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Unsharp masking using quadratic filter for the enhancement of fingerprints in noisy background

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ABSTRACT

The paper summarizes the design and implementation of a quadratic edge detection filter based on Volterra series. The filter is employed in an unsharp masking scheme for enhancing fingerprints in a dark and noisy background. The proposed filter can account for much of the polynomial nonlinearities inherent in the input image and can replace the conventional edge detectors like Laplacian, LoG, etc. The application of the new filter is in forensic investigation where enhancement and identification of latent fingerprints are key issues. The enhancement of images by the proposed method is superior to that with unsharp masking scheme employing conventional filters in terms of the visual quality, the noise performance and the computational complexity, making it an ideal candidate for latent fingerprint enhancement.

1. Introduction

As crime rate increases steadily, fingerprint enhancement and consequent identification always remain key areas of research. Fingerprint is the impression left on a surface by the friction caused by the ridges on a finger or any part of hand and is a unique biometric identifier. The print is composed of dark ridges and light valleys [1,2]. Identification of fingerprints [3–5] is a key process in access control and in forensic sciences. In the former case, the fingerprints are less noisy and do not require much preprocessing. But the prints taken from crime scenes are blurred and noisy and so require enhancement of ridges to ease identification. The ridges in fingerprints carry significant amount of biometric information and they can be enhanced by improving the edge features of the image. Edges in images are formed by discontinuities in spatial, geometrical or photometric properties of objects [6]. Although edges are formed by high frequency components, simple high pass filtering does not suffice in detecting and improving edges as it blurs the image. Segmentation of images is done based on texture [7–9] and mathematical morphology [10,11]. Generally, edges are detected by the computation of the derivative of the image. This computation is very noise sensitive as noise appears as false edges in an image. So the chief performance criterion of an edge detector becomes the invulnerability to noise. The gradient based edge detectors [6,12] in the linear domain are

1. Laplace filter
2. Sobel filter
3. Laplacian of Gaussian (LoG)
4. Canny filter

Although Sobel filter has the advantage in speed, it suffers from lack of edge resolution. The Laplace filter and Canny filter have reasonably good edge resolution but are highly susceptible to noise. LoG filter had good resolution of edges as well as moderate noise invulnerability. But even the LoG does not suffice to enhance edges in images mixed with noise. Under such conditions, polynomial filters [13] perform better in detecting edges with high enough resolution. Images are formed by nonlinear processes and human vision is inherently nonlinear. So employing polynomial methods for image processing and analysis become a natural alternative. Much of the nonlinearities can be modeled by the quadratic term alone and hence the efforts in the design and implementation of quadratic filters. The present work proposes a quadratic filter based on Volterra series for enhancing noisy fingerprints. Although the idea of modeling nonlinearities by power series was proposed a century back by Vito Volterra, the practical applications were hampered by the large computational complexity. Recently, with increase in computational resources,

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interest is renewed in developing Volterra systems for signal and image processing with consequent enhancement of features that is otherwise not achievable with linear filters.

2. Literature survey

Fingerprint preprocessing falls into two categories, the spatial domain filtering techniques and the transform domain techniques, the latter type being more popular. The second category mostly uses Gabor filters [14,15] for fingerprint classification and enhancement. Directional Fourier filtering has been proposed [16] for automatic fingerprint identification system. In the spatial filtering domain, directional median filter [17] is used for fingerprint enhancement. Use of quadratic filters based on Volterra series, which current work is relied on, for fingerprint preprocessing has not been reported.

The theory of Volterra functionals was developed by Vito Volterra to model nonlinear systems as parallel combinations of linear and polynomial systems of increasing order, in the year 1887. Weiner applied Volterra series to Brownian motion [18] to develop analytic functionals. The work in polynomial systems was relegated for a long time because of the lack of resources to handle the increased computational complexity. Towards the end of 1980s work in implementation of polynomial systems was revived with the help of increased computational resources. Inherent nonlinearities in images can be modeled with polynomial systems and many classes of quadratic filters were developed for edge preserving noise smoothing, edge extraction, image interpolation, etc. Quadratic filter was employed for edge detection [19] and processing document images. A similar strategy has been used in this work to enhance noisy ridges.

3. Discrete Volterra series

Although the theory of linear systems is very advanced and useful, most of the real life and practical systems are nonlinear. Mild polynomial nonlinearities can be modeled by Volterra power series. An Nth order Volterra filter [20,21] with input vector $x[n]$ and output vector $y[n]$ is realized by

$$y[n] = h_0 + \sum_{r=1}^{\infty}\sum_{n_1=1}^{N}\sum_{n_2=1}^{N}\cdots\sum_{n_r=1}^{N} h_r[n_1, n_2, \ldots, n_r].\; x[n-n_1]x[n-n_2]\cdots x[n-n_r] \tag{1}$$

h_0 is the output offset when no input is present and r indicates the order of nonlinearity. The impulse response term $h_r[n_1, n_2, \ldots, n_r]$ is the rth order Volterra kernel, identification of which is one of the key issues in polynomial signal processing. The condition $r=1$ results in an LTI system and h_1 defaults to the impulse response. A quadratic filter results when $r=2$, which can cover much of the nonlinearity. One key advantage in using Eq. (1) is that the quadratic filter can be added in parallel with the linear filter. Although higher order terms can be added similarly, computational complexity becomes formidable. For a quadratic system,

$$y[n] = h_0 + \sum_{n_1=1}^{N} h_1[n_1]x[n-n_1] + \sum_{n_1=1}^{N}\sum_{n_2=1}^{N} h_2[n_1, n_2]x[n-n_1]x[n-n_2] \tag{2}$$

or equivalently by the matrix equation:

$$Y[n] = h_0 + X^T[n]H_1 + X^T[n]H_2X[n] \tag{3}$$

where

$$X[n] = [x(n)\;\; x(n-1)\;\; \cdots\;\; x(n-N+1)]^T \tag{4}$$

$$H_1 = [h_1(0)\;\; h1(1)\;\; \cdots\;\; h_1(N-1)]^T \tag{5}$$

and

$$H_2 = \begin{bmatrix} h_2(0,0) & h_2(0,1) & \cdots & h_2(0,N-1) \\ h_2(1,0) & h_2(1,1) & \cdots & h_2(1,N-1) \\ h_2(2,0) & h_2(2,1) & \cdots & h_2(2,N-1) \\ \vdots & \vdots & \ddots & \vdots \\ h_2(N-1,0) & h_2(N-1,1) & \cdots & h_2(N-1,N-1) \end{bmatrix} \tag{6}$$

3.1. 2-D quadratic filter

The two dimensional quadratic filter is governed by the equation

$$y[n_1, n_2] = \sum_{m_{11}=0}^{N_1-1}\sum_{m_{12}=0}^{N_2-1}\sum_{m_{21}=0}^{N_1-1}\sum_{m_{22}=0}^{N_2-1} h_1[m_{11}, m_{12}, m_{21}, m_{22}] \times x[n_1-m_{11}, n_2-m_{12}]x[n_1-m_{21}, n_2-m_{22}] \tag{7}$$

Eq. (7) can be represented in the matrix form as

$$y[n_1, n_2] = \mathbf{X}^T[n_1, n_2]\mathbf{H}_2\mathbf{X}[n_1, n_2] \tag{8}$$

The quadratic kernel $\mathbf{H}_2$ has $N_1N_2 \times N_1N_2$ elements and each element consists of N_2^2 sub-matrices $\mathbf{H}(i,j)$ with $N_1 \times N_2$ elements given as

$$\mathbf{H}_2 = \begin{bmatrix} \mathbf{H}(0,0) & \mathbf{H}(0,1) & \cdots & \mathbf{H}(0,N_2-1) \\ \mathbf{H}(1,0) & \mathbf{H}(1,1) & \cdots & \mathbf{H}(1,N_2-1) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{H}(N_2-1,0) & \mathbf{H}(N_2-1,1) & \cdots & \mathbf{H}(N_2-1,N_2-1) \end{bmatrix} \tag{9}$$

where each sub-matrix $\mathbf{H}(i,j)$ is given by

$$\mathbf{H}(i,j) = \begin{bmatrix} h(0,i,0,j) & \cdots & h(0,i,N_1-1,j) \\ h(1,i,0,j) & \cdots & h(1,i,N_1-1,j) \\ \vdots & \vdots & \vdots \\ h(N_1-1,i,0,j) & \cdots & h(N_1-1,i,N_1-1,j) \end{bmatrix} \tag{10}$$

The principal issues in Volterra systems are the identification of the kernel H_2 [22–24] and its computationally efficient implementation. Unlike in linear filtering, there are no general design methods for finding H_2. Design of two dimensional kernels for specific applications can be done using methods like optimization, bi-impulse response method [25], etc. The current work uses optimization of mean square error using Powell method. The second step is in realizing the kernel with minimum computational complexity [26,27]. Eq. (8) can be viewed as a filtering operation on the Kronecker product of $\mathbf{X}[n_1, n_2]$ with itself by the filter kernel H_2. A feasible implementation can be done with appropriate decomposition of H_2 like LU or SVD decomposition.

4. Methodology

Enhancement of noisy fingerprints is made possible with unsharp masking scheme in which a scaled version of the edges separated from the fingerprints is added with the noisy prints. The scheme as given in Section 5 is proposed for enhancing fingerprint in noisy background. It relies on a quadratic edge detection filter. The flow of work is as depicted in Fig. 1. The first phase of work is in designing the edge detection kernel H_2. The design is based on the minimization of mean square error between a synthetic true edge and its noisy version. The second phase is the computationally efficient implementation of H_2 based on singular value decomposition. These phases are discussed in Section 6. In the last phase, testing of the filter is done with standard images corrupted by impulsive and Gaussian noise of different noise

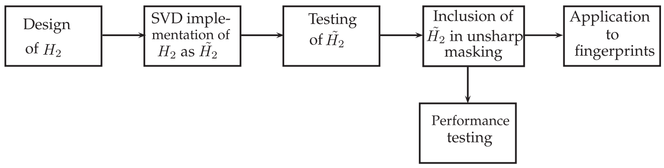

Fig. 1. Flow of work.

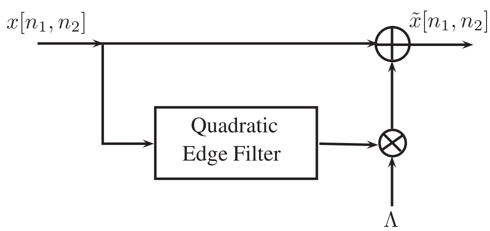

Fig. 2. Unsharp masking with quadratic filter.

variances and the model is validated in terms of edge preservation in the presence of noise. The unsharp masking scheme based on quadratic filter is applied on noisy fingerprints and the performance is compared with schemes employing Gabor, Laplace, Sobel, Canny and LoG filters in terms of the average signal to noise ratio, peak signal to noise ratio and the visibility of ridges. The experiments are detailed in Section 7. The results of various experiments are detailed in Section 8.

5. Unsharp masking with quadratic filter

Unsharp masking is a contrast enhancement scheme [13] in which a high pass filtered and scaled version of an image is added with itself. The high pass filter enhances the edges and the addition of edges improves the overall contrast of the image. The chief difficulty with this scheme is that the edge detection high pass filters commonly employed are very sensitive to noise as noise appears as false edges. It is observed that quadratic edge detectors are very noise immune and have better edge detection characteristics than Laplacian and LoG filters. The unsharp masking scheme with quadratic edge detection filter is shown in Fig. 2. The edges in the input image $x[n_1, n_2]$ are separated by the quadratic filter. They are then scaled by a factor Λ and are added with the input image to yield the enhanced version $\tilde{x}[n_1, n_2]$. The scale factor Λ is chosen in such a way that there is improvement in $\tilde{x}[n_1, n_2]$ in respect of visual quality as well as in performance criteria like SNR, PSNR, etc.

6. Design of quadratic edge detector

It is proposed that a quadratic filter can enhance the edges better than Laplacian or LoG filter. The principal issue in employing a quadratic filter is the identification of its kernel H_2. Powell optimization [28] is used for obtaining H_2 as this algorithm has a fast rate of convergence. A synthetic edge with compressed gray scale values added with noise denoted as $x[n_1, n_2]$ of 9×9 dimension is simulated. A desired sharp synthetic edge $y_d[n_1, n_2]$ of identical dimension is also simulated. Assume that the output of the quadratic filter is $y[n_1, n_2] = \mathbf{X}^T[n_1, n_2]\mathbf{H}_2\mathbf{X}[n_1, n_2]$. Let the mean square error between $y_d[n_1, n_2]$ and $y[n_1, n_2]$ be ξ.

$$\xi = E[|y_d[n_1, n_2] - \mathbf{X}^T[n_1, n_2]\mathbf{H}_2\mathbf{X}[n_1, n_2]|^2] \tag{11}$$

ξ is minimized to yield an optimum H_2. H_2 is plotted as in Fig. 3. The kernel H_2 is not completely isotropic. It becomes zero at the co-ordinates $(i, N-i)$ for $1 \le i \le N-1$, creating a wedge like minimum

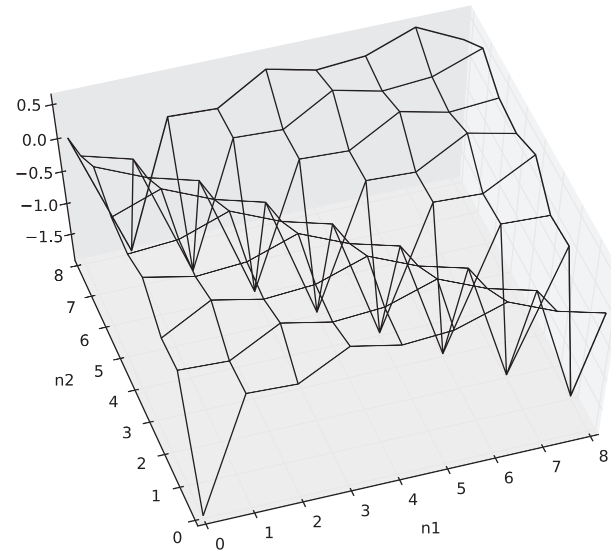

Fig. 3. Surface plot of the quadratic kernel.

Table 1
Structural similarity index of images on unsharp masking using various edge detection filters for identical noise variances.

Filter	Mean SSIM (impulsive)	Mean SSIM (Gaussian)
Quadratic	0.9824	0.9854
LoG	0.9821	0.9695
Canny	0.6660	0.8660
Gabor	0.5968	0.7509
Laplacian	0.0018	0.0012

parallel to the main diagonal. There are local minima parallel to this. The H_2 surface has high pass filter characteristics, making it suitable for edge detection. Once H_2 is computed, it is required to implement it as a computationally simple structure. The direct implementation as in Eq. (8) results in large computational complexity. Instead, SVD decomposition [29] is performed on H_2 to yield an approximation $\tilde{H}_2$ as

$$\tilde{H}_2 = \sum_{i=1}^{\rho} \lambda_i S_i S_i^T \tag{12}$$

where λ_i are the singular values with $\lambda_i > \lambda_j$ for $i < j$ and each S_i is a 9×1 eigen vector. The singular values and singular vectors of H_2 are tabulated in Table 2. The value of ρ is selected in such a manner that the Frobenius norm $\|H_2 - \tilde{H}_2\|$ is minimum. Each S_i can be resized as a 3×3 FIR image filter that is equivalent to $H(i,j)$ in Eq. (9). The outputs of FIR filters are squared and a weighted sum with λ_i values yields the filter output. The structure of the filter is as in Fig. 4.

7. Design of experiment

The filter kernel $\tilde{H}_2$ designed in the last section is simulated in Python with the help of scipy and pylab modules. In the first phase, $\tilde{H}_2$ is tested for visual performance and quantitative parameters with the help of known image edges that are corrupted by impulsive and Gaussian noise of known variances. The filter is then included in the unsharp masking scheme and fingerprints are filtered. Two sets of fingerprints are used in the experiment. The first set came from a fingerprint reader of 356×328 resolution and are not noisy. Hundred volunteers

Table 2
Table of singular values and singular vectors of H_2.

λ_i	S_1	S_2	S_3	S_4
3.2783	−0.3333	−0.3333	−0.3333	−0.3333
2.9284	−0.0570	0.4337	−0.3768	−0.0570
2.9284	0.4680	−0.1846	−0.2833	0.4680
2.8494	−0.0388	0.2723	0.4559	0.4262
2.8494	−0.4698	−0.3848	−0.1199	0.2013
2.8467	0.09977	−0.2513	0.3726	−0.4489
2.8467	−0.4607	0.3988	−0.2888	0.1440
2.7422	0.4690	0.0344	−0.4570	−0.1931
2.7422	−0.0478	−0.4702	−0.1155	0.4300
S_5	S_6	S_7	S_8	S_9
−0.3333	−0.3333	−0.3333	−0.3333	−0.3333
0.4337	−0.3768	−0.0570	0.4337	−0.3768
−0.1846	−0.2833	0.4680	−0.1846	−0.2833
0.1971	−0.1243	−0.3875	−0.4694	−0.3317
0.4282	0.4547	0.2685	−0.0434	−0.3350
0.4711	−0.4364	0.3491	−0.2197	0.0638
0.0182	−0.1783	0.3168	−0.4171	0.4671
0.3900	0.3286	−0.2759	−0.4244	0.1285
0.2649	−0.3381	−0.38225	0.2053	0.4536

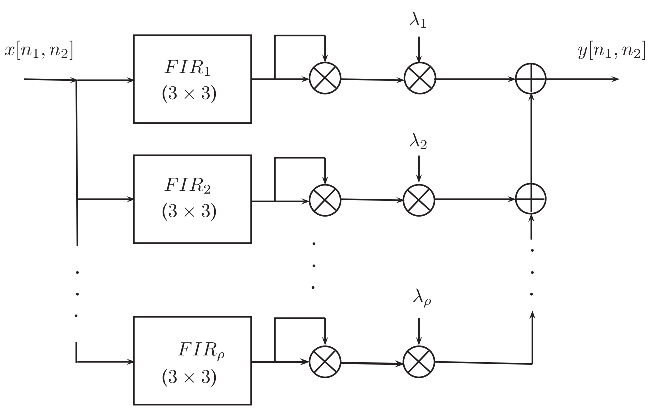

Fig. 4. Realization of H_2 by singular value decomposition.

contributed their fingerprints, testing of which is done to establish the statistical soundness of the values of performance parameters. The second set of fingerprints are taken by a 12 mega-pixel Sony cybershot digital camera. This set is of latent prints and are naturally noisy. Both sets are imported into Python using the image processing module and are subjected to unsharp masking to yield enhanced ridges. The filtered images are compared with those processed by unsharp masking based on edge detectors like Laplacian, Laplacian of Gaussian (LoG), Canny, Gabor and Sobel filters in terms of visual quality.

In the second phase of experiment, the performance of the unsharp masking scheme with quadratic filter is determined as in Fig. 5. Hundred fingerprints, each with dimension 356×328 pixels, corrupted by impulsive/Gaussian noise of known variance are applied to Sobel, LoG, Canny and quadratic filters and the outputs are compared. The improvement in signal to noise ratio is computed. The structural similarity index (SSIM) and sharpness of ridges are computed for all the 100 images for different additive noise variances and the average values of the parameters are computed. This is done to ensure the statistical soundness of the values of performance parameters.

In the final phase of experiment, the time of computation for various filters for input images of different dimensions is ascertained and compared. The results of the experiments are in Section 8.

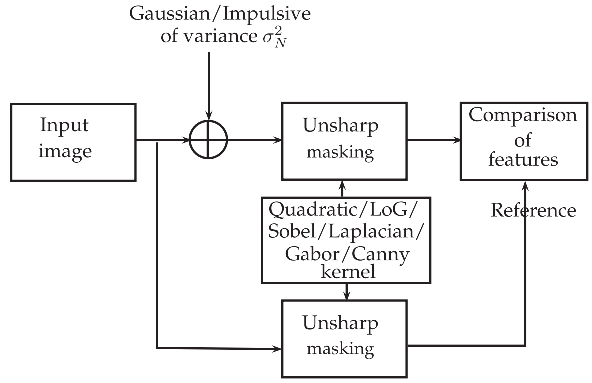

Fig. 5. Testing of unsharp masking.

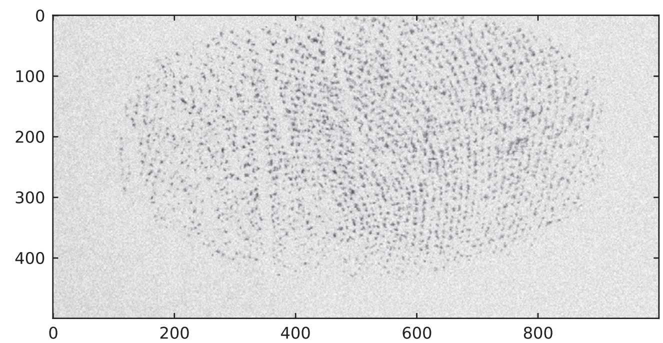

Fig. 6. Fingerprint corrupted by impulsive noise variance 50.

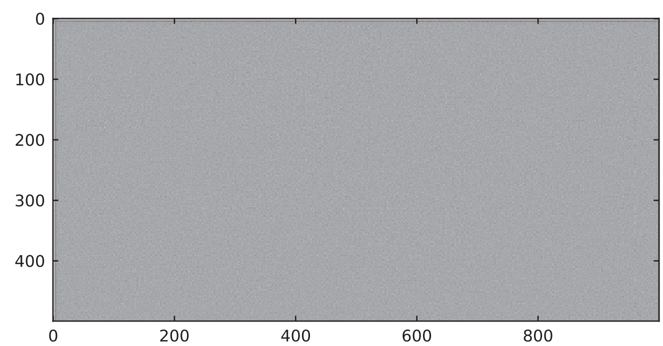

Fig. 7. Output with Gabor filter for impulsive noise variance 50.

8. Results and analysis

The filtering experiments conducted on noisy fingerprints with the quadratic filter yielded enhanced outputs that are visually better than the ones yielded by unsharp masking with Laplacian, Sobel, Canny or LoG filters. Testing with impulsive noise gave rise to the results in Figs. 6–11. The input fingerprint corrupted by impulsive noise of variance 50 is shown in Fig. 6. Fig. 7 shows the result of unsharp masking based on Gabor filter. Although Gabor filter performs well in noiseless cases, it does not enhance noisy ridges. The reviewer pointed out the need for comparison with Canny edge detector based unsharp masking. The scheme with Canny detector offered more enhancement in contrast but yielded broken ridges, especially in areas where the ridges are lost in noise as shown in Fig. 8. LoG filter yields continuous ridges but with limited enhancement as shown in Fig. 9. The gradient based Laplacian filter is very noise prone and the corresponding unsharp masking scheme yields no output as in Fig. 10. The output of unsharp masking using SVD based quadratic filter is as in Fig. 11. The fingerprint is enhanced with

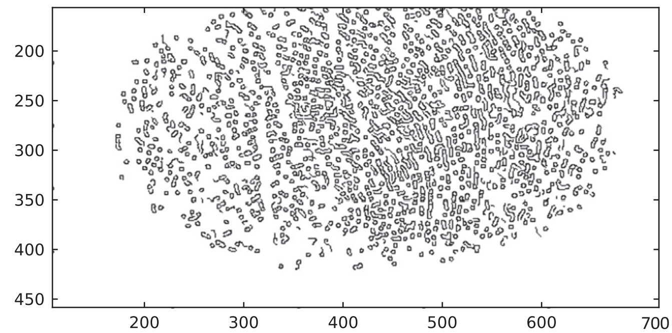

Fig. 8. Output with Canny filter for impulsive noise variance 50.

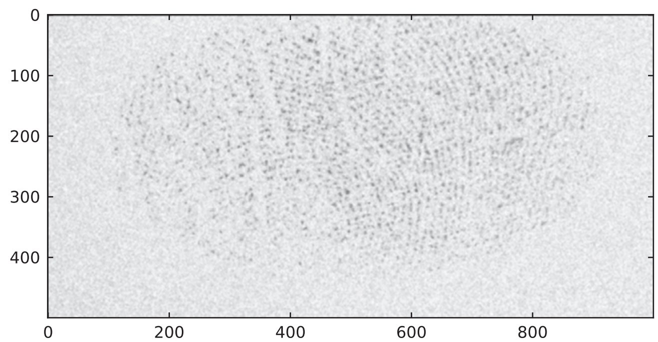

Fig. 9. Output with LoG filter for impulsive noise variance 50.

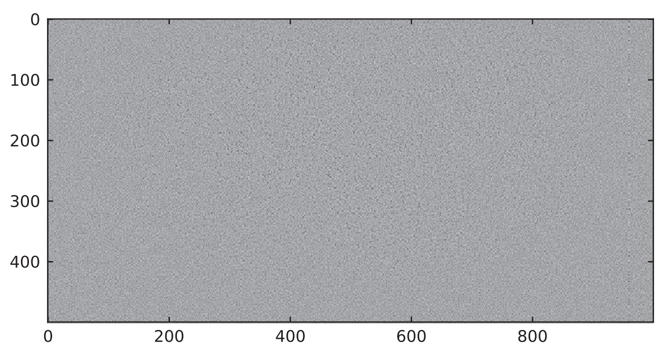

Fig. 10. Output with Laplacian filter for impulsive noise variance 50.

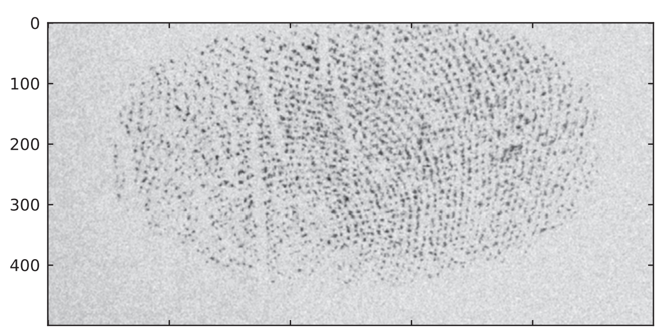

Fig. 11. Output with quadratic filter for impulsive noise variance 50.

visible ridges. Quadratic filter gives out enhanced ridges even at an impulsive noise variance of 200, a noise level at which other filters do not distinguish the ridges.

Fingerprint corrupted by Gaussian noise of variance 30 as in Fig. 14 is subjected to unsharp masking based on various filters. Unsharp masking using Gabor and Laplacian filters do not result in any enhancement as both the filters are susceptible to noise. LoG

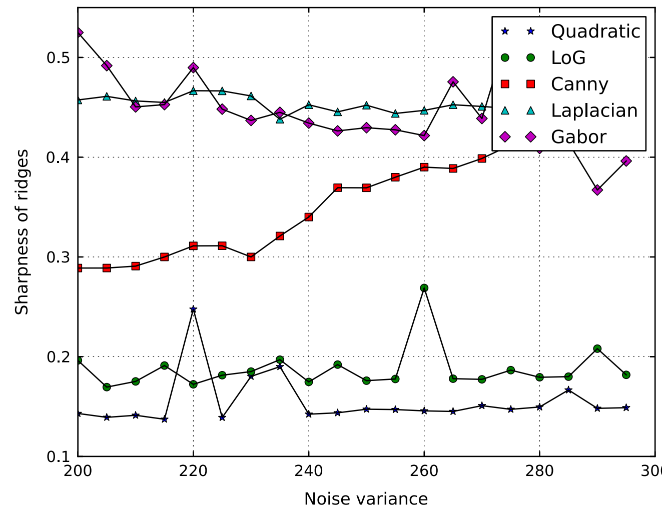

Fig. 12. Crispness of edges with impulsive noise.

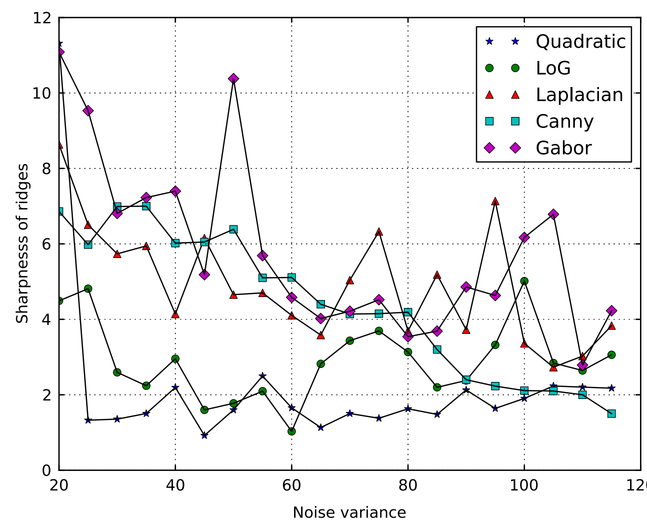

Fig. 13. Crispness of edges with Gaussian noise.

performs as shown in Fig. 15. Its ability to enhance ridges is decreased with Gaussian noise even at lower variance than impulsive noise. The result of scheme based on Canny edge detector is shown in Fig. 16. SVD based quadratic filter gives a visually enhanced output as in Fig. 17. It is imperative to quantify the visual quality of the outputs of unsharp masking based on various edge detection filters. The four parameters used for this purpose are

1. Signal to noise ratio.
2. Sharpness of ridges.
3. Structural similarity index [30].
4. Computational complexity.

8.1. Improvement in signal to noise ratio and peak signal to noise ratio

The improvement in signal to noise ratio and peak signal to noise ratio is computed as per the experimental setup in Fig. 5. The SNR is expressed as

$$\mathrm{SNR} = 10\log_{10}\left[\frac{\sum_{n_1}\sum_{n_2} r^2_{[n_1,n_2]}}{\sum_{n_1}\sum_{n_2}[r^2_{[n_1,n_2]} - t^2_{[n_1,n_2]}]}\right] \quad (13)$$

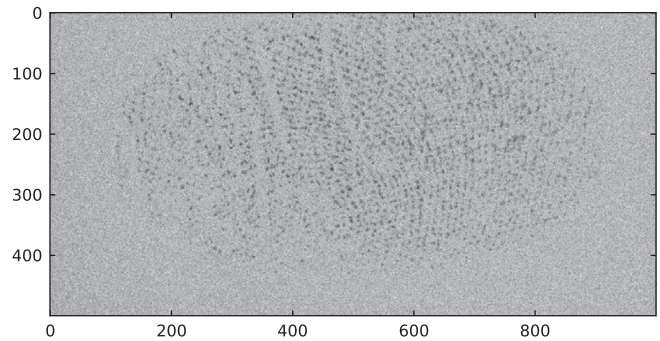

Fig. 14. Fingerprint corrupted by Gaussian noise variance 30.

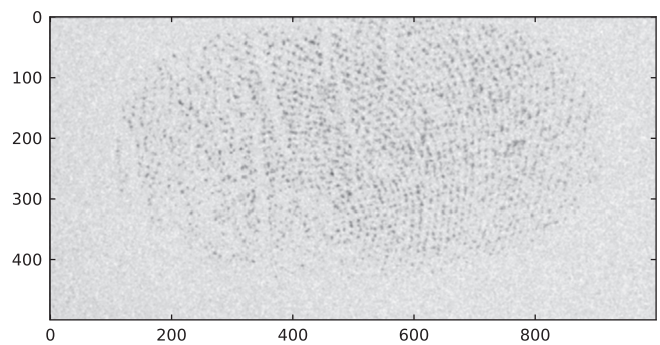

Fig. 15. Output with LoG filter for Gaussian noise variance 30.

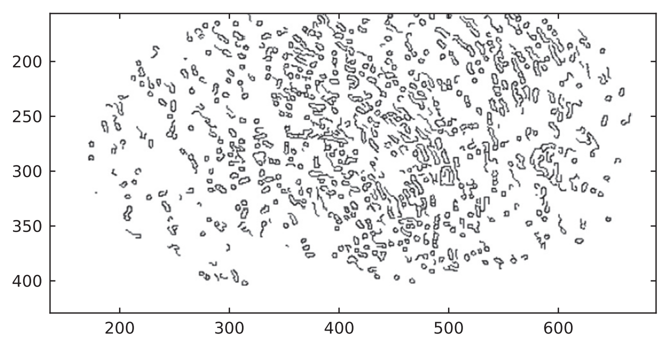

Fig. 16. Output with Canny filter for Gaussian noise variance 30.

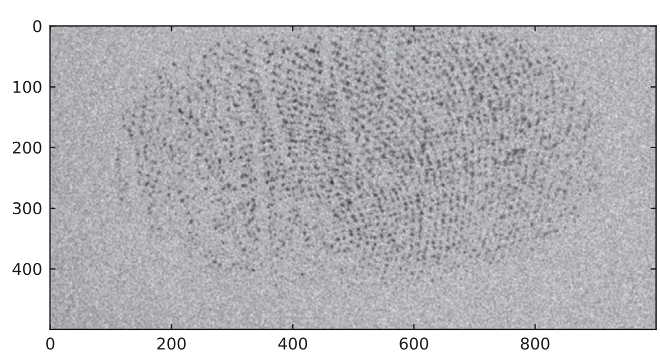

Fig. 17. Output with quadratic filter for Gaussian noise variance 30.

The peak value of the SNR is expressed as

$$\mathrm{PSNR} = 10\log_{10}\left[\frac{\max(r^2_{[n_1,n_2]})}{\frac{1}{N_1N_2}\sum_{n_1}\sum_{n_2}[r^2_{[n_1,n_2]} - t^2_{[n_1,n_2]}]}\right] \tag{14}$$

where r denotes the reference image and t denotes the test image. N_1N_2 is the size of the image. The improvement in signal to noise ratio and in PSNR is tabulated in Table 3. It is seen that unsharp masking with quadratic filter performs best with impulsive noise. It has a ≈4 dB advantage in signal to noise ratio compared to LoG filter. With Gaussian noise, the performance degrades for smaller noise variances but quadratic filter offers ≈2 dB improvement in SNR compared with LoG filter.

8.2. Sharpness of ridges

The sharpness of ridges in the enhanced fingerprint is decided by the noise invulnerability of the edge detection filter. A numerical figure of merit of the edge detection filter [31] is given as

$$\kappa = \frac{1}{N_1N_2}\sum_{n_1}\sum_{n_2}\frac{|\sigma^2_{I[n_1,n_2]_{test}} - \sigma^2_{I[n_1,n_2]_{ref}}|}{\sigma^2_{I[n_1,n_2]_{ref}}\mu_{I[n_1,n_2]_{ref}}} \tag{15}$$

$\sigma^2_{I[n_1,n_2]_{test}}$ is the localized variance (here a 3×3 pixel window is used to match the size of the filter mask) of the test image and $\sigma^2_{I[n_1,n_2]_{ref}}$ is that of the reference image. The localized mean of the reference image is $\mu_{I[n_1,n_2]_{ref}}$. For estimating the sharpness of ridges, 100 test images are formed by adding impulsive noise of variance ranging from 200 to 300 in steps of 5 to the outputs of the fingerprint reader. These input images are then normalized and applied to unsharp masking based on Laplacian, LoG, Sobel, Canny and quadratic filters. The normalized, noisy input image is taken as the reference image and the normalized outputs of various filters are taken as test images. The variances and mean values are computed over a 3×3 pixel mask and summation is done all over the area of image. The 100 values, each computed for 20 noise variance values, are averaged and plotted as in Fig. 12. It is seen that the parameter is the lowest for quadratic filter and it remains fairly constant as noise variance increases. This is indicative of the noise invulnerability and preservation of ridges of quadratic filter. LoG filter has a higher value and shows fluctuations as noise variance increases. Canny filter has a poorer value for κ. Laplacian and Gabor perform worse than Canny. The plots in Fig. 12 are consistent with the claim on visual quality based on Fig. 11. The entire procedure is repeated for Gaussian noise of variance ranging from 20 to 120 in steps of 5. The average sharpness of ridges for 100 fingerprints is plotted as in Fig. 13. The mean value of κ is higher than that with impulsive noise, indicating the degradation of performance in the presence of Gaussian noise. Here also, the parameter is the smallest for quadratic filters. LoG filter performs better than Laplacian, Canny and Gabor filters.

The parameter κ should be zero when no noise is present and it increases monotonically as degradation of edges by noise increases. Table 4 summarizes the values of κ for impulsive and Gaussian noise. The performance parameter is the lowest for unsharp masking with quadratic filter, indicating its noise invulnerability and the visibility of ridges.

Table 3
Signal to noise ratio improvement for various filters.

Noise	Filter	SNR (dB)	PSNR (dB)
Impulsive	Quadratic	20.13	21.89
	LoG	16.16	18.59
	Canny	13.45	15.36
	Laplacian	10.77	11.20
	Sobel	7.79	10.22
Gaussian	Quadratic	21.1	22.04
	LoG	18.92	19.86
	Laplacian	11.63	12.58
	Sobel	10.56	13.50
	Canny	9.33	12.10

Table 4
Sharpness of ridges for various filters.

Filter	Impulsive	Gaussian
	κ	κ
Quadratic	0.1432	1.3547
LoG	0.1962	2.5951
Sobel	0.2990	3.1510
Canny	0.2908	6.9900
Laplacian	0.4574	5.7358

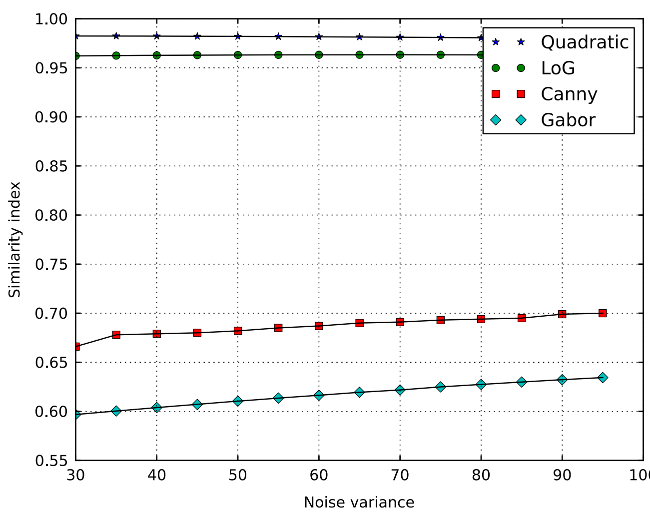

Fig. 18. SSIM for impulsive noise.

8.3. Structural similarity index (SSIM)

A common measure that is used to quantify the quality of an image is the mean square error [32–35] which has many demerits. To overcome these demerits, Wang et al. [30,36] proposed the structural similarity index (SSIM) to quantify the "visual quality" of the image. The similarity index between the images $\mathbf{x}$ and $\mathbf{y}$ is given as

$$\mathrm{SSIM}(\mathbf{x},\mathbf{y}) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(2\mu_x^2 + 2\mu_y^2 + C_1)(2\sigma_x^2 + 2\sigma_y^2 + C_2)} \tag{16}$$

The parameters μ_x and μ_y are the means and σ_x^2 and σ_y^2 are the variances of $\mathbf{x}$ and $\mathbf{y}$ respectively. σ_{xy}^2 is the covariance between $\mathbf{x}$ and $\mathbf{y}$. C_1 and C_2 are non-zero constants included to avoid unstable results when $\sigma_x^2 + \sigma_y^2$ or $\mu_x^2 + \mu_y^2$ is very close to zero. When $\mathbf{x}$ and $\mathbf{y}$ are identical, SSIM is unity and degrades when the structural differences between $\mathbf{x}$ and $\mathbf{y}$ increases.

In the current experiment, SSIM is used to ascertain the improvement in the quality of fingerprints on unsharp masking using various edge detection filters. As shown in the experimental set up in Fig. 5, impulsive noise of variance ranging from 30 to 100 is added with 100 test fingerprints ($\mathbf{x}$) and the unsharp masked outputs ($\mathbf{y}$) using various edge detection filters are obtained. The values of SSIM between $\mathbf{x}$ and $\mathbf{y}$ are computed with $C_1 = C_2$ and plotted for different noise levels. The plot is as shown in Fig. 18. The expected values of SSIM are given in Table 1. It is seen that SSIM, which is indicative of the ability to enhance the fingerprints and the invulnerability to noise, is the largest for unsharp masking using quadratic filter with the numerical value approximately at 0.98. LoG filter has the next best value of SSIM with the numerical value approximately at 0.96. Also, SSIM for both quadratic and LoG remain constant as noise variance increases. Canny filter has an index approximately 0.3 below LoG and it increases as noise variance increases. SSIM for Gabor filter is still below that of Canny. The SSIM for Laplacian is far smaller and is not shown on the graph.

The computation of SSIM is repeated for 100 fingerprints corrupted by Gaussian noise of variance ranging from 30 to 100 using various filters and plotted as in Fig. 19. The graph shows a clear advantage in using quadratic filter. The SSIM ranges from 0.99 to 0.98 as Gaussian noise power varies from 30 to 100. Its mean SSIM is ≈0.16 above that of LoG and it falls as the noise power increases. The SSIM for Canny filter is approximately 0.85 and is consistently above Laplacian and Gabor but below quadratic and LoG filters. Laplacian and Gabor filters perform equally bad in maintaining the structure of the image corrupted by Gaussian noise. The relatively high structural similarity index arising from

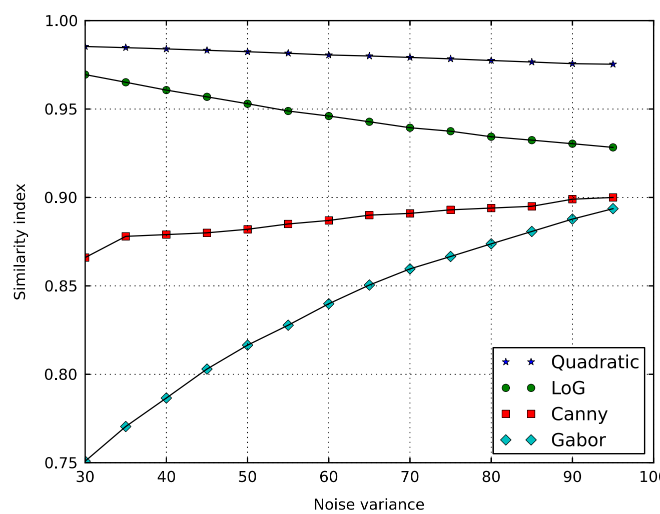

Fig. 19. SSIM for Gaussian noise.

Table 5
Time of computation in seconds for various image filters.

Image size (pixels)	Laplacian	LoG	Sobel	Canny	Gabor	Quadratic (SVD)
356 × 328	0.5615	0.70	0.0567	289	0.2753	0.2555
512 × 512	1.368	1.688	0.135	351	0.6369	0.5932

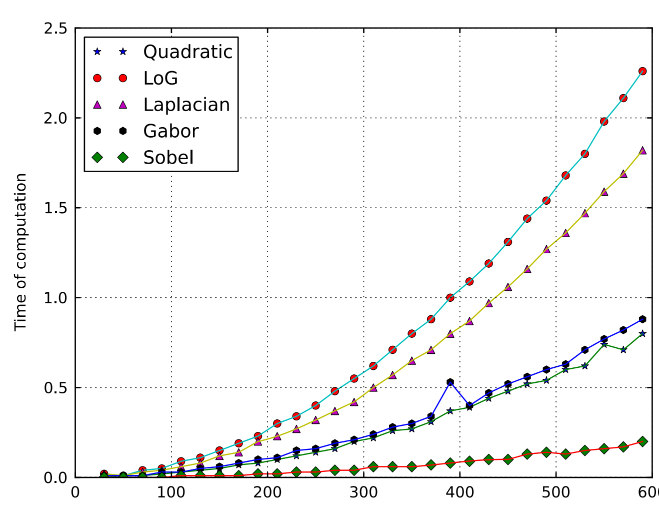

Fig. 20. Computational complexity for various filters.

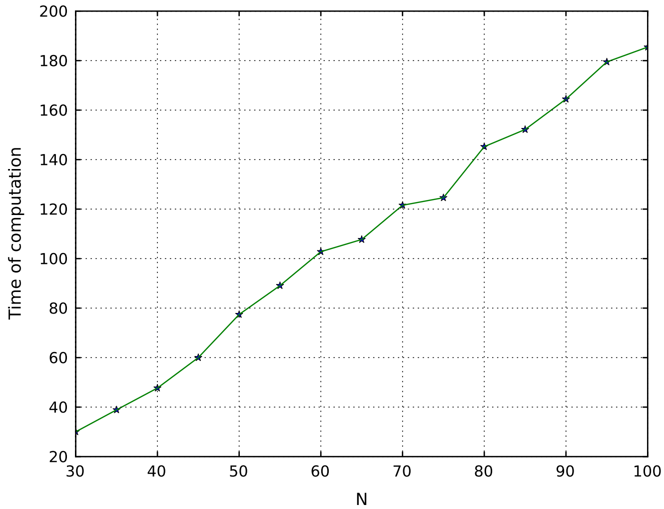

Fig. 21. Computational complexity for Canny filter.

quadratic filtering as given in Table 1 and the plots in Figs. 18 and 19 are consistent with the enhanced visual quality of fingerprint in Figs. 11 and 17.

8.4. Computational complexity

One major challenge in working with quadratic filter is the computational complexity, the comparison of which is done by estimating the time taken for filtering. A random $N \times N$ image is subjected to unsharp masking based on various filters discussed and the times of computation are found for different values of N and listed in Table 5. The plot between time of computation and size of the image is as in Fig. 20. Canny filter is the slowest in extracting edges. It takes nearly 351 seconds to filter a 512×512 fingerprint image. The complexity increases linearly with the size of the image as shown in Fig. 21. The time of computation for Laplacian, LoG, quadratic and Sobel is as in Fig. 20. LoG filter is the slowest followed by Laplacian and Gabor filters. Complexity of LoG and Laplacian follows square law relationship with size of the image (N) but that of Gabor filter

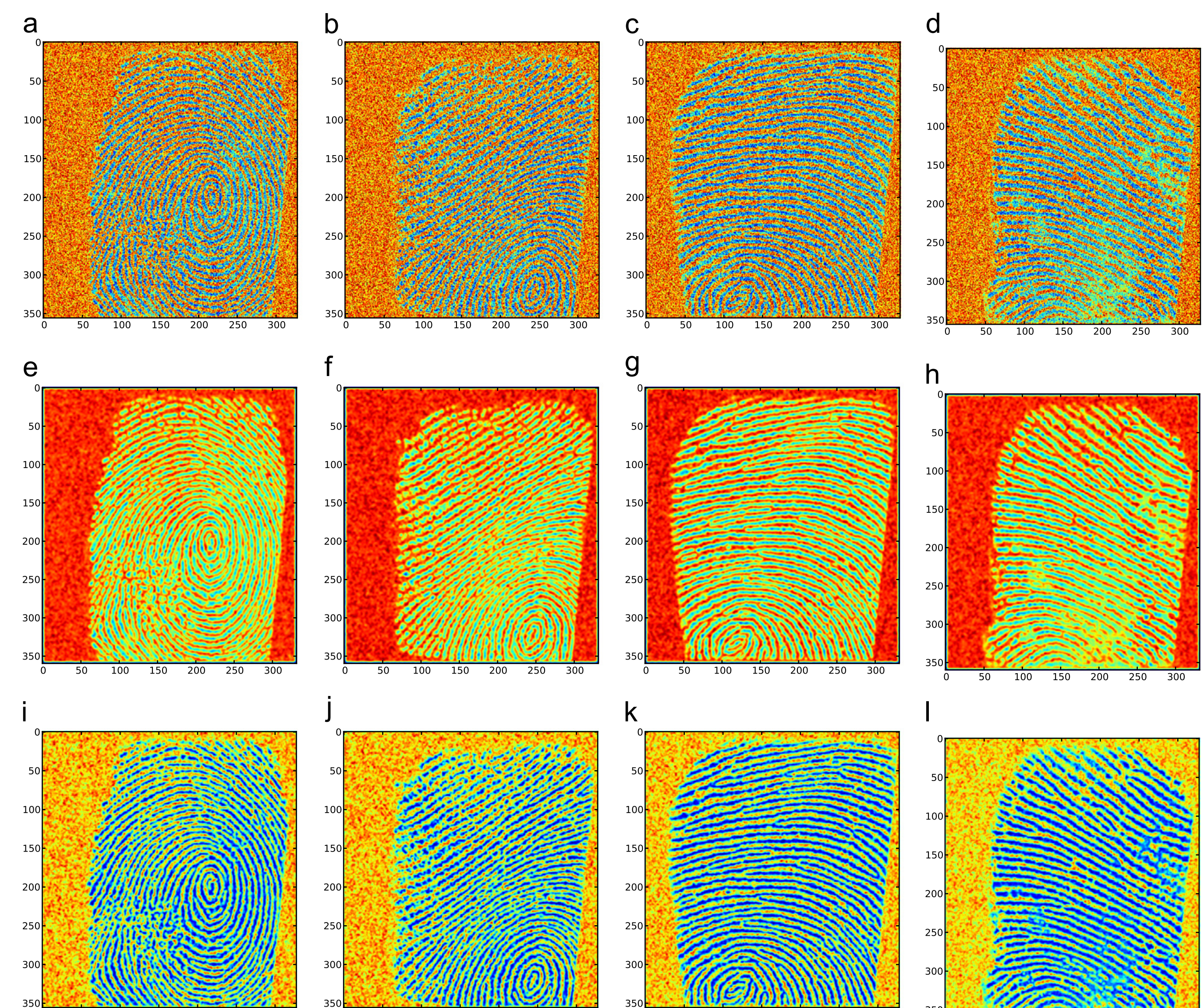

Fig. 22. Input fingerprints corrupted by impulsive noise (row 1) outputs of LoG filter (row 2) outputs of quadratic filter (row 3): (a) print 1; (b) print 2; (c) print 3; (d) print 4; (e) output (LoG); (f) output (LoG); (g) output (LoG); (h) output (LoG); (i) output (quad); (j) output (quad); (k) output (quad); and (l) output (quad).

increases at a smaller rate with N. It is observed that the time of computation for quadratic filter is consistently lower than LoG, Laplacian and Gabor filters. It takes 0.5932 seconds to filter a 512×512 fingerprint image. The main disadvantage of quadratic filters, viz. the computational complexity, is overcome by the SVD based implementation. It has roughly half the computations compared to Laplacian or LoG filters. Although Sobel filter is the fastest it failed to enhance the fingerprints.

In the comparison of various edge detection filters, SVD implementation of quadratic filter exhibits greater SNR and PSNR and offers sharper fingerprint ridges. The largest structural similarity between the uncorrupted fingerprint and the filtered version and the small computation time required makes quadratic filter a unique choice in the enhancement of latent fingerprints.

9. Inferences and conclusion

A simple unsharp masking scheme employing a quadratic Volterra edge detection filter is used to enhance noisy fingerprints similar to latent prints in crime scenes. The kernel of quadratic filter H_2 is designed by Powell method of optimization. As the direct implementation of H_2 is computationally challenging, singular value decomposition is performed on H_2 to yield a multichannel implementation that performs fast filtering. The salient feature of the unsharp masking is the noise invulnerability of edge detector. Most edge detectors based on spatial gradient perform poorly in presence of noise. The quadratic filter is found to have better edge detection properties even under extremely noisy conditions. The average signal to noise ratio by unsharp masking with SVD based quadratic filter is approximately 2–4 dB above that with conventional filters with nearly half the time of processing. It also preserves the structure and the sharpness of ridges better than other filters. The nearest competitor to quadratic filter is the LoG filter. A comparison between the outputs of unsharp masking based on quadratic and LoG filters that are driven by fingerprints corrupted by impulsive noise of variance 200 is as shown in Fig. 22. The ridges are enhanced by the quadratic filter much better than that rendered by unsharp masking by LoG and other filters. Fig. 23 shows the comparison between the outputs of

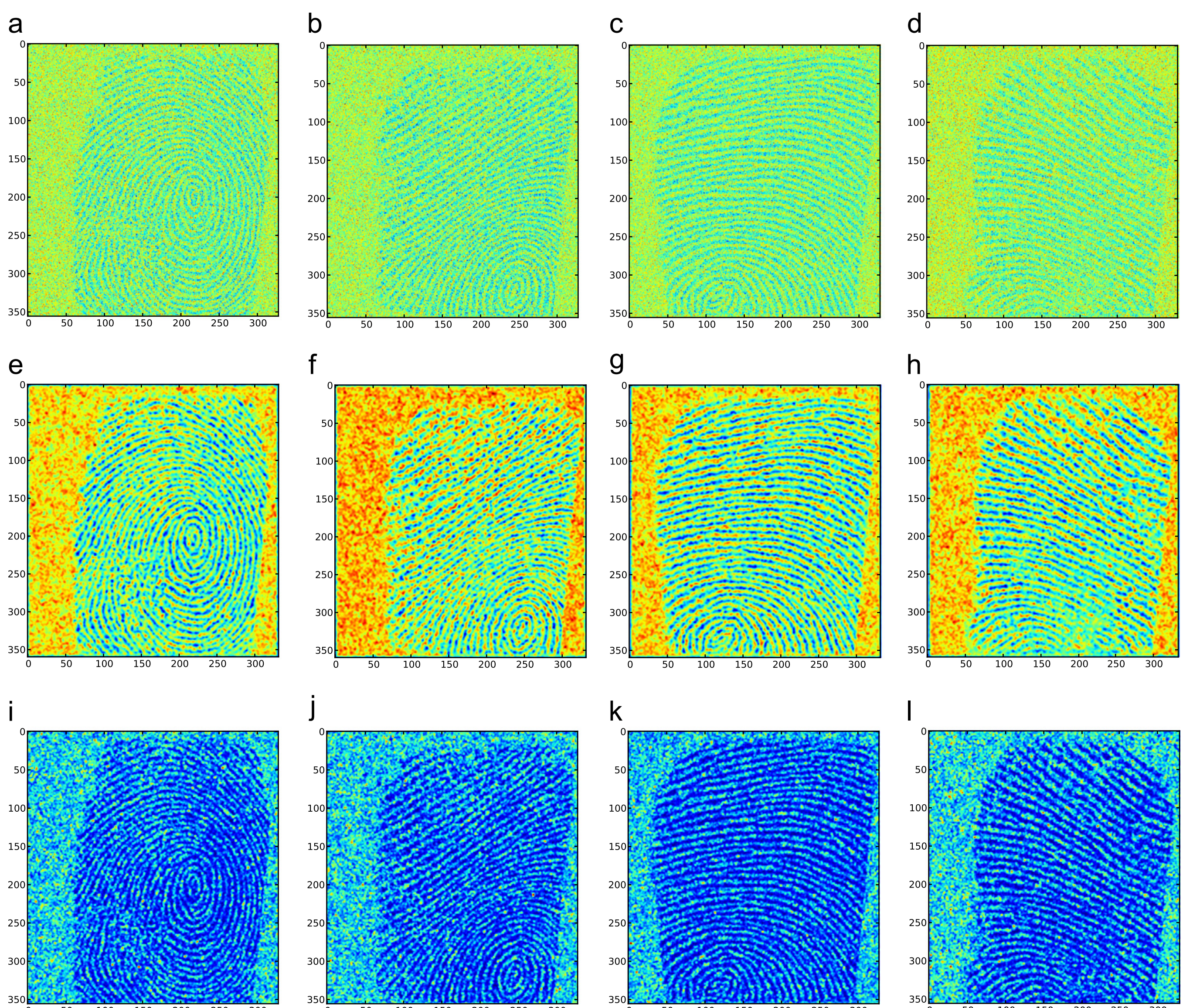

Fig. 23. Input fingerprints corrupted by Gaussian noise (row 1) outputs of LoG filter (row 2) outputs of quadratic filter (row 3): (a) Print 1; (b) Print 2; (c) Print 3; (d) Print 4; (e) output (LoG); (f) output (LoG); (g) output (LoG); (h) output (LoG); (i) output (quad); (j) output (quad); (k) output (quad); and (l) output (quad).

unsharp masking by quadratic and LoG filters driven by fingerprints corrupted by Gaussian noise of variance 150. The scheme based on quadratic filter has remarkable advantage in terms of enhancement compared to those based on LoG and other filters. It is thus concluded that the proposed quadratic filter based unsharp masking scheme is well suited for enhancing latent fingerprints from crime scenes and can outperform conventional filters.

Conflict of interest

None declared.

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