Wavelet Transforms, Contourlet Transforms and Block Matching Transforms for Denoising of Corrupted Images via Bi-shrink Filter

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Abstract

Objectives: Image Denoising refers to the recovery of an image that has been corrupted by noise due to poor quality of image acquisition and transmission. Accordingly, there is a need to reduce the noise present in the image as a consequence of the denoised image formed. Methods/Statistical Analysis: This paper presents Image denoising using Wavelet transforms, Contourlet transforms and Block Matching Transforms governed by bivariate shrinkage (Bi-shrink) filter techniques. The Wavelet transform uses up-sampling, down-sampling, low pass filter and high pass filter to perform denoising operation, the Contourlet transform uses up-sampling, down-sampling, low pass filter and high pass filter and directional filter banks to perform denoising operation, the Block Matching Transform uses Haar Transforms, Discrete cosine transforms and Karhunen Loeve transform to perform denoising operation. Findings: The performance of wavelet transforms, Contourlet transforms and Block Matching Transforms are evaluated for Reference images (such as towers, shades and ruler images) corrupted by gaussian noise and salt and pepper noise, by computing two error metrics Peak Signal to Noise Ratio (PSNR) and Execution Time (ET) with help of shrinkage function. Programming these using MATLAB R2014a by exploring its wavelet transform, Contourlet transform, image processing and signal processing toolboxes and the values are presented in tabular forms and discussed in the section 6. In this paper the block matching haar discrete cosine transform is proposed for denoising of images (especially for those images possessing detailed textures) that works through haar transform and discrete cosine transform outstrips the basic transform discrete wavelet transform and semi translation invariant contourlet transform. For the images corrupted by Gaussian noise and denoised by the proposed transform outstrips the basic transform "Discrete Wavelet Transform by PSNR=6.71 dB, ET=25.89 sec" and "Semi Translation Invariant Contourlet Transforms by PSNR=5.49 dB, ET=5.89 sec". For the images corrupted by Salt and Pepper noise and denoised by the proposed transform outstrips the basic transform "Discrete Wavelet Transform by PSNR=21.15 dB, ET= 0.27 sec" and "Semi Translation Invariant Contourlet Transforms by PSNR=20.05 dB, ET= 5.80 sec". Application/Improvements: In this paper Block Matching Haar Discrete cosine transform is proposed to overcome the limitations of wavelet transforms and Contourlet transforms, hence to attain the trade-off between high peak signal to noise ratio and less execution time. Results and Discussion section illustrates the efficacy of the proposed transform in terms of peak signal to noise ratio, execution time and visual quality of images.

Keywords: Bi-variate Shrinkage and Image Denoising, Block Matching Transforms, Contourlet Transforms, Wavelet Transforms

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1. Introduction

It is very common that the images are often corrupted with noise during acquisition or transmission over a communication channel. The need for efficient image denoising techniques is fully-fledged with the massive production of digital images and videos that are often taken in poor conditions. Image denoising is used to find the best estimate of the original image given its noisy version. Plenty of denoising methods exist, originating from various disciplines such as probability theory, statistics, partial differential equations, linear and nonlinear filtering, spectral and multi-resolution analysis.

Image denoising can take place in two different domains: time-space domain and transform domain. In sequence there are two techniques of image denoising in transform domain: time-frequency domain and time-scale domain. With the nearly two decades of research in the area of image processing, it is found that image denoising in transform domain does the job more efficiently than the other domain of image denoising. Denoising of corrupted images is done by image transforms that refers to a class of unitary matrices used for representing images, an image is expanded in terms of a discrete set of basis elements called basis images. The transform-domain denoising techniques typically assume that image can be well approximated by a linear combination of few basis elements by preserving the few high-magnitude transform coefficients that convey mostly the energy of image and discarding the rest which are mainly due to noise, so that the image can be effectively estimated. Wavelet Transforms are chosen as they allow time-frequency localization, the ability of processing of geometrical structures such as smoothness of curves, edges by wavelet transforms are limited to very few directions. To overcome the limitations Contourlet Transforms are opted with its dominant features anisotropy and directionality and to improve PSNR Block Matching Transforms are selected.

1.1 Wavelet Transforms

Wavelets have special ability to examine signal simultaneously in both time and frequency i.e. time-frequency localization that led to the development of variety of wavelet based methods for signal manipulation, signal denoising signal compression etc. The wavelet transform, a 2-D transform excels with its basic functions such as multi-scale and multi-dimensional, and properties such as Multiresolution, localization and critical sampling. “Wavelet partitions plane into congruent four-sided figure of square sided length i.e. variable length (l) and variable width (w) that are related by w = l and constructs a system of renormalized Wavelets smoothly localized near each four-sided figure” as a consequence Wavelet transform involves square scaling $^2$.

In this paper Dual Tree Complex Wavelet Transforms (DTCWT) is considered that entails two filters namely analysis filter bank and synthesis filter bank. By Analysis filter bank, signal is decomposed into low pass filtered coefficients and high pass filtered coefficients and each of these filtered are down sampled by 2, hence wavelet coefficients are obtained. By synthesis filter bank, these wavelet coefficients are up sampled by 2 and reconstructed into a signal.

Wavelet function, forward Wavelet transform and Inverse Wavelet transform are defined by expressions (1), (2) and (3) respectively.

\[
\psi_{a,b}(x) = \frac{1}{\sqrt{a}} \psi\left(\frac{x - b}{a}\right)
\]

\[
W_T(a, b) = \int f(x) \frac{1}{\sqrt{a}} \psi\left(\frac{x - b}{a}\right) dt
\]

\[
f(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_T(a, b) \psi_{a,b}(x) da db
\]

Here, a is scaling parameter and b is translation parameter.

2. Contourlet Transforms

The Contourlet transform is inspired by human visual system which can capture the smoothness of contours of images with different elongated shapes and in variety of directions. The contourlet transform, a 2-D transform like DTCWT is an efficient transform in addition it has basic features such as multi-scale and multi-dimensional and properties such as Multiresolution, localization, directionality, critical sampling and anisotropy, dominant feature is contours of original images can be captured effectively with a few coefficients.

The Contourlet transform is the simplidirectional extension for wavelet that fixes its sub band mixing problem and improves its directionality. Contourlets includes spatial band-pass filtering operation to isolate different scales and occur at all scales, locations and orientations. Contourlets exhibit variable anisotropy “Contourlet partitions plane into congruent four-sided figure of dyadic side length i.e. variable length, l and variable width, w that are related by $w = l^2$ & $l = w^2$ where, one of the parameter
is the reference, and constructs a system of renormalized Contourlets smoothly localized near each such four-sided figure as a consequenceContourlet transform involves parabolic scaling.

The Translation Invariant Contourlet Transform (TICT) is inspired by human visual system which can capture the smoothness of contours of images with different elongated shapes and in variety of directions. This transform usages a two-fold filter bank structure to get smooth contours of images that comprises two filter banks, first one is Laplacian Filter Bank (LFB) used to capture point discontinuities and second one is Directional Filter Bank (DFB) used to form these point discontinuities into linear structures. The Contourlet function, forward Contourlet Transform and Inverse Contourlet Transform are defined by expressions (4), (5), and (6) respectively.

\[ \psi_{a,b,\theta}(x) = \frac{1}{\sqrt{a}} \cdot \psi \left[ \frac{x_1 \cos \theta + x_2 \sin \theta - b}{a} \right] \]  
\[ C_T(a, b, \theta) = \int \psi_{a,b,\theta}(x) f(x) dx \]  
\[ f(x) = \int_0^{2\pi} \int_0^\infty C_T(a, b, \theta) \psi_{a,b,\theta}(x) \frac{da}{a^3} \frac{db}{4\pi} \frac{d\theta}{4\pi} \]  

Here, \( a > 0 \) is a scaling parameter, \( b \) is translation parameter and \( \theta \) is the orientation parameter. These Contourlets are constant along the lines \( x_1 \cos \theta + x_2 \sin \theta \) using common \( b \) \& \( \theta \) and different scales of \( a \), it is possible to efficiently approximate the singularities along a line.

### 3. Block Matching Transforms

Block Matching Transforms performs operations in three dimensions first 3D group is built by stacking up the matched patches in order to speed up the process, one reference patch is considered and the other patches are stacked to it that are closest to the reference patch. Once the 3D-block is built the collaborative filtering is applied to the group, followed by a shrinkage function hence transform coefficients are obtained for each patch and these coefficients are aggregated i.e. arranged in order.

In this paper two types of block matching transforms are examined and programmed first one is Block Matching Haar Discrete cosine transform (BMHD), it uses discrete cosine transform for each patch in 3D block and Haar transform in third dimension of 3D block then transform coefficients are obtained. The second one is Block Matching Haar Karhunen Loeve transform (BMHKL), it uses Karhunen Loeve transform for each patch in 3D block and Haar transform in third dimension of 3D block then the transform coefficients are obtained.

### 4. Image Denoising

The block diagram presented in Figure 1 describes the denoising of images by using wavelet transforms, contourlet transforms and Block Matching Transforms.

The four steps involved in image denoising that uses shrinkage function is shown in Figure 1 are as follows:

a. Add noise to the input image.
   • In this step Gaussian noise (salt & pepper noise) is added to the input image and noise is assumed to be stationary and uncorrelated with image.

b. Apply forward transform to the noisy image.
   • In this step pixels of noisy image are transformed into coefficients.

c. Apply threshold technique with the help of bi-variate Shrinkage to the coefficients.
   • In this step manipulate the coefficients in a way such that magnify the coefficients, where signal to noise ratio is high and condense coefficients where signal to noise ratio is low.

d. Apply inverse transforms to the shrinked and thresholded coefficients.
   • In this step manipulated coefficients are transformed into pixels of denoised image.

![Figure 1. Block diagram of image denoising.](image-url)
Here, $R$ is the maximum value in the input image data type. If the pixels of the digital image is represented using $n$ bits, then $R = 2^n - 1$. In this paper we have considered grey scale digital images that are represented using 8 bits, i.e. $R = 2^8 - 1 = 255$, $f(x, y)$ is the input image (original image), $f(x, y)$ is the output image (may be either noised image or denoised image using wavelet transforms and contourlet transforms) and $M, N$ are the number of rows and columns of the image respectively. The larger the PSNR, the better is the denoising as it is preferred.

5.2 Execution Time (ET)

It calculates the time taken to denoise the noised image and is figured by (8). It is the time difference between End Of Computation (EOC) and start of computation (SOC).

$$ET = EOC - SOC$$ (8)

The lesser the execution time the better the performance.

5.3 Shrinkage Function

The methods for Denoising of images depend on three factors shrinkage function $'S''$, and threshold $'\lambda''$. The shrinkage function is explained in detail as bivariate shrinkage and thresholds are calculated either globally with one threshold for all the coefficients or on a level dependent basis with $k$ different thresholds for different levels.

5.4 Bivariate Shrinkage Function

The denoising of an image corrupted by independent Gaussian noise with variance $\sigma^2_\eta$ is considered. Let $w_{2k}$ represent the parent of $w_{1k}$ (here $w_{2k}$ is the wavelet coefficient at the same position as the $k^{th}$ wavelet coefficient $w_{1k}$, but at the next coarser scale). Let us formulate this in wavelet domain as $\gamma_{1k} = w_{1k} + \eta_{1k}$ and $\gamma_{2k} = w_{2k} + \eta_{2k}$ that specifies the statistical dependencies between a coefficient and its parent, $\gamma_{1k}$ and $\gamma_{2k}$ are noisy observations of $w_{1k}$ and $w_{2k}$. In addition $\eta_{1k}$ and $\eta_{2k}$ are noise samples, hence can be generalised as (9)

$$\Rightarrow y_k = w_k + \eta_k$$ (9)

Because $\eta_k = (\eta_{1k}, \eta_{2k})$, $w_k = (w_{1k}, w_{2k})$ and $y_k = (\gamma_{1k}, \gamma_{2k})$. Henceforth, the coefficient $\eta_k$ will be let as default to reduce complexity for further quantitative analysis and is shown in (10)

$$\Rightarrow y = w + \eta$$ (10)

From the standard Maximum A Priori (MAP) estimator the corrupted observation $y$ is formulated as (11)

From the distribution function of sum of two statistically independent random variables (10) $p_y(w|y)$ is expressed as (12).

$$p_y(w|y) = p_\eta(y)p_w(w)$$ (12)

$$\Rightarrow \hat{w}(y) = arg max[p_\eta(y)p_w(w)]$$ (13)

A Gaussian bivariate probability density function for the noise is specified by (14)

$$\Rightarrow p_\eta(y) = \frac{1}{\sqrt{2\pi\sigma_\eta^2}} exp\left(-\frac{\eta^2}{2\sigma_\eta^2}\right)$$ (14)

A non-Gaussian bivariate probability density function for the coefficient and its parent is quantified by (15)

$$\Rightarrow p_w(w) = \frac{3}{2\pi\sigma^2} exp\left(-\frac{\sqrt{3}}{\sigma} \sqrt{w_1^2 + w_2^2}\right)$$ (15)

By substituting (13) and (14) in (12) and by solving the maximum a priori estimator $\hat{w}(y)$ is derived as

$$\Rightarrow \eta_k = \begin{cases} 0 & if \quad \eta_k \leq 0 \\ \eta_k & otherwise \end{cases}$$

The expression (16) is interpreted as a bivariate shrinkage function, $\sigma^2_{\eta}$ is marginal variance of wavelet coefficient and requires the prior knowledge of the noise Variance $\sigma^2_{\eta}$.

6. Results and Discussion

The performance of Wavelet transforms, Contourlet transforms and Block Matching Transforms are evaluated for reference images such as towers, shades and ruler corrupted by Gaussian Noise and Salt & Pepper noise. Programming these transforms using MATLAB R2014a by exploring its wavelet transform, contourlet transform, image processing and signal processing toolboxes, the evaluation metrics namely peak signal to noise ratio and execution time are presented in tabular forms and discussed in the following sub sections.

6.1 Images Corrupted by Gaussian Noise

The performance of wavelet transforms, Contourlet transforms and Block Matching Transforms are evaluated
for towers, shades and ruler images corrupted by Gaussian Noise as follows:

1. Each of the reference image(s) shown in first column of Table 1 is corrupted with Gaussian Noise (additive noise) as shown in second column of Table 1.
2. The noised images are first subjected to linear forward transform techniques namely linear forward wavelet transforms; hence respective wavelet transform coefficients are achieved.
3. Then a non-linear hard thresholding techniques with help of shrinkage function is applied to the wavelet transform coefficients; at the end, wavelet transform coefficients are subjected to linear inverse transform technique namely linear inverse wavelet transforms. The de-noised images are shown in third column and fourth columns of Table 1 for DWT and DTCWT methods, respectively.
4. The step 2 and step 3 are repeated for Contourlet Transforms and the de-noised image(s) are shown in fifth and sixth columns of Table 1 for TICT and STICT techniques respectively.
5. The step 2 and step 3 are repeated for Block Matching Transforms and the de-noised image(s) are shown in fifth and sixth columns of Table 1 for BMHD and BMHKL techniques respectively.

6. Evaluation metrics PSNR and ET for the Wavelet Transforms, Contourlet Transforms and Block Matching Transforms are evaluated for images corrupted by Gaussian noise and hence its values are tabulated in Tables 2 and 3 respectively.

6.1.1 Observations from Tables 2 and 3 for Images Corrupted by Gaussian Noise

- From Table 2 it is observed that as \( \sigma_{\eta} \) increases peak signal to noise ratio decreases from 37.89 dB to 31.55 dB in case of towers image using block matching Haar Karhunen Loeve transform. Shades image shows better performance in terms of PSNR with respect to towers image and rulers image. But in general as \( \sigma_{\eta} \) increases the PSNR decreases as it is evident.
- From Table 3 it is perceived that execution time is very less using Discrete Wavelet Transforms say 0.25 sec for Rulers image and execution time is very high say 349.49 sec for Shades image using block matching Haar Karhunen Loeve transform.
- From Table 2 and Table 3 it is inferred that BMHD has high PSNR and less ET say 56.01 dB and 25.20 sec respectively for Shades image. BMHKL is better in terms of PSNR but being more complex transform not useful for practical real time implementations.

Table 1. Displays (i) Input image (ii) Noised image (iii) Denoised image using DWT (iv) Denoised image using DTCWT (v) Denoised image using TICT (vi) Denoised image using STICT (vii) Denoised image using BMHD (viii) Denoised image using BMHKL for tower, shade and ruler images corrupted by Gaussian noise

| (i) Input Image | (ii) Noised Image | Denoised Images using |
|-----------------|-------------------|----------------------|
|                 |                   | (iii) DWT (iv) DTCWT | (v) TICT (vi) STICT | (vii) BMHD (viii)BMHKL |
| Towers Image    | ![Image](image1)  | ![Image](image2)     | ![Image](image3)   | ![Image](image4) |
| Shades Image    | ![Image](image5)  | ![Image](image6)     | ![Image](image7)   | ![Image](image8) |
| Ruler Image     | ![Image](image9)  | ![Image](image10)    | ![Image](image11)  | ![Image](image12) |
Table 2. PSNR (dB) among Input Image (II), Noised Image (NI) and Denoised Image (DI) using three different transforms for Gaussian noise

| $\sigma_z / \sigma_x$ | WT DWT | CT DTCWT | BMT TICT | BMHD | BMHKL |
|---------------------|--------|----------|----------|------|-------|
| **PII & NI (Gaussian noise)** |        |          |          |      |       |
| Towers Image        |        |          |          |      |       |
| 5 / 34.14           | 34.63  | 35.73    | 35.65    | 36.24| 37.71 | 37.89 |
| 10 / 28.12          | 32.07  | 32.66    | 32.91    | 33.25| 34.26 | 34.49 |
| 15 / 24.61          | 30.58  | 30.99    | 31.36    | 31.59| 32.52 | 32.73 |
| 20 / 22.13          | 29.52  | 29.86    | 30.25    | 30.47| 31.37 | 31.55 |
| Shades Image        |        |          |          |      |       |
| 5 / 34.14           | 46.77  | 46.85    | 46.93    | 47.83| 56.01 | 56.68 |
| 10 / 28.12          | 42.33  | 42.40    | 42.50    | 43.39| 49.36 | 49.91 |
| 15 / 24.60          | 39.60  | 40.00    | 40.06    | 40.92| 45.22 | 45.94 |
| 20 / 22.10          | 37.60  | 38.27    | 38.34    | 39.19| 42.71 | 43.53 |
| Ruler Image         |        |          |          |      |       |
| 5 / 34.14           | 36.25  | 36.36    | 39.00    | 39.49| 51.80 | 55.72 |
| 10 / 28.12          | 31.10  | 31.14    | 33.38    | 33.67| 45.68 | 49.48 |
| 15 / 26.60          | 27.89  | 28.09    | 30.01    | 30.43| 42.02 | 45.50 |
| 20 / 22.10          | 25.79  | 26.17    | 27.64    | 28.14| 39.14 | 42.39 |

Table 3. Execution time (sec) taken by three different transforms for Gaussian noise

| $\sigma_z$ | WT DWT | CT DTCWT | BMT TICT | BMHD | BMHKL |
|------------|--------|----------|----------|------|-------|
| **PII (Gaussian noise)** |        |          |          |      |       |
| Towers Image |        |          |          |      |       |
| 5           | 0.27   | 1.97     | 36.42    | 30.77| 21.10 | 343.58|
| 10          | 1.03   | 2.23     | 34.24    | 30.88| 21.00 | 324.91|
| 15          | 0.69   | 1.62     | 31.73    | 31.36| 21.70 | 317.43|
| 20          | 0.69   | 1.87     | 36.36    | 40.12| 22.00 | 322.36|
| Shades Image |        |          |          |      |       |
| 5           | 0.30   | 1.26     | 35.12    | 32.42| 25.20 | 338.77|
| 10          | 0.28   | 1.24     | 30.65    | 32.56| 26.80 | 341.57|
| 15          | 0.28   | 1.24     | 31.27    | 29.61| 25.80 | 341.01|
| 20          | 0.30   | 1.58     | 31.52    | 33.58| 26.80 | 349.59|
| Ruler Image  |        |          |          |      |       |
| 5           | 0.50   | 4.88     | 37.79    | 36.20| 13.80 | 344.68|
| 10          | 0.27   | 1.27     | 30.22    | 29.91| 13.90 | 345.90|
| 15          | 0.28   | 1.67     | 31.26    | 26.13| 13.80 | 338.02|
| 20          | 0.25   | 1.84     | 31.22    | 28.04| 13.80 | 340.16|
6.2 Images Corrupted by Salt and Pepper Noise

The performance of wavelet transforms, contourlet transforms and Block Matching Transforms are evaluated for towers, shades and ruler images corrupted by salt & pepper noise as follows:

1. Each of the reference image(s) shown in first column of Table 4 is corrupted with salt & pepper noise (black and white noise) and is shown in second column of Table 4.
2. The noised images are first subjected linear forward transform techniques namely linear forward wavelet transforms; hence respective wavelet transform coefficients are achieved.
3. Then a non-linear hard thresholding techniques with help of shrinkage function is applied to the wavelet transform coefficients, at the end wavelet transform coefficients subjected to linear inverse transform techniques namely linear inverse wavelet transforms, and the de-noised images are shown in third column and fourth columns of Table 4 for DWT and DTCWT methods respectively.
4. The step 2 and step 3 are repeated for Contourlet Transforms and the de-noised image(s) are shown in fifth and sixth columns of Table 4 for TICT and STICT techniques respectively.
5. The step 2 and step 3 are repeated again for Block Matching Transforms and the de-noised image(s) are shown in seventh column of Table 4 for BMHD technique.
6. Evaluation metrics $PSNR$ and $ET$ for the Wavelet Transforms, Contourlet Transforms and Block Matching Transforms are evaluated for images corrupted by salt & pepper noise, and hence its values are tabulated in Tables 5 and 6 respectively.

6.2.1 Observations from Tables 5 and 6 for Images Corrupted by Salt and Pepper Noise

- From Table 5 it is observed that as $\sigma_n$ increases peak signal to noise ratio decreases from 28.42 dB to 26.46 dB in case of towers image using block matching Haar discrete cosine transform. Shades image shows better performance in terms of PSNR with respect to Towers image and Rulers image.
- From Table 6 it is observed that execution time is very less using Discrete Wavelet Transforms say 0.24 sec for Shades image and execution time is very high say 11.92 sec for Rulers image using Block Matching Haar Discrete cosine transform.

| Table 4. Displays (i) Input image (ii) Noised image (iii) Denoised image using DWT (iv) Denoised image using DTCWT (v) Denoised image using TICT (vi) Denoised image using STICT (vii) Denoised image using BMHD for tower, shade and ruler images corrupted by salt and pepper noise |
|---|---|---|---|---|---|---|
| (i) Input Image | (ii) Noised Image | Denoised Images using | (iii) DWT | (iv) DTCWT | (v) TICT | (vi) STICT | (vii) BMHD |
| Towers Image | | | | | | |
| | | | | | | |
| Shades Image | | | | | | |
| | | | | | | |
| Ruler Image | | | | | | |
Table 5. PSNR (dB) among Input Image (II), Noised Image (NI) and Denoised Image (DI) using three different transforms for Salt and pepper noise

| σ_η/PSNR (dB) (II & NI) | WT | CT | BMT |
|-------------------------|----|----|-----|
|                         | DWT | DTCWT | TICT | STICT | BMHD |
| PSNR (dB) II & DI (salt & pepper noise) |
| Towers Image            |     |       |      |       |      |
| 5 / 18.38               | 18.99 | 19.31 | 19.71 | 20.09 | 28.42 |
| 10 / 15.37              | 17.76 | 18.52 | 20.64 | 21.49 | 27.32 |
| 15 / 13.62              | 19.37 | 20.94 | 22.21 | 22.78 | 25.96 |
| 20 / 12.35              | 20.42 | 21.76 | 22.21 | 22.60 | 24.14 |
| Shades Image            |     |       |      |       |      |
| 5 / 16.20               | 17.74 | 18.04 | 18.23 | 18.39 | 38.89 |
| 10 / 14.77              | 15.64 | 16.67 | 17.52 | 18.39 | 32.83 |
| 15 / 12.92              | 16.38 | 17.64 | 19.93 | 21.04 | 28.14 |
| 20 / 11.62              | 18.00 | 18.79 | 20.67 | 21.58 | 24.00 |
| Ruler Image             |     |       |      |       |      |
| 5 / 15.96               | 16.06 | 16.14 | 16.31 | 16.27 | 27.12 |
| 10 / 12.98              | 13.43 | 13.47 | 14.09 | 14.80 | 23.38 |
| 15 / 11.23              | 12.71 | 13.14 | 14.34 | 14.26 | 19.27 |
| 20 / 9.99               | 12.40 | 13.18 | 13.21 | 13.83 | 16.09 |

Table 6. Execution Time (sec) taken by three different transforms for Salt and pepper noise

| σ_η | WT | CT | BMT |
|-----|----|----|-----|
|     | DWT | DTCWT | TICT | STICT | BMHD |
| Execution Time (sec) (salt & pepper noise) |
| Towers Image |
| 5    | 1.97 | 2.80 | 10.84 | 9.33 | 5.10 |
| 10   | 1.05 | 2.56 | 10.79 | 9.09 | 4.80 |
| 15   | 1.43 | 2.53 | 10.65 | 9.15 | 4.30 |
| 20   | 1.05 | 2.60 | 10.71 | 9.32 | 3.70 |
| Shades Image |
| 5    | 0.29 | 1.24 | 10.77 | 9.12 | 5.10 |
| 10   | 0.24 | 1.23 | 10.71 | 9.13 | 4.90 |
| 15   | 0.29 | 1.23 | 10.73 | 9.12 | 4.30 |
| 20   | 0.28 | 3.09 | 10.80 | 9.16 | 4.00 |
| Ruler Image |
| 5    | 0.31 | 1.63 | 11.92 | 9.87 | 3.20 |
| 10   | 0.27 | 1.33 | 10.56 | 9.30 | 2.90 |
| 15   | 0.30 | 1.30 | 10.62 | 9.41 | 2.80 |
| 20   | 0.26 | 1.31 | 10.69 | 9.15 | 2.60 |
From Tables 5 and 6 it is inferred that Block Matching Haar Discrete cosine transform has high PSNR and less ET say 38.89 dB and 5.10 sec respectively for shades image.

7. Conclusion and Future Scope

We studied, analyzed and programmed two Wavelet Transforms (WT) namely Discrete Wavelet Transforms (DWT) and Dual Tree Complex Wavelet Transforms (DTCWT), two Contourlet Transforms (CT) namely Translation Invariant Contourlet Transform (TICT) and Semi Translation Invariant Contourlet Transform (STICT), two Block Matching Transforms (BMT) namely Block Matching Haar Discrete cosine transform (BMHD) and Block Matching Haar Karhunen Loeve transform (BMHKL) for de-noising of reference images corrupted by four different kinds of noises namely Gaussian noise, Salt & Pepper noise, Speckle noise and Poisson noise.

It is concluded that the proposed Block Matching Haar Discrete cosine transform (BMHD) for denoising of images (especially for those images possessing detailed textures) that works through Haar transform and discrete cosine transform outstrips.

1. Discrete Wavelet Transform, a basic transform in terms of improved peak signal to noise ratio say 6.71 dB, in less Execution Time say 25.89 sec.
2. Semi Translation Invariant Contourlet Transforms, in terms of improved peak signal to noise ratio say 5.49 dB, but more Execution Time say 5.89 sec.
3. Block Matching Haar Karhunen Loeve transform, an advanced transform though peak signal to noise ratio is improved say 56.68 dB but its execution time is too high say 349.59 sec as it is not acceptable in practice.

These transforms can be used for removing noises in videos. Typical video noise types are as follows: one is Analog noise such as High frequency interference (dots, short horizontal color lines, etc.), Brightness and color channel interference and Video reduplication – false contouring appearance. Another one is Digital noise such as low bit rate artifacts, low and medium bitrates artifact especially on animated cartoons and Blocks (slices) damage in case of losses in digital transmission channel or problem with the disk.

8. References

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