((y-y_r)/(x-x_r)). \tag{10}$$

Here, b and k denote the width and the number of sectors of each band, respectively. Also, i takes value from 0 to $(B\times k-1)$, where B is the number of concentric bands encircling the reference point (x_r,y_r). Note that the values of b, k and B are dependent on both the size and resolution of the fingerprint images that one is working with. In our own experiments, $b = 20$, $k = 16$, and $B = 4$ were used.

3.3 Spectral Decomposition using Gabor Filters

A bank of Gabor filters, oriented in eight different directions, is used in filtering the region of interest in order to obtain the spatial frequency along a particular orientation. Prior to filtering, the region of interest is normalized in order to minimize the errors introduced by noises and other deformations occurred during fingerprint capture.[3]

Each of the Gabor filters used in [8] is even symmetric and has the following general form:

$$G(x,y;f,\theta) = \exp\left\{\frac{-1}{2}\left[\frac{x'^2}{\delta_{x'}^2} + \frac{y'^2}{\delta_{y'}^2}\right]\right\}\cos(2\pi f x'), \tag{11}$$

where

$$x' = x\sin\theta + y\cos\theta, \tag{12}$$

$$y' = x\cos\theta - y\sin\theta. \tag{13}$$

Here, f denotes the frequency of the sine wave along one of the eight directions θ (0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135°, and 157.5°), measured from the x-axis. $\delta_{x'}$ and $\delta_{y'}$ are the widths of the Gaussian envelope along the x' and y' axes, respectively. In actual implementation, the filter mask is set to size 33 by 33 pixels.

3.4 Compute the FingerCode

Every sector S_i of the eight filtered images provides one value for the $k\times B\times 8$ dimensional FingerCode. This value, $V_{i\theta}$, is the *average absolute deviation* (AAD) from the mean of the particular filtered image that S_i belongs to, and is defined as:

$$V_{i\theta} = \frac{1}{n_i}\left(\sum_{n_i}\left|F_{i\theta}(x,y) - P_{i\theta}\right|\right). \tag{14}$$

where $F_{i\theta}(x,y)$ is the θ-direction filtered image for sector S_i.

---

[3] Refer to [8] p.851 for the method of normalizing the region of interest prior to filtering.

4. LEARNING EXAMINER-CENTRIC SEMANTIC SPACE

In this section, we will first discuss how to incorporate an examiner's subjective judgment through relevance feedback by iteratively updating the distance matrix. Then, we will explain the dimensionality reduction process by which both the semantic space and mapping function that can embed a novel fingerprint in the semantic space directly for classification can be obtained. Our novelty lies in the use of a recently proposed dimensionality reduction method called *T*win *K*ernel *E*mbedding (TKE) and its out-of-sample extension to achieve these learning outcomes.

4.1 Relevance feedback

Relevance feedback is closely linked with information retrieval in the literature. The goal is to exploit user's subjective judgment to improve the quality of retrieval often measured in terms of the precision and recall metrics. As data other than texts such as images and multimedia proliferate, studies on relevance feedback for Content-based Image Retrieval (CBIR) systems grew. In this research, we exploit relevance feedback to incorporate a fingerprint examiner's subjective judgment in the formation of a *personalized* and *persistent* semantic space for classification. The idea has similarities to long-term learning in image retrieval proposed in [3,4], but differ both in the application and the method of learning. In terms of application, we are concerned with classification of novel fingerprints rather than retrieval of similar images, as in the case of [3,4]. The difference in the method of learning will be explained in further details in the next sub-section on dimensionality reduction.

The relevance feedback procedure can be summarized as follows. Input are the m by m distance matrix and a parameter k indicating the number of fingerprints in the feedback. By either accepting an image picked by the examiner or selecting an image q randomly from the database, it returns a subset of images (excluding q) that are based on smallest distances. The examiner then indicates as positive or negative examples those images that are judged similar or dissimilar based on prior experiences. Based on the set of positive and negative examples, their entries in the distance matrix will be updated. In this work, we also exploit the apriori *class* information by adjusting entries for fingerprints that belong to the same classes as those of the positive and negative examples which was not done in [3,4]. The relevance feedback procedure repeats until the examiner is satisfied. The output is a modified distance matrix that has *learnt* the subjective judgment of the examiner. The pseudo code of the overall procedure is given in Table 1.

Table 1. Pseudo code of relevance feedback procedure.

INPUT: $m \times m$ distance matrix, k
OUTPUT: updated $m \times m$ distance matrix
UPDATE FUNCTION: $\sigma(d) = \dfrac{1}{1+\exp\left(\log\left(e^{d}\right) \pm \delta\right)}$ where $+\delta$/$-\delta$ for positive/negative images respectively.

```
bool satisfied = FALSE;
while (not satisfied)
  if (examiner selects an image)
      q = selected image;
  else
     generate a random number;
     select an image q from the database;
  end
  display the nearest k images to image q based on smallest distances (excluding q);
  the examiner selects both positive and negative examples;
  for (positive images i that are similar to q)
       update their entries in the distance matrix by d_iq = d_qi = δ(d_iq);
  end
  for (negative images i' that are not similar to j)
       update their entries in the distance matrix by d_i'q = d_qi' = δ(d_i'q);
  end
  if (the examiner is satisfied) satisfied = TRUE; end
end
return updated distance matrix;
```

4.2 Dimensionality Reduction

As mentioned above, the construction of an examiner's semantic space and the mapping function for embedding novel fingerprints is being cast as a dimensionality reduction problem. In essence, we seek a lower-dimensional representation of the original high-dimensional features space that preserves (and reflects) the examiner's subjective judgment as close as possible. Future classification of novel fingerprints can thus be performed in the newly constructed semantic space which is expected to be more efficient and more amiable to visualization.

Similar to relevance feedback, this idea is inspired by the long term learning model proposed in [3][4]. However, there are several differences which will become clear in the following comparison.

Table 2. Comparison of He et al. (2004) [3]'s dimensionality reduction procedure and the one adopted in this paper.

He et al. (2004) [3]	**This Paper**
<u>Steps</u> 1. Update distance matrix by relevance feedback; 2. Construct neighborhood graph by *k*NN; 3. Apply Laplacian Eigenmaps (LE); 4. LE semantic space without a mapping function; 5. Using FingerCode and LE embeddings, train a Radial Basis Function Neural Network to obtain the mapping function; 6. Use mapping function to embed novel images in *approximated* LE semantic space for retrieval.	<u>Steps</u> 1. Update distance matrix by relevance feedback; 2. Apply TKE with out-of-sample extension; 3. TKE semantic space with a mapping function; 4. Use mapping function to embed novel fingerprints in TKE semantic space for classification.

One might notice in the above comparison that [3]'s dimensionality reduction procedure requires two stages (Steps 2-4 and Step 5) to arrive at the actual semantic space with the mapping function. In contrast, ours is a more direct process that requires only one stage (Steps 2-3). Also, the semantic space constructed in [3] is *approximate*, which is obtained by a previous training step using a neural network. The semantic space constructed by our method is not an approximated one, which is obtained directly through TKE's out-of-sample extension. In the next sub-section, we will only venture to describe briefly the TKE method and its out-of-sample extension while referring the interested readers to [5,6] for a more thorough explanation.

4.2.1 TKE with Out-of-Sample Extension

Like many dimensionality reduction algorithms, TKE has been designed to facilitate information analysis involving very high dimensional data. What sets TKE apart from most DR methods is its capability in dealing with non-vectorial data directly. Non-vectorial data occurs naturally in many modern application domains, such as bioinformatics, structured and semi-structured document analysis, and knowledge management. While it is possible to apply a vectorization process to turn many naturally non-vectorial data into vectors, the degree of information loss could be difficult to quantify exactly. The computational tool that underpins TKE's ability to process non-vectorial data is the arsenal of kernel based methods derived in the last decade by machine learning researchers.

Two questions arise naturally as to the suitability of TKE in meeting the conditions required in this research. First, while TKE is specially designed for non-vectorial data, it can likewise operate on vectors like FingerCode by applying a linear kernel which is computed as a canonical dot product between two vectors. Second, the out-of-sample extension facility that we recently added to TKE enables it to obtain the mapping function necessary for embedding novel fingerprints into the examiner's semantic space directly for classification.

These simple notations are used in the following description. The FingerCode in the input (or *features*) space are denoted by y_i ($i = 1,\ldots,N$) while x_i ($i = 1,\ldots,N$) their embeddings in the embedding (or *semantic*) space. $\mathbf{Y}$ and $\mathbf{X}$ denote the set of input data and the set of embeddings, respectively. Because we are dealing with vectorized data in this work, both $\mathbf{Y}$ and $\mathbf{X}$ are considered as matrices consisting of rows of vectors. Also, $x_i{\cdot}x_j$ denotes the inner product of x_i and x_j, while $y_i{\cdot}y_j$ denotes the inner product of y_i and y_j similarly.

[4] Refer to [3] Section 3.2 and Section 3.3 for a detailed description of their dimensionality reduction process.

The core idea behind TKE is reproducing the relational structure among input data as faithfully as possible in the low-dimensional embedding space through matching a pair of kernel Gram matrices, one for the input space and another for the embedding space. In essence, it is attempting to minimize the following objective function:

$$L = -\sum_{ij} k_x(x_i, x_j) k_y(y_i, y_y) + \lambda_k \sum_{ij} k_x(x_i, x_j) + \lambda_x \|x_i\|^2 \tag{15}$$

where $k_y(.,.)$ is the kernel function on the input data and $k_x(.,.)$ the kernel function on the embeddings.

In this work, we make use of a *quasi* kernel as $k_y(.,.)$ that is derived from the distance matrix using a similar formulation as [9]. The choice of $k_x(.,.)$ can either be a linear or a radial basis function kernel [10]. In the optimization function L, the first term ensures the relational structures in the input space is matched as close as possible to that in the embedding space. The second and third terms are for regularization in order to control the norms of the kernel and the embeddings. λ_k and λ_x are parameters to adjust the degree of regularization. Since there is no closed form solution for **X**, we employ a gradient descent algorithm to minimize (15), while giving it a start state obtained using another DR method like KPCA.

Next, we will explain briefly how to incorporate the out-of-sample extension in TKE. This is basically done by rewriting the objective function L by means of a mapping function for the elements of **X** in terms of the elements of **Y**, given as:

$$f(y) = \sum_{i=1}^{N} \alpha_i k(y_i, y) \tag{16}$$

which defines a class of smooth functions as proved in [10][5]. $k(.,.)$ can be any valid kernel, but here we simply set it as k_y. In conclusion, given a set of input data **Y** and the kernel $k_y(.,.)$, the following algorithm returns the optimal embeddings **X** and the mapping function **A**.

Table 3. Pseudo code for TKE with out-of-sample extension algorithm.

INPUT: $N \times N$ kernel Gram matrix, k_y
PARAMETERS: λ_k, λ_x, k for kNN filtering and target dimension d
OUTPUT: **X**, **A** (or α_{mj}'s) matrices
PROCEDURE:
(1) Initialization: use another dimensionality reduction method or KPCA if data is non-vectorial in order to obtain the start state for **X**.
(2) Filtering: Use kNN to filter $\mathbf{K_y}$, which is the kernel Gram matrix for $k_y(.,.)$.
(3) Optimization: Minimize L in equation (15) by conjugate gradient algorithm iteratively until it reaches certain termination condition to obtain the optimal **A**.
(4) Projection: Obtain the final embeddings in the semantic space by the following:

$$\mathbf{X} = \mathbf{K_y A} \tag{19}$$

(5) Prediction: For novel input data $\mathbf{Y}_N$, compute

$$\mathbf{K}_N = k_y(\mathbf{Y}_N, \mathbf{Y}), \tag{20}$$

where

$k_y(\mathbf{Y}_N, \mathbf{Y})$ is a short form of $|\mathbf{Y}_N| \times |\mathbf{Y}|$.

Then, use

$$\mathbf{X}_N = \mathbf{K}_N \mathbf{A} \tag{21}$$

to obtain the new embeddings.

[5] Actually, we modify (16) slightly to meet our objective as:

$$f_j(y_i) = \sum_{m=1}^{N} \alpha_{mj} k_y(y_i, y_m), \tag{17}$$

and let

$$x_{ij} = f_j(y_i). \tag{18}$$

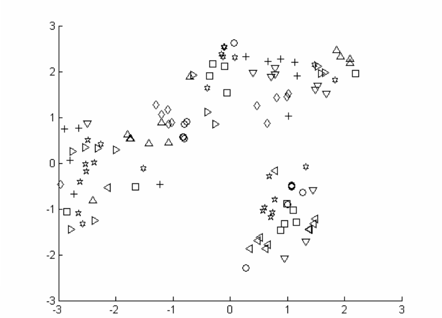
where x_{ij} is the j-th component of x_i.

5. EXPERIMENTAL EVALUATION

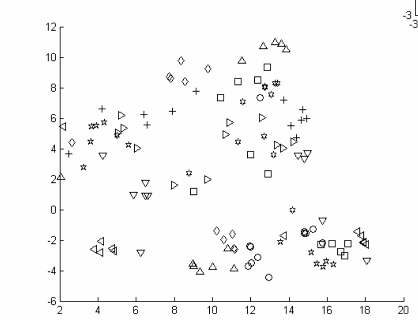
A set of experiments was conducted on a subset of the Fingerprint Verification Competition 2002 (FVC2002)'s Db2 database. The fingerprints were captured by an optical sensor. The image size is 296 × 560 pixels while the resolution is 569 dpi. The Db2 database is divided into two sets, Db2_a and Db2_b. The width and depth of the Db2_a set are 100 and 8 respectively, meaning there are 100 fingers each having 8 impressions. Similarly, the width and depth of the Db2_b set are 10 and 8 respectively. Altogether, Db2 has 880 fingerprint images.

For our experiments, we randomly select twenty fingers from Db2. Six of the eight impressions in each finger are taken to form the initial database, totaling 120 fingerprint images. In other words, the dimension of the initial distance matrix is 120 × 120. The remaining two impressions from each finger are grouped to form the set of novel fingerprints to test the quality of classification. Although the database size here is limited, it is adequate to illustrate the benefits of the proposed learning framework. In production setup, we would expect a larger database for the fingerprint examiners to work with.

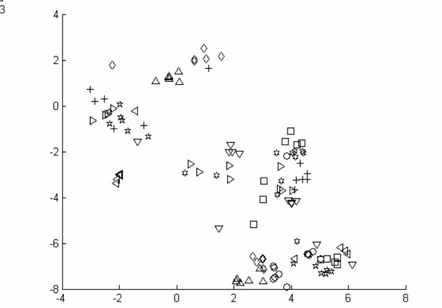
In Figures 3(a)-(e), the semantic space before relevance feedback, after 50 times, after 100 times, after 150 times and after 200 times are shown respectively. *k* is set to 10 in order to avoid degrading the quality of feedback. It is clear that as relevance feedback repeats the clusters of fingerprints are becoming more and more compact. This is consistent with the improvement in quality of classification as subjective judgment is increasingly incorporated into the distance matrix.



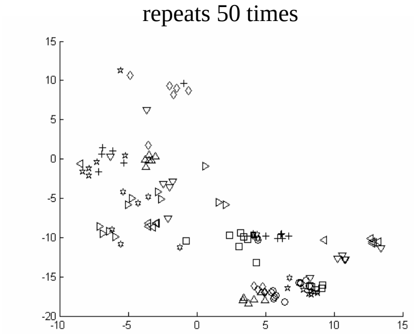
(a) Semantic Space in 2-dim without relevance feedback



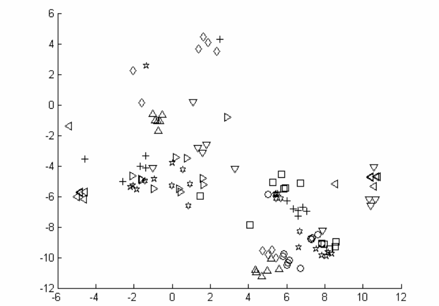
(b) Relevance feedback repeats 50 times



(c) Relevance feedback repeats 100 times



(d) Relevance feedback repeats 150 times



(e) Relevance feedback repeats 200 times

Fig. 3. Semantic space embedded in two dimensions by TKE before and after 50, 100, 150 and 200 relevance feedback iterations.

In Table 4, we compare the quality of classifying the set of 40 test fingerprints between the baseline (that is simply using the initial distances), semantic space in 2-dimension before and after certain number of relevance feedback. The metric used is the *k*-NN classification errors. While the initial semantic space has worse classification quality than the baseline (due to information loss in DR), the quality improves as the examiner's subjective judgment is increasingly incorporated.

Table 4. Comparing classification quality between baseline, semantic space in 2-dim before and after relevance feedback.

Case / Errors	Baseline	No relevance feedback	50 times	100 times	150 times	200 times
1-NN	7	26	17	20	14	10
2-NN	6	25	17	21	14	9
3-NN	10	28	17	19	16	10
4-NN	12	28	17	20	19	13
5-NN	19	29	17	20	20	15
6-NN	30	34	28	25	24	22

6. CONCLUSIONS

In this paper, by exploiting relevance feedback from fingerprint examiners, a personalized and persistent semantic space over the database of fingerprints for each examiner can be incrementally learned. The fingerprint features that induce the initial features space from which semantic spaces are being learned were obtained by multispectral decomposition of fingerprints (taken as texture images) using a bank of Gabor filters. In this learning framework, we apply the out-of-sample extension of a recently developed dimensionality reduction method, called *T*win *K*ernel *E*mbedding (TKE), to learn both the semantic space and the mapping function for classifying novel fingerprints. Experimental evaluation verifies the potential of this learning framework for examiner-centric fingerprint classification.

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