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Enhancement of feature extraction for low-quality fingerprint images using stochastic resonance

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ABSTRACT

This paper presents a new approach to enhancing feature extraction for low-quality fingerprint images by adding noise to the original signal. Feature extraction often fails for low-quality fingerprint images obtained from excessively dry or wet fingers. In nonlinear signal processing systems, a moderate amount of noise can help amplify a faint signal while excessive amounts of noise can degrade the signal. Stochastic resonance (SR) refers to a phenomenon where an appropriate amount of noise added to the original signal can increase the signal-to-noise ratio. Experimental results show that Gaussian noise added to low-quality fingerprint images enables the extraction of useful features for biometric identification. SR was applied to 20 fingerprint images in the FVC2004 DB2 database that were rejected by a state-of-the-art fingerprint verification algorithm due to failures in feature extraction. SR enabled feature extraction from 10 out of 11 low-quality images with poor contrast. The remaining nine images were damaged fingerprints from which no meaningful features can be obtained. Improved feature extraction using SR decreases an equal error rate of fingerprint verification from 6.55% to 5.03%. The receiver operating characteristic curve shows that the genuine acceptance rates are improved for all false acceptance rates.

1. Introduction

Fingerprint verification has been widely accepted as a key biometric identification technique in commercial and law enforcement applications. Most commercially available fingerprint recognition systems depend on reliable extraction of feature points from fingerprint images for matching with reference features (Maltoni et al., 2003). Fingerprint recognition fails when no distinct features can be extracted from input fingerprint images. Such low-quality fingerprint images usually contain weak patterns of ridges and valleys due to the surface conditions of the fingertips, humidity, improper finger pressure, or even irregular ridge patterns caused by skin damage, wrinkles, or cracks. Fingerprint feature extractors reject an input fingerprint image if any meaningful fingerprint feature cannot be obtained. Such rejection helps prevent unnecessary matching of images that will subsequently result in incorrect matches.

This preprocessing can be more critical in one-to-many identification systems. However, biometric identification systems with high input rejection rates have limited usability due to frequent failure in enrollment and recognition. Fingerprint recognition systems include an image enhancement component to help a feature extractor find reliable features from low-contrast input fingerprint images. Fingerprint enhancement techniques are often based on local ridge directional binarization (Ratha et al., 1995), Gabor filter (Hong et al., 1998), short-time Fourier transform (Chikkerur et al., 2007), and the wavelet transform (Hsieh et al., 2003). However, these techniques have demonstrated limited capability for low-quality fingerprint images with faint or saturated ridge patterns.

Low-quality fingerprint images are often found in forensic applications. Latent fingerprints from crime scenes are generally captured in challenging ambient environments resulting in poor quality images with complicated backgrounds. Recent research in semi-automatic fingerprint recognition for latent fingerprints (Yoon et al., 2010; Jain et al., 2008) proposed manual editing or insertion of feature points to generate fingerprint features. The proposed approaches address real-time automatic fingerprint recognition where fingerprints are captured from live fingerprint sensors with no supervising operators.

Stochastic resonance (SR) refers to a phenomenon where the output of a nonlinear system experiences an increase in the signal-to-noise ratio as the amplitude of input noise rises. When the signal coming from an object is below a sensory detection level, SR can enhance detection of the faint signal by adding a small amount of noise to it (Bulsara and Gammaitoni, 1996). SR was first introduced to explain the periodicity of the Earth's ice-ages

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(Wiesenfeld and Moss, 1995). It has been observed that adding noise to a weak signal can enhance its detectibility by the peripheral nervous systems of many biological systems including mechanoreceptor hair cells of crayfish, which gets warnings of approaching bass using a periodic fin motion. In image processing applications, improvement of depth perception of autostereograms has been demonstrated by adding a random dot pattern to original stereograms (Ditzinger et al., 2000). Color object segmentation performance in noisy conditions can be improved by adding white Gaussian noise to each RGB plane (Janpaiboon and Mitaim, 2006).

This paper presents stochastic resonance for enhancing feature extraction from low-quality fingerprint images. Fingerprint feature extractors usually fail to detect reliable features from extremely weak or saturated images. SR enables the detection of fingerprint features from low-quality images that are rejected by a feature extractor. A small amount of noise added to weak or saturated fingerprint images can help feature extractors detect the features useful for fingerprint matching. Faint fingerprint patterns are enhanced by the Gaussian noise added to the original image. This study aims at improving the quality of faint fingerprint patterns by adding the Gaussian noise to the original signal to enhance feature extraction from low-quality fingerprint images.

Experiment results with low-quality fingerprint images from the FVC2004 DB2 database show that the SR with an appropriate amount of the noise increases the success rate of feature extraction for low-quality fingerprint images. A fingerprint verification algorithm VeriFinger® (Neurotechnology, 2009) is used in the tests. As we gradually increase the Gaussian noise level, the feature extraction success rate also increases. The success rate decreases when the amount of noise exceeds an optimal level. In the FVC2004 DB2 database, 20 fingerprint images are rejected by the feature extractor. Among the 20 rejected fingerprints, 11 images are labeled as low-quality images since they are captured from reasonably good ridge patterns, but with poor sensing quality. For the remaining nine images, feature extraction is practically impossible since a large portion of the fingerprint pattern is damaged. SR enables feature extraction of 10 out of 11 low-quality fingerprint images. The SR-based feature extraction enhancement decreases the equal error rate for matching from 6.55% to 5.03%.

2. Fingerprint feature extraction

Most fingerprint recognition systems utilize minutiae points as features such as the location and angle information of ridge endings and bifurcations (Hong et al., 1998). Other feature extraction approaches use texture information of the fingerprint in order to overcome the sensitiveness of ridge pattern quality (Jain et al., 2000). However, a minutiae-based approach is generally accepted by a majority of developers since it outperforms other approaches in terms of reliability and matching accuracies. A hybrid fingerprint matching scheme using the minutiae and ridge flow information shows higher matching performance than using the minutiae only (Ross et al., 2002). However, the performance of this approach is limited if the minutiae and ridge flow features are not available for low-quality fingerprints.

Feature extraction involves common image processing components such as preprocessing, segmentation and image enhancement. Local variance and directional clearness are used in fingerprint segmentation algorithms to distinguish a fingerprint from the background. The Gabor filter has been the most popular approach to enhance fingerprint ridge and valley patterns in gray level (Hong et al., 1998). The Gabor filter is a powerful directional noise removal filter that creates smooth ridge patterns from a noisy fingerprint image. A Gabor filter can eliminate small holes or cuts on ridges and remove small noisy patterns in valleys. After image enhancement filtering, an image thresholding is employed to create a binary image. Then a thinning process follows to remove unnecessary pixels in a ridge pattern. Minutiae (Ratha et al., 1995) are extracted by comparing a pixel in a ridge pattern with its neighboring pixels.

Feature extractors reject a fingerprint image when the amount of reliable fingerprint features is not sufficient for verification. Depending on the quality of input fingerprint image, the rejection of feature extraction is decided at every step from preprocessing to the detection of minutiae. When an image is partially degraded, only a region of discernable ridge and valley patterns may be used for feature extraction, which can result in failure in feature extraction or matching due to a small number of feature points. Gabor filters may not be able to recover fingerprint patterns since local direction or distance of the ridge flows are not well defined in low-quality images.

Even in the minutiae detection step, feature extraction fails if only a small subset of minutiae can be generated since a few minutiae may lead to inaccurate matching with an imposter fingerprint. Fingerprint matching may be not reliable when only a partial set of minutiae is used. Fingerprint image quality is related to age, occupation, and the sensor's operating conditions. Research (Modi and Elliott, 2006) shows that fingerprint images from a group of elderly people are low in quality with a large number of spurious minutiae. Low-quality fingerprint images caused by dry or wet skin conditions, improper pressure applied to the sensors, and weak ridge patterns may contain meaningful fingerprint patterns. However, fingerprint feature extractors often fail to extract features due to a weak signal below detection level of the sensor.

3. Stochastic resonance

In general, noise is an unwanted signal that decreases the signal-to-noise ratio (SNR) of signal processing systems. In some feedback nonlinear systems, however, noise can amplify a faint signal. This phenomenon, known as stochastic resonance (SR), occurs when a nonzero optimum noise enhances an external signal in a nonlinear dynamical system. SR can be observed in visual enhancement of a low-quality image. Fig. 1 shows how adaptive pixel noise based on a Gaussian distribution can improve visual perception of a low-quality fingerprint image. An original image obtained from a dry finger has faint ridge and valley patterns as shown in Fig. 1(a). Such weak patterns often make it difficult to segment the foreground and to distinguish it from the latent fingerprint patterns left in the previous session. An optimal amount of Gaussian noise added to the original image enhances visual quality of the fingerprint patterns (Fig. 1(b)). However, if the noise is too strong, it can degrade the image and make feature extraction difficult (Fig. 1(c)). Stochastic resonance enhances visual quality of latent fingerprints as shown in Fig. 1(d)–(f). A low contrast latent fingerprint image (Fig. 1(d)) is visually enhanced with an optimal noise (Fig. 1(e)) but some weak fingerprint patterns are overshadowed by strong noise (Fig. 1(f)).

SR includes three basic components: a nonlinearity, a weak coherent input, and a noise source (Gammaitoni et al., 1998). With these three components, a system may demonstrate a resonance-like behavior in SNR as a function of the noise. In many cases, the noise parameter is defined by a noise level that characterizes the noise behavior and strength. In this paper, a fingerprint feature extractor is used instead of a threshold nonlinearity to determine if features can be extracted from a fingerprint image. Low-quality fingerprint images will act like a weak coherent input. Gaussian

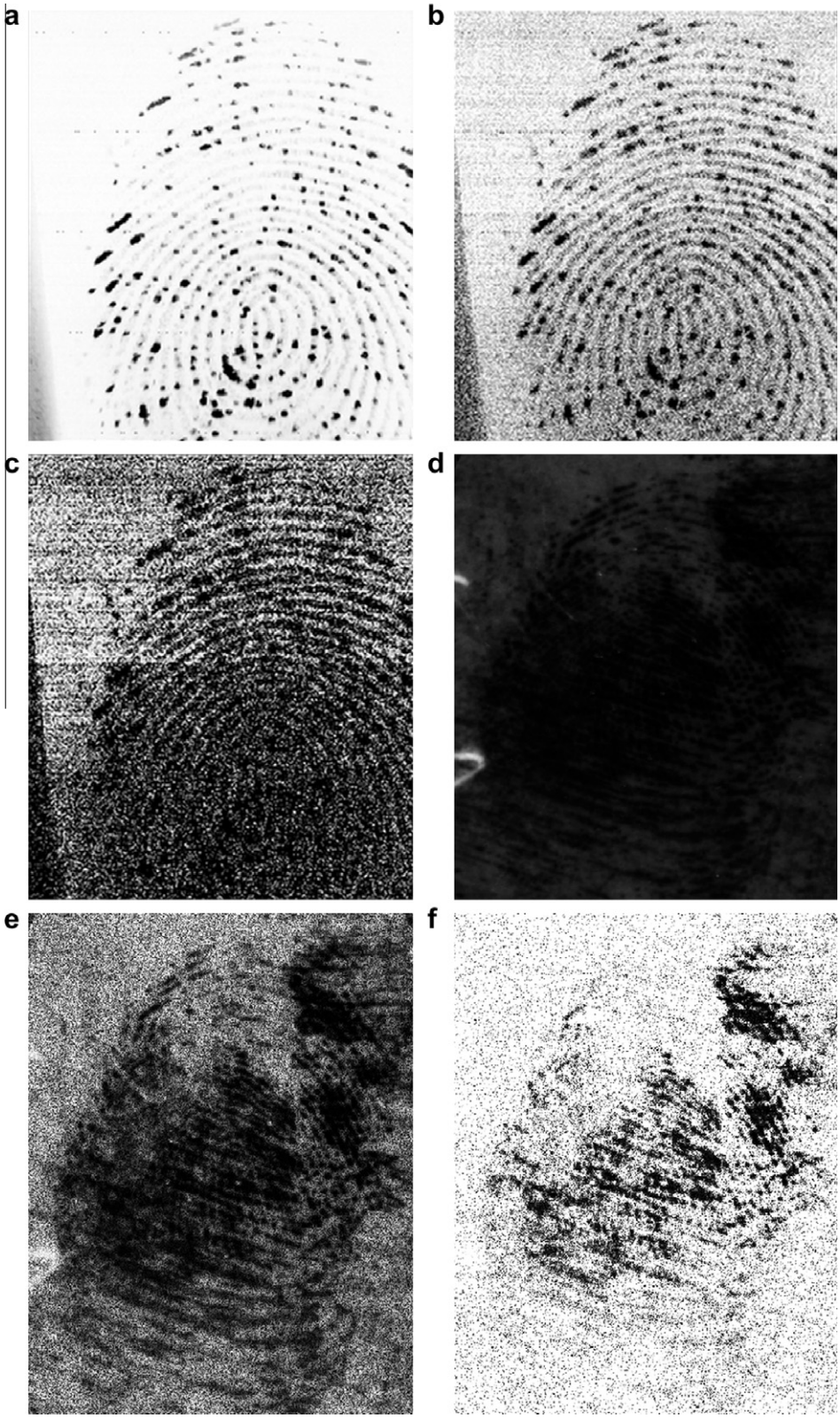

Fig. 1. Stochastic resonance for visual enhancement of a low-quality fingerprint image: (a) A dry fingerprint; (d) A latent fingerprint; (b), (e) SR enhanced images with a nonzero optimal noise to (a),(d); (c), (f) Degraded images by excessive noise of (a),(d).

noise is used to demonstrate usefulness of SR in fingerprint feature extraction. The feature extraction success rate demonstrates a resonance-like behavior as shown in Section 5. The success rate shows a peak corresponding to a nonzero optimal noise level.

4. Enhancing feature extraction with stochastic resonance

A feature extractor can be considered as a binary nonlinear system that determines whether a set of meaningful features can be

extracted from a faint image. The feature extraction process is defined in Eq. (1), where I indicates an input fingerprint image and f is an indicator function for the success in feature extraction. The indicator function returns 1 if feature extraction succeeds, i.e., the extracted features are good enough for reliable matching.

$$f(I) = \begin{cases} 1 & \text{Extraction Success} \\ 0 & \text{Extraction failure} \end{cases} \tag{1}$$

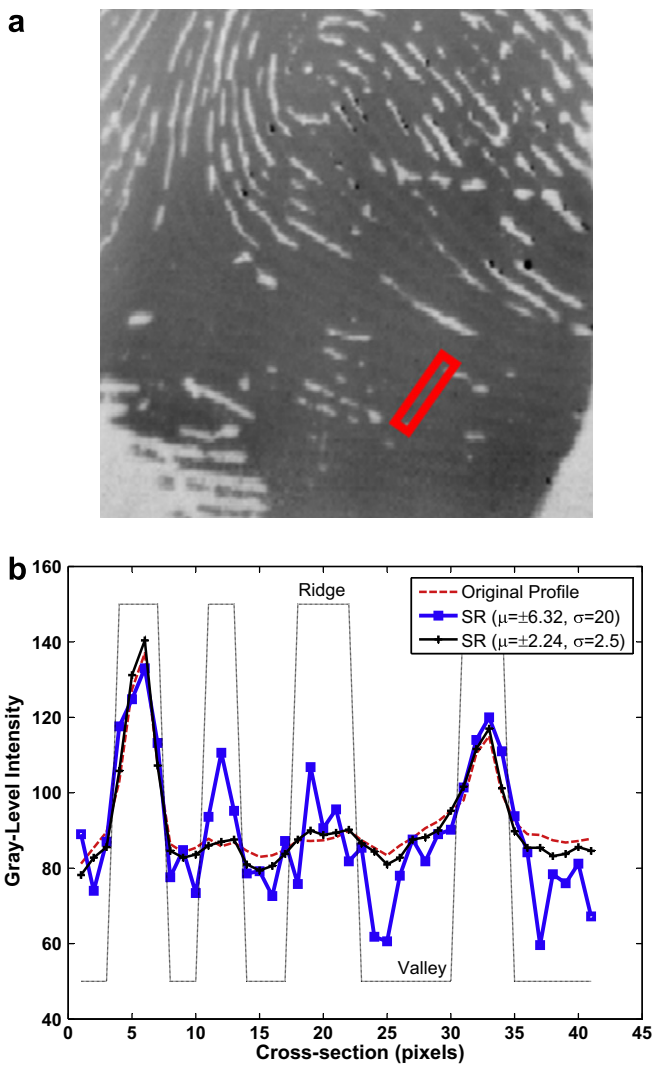

Fig. 2. Enhanced ridge and valley patterns with stochastic resonance: (a) A low-quality fingerprint image and the region of interest, (b) Brightness intensity profiles of a poor quality area with different amount of noise added.

An SR-enhanced image $I_e(x, y)$ is obtained from an input image $I(x, y)$ and an additive noise $w(x, y)$ with a Gaussian distribution $N(\mu, \sigma^2)$.

$$I_e(x, y) = I(x, y) + w(x, y) \tag{2}$$

In the SR enhancement process, the mean of the noise being added has different signs depending on the type of fingerprint component, ridge or valley. The NIST feature extractor (Watson et al., 2008) determines the direction of a ridge (and valley) pattern for local image blocks. A directional window, rotated according to the ridge orientation, finds the average intensity m_w of pixels in the window and the average intensity m_c of pixels in the center column of the window. If $m_c < m_w$, then the center pixel is considered in a dark region (the ridge in the fingerprints used in this paper) and the noise has a negative mean ($-\mu_0$). We consider the center pixel to be in a bright region (the valley) if $m_c \geqslant m_w$ and the mean is a positive value (μ_0).

$$\mu = \begin{cases} \mu_0 & \text{if } m_c \geq m_w \\ -\mu_0 & \text{if } m_c < m_w \end{cases} \tag{3}$$

Fig. 2 demonstrates that the noise used in the SR process improves the alternating intensity pattern of the ridge and valley in a low-quality fingerprint. The intensity profile of a small region (5×41 pixels), averaged over 5 pixel rows, shows enhanced contrast of the ridge and valley when SR was applied. Only two out of four ridges were visible in the original image due to the lack of intensity contrast. The SR enhancement improved the visual quality of all four ridge and valley patterns. The mean and standard deviation grow gradually as the noise level increases.

Fig. 3 shows a diagram of the SR-based fingerprint feature extraction enhancement. An optimal noise level can be estimated by an iterative method using stochastic gradient ascent (Mitaim and Kosko, 2004). An initial noise level is chosen arbitrarily. Each iteration, the noise level grows at a fixed increment until the feature extractor could find sufficient features. Fingerprint quality measures can be considered as an alternative way to determine an optimal noise level. We used the fingerprint image quality software from the NIST and Aware, Inc. to investigate the relationship between image quality and feature extractability. The 20 feature extraction failures received low scores in both quality checkers. However, the feature extractor could extract features from many other images of low-quality scores. Our SR enhancement takes the minimum noise level that enables feature extraction for computational efficiency. Feature extractors generate fingerprint features when the input image is of an acceptable quality. If no fingerprint template is generated until the noise parameter reaches a predefined limit, the fingerprint image is regarded as a failure in feature extraction.

For a given image database, the feature extraction success rate can be defined by the number of feature extraction success cases out of the number of whole images in the database. The feature

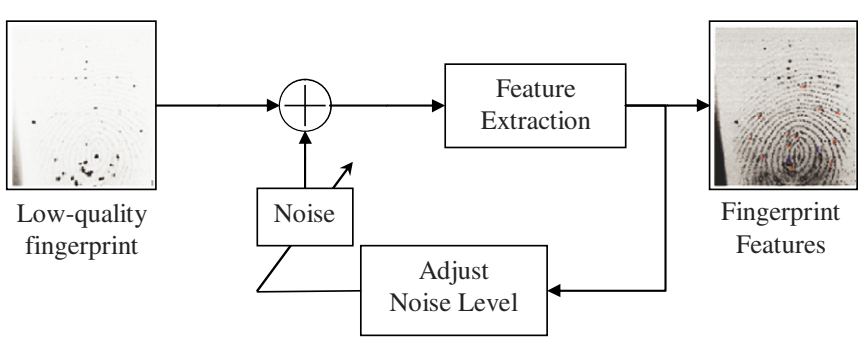

Fig. 3. Fingerprint feature extraction using stochastic resonance.

extraction success rate $R(\sigma)$ for the SR enhancement for a given standard deviation σ can be measured by

$$R(\sigma) = \frac{1}{K}\sum_{i=1}^{K} f(I_e^i(\sigma)) \tag{4}$$

where $I_e^i(\sigma)$ denotes ith SR-enhanced image generated with a given parameter σ and K denotes the number of trials to calculate an average success rate.

5. Experiment results

We carried out a matching test for the 800 fingerprint images in the FVC2004 DB2 database to compare the performance of SR enhancement in feature extraction and matching. This study also uses VeriFinger® version 5.0 from Neurotechnology, a fingerprint verification algorithm that supports FVC2004 database. The FVC2004 DB2 database was constructed using an optical fingerprint sensor (DigitalPersona U.are.U 4000). Among various databases for fingerprint verification competition (FVC), the FVC2004 database contains collected fingerprint images with different touch pressures, skin conditions (dry and wet fingerprints), and finger positions (Cappelli et al., 2006). This database is challenging for feature extraction and matching algorithms with wide variations in fingerprint sample quality. In particular, different touch pressures and skin humidity generate more low-quality fingerprint images than any other FVC databases. For 800 fingerprint images in the database, the feature extractor failed to extract meaningful features from 20 images, among which 11 low-quality images have weak or saturated ridge patterns due to skin conditions and the rest nine images contain damaged fingerprint patterns. Feature extraction from the damaged fingerprint is usually practically impossible or not meaningful for matching.

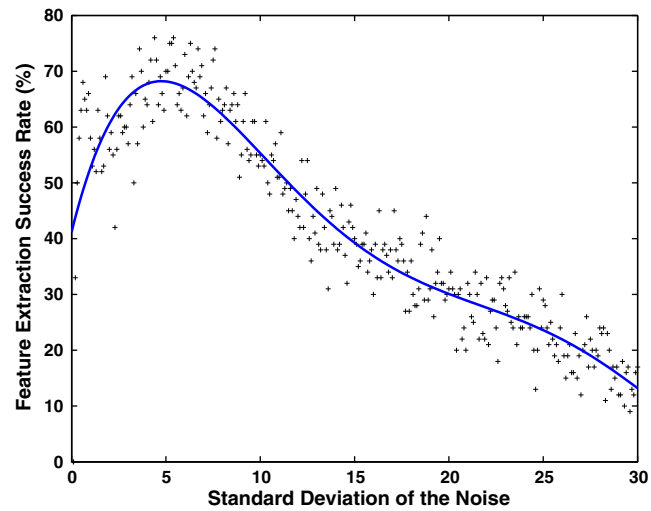

Fig. 5. Resonance in fingerprint feature extraction success rate with Gaussian noise.

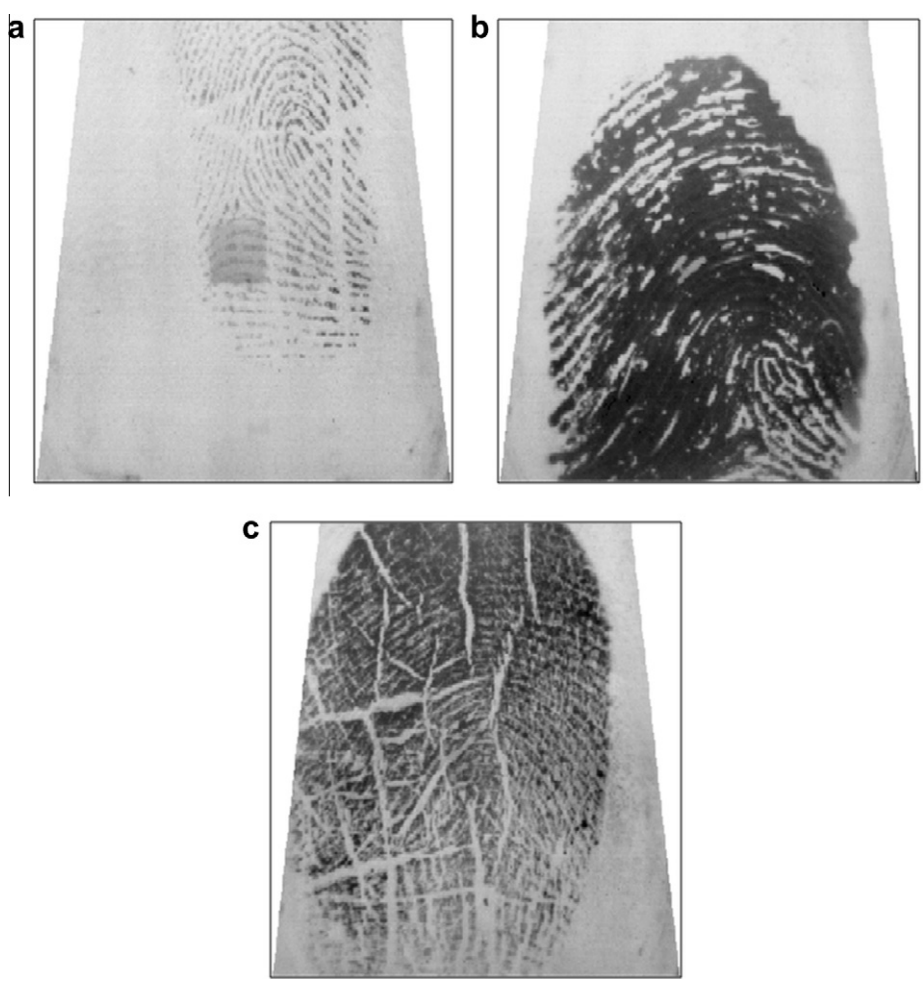

Fig. 4. Image samples of feature extraction failure: (a) Dry fingerprint, (b) Wet fingerprint, (c) Damaged fingerprint patterns.

Fig. 4 shows three examples of fingerprint images that are commonly found in feature extraction failure cases. Dry fingerprints tend to produce weak ridge patterns while wet fingerprints are responsible for saturated patterns. For a dry fingerprint image given in Fig. 4(a), feature extractors were unable to distinguish weak fingerprint patterns from the background since feature extractors do not accept residual patterns on the sensor surface. The image contrast of a wet fingerprint is generally lower than dry objects. Excessive moisture of wet fingers does not have sufficient ridge patterns for the sensors to produce fingerprint patterns of high contrast. Feature points from damaged fingerprint patterns are not generally acceptable since no meaningful matching results can be expected from minutiae based technologies.

In SR enhancement, Gaussian noise is added to 20 fingerprint images rejected in feature extraction. The standard deviation of Gaussian noise changes from 0 to 30.0 at a 0.1 increment step, and the feature extraction success rate is averaged over 100 trials ($K = 100$). Fig. 5 shows that the feature extraction success rate $R(\sigma)$ increases and reaches its maximum as the standard deviation of Gaussian noise grows. The feature extractor starts detecting the features from the standard deviation of $\sigma = 0.2$ and maximum success rate is achieved with $\sigma = 4.9$. Fig. 6 shows the minutiae points generated by the feature extractor with different amounts of noise. Before SR enhancement, the feature extractor could not detect meaningful minutiae points from the image. The feature extractor detects 22 fingerprint features with the noise of standard deviation $\sigma = 5.0$ as in Fig. 6(b). The number of minutiae points detected decreases to 10 with stronger noise with $\sigma = 17.9$.

Eleven images out of the 20 rejected are low-quality fingerprint images obtained from the fingers with reasonably good ridge patterns, but from poor sensing conditions. The remaining nine images came from damaged finger patterns, which are not generally acceptable in minutiae-based feature extraction regardless of the capturing quality. When feature extraction succeeds for each

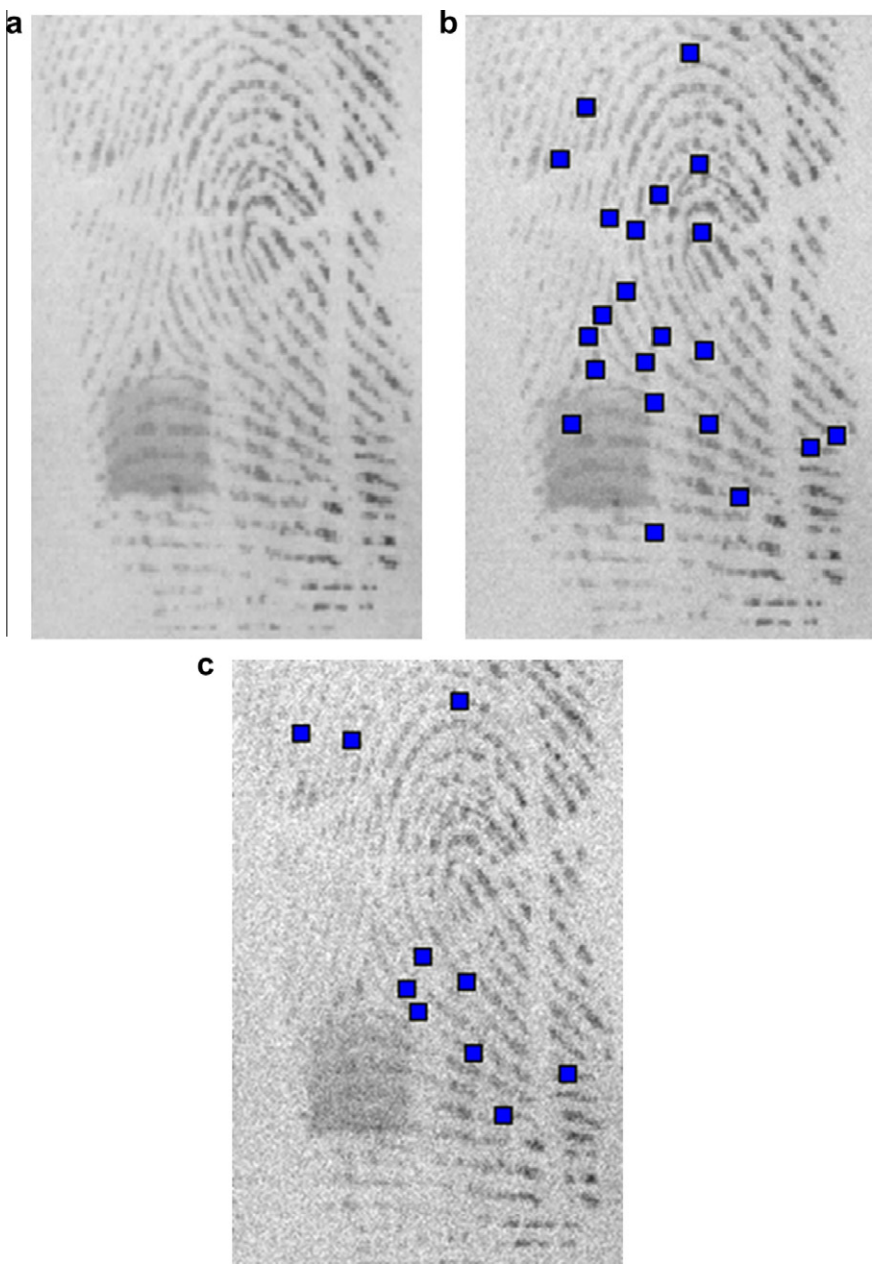

Fig. 6. Feature extraction results from different standard deviation of noise: (a) Original image, (b) SR enhancement with $\sigma = 5.0$, (c) SR enhancement with $\sigma = 17.9$.

Table 1
Feature extraction success rate and equal error rate for FVC 2004 DB2.

	No enhancement	Histogram equalization	SR enhancement
Feature extraction success rate	–	5/11	10/11
EER	6.55%	6.15%	5.03%

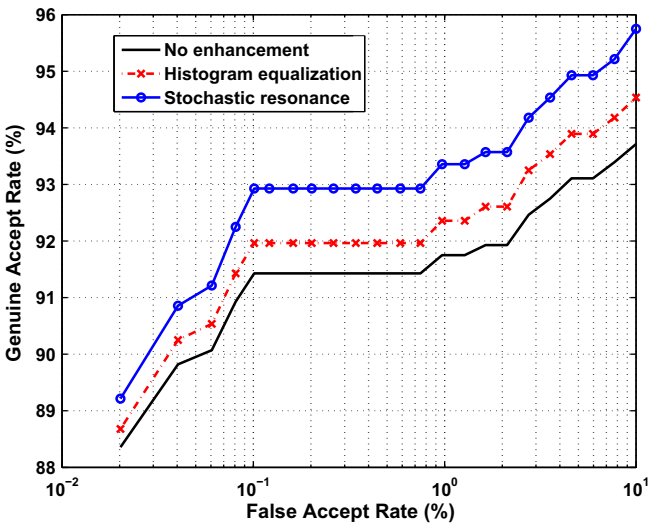

Fig. 7. Comparisons of ROC curves for feature extraction enhancement using the SR and histogram equalization.

of the eleven low-quality fingerprint images with a minimum amount of noise added, the resultant fingerprint template generated from the noisy image is used for matching. The average standard deviation of the noise to enable feature extraction from the rejected fingerprint images in the FVC DB2 database was approximately $\sigma = 7.3$, therefore 73 iterations were required to generate a fingerprint template. For comparison purposes, the SR enhancement and a conventional image enhancement technique with histogram equalization are applied to the same rejected images. Table 1 summarizes the effect of SR enhancement for feature extraction success rate and matching accuracies of low-quality images. The SR enhancement enables feature extraction of 10 images out of 11 low-quality images, while histogram equalization helps detect fingerprint features from only five images. The equal error rate (EER) of 6.55% for no enhancement is dropped to 6.15% after histogram equalization and 5.03% after SR image enhancement.

Matching accuracies of SR and histogram equalization as well as no enhancement are compared in the form of a receiver operating characteristic (ROC) curve in Fig. 7. These ROC curves reveal the matching accuracy improvement found from EER. SR enhancement produces better genuine acceptance rate than histogram equalization and no enhancement in the entire range of false acceptance rates.

6. Conclusions

This paper presents a stochastic resonance approach for enhancing feature extraction from low-quality fingerprint images. Fingerprint feature extraction is improved by adding Gaussian noise to the original low-quality fingerprint images that were rejected by feature extractors. With the FVC2004 DB2 database and the VeriFinger® fingerprint verification algorithm, eleven fingerprint images fail in feature extraction due to poor sensing conditions, i.e., dry or wet sample fingerprint images. Nine images are rejected by poor fingerprint patterns with severe wrinkles or cracks. The SR enhancement enables feature extraction of 10 images out of 11 low-quality fingerprint images. However, no feature extraction was possible from nine damaged fingerprint images. In terms of matching performances, the equal error rate is improved from 6.55% to 5.03%, and the ROC curve shows that genuine acceptance rates are improved for all false acceptance rates.

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