Learning Partitioned Least Squares Filters for Fingerprint Enhancement

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Abstract

Fingerprint images contain varying amount of noise because of the limitations of the fingerprint acquisition process. It is often necessary to enhance such noisy fingerprint images so that the features extracted from them are reliable. We propose a novel approach to fingerprint enhancement where a set of filters are learned using the “learn-from-example” paradigm. An expert provides the ground truth information for ridges in a small set of representative fingerprint images. The space of local fingerprint patterns in a small neighborhood is partitioned into a set of expressive yet computationally simple classes. A filter is learnt for each partition by finding the optimal linear mapping (in least-square sense) from the input to the enhanced space. The proposed approach offers distinct performance and speed advantages for a wide variety of fingerprint images.

1. Introduction

An ideal fingerprint image is characterized by smoothly flowing patterns of ridges and valleys. The naturally occurring ridge discontinuities, commonly known as the minutiae, are the prevalent and well-accepted class of fingerprint features. In practice, a significant fraction of fingerprint images is far from being ideal, i.e., is of poor quality because of the limitations of the fingerprint acquisition process, epidermal characteristics, and other reasons [2]. For a poor quality fingerprint as input, a feature extractor typically fails to identify genuine minutiae while identifying a significant number of spurious minutiae which may result in erroneous identification. It is, therefore, necessary to enhance the fingerprint image to ensure proper performance of the feature extractor and the verification system. In general, the problem of fingerprint enhancement is hard to solve and not surprisingly the existing enhancement schemes suffer from the trade-off between computational efficiency and the quality of enhancement. Computational efficiency is a mandatory requirement in on-line verification systems while high quality enhancement is necessary to improve the reliability of the verification system. All existing fingerprint enhancement techniques are, in principle, based on the estimation of local ridge orientation and frequency, followed by convolution with a filter tuned to that orientation and frequency. Hong et al. [2] describe an enhancement technique that uses a Gabor filter bank. The Gabor filters are characterized by orientation, frequency, and sensitivity. Enhancement by global pre-filtering in the frequency domain by a set of bandpass filters is described in [5]. O’Gorman proposed the use of oriented matched filter masks in [4], and reported a method to quantify and justify the functional relationships between image features and filter parameters. Kamei and Mizoguchi defined an energy function for selecting the image features from a set of bandpass-filtered images according to a smoothness measure [3]. When small sized filters are used, blocky artifacts are created, and some regions are poorly enhanced or false ridge structures are generated. When large sized filters are used, the enhancement process takes a disproportionately long time compared to the feature extraction and verification.

In this paper, we describe a novel technique to achieve high quality enhancement without sacrificing computational efficiency. We propose a computationally simple yet expressive scheme to partition the space of local fingerprint characteristics. We learn the enhancement filter coefficients for each partition using a “learn-by-example” paradigm. These filters are generated as optimal linear mappings in the least-squares sense. The proposed enhancement tech-
nique is adaptable to different fingerprint populations and acquisition conditions. The rest of the paper is organized as follows. The proposed technique along with the relevant background about least squares enhancement is described in section 2. Several methods of evaluating the enhancement result are presented in section 3. Conclusions and future work is described in section 4.

2. Least squares enhancement

Let us define a neighborhood around a candidate fingerprint image pixel $i$, and an enhancement filter to be applied to pixel $i$, as shown in Fig. 1. In this case the neighborhood is an rectangular window. The filter is also defined in the same window. Assume $k = nm$. Now define a vector $X_i = [x_1^i, x_2^i, \ldots, x_k^i]$ by ordering the fingerprint pixel intensities in the i-th window, and a corresponding filter function $W_i = [w_1^i, w_2^i, \ldots, w_k^i]$. Also define a vector of expert-provided ridge intensities, where $y_i$ is the ridge intensity at pixel $i$, and $N$ is the number of pixels in the fingerprint. Also assume that the input fingerprint pixels are classified into a set of $M$ mutually exclusive partitions, defined as $\Omega_1, \Omega_2, \ldots, \Omega_M$, such that $\Omega_m \cap \Omega_n = \emptyset$ for $m \neq n$. For each partition $p(X_i)$, a specific least squares filter $W_p(X_i)$ is obtained according to the solution of a least-square mapping problem.

2.1. Learning Enhancement Mappings

Let $X_p = [x_1, x_2, \ldots, x_{N_p}]^T$ be the matrix of observed samples belonging to partition $P$, and $y_p = [y_1, y_2, \ldots, y_{N_p}]^T$ be the corresponding vector of enhanced values. $X_p$ is of size $N_p \times k$. Let $R_p$ and $P_p$ be the cross-correlation and conditional correlation matrices, respectively, for the partition $P$. Thus, the partitioned least squares (PLS) filter for the $P$-th partition is obtained by minimizing

$$(X_p w_p - y_p)^T (X_p w_p - y_p)$$

w.r.t. $w_p$. It can be easily verified that

$$w_p = (X_p^T X_p)^{-1} X_p^T y_p = R_p^{-1} P_p.$$  

minimizes Equation (2). As long as $N_p \geq k$, practically it is guaranteed that $X_p$ is nonsingular, since the input fingerprint space is inherently noisy due to imaging process. For ensuring robustness and good generalization ability, it is essential that filter coefficients for each partition are learnt from a sufficiently large number of samples, i.e., $N_p \gg k$. Note that both matrices are estimated directly from the training data. This provides an effective means for tuning the enhancement process to the imaging condition and target population. We would like to point out that the filter size $k$ does not need to be the same for all partitions. In fact we recommend it is different for proper utilization of computational resources (for example, if the input fingerprint space is partitioned into less noisy and noisy categories, then smaller filters can be applied in less noisy regions).

2.2. Partitioning of Fingerprint Space

The generation of observation space partitions and the partitioned least squares filters jointly determine the performance of enhancement [1]. Unfortunately, the joint optimization of these components results in a set of non-linearly coupled equations. Previously reported partition-based image restoration methods have decoupled the optimization. The well-known LBG algorithm has been used to partition the observation (input) space [1], while minimizing the total distortion in input space. But vector quantization (VQ) is not likely to discover those spatial features, i.e., minutiae, which are particularly important in the fingerprint verification process but seldom occur (compared to non-minutiae points) in fingerprints. Furthermore, only computationally simple partitionings can be used to ensure fast on-line performance. VQ does not satisfy this requirement either. Our proposal is to design a large number of simple, yet expressive partitions for fingerprints. As in the existing methods, the local orientation and ridge spacing play a vital role in our partitioning scheme. Local orientation and ridge spacing are estimated according to [2]. Additional partitions are generated according to local amplitude (i.e., contrast), and ridge/valley/transition (analogous to phase). Amplitude partitioning is introduced to learn the filter gains according to local amplitude. This enables generation of a filter with larger gain in low contrast regions and vice versa, and binary ridge maps can be obtained from the enhanced image using a simple global threshold. Ridge/valley/transition region labeling enables definition of separate filters for those regions. Qualitatively ridge filters tend to produce steeper ridges, whereas valley filters tend to create deeper valleys. Note that the proposed approach does not attempt to estimate the noise variance and specify that in filter design - rather it tries to estimate the filter function as an optimal mapping in the least squares sense from the input fingerprint to ridge-map space for that noisy partition. It is very hard, but if not impossible, to predict what characteristics should be used for partitioning without experimentation. Intuitively, partitions that convey mutually exclusive information are expected to yield the best enhancement results.

- Orientation and Frequency Partitioning

The local orientation ranges from 0° to 180°, and are partitioned uniformly in 4-8 regions. Because of inherent inaccuracies in orientation measurement, a large number of partitions based on orientation
does not necessarily improve the enhancement performance. Similarly, the fingerprint space is partitioned uniformly into 2-6 classes based on ridge frequency.

- **Amplitude Partitioning**
  Qualitatively, amplitude captures the local ridge-to-valley contrast. Local amplitude is estimated using the projection of the pixel intensities along a line segment perpendicular to the orientation vector and passing through pixel. A similar procedure is employed in [2] for ridge frequency estimation. The average of peak-to-valley heights gives the amplitude for the candidate pixel. For a wide variety of fingerprints, it is enough to partition the fingerprint space into 3-6 uniform amplitude partitions. Amplitude partitioning produces uniform ridge-to-valley contrast in the enhanced image.

- **Ridge/valley/transition Partitioning**
  Once the maximum and minimum of the underlying sinusoid at a candidate pixel are calculated, the pixel is labeled (1) a ridge pixel if its intensity ≤ (minimum + 0.33 × amplitude), (2) a valley pixel if its intensity ≥ maximum − 0.33 × amplitude). Otherwise it is labeled a transition pixel. More granular partitioning is also possible. Note that ridge/valley/transition partitioning is analogous to partitioning based on phase of the underlying sinusoid.

2.3. Overall algorithm

The proposed technique involves an off-line training stage and an on-line image filtering stage. Given a small but representative set of fingerprints and the corresponding set of binary ridge maps (drawn by an expert), a set of adaptive least squares enhancement filters are learnt off-line. One such training pair is shown in Fig. 3. On-line enhancement is achieved by convolving the fingerprint image with appropriate filters. Good on-line enhancement performance is achievable when the training set is a good representative of the input fingerprint images. A single enhancement filter cannot give good performance over a large number of input fingerprints, since least square estimation of filter coefficients is susceptible to outliers. The idea is to partition the space of local fingerprint characteristics and generate a least-square filter for each partition. Using the simple, intuitive, and computationally efficient scheme of partitioning based on distinct local properties such as orientation, frequency, amplitude, and ridge/valley transitions described in the previous section, we learn the filters. These filters can be used on an input fingerprint image by convolving the right filter learnt in the learning step.

3. Enhancement Performance

The purpose of enhancement is to improve the clarity of ridges and valleys of the fingerprint images, so that the subsequent minutiae extraction can be performed better. Of course, the ultimate criterion of evaluating the fingerprint enhancement in the context of an automatic fingerprint identification system (AFIS) is the improvement in false accept rate (FAR) and false reject rate (FRR) of the verification module. Performance of an enhancement algorithm can also be subjectively measured by visual inspection of enhanced images by an expert(s). Fig. 4 visually demonstrates the effectiveness of the proposed enhancement technique on a noisy fingerprint image. A precise and consistent performance evaluation of an enhancement scheme is not possible with visual examples alone. On the other hand, peculiarities of feature extraction and verification modules can bias the evaluation of the enhancement technique. We report here the module-level as well as system-level performances of the proposed enhancement technique. The module-level
Figure 2. Partitioning of local fingerprint patterns for enhancement. \( n1, n2, \) and \( n3 \) are, respectively, the number of orientation, frequency and amplitude partitions.

Performance is measured in terms of an enhancement error metric, as well as the overall quality of the enhanced images. The enhanced images are globally thresholded at 128 to generate the binary ridge map. This ridge map is compared with the expert-provided ridge maps. Enhancement error is computed as,

\[
enhancement\ error = \sqrt{\frac{\sum (R(i) - E(i))^2}{total\ number\ of\ pixels}}, (3)
\]

where \( R(i) \) and \( E(i) \) are, respectively, the binary (0/255) expert-provided and enhanced values at the i-th fingerprint pixels. Background pixels are not used for computation. Lower enhancement error means better enhancement filtering. Fig. 5(a) shows the improvement of enhancement error with number of partitions for a noisy training set. In this experiment, 6 orientation partitions, 5 frequency partitions, 5 amplitude partitions, and 3 phase partitions are used. Filters are trained using a training set of 10 images. An in-house algorithm is used for overall quality measurements of fingerprint images. The quality assessment algorithm divides the fingerprint image into smaller blocks and determines the overall quality of the fingerprint to be a weighted sum of qualities of the blocks. The weighting function emphasizes the qualities of the blocks closer to the center of the fingerprint and considers the qualities of the peripheral blocks less important. The quality of a block is determined by analyzing the statistical properties (mean and standard deviation) of the pixel gray levels in the given block and those in the neighboring blocks. The overall quality improvement due to the proposed enhancement scheme is also described in Fig. 5(b) for a typical set of 10 images from NIST-9 database. The system-level performance of the proposed enhancement technique is measured using the FRR and FAR of an verification engine [6] for a data set of 52 images arbitrarily selected from a database of optically acquired livescan fingerprints. The ROC curves are drawn in Fig. 6.

4. Conclusions

We propose an original technique for fingerprint enhancement in this article, and demonstrate its performance for on-line authentication. The proposed approach can be "tuned" easily for different sensors and imaging conditions. Contrary to the existing model-driven methodology, the proposed approach is completely data-driven, and enhancement filters are learned as optimal linear mappings from the input observed fingerprint space to the enhanced fingerprint space. A computationally simple yet expressive partitioning scheme is proposed to reduce the effect of outliers during least square estimation by defining new partitions corresponding to the outliers themselves. In addition to the well-known orientation and ridge frequency partitionings, amplitude and phase partitionings are performed in the current implementation.
Figure 3. Training fingerprint set. (a) A representative fingerprint. (b) Expert-provided corresponding ridge maps.

Figure 4. Visual improvement due to partitioned least squares enhancement. (a) Original fingerprint image. (b) Enhanced image.

References


Figure 5. Least-squares enhancement performance. (a) Effect of number of partitions on enhancement error. (b) Overall quality improvement due to least-squares enhancement.

Figure 6. The receiver operating characteristics (ROC) comparing the matching performance improvement in 52 fingerprint database due to enhancement using the proposed approach.