Denoising of Fingerprint Images using Q-shift Complex Wavelet Transform

V. Sekar
Central Instrumentation and Service Laboratory,
University of Madras,
Maraimali (Guindy) Campus,
Chennai- 600 025

M. K. Gayathri
Central Instrumentation and Service Laboratory,
University of Madras,
Maraimali (Guindy) Campus,
Chennai – 600 025

D. Nedumaran
Central Instrumentation and Service Laboratory,
University of Madras,
Maraimali (Guindy) Campus,
Chennai – 600 025

ABSTRACT
In this paper, we present a novel image denoising method using Q-shift with Dual Tree Complex Wavelet Transform (QDTCWT) for denoising fingerprint images. The DTCWT is an over complete wavelet transform with limited redundancy and generates complex coefficients in parallel using a dual tree of wavelet filters. But, low pass delay produces a Hilbert pair relationship between two trees. This is well addressed by Q-shift filters for improving orthogonality and symmetry properties in level 2 and below. QDTCWT have features like linear phase, tight frame, compact spatial support, good frequency domain selectivity with low sidelobe levels, approximate shift invariance, and good directional selectivity in two or more dimensions. This provides the QDTCWT basis mainly useful for de-noising purposes with high degree of shift-invariance and better directionality compared to the other traditional methods. The proposed algorithm has been designed in the MATLAB^{TM} environment and tested in the fingerprint images obtained from the FVC2004 database for denoising. The performance and efficiency of the algorithm are estimated by calculating various quality metrics and compared with the advanced methods already practiced in fingerprint image denoising. The results of this study revealed that the QDTCWT algorithm is capable of producing high quality finger print images with greater fidelity, high robustness and accuracy over the other traditional denoising methods.

General Terms
Bio-metrics, Fingerprint, Wavelet

Keywords
Fingerprint, Denoising, Q-shift Dual Tree Complex Wavelet, performance metrics

1. INTRODUCTION
Fingerprints are the ridge and furrow pattern on the tip of the finger and are used for personal identification of human subjects [1]. Efficient representation of finger prints information is a critical task, which has been achieved through structural transforms and fast algorithms. Several methods have been used to solve the denoising problems in image analysis and pattern recognition. Generally, the denoising techniques have been categorized into spatial and frequency domain techniques. In spatial domain, adaptive spatial filter is one of the best filtering techniques to restore the heterogeneous pixel characteristics perfectly. Wiener constrained least squares, Lucy Richardson and Blind deconvolution methods are some of the examples of frequency domain filtering techniques. Geman et al [2] introduced a priori constraints deconvolution model using Markov random field (MRF) framework to achieve good estimation and optimization solution in getting acceptable images. Further, the regularization is achieved through denoising process based a priori term [3]. K. Knešaurek and J. Machac [4] implemented Fourier wavelet deconvolution technique in PET images using Butterworth filter and Daubechies wavelet function, which results in 25% increase in the contrast ratio of lungs with 2% increase in noise of the restored image. But, fingerprint images containing smooth curves as edges, which cannot be efficiently captured by the normal wavelet transform due to redundant and non-redundant types of wavelets used for denoising. Initially, decimated discrete wavelet transform (DWT) was used in image denoising algorithms, which has non-redundant orthogonal property [5-9]. Due to the non-redundant property, the DWT has the disadvantages of shift in sensitivity, directionality and phase information. Although the stationary wavelet transform (SWT) reduces this problem substantially, but it is computationally expensive [10]. Several other mathematical algorithms [11-13] have also been proposed for solving image processing problems using complex wavelets. The DTCWT is an efficient tool for a variety of image processing applications such as de-noising, edge detection, restoration, enhancement, and compression. In the present work, we have attempted the Q-shift with DTCWT algorithm for denoising fingerprint images.

The remainder of the paper is organized as follows: Section I describes the basics of DTCWT transform, section II deals with Q shift analysis, section III focuses on fingerprint denoising, section IV emphasizes the experimental results, and section V describes the conclusions arrived in this work.

2. DUAL TREE COMPLEX WAVELET TRANSFORM
The recent development in wavelet-related research is the design and implementation of 2-D multiscale transforms that represent edges more efficiently than the DWT. Kingsbury's complex dual-tree wavelet transform (DTCWT) is an outstanding example, which generates complex coefficients by using a dual tree of wavelet filters for obtaining their real and imaginary parts separately (Fig.1). The outputs of each tree are down sampled by summing the outputs of the two trees during reconstruction. It is

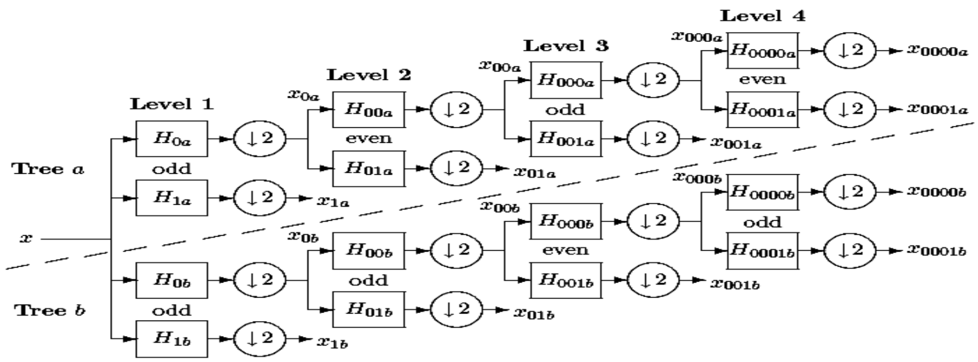

Fig 1 Filter Bank Structure of 4 Level Dual Tree Complex Wavelet

very useful to suppress the aliased components of the signal and achieve approximate shift invariance. Also, it provides the complex wavelet basis mainly useful for de-noising purposes with high degree of shift-invariance and better directionality compared to the real DWT. Further, the DTCWT has solved the problem of inability of perfect reconstruction and good frequency portioning using complex wavelets [14].

For 2-D image signals, filter banks with the pair of trees are applied to the columns and the rows of the image and is represented by

$$\psi(m,n)=\psi(m)\psi(n) \qquad \ldots (1)$$

where $\psi(m)$ is a complex wavelet which gives,

$$\psi(m)=\psi_h(m)+j\psi_g(m) \quad \ldots (2)$$

where $\psi_h(m)$ and $\psi_g(m)$ are both real-valued wavelets. So, $\psi(m,n)$ can be expanded as,

$$\begin{aligned}\psi(m,n)&=[\psi_h(m)+j\psi_g(m)][\psi_h(n)+j\psi_g(n)]\\&=[\psi_h(m)\psi_h(n)-\psi_g(m)\psi_g(n)]+\\&\quad j[\psi_h(m)\psi_g(n)+\psi_g(m)\psi_h(n)]\end{aligned} \quad \ldots (3)$$

The sum of two separable wavelets obtained from the real part of the above complex wavelets is given in equation 4.

$$\mathrm{Re}\mathit{al\ part}\ \{\psi(m,n)\}=\psi_h(m)\psi_h(n)-\psi_g(m)\psi_g(n) \quad \ldots (4)$$

The complex wavelet $\psi(m)=\psi_h(m)+j\psi_g(m)$ is approximately analytic therefore $\psi_h(m)$ is approximately the Hilbert transform pair of $\psi_g(m)$, and hence $\psi_g(m)=H\{\psi_h(t)\}$. Also, $\psi_h(m)\psi_h(n)$ is the HH wavelet of a separable 2-D real wavelet transform implemented using the filters $\{H_{oa}, H_{1a}\}$. $\psi_g(m)\psi_g(n)$ is also the HH wavelet of a real separable wavelet transform , but it is implemented using the filters $\{H_{ob}, H_{1b}\}$.

Repeating the above procedure will result in five more oriented real 2-D wavelets. Then, the six wavelets can be written as:

$$\psi_i(m,n)=\frac{1}{\sqrt{2}}(\psi_{1,i}(m,n)-\psi_{2,i}(m,n)) \qquad \ldots (5)$$

$$\psi_{i+3}(m,n)=\frac{1}{\sqrt{2}}(\psi_{1,i}(m,n)-\psi_{2,i}(m,n)) \qquad \ldots (6)$$

where i = 1, 2, 3. For the orthonormal operation the normalization value $1/\sqrt{2}$ is used. In case of real 2D filter banks, the three high-pass filters have orientations of 0^0, 45^0 and 90^0; for the complex filters, the six subband filters are oriented at $\pm 15^0$, $\pm 45^0$, $\pm 75^0$. Fig. 1 shows that there is no link between the 2 trees, so that the parallel implementation of filters is possible during algorithm execution. Also, the first stage of filters is different from other stages. Further, complex arithmetic is not needed in any of these stages. In addition to this, the DTCWT has the following properties, which improves the efficiency of denoising in images.

(i) Approximation of shift invariance.
(ii) Good selectivity and directionality in 2–dimensions.
(iii) Perfect reconstruction (PR) using short linear phase filters.
(iv) Four times redundant for images (4:1).
(v) Efficient order – N computation – only 4 times the simple DWT.

3. Q- SHIFT DUAL TREE COMPLEX WAVELET TRANSFORM

DTCWT approach doesn't address the odd/even filter characteristics due to sub-sampling asymmetry structure and biorthogonal nature of filters sets for wanting of linear phase requirements, which results in non-preservation of energy between the signal and transform domains [14]. These drawbacks have been overcome with the more recent form of dual tree approach known as a Q-shift dual tree [15]. In the Q-shift dual tree approach, two sets of filters have been used such as the filters at level 1, and the filters at all higher levels. The filters beyond level 1 have even length but are no longer strictly linear phase. Extension of Q-shift dual tree in 2D produces three sub images in each of spectral quadrants 1 and 2 giving six band-pass sub images of complex coefficients at each level, which are strongly oriented at angles of ±15°, ± 45°, ±75°. The strong orientation occurs because complex filter can separate positive from negative frequencies vertically and horizontally. The resulting image from transformation shows good rotational invariance, because each image has coefficients from all six directional subbands at the given wavelet level. As a result, the Q-shift dual tree transform retains good shift invariance and directionality properties of the original while improving the sampling structure.

3.1 Fingerprint Image Denoising

A fingerprint image consists of non-ridge area, high quality ridge area, and low quality ridge area. It is well known that low quality ridge area in the fingerprint images would cause serious effects, which deteriorate the quality of the image. In order to decrease the effects caused by low quality area, the improved QDTCWT has been applied in the local areas of the fingerprint image. The resulting sub-image is extracted from the original fingerprint image in the complex wavelet transform domain using QDTCWT. Then, according to the characteristics of the subimage data, the denoised fingerprint subimage adaptively spread spectrum and add into the host subimage QDTCWT coefficients.

3.2 DTCWT Denoising Algorithm

1. Input the noisy fingerprint image (size 512x512).
2. Select the window (size is set to 5x5)
3. Calculate the forward QDTCWT transform of the selected window data. In our particular example, we calculate four levels of the transform applying reflection boundary conditions.
4. Estimate the noise variance from a median-absolute-deviation estimator applied to the coefficients at the finest scale level. This approach gave a value of 0.084 for the noise standard deviation of the wavelet coefficients.
5. Select the threshold value T using Bays thresholding scheme and apply the soft threshold method level-by-level to obtain a new array of QDTCWT coefficients.
6. Obtain the denoised image by inverse computation of QDTCWT.

4. EXPERIMENTAL RESULTS

The experimentation has been performed on three FVC2004 fingerprint database (DB1_B, DB2_B, DB3_B,) [15]. We randomly selected 200 fingerprint images from the above database. The study was made in whorl, arch, tent arch, right loop, left loop, and mixed types of fingerprints. To extract the rich details of the fingerprint image, a 4-level QDTCWT is applied to the normalized image. To avoid problems with boundary conditions, the fingerprint image is padded with zero before applying the algorithm. This padding was removed prior to inverse transform. To compare the efficiency of the QDTCWT algorithm, the fingerprint images were subjected to several other established denoising algorithms such as stationary wavelet transform (SWT) [8], NeighShrink (NS) [16], and ProbShrink (PS) [17]. The original and denoised fingerprint output images obtained from these algorithms are shown in fig.2.

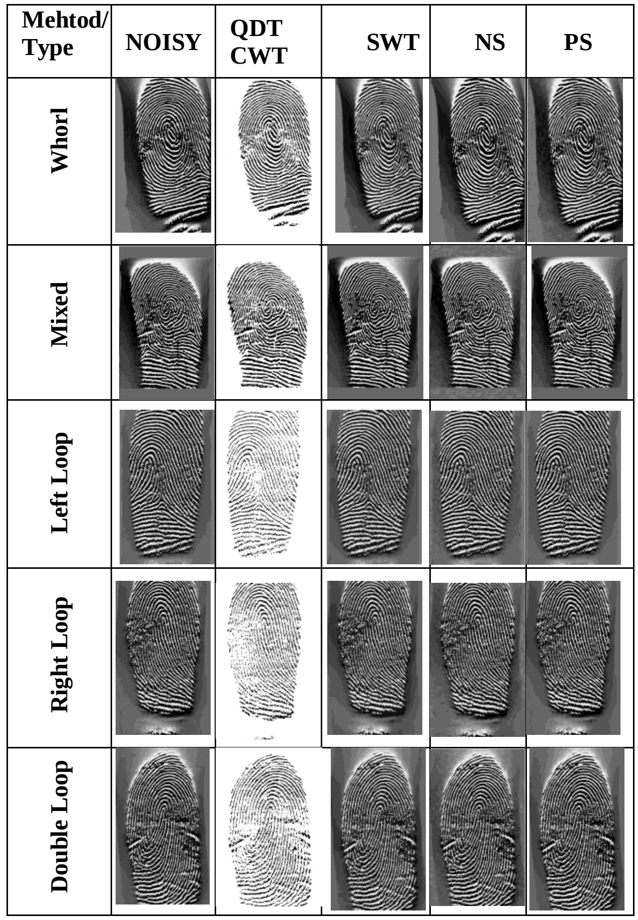

Fig 2 Noisy and Denoised images of five types of fingerprint images using four-different denoising filters

Also, to estimate the performance of the algorithm quantitatively, several traditional performance metrics such as Average Difference (AD), Mean Square Error (MSE), Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), Maximum Difference (MD), Normalized Absolute Error (NAE), Signal to Noise Ratio (SNR), Structural Content (SC), Coefficient of Correlation (CoC), Normalized Cross Correlation (NCC), Image Quality Index (IQI), Average Signal to Noise Ratio (ASNR), Image Variance (IV), Noise Standard Deviation (NSD), Effective number of Looks (ENL) and Mean Structural Similarity Index Measure (MSSIM) [18-24] have been calculated. The calculated performance metrics are given in table 1.

Further, the QDTCWT algorithm concentrates a large amount of effort in preserving the ridge pattern, which plays a critical role in the minutiae extraction algorithm when the quality of the input fingerprint image is poor. To better illustrate our approach, we applied the proposed QDTCWT algorithm in real fingerprint images and the results obtained were analyzed in both qualitative and quantitative points of view. Also, performance of a QDTCWT algorithm was subjectively measured by visual inspection of enhanced images by experts. Fig. 2 visually demonstrates the effectiveness of the proposed algorithm on fingerprint images. The quantitative performance metric values also clearly showed that the QDTCWT algorithm exhibits excellent performance in denoising over the other traditional techniques. The performance metrics calculated are graphically represented in fig 3. The system level performance of the proposed algorithm is measured in both encryption and decryption part of network cryptography software and the measured value lies within the theoretical limit.

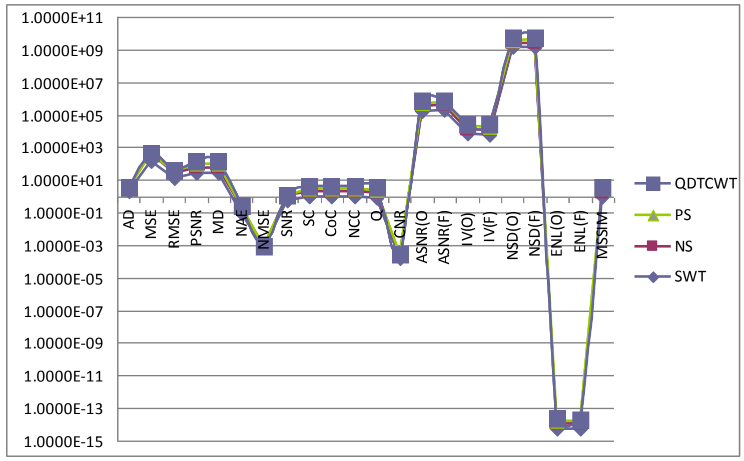

Fig 3 Graphical representation of the performance metrics given in Table 1

Table 1 Performance metrics calculated for the four denoising algorithm for the whorl type fingerprint image

Parameters	SWT	NS	PS	QDTCWT
AD	2.000463	1.421328	0.046488	0.046953
MSE	144.6772	294.7043	11.36686	11.48053
RMSE	12.02818	17.16695	3.37147	3.38829
PSNR	27.00491	23.46742	39.1089	39.49999
MD	27.00491	23.46742	39.1089	39.49999
NAE	0.087346	0.122766	0.014653	0.014799
SNR	0.579132	0.502006	0.035032	0.035382
SC	1.028819	1.029069	1.003746	1.013783
CoC	0.990521	0.977373	0.999052	1.009042
NCC	0.981455	0.976357	0.99776	1.007738
IQI	0.834323	0.713396	0.898918	0.907907
ASNR(O)	1.71E+05	1.71E+05	1.71E+05	1.73E+05
ASNR(F)	1.87E+05	1.84E+05	1.72E+05	1.74E+05
IV(O)	6.49E+03	6.49E+03	6.49E+03	6.59E+03
IV(F)	5.69E+03	5.79E+03	6.45E+03	6.55E+03
NSD(O)	1.30E+09	1.30E+09	1.30E+09	1.31E+09
NSD(F)	1.35E+09	1.34E+09	1.30E+09	1.31E+09
ENL(O)	5.39E-15	5.39E-15	5.39E-15	5.45E-15
ENL(F)	5.17E-15	5.23E-15	5.38E-15	5.43E-15
MSSIM	0.908134	0.846166	0.962948	0.972577

5. DISCUSSION AND CONCLUSIONS

In this work, we have studied fingerprint image denoising using QDTCWT with Bays thresholding technique. The QDTCWT algorithm was developed in the MATLAB 7.1, and tested over 200 different types of fingerprint images. Fifteen performance metrics have been calculated and compared for estimating the efficiency of the QDTCWT algorithm. The results obtained from this study shows that the performance and efficiency of the QDTCWT algorithm exhibits excellent denoising characteristics in preserving the edges (valleys and ridge) patterns very well than the other three methods. Hence, this algorithm might be useful in the areas of minutiae detection, matching, verification and identification. Also, the Q-shift approach increases the accuracy of denoising, which is indicative from the clear ridge patterns (fig.2). Further, small translations do not affect the magnitudes of the complex coefficients due to its shift invariance property, which improve the efficiency of denoising in fingerprint images. The soft thresholding method makes the threshold of noisy wavelet coefficients a near-optimal.

Thus, the Q-shift complex wavelet transform provides near-ideal sparsity of representation for both ridges and valleys, which results in more stable magnitude for the ridge and valley patterns. Finally, the QDTCWT with lifting scheme will further increase the computational speed of the algorithm.

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