IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Volume-3, Issue-12 E-ISSN: 2347-2693

Effectiveness of Symlets in De-noising Fingerprint Images

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www.ijcseonline.org

Received: 22/Nov/2015 Revised:05/Dec/2015 Accepted:22/Dec/2015 Published: 31/Dec/21015

***Abstract*—**This paper examines the effectiveness of symlets in de- noising fingerprint images. The 'fingerprint' test image is corrupted with Additive White Gaussian Noise and the noisy image is de-noised using Discrete Wavelet Transform employing symlet wavelets of different orders. The effectiveness of de-noising with each member of the selected set of members of the symlet wavelet family is examined with the standard performance measures namely the MSE and PSNR, along with the apparent visual quality of the de-noised images. The study is repeated with a set of random values for the noise variance.

***Keywords*—**Symlets; Vanishing moments; Orthhogonal wavelets;Discrete wavelet transform;AWGN, Thresholding

I. INTRODUCTION

Images play a very important role in all fields of knowledge. They give accurate information about positions, dimensions and inter-relationships of objects [1]. This fact necessitates the requirement of clean images. It is far more important in the case of fingerprint images. Finger prints are of high importance in forensic investigation and for identity purposes by governmental agencies. Therefore it is needless to say that minimization of error is of utmost importance when we deal with fingerprint images. Hence it was contemplated that special investigation should be made for effective de-noising of such images. Recently, wavelets have emerged as a promising tool for image processing. De-noising using wavelets replace use of the traditional Fourier transform with wavelet transforms. The advantage of wavelet transforms over Fourier transform is that the basis function used in the case of the former can be selected by the scientist, whereas in the case of the latter, the basis function is fixed [2]. In addition wavelet transforms can analyze an image at different resolutions, thus the finer as well as coarse details of the image can be observed. This has prompted to examine the applicability of the least asymmetric wavelet family which is the symlet family(the word 'symlet' stands for 'symmetric wavelet'), in de- noising fingerprint images. Also it has been pointed out that sym 6 gives good performance for de-noising of MRI images [3].This has also given an impetus to examine the performance of more members of the symlet family, and that in the context of de-noising fingerprint images.

II. MATERIALS AND METHODS

A. Symlets

Symlets are a family of orthogonal wavelets having the highest number of vanishing moments for any particular support, in addition to having the least asymmetry.

(i) Symmetry

In fact symlets are not symmetric in the strict sense; instead they have the least amount of asymmetry for a given support. Hence they are actually 'near symmetric wavelets'. This fact is what makes them important. In fact they have better symmetry than another family of orthogonal wavelets namely the Daubechies wavelet family [4]. Symmetry of the filter coefficients is desirable since it results in linear phase of the transfer function [5]. The human vision system tolerates symmetric errors of perception more than asymmetric errors. Image boundaries can be handled better if symmetric filters are employed.[6].

(ii) Orthogonality

Symlets come under the class of orthogonal wavelets. This implies that the wavelet transform has an orthogonal transformation matrix, i.e., the matrix has its transpose as the inverse. They are also unitary (lossless)[7].This makes the calculation of the transform coefficients simple.

(ii) Compact support

'Support' indicates the length in time, within which the wavelet is non-zero.[6]. Symlets are wavelets having compact support. This means that the symlet wavelet filters are finite impulse response (FIR) filters, hence the filter values drop to zero outside a finite duration of time [8].

A symlet is referred to as 'sym N', where N is the order of the wavelet. Then a symlet has a length of '2N' for its filter and has a support width of 2N-1.

(iv) Vanishing moments

A wavelet $\Psi(x)$ has v vanishing moments [9] if it satisfies:

$$x^p \Psi(x) dx = 0,\ p = 0,1,2, \ldots, v-1 \quad (1)$$

Then $\Psi(x)$ can suppress polynomials of order up to v. A symlet of order N has N vanishing moments.

In this study we employ several symlets - symlets of order 2 to 8 so that we can also track the variation in de-noising performance with variation in the wavelet order. Figure 1 shows the symlets employed in the study.

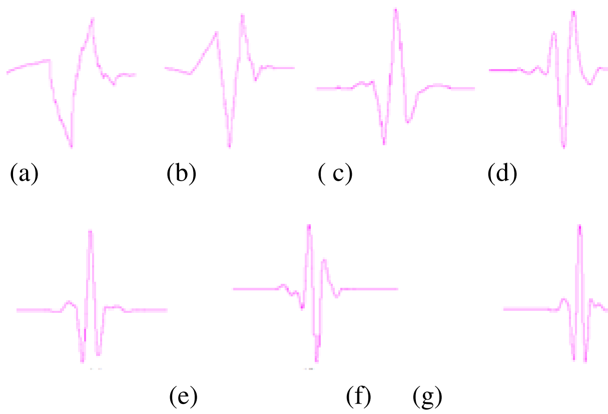


Figure 1.(a) sym 2, (b) sym 3, (c) sym 4, (d) sym 5 (e) sym6, (f) sym 7 and (g) sym 8

B. Addition of noise

For investigating the de-noising performance, we have to first create a noisy image. This is made possible by corrupting the original fingerprint image. We select Additive White Gaussian Noise (AWGN) for this purpose. AWGN is selected because it is the type of noise that is usually found in digital images [10].

Also, several random variables of different PDFs can together be approximated by the Gaussian pdf, as established by the central limit theorem [11]. Therefore Gaussian noise can represent the effect of a combination of noise types with various distributions.

Gaussian noise is characterized by the Gaussian pdf [12] described as:

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \quad (2)$$

where μ is the mean and σ is the standard deviation of the random noise. Every pixel r(x,y) in the noisy image is the sum of the original pixel p(x,y) of the element and the random Gaussian noise value n(x,y), since the noise is additive [13], i.e.,

$$r(x, y) = p(x, y) + n(x, y) \quad (3)$$

The de-noising is carried out using AWGN with '0' mean and a random set of values of noise variance listed as 0.0275, 0.05 and 0.07, all in a 0 --1 scale. The de-noising process basically comprises the following procedure:

1. Decompose the noisy image. This results in the generation of a number of coefficients.
2. Adopt an appropriate threshold strategy and apply the threshold function to the coefficients.
3. Reconstruct the image from the coefficients that remain after application of the threshold.

The Discrete Wavelet Transform (DWT) and the fingerprint image of size 512x 512 are used for the study. It is observed that the decomposition of the fingerprint image at three or more levels results in blurring which renders the resultant image useless. Hence the whole study is carried out at two levels of decomposition.

C. Thresholding

'Hard thresholding' and 'soft thresholding' are the two major thresholding techniques usually adopted. Hard thresholding involves complete elimination of coefficients whose values are below the threshold value. It results in artifacts in the de-noised image [14]. But in soft thresholding, we eliminate the coefficients whose values fall below the threshold and simultaneously shrink the remaining coefficients towards zero. This strategy precludes occurrence of sharp discontinuities in the reconstructed image and gives visually better images [15]. This fact has made us choose soft thresholding for our work.

D. Performance measures

The factors used to assess the effectiveness of de-noising performance are the Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR). These two parameters are calculated using the following formulae:

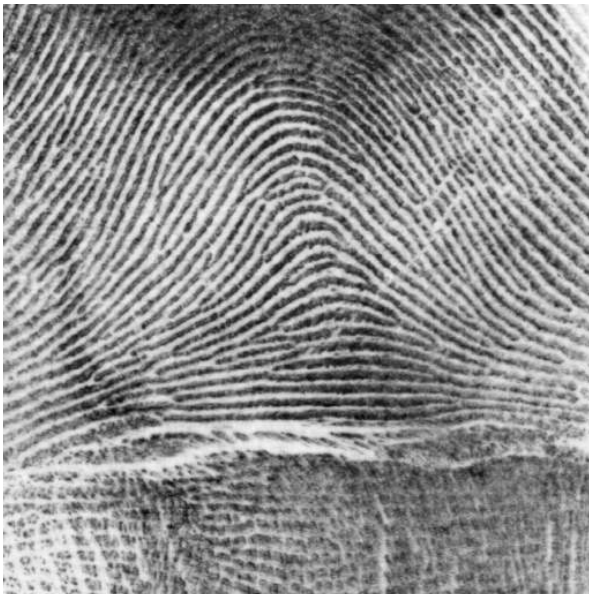
$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(X(i,j) - X'(i,j))^2 \quad (4)$$

$$\mathrm{PSNR} = 10\log\left(\frac{255^2}{\mathrm{MSE}}\right)\ \mathrm{dB} \quad (5)$$

where X is theoriginalimage and X′is the de-noised image [16]. Also the quality of the de-noised images is compared by means of physical observation since there exists no other consensual method for assessment of visual quality of de-noised images [17].

III. RESULTS AND DISCUSSIONS

Figure 2 shows the original noise-less image. Figures 3,4 and 5 show the noisy images (input 1, input 2 and input 3) with AWGN of variances 0.0275, 0.05 and 0.07 respectively.

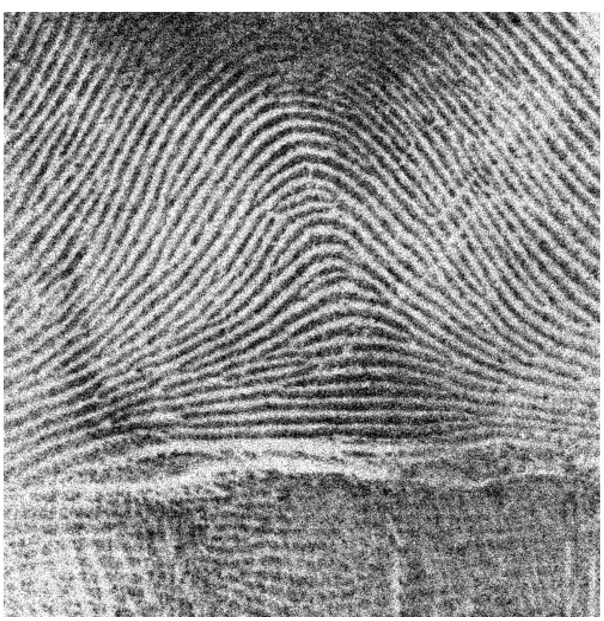


.Fingerprint image

Figure 2. Original image

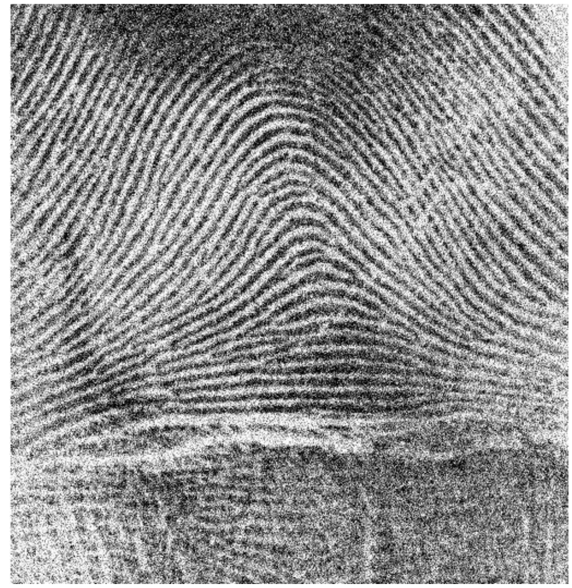
Table 1 shows the values of MSE obtained on de- noising the images with variances 0.0275, 0.05 and 0.07, using the wavelets sym 2 to sym 8.It can be seen that sym2 gives the lowest values of MSE on de- noising each of the three corrupted images, i.e., the lowest MSEs (and correspondingly the highest PSNRs) are obtained with the symletof smallest filter length.

Table 2 shows the percentage reduction in MSE of each of the de-noised images, compared to the MSE of the



.Input 1

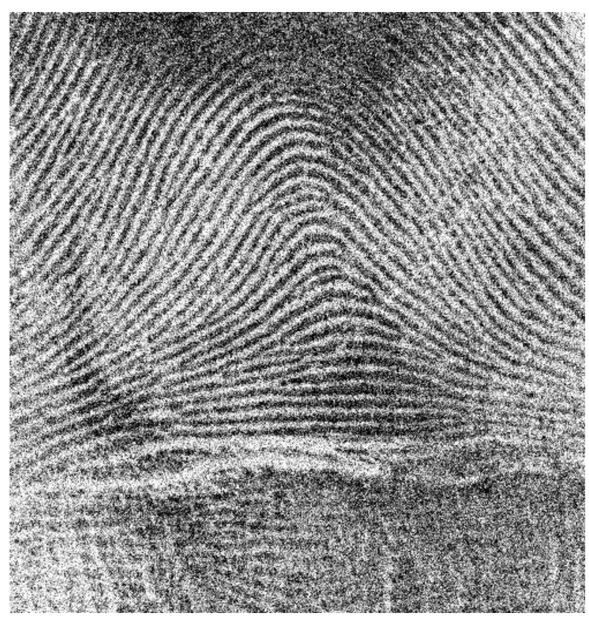
Figure 3. Image with variance 0.0275



Input 2

Figure4. Image with variance 0.05

corresponding noisy image used. It can be seen from this table that the percentage reduction in MSE of de-noisedimage increases with increase in the variance of noise in the input image. This fact points to thatsymlets are especially suited for de-noising of highly corrupted fingerprint images. Table 3 enables a quick reference of the MSE and variance of each input image, the lowest MSE and the corresponding percentage reduction in MSE obtained by de-noising each of the three input images.As seen from this



Input 3

table the

Figure 5. Image with variance 0.07

Table 1. MSE results of de-noising for different noise variances.

Wavelet	MSE		
	v=0.0275	v=0.05	v=0.07
sym2	47.8234	49.1659	49.2848
sym3	48.4097	49.3121	49.7223
sym4	48.1091	49.5225	49.9789
sym5	48.4401	49.9560	50.3211
sym6	48.7931	50.3911	50.5147
sym7	48.8273	50.1122	50.5164
sym8	48.3732	49.6325	50.1331

Table 2. MSEs of noisy images and percentage of reduction of MSE in de-noised images

MSE of input image		Input 1	Input 2	Input 3
		103.5519	109.0983	111.5002
Wavelet	% Reduction in MSE			
sym 2		53.82	54.93	55.80
sym 3		53.25	54.80	55.41
sym 4		53.54	54.61	55.18
sym 5		53.22	54.21	54.87
sym 6		52.88	53.81	54.70
sym 7		52.85	54.07	54.69
sym 8		53.29	54.51	55.04

highest value of percentage reduction in MSE of de-noised images which is 55.80% is obtained for the input image with the highest value of noise variance employed. This corresponds to an increase of PSNR from 27.6580 dB of the noisy image to 31.2037 dB of the de-noised image, by a value 3.5457 dB. The input images used in the study have very high MSEs (exceeding 100) and the percentage of reduction in MSE of the corresponding de-noised images exceed 50%, reaching a maximum of 55.8%. This high reduction in MSE is highly desirable. It may also be noted that complete removal of noise is impossible because thresholding will invariably remove a part of the signal also [7]. Hence this appreciably good result proclaims the suitability of symlets in de- noising fingerprint images.

Table3.Variance and MSE of noisy images, lowest output MSEs and percentage reduction in MSE

Variance of input image	MSE of input image	Lowest output MSE obtained	Reduction in MSE %
0.0275	103.5519	47.8234	53.82
0.05	109.0983	49.1659	54.93
0.07	111.5002	49.2848	55.80

Table1 also shows that when de-noised with any particular symlet the MSE increases as the noise variance of the input image increases, which is an expected result.

Figure 6 shows the PSNRs plotted against the symlet orders, for the different noise variances. It is seen that the PSNR is highest for noise variance of 0.0275. This means, for low noise value of input image the output image has high PSNR as what is expected. The PSNRs have an irregular variation, generally decreasing, with increase in symlet order. Symlets

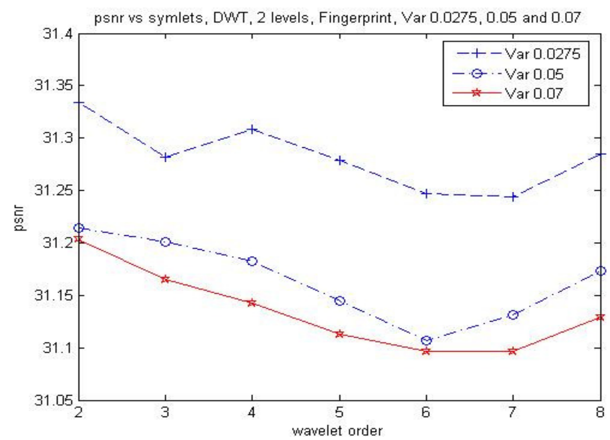


Figure 6. PSNRs plotted against the symlet orders

of order 5, 6 and 7 have low values of PSNR compared to the other symlets considered for the study.

Figures 7, 8 and 9 show the de-noised images with the lowest MSE (highest PSNR) for images of variance 0.0275, 0.05 and 0.07 (input 1, input 2 and input 3) respectively.

It is seen that the visual quality of the de-noised images is high and agree with the implications of obtained variations in MSE. Hence we establish that symlet wavelets are highly suited for de-noising fingerprint images. Inspection of the de-noised images shows that the ridges and the minutiae are visible which means that the de-noised images preserve the details in the original image.

De-noised image of lowest MSE (for input 1)

Figure 7.De-noised image of lowest MSE (47.8234) for input 1

De-noised image of lowestMSE for input 2

Figure 8.De-noised image of lowest MSE (49.1659) for input 2.

De-noised image of lowestMSE for input 3

Figure 9.De-noised image of lowestMSE (49.2848) for input 3

IV. CONCLUSION

This paper presents an investigation of the effectiveness of symlet wavelets in the de-noising of fingerprint images. It has been found that the symlet of lowest order which is sym2, gives the best de-noising performance for all values of variance of the input image. The percentage reduction in MSE of de-noised image increases with increase in the variance of noise in the input image. This points to the fact that symlets are especially suited for de- noising of highly corrupted fingerprint images. A reduction of approximately 56% of noise in highly corrupted fingerprint image could be obtained with sym2. This corresponds to an increase in PSNR by 3.5457dB. Symlets of larger orders also give more than 50% reduction in MSE; however the actual variation of MSE with symlet order is not strictly regular but has a generally decreasing nature. Also the de-noised images have appreciably good visual quality.

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