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Resolution Enhancement of Images Using DTCWT and NLM

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***Abstract*—Resolution enhancement (RE), a process of improving the quality of an image. Resolution enhancement is basically obtained by regaining high frequency contents of image. Without which the output will be a blurred image. In this paper a new approach in wavelet domain using dual-tree complex wavelet transform (DT-CWT) and nonlocal means (NLM) filter for RE of the images is implemented. An input image is decomposed by DT-CWT to obtain high-frequency sub bands. The high-frequency sub bands and the low-resolution (LR) input image will be interpolated using the bicubic interpolation in proposed work. The high frequency sub bands are passed through an NLM filter to reduce the artifacts generated by DT-CWT. The filtered high-frequency sub bands and the LR part of input image are added using inverse DTCWT for obtaining resolution-enhanced image. DT-CWT provides superior resolution and greater performance ratio because of its nearly shift invariant and directional selective properties. The results are compared in terms of PSNR, MSE for existing techniques.**

***IndexTerms*—DT-CWT, Bicubic interpolation, RE, NLM, PSNR**

I. INTRODUCTION

Resolution is the quality of an image.Three types of resolutions which affect quality of image spatial, spectral, and temporal. So for improving quality of image resolution enhancement (RE) is desirable.For resolution enhancement, interpolation is widely used [2], [3].Some of the commonly used interpolation techniques are nearest neighbor, bilinear, bicubic.

RE schemes not using wavelets suffer from blurring of an image because of loss of high-frequency contents. That would have been the major drawback for REschemes.So therefore new approach has been started in the wavelet domain. In recent years many algorithms such as DWT [7], SWT [8], and DT-CWT [9] have been proposed. There are some conventional schemes such as nearest neighbor, bilinear, and bucolic interpolations and wavelet zero padding, this RE scheme using DT-CWT and bicubic interpolations were compared withconventional schemes [9].

Note that, artifacts in RE image causes due to property of shift variant and lack of directionality of DWT.In case of DT-CWT; it is almost shift invariant and directional selective [13].

In this paper, DT-CWT-NLM-RE technique is used by additional use of bicubic interpolation. Note that Perfect reconstruction can be achieved by help of DT-CWT with well-balanced frequency responses [13] [14].

DT-CWT is more advantageous than traditional DWT because it gives more promising resultsafter the modifying the wavelet coefficients. Since the bicubic interpolation offer less aliasing, sharpness, and minimal ringing, it is therefore a good choice for RE. For further enhancement of performance of DT-CWT-NLM-RE NLM filtering [15] which reduces the artifacts. The results for this method are compared with the best performing RE techniques [5], [7]–[9].

II. NON LOCAL MEAN FILTER

The NLM filter is an improved version of neighborhood filtering algorithms. Basically assumption is that, animage content repeat itself in within some neighborhood [15] and in neighboring frames [16]. In NLM weighted sum of the surrounding pixels Y (p, q) (same frame and in the neighboring frames [16]) is taken which helps to compute denoised pixel x (p, q). In noise contaminated images this feature helps to calculate the pixel value. To calculate the denoised pixel x(p,q) following formula can be used [1]

$$x(p,q) = \frac{\sum_{m=1}^{M} \sum_{(r,s)\epsilon N(p,q)} Y_m(r,s) K_m(r,s)}{\sum_{m=1}^{M} \sum_{(r,s)\epsilon N(p,q)} K_m(r,s)} \quad (1)$$

where m denotes frame index, and N indicate the neighborhood of the pixel at pixel (p, q). K is the filter weights,i.e.

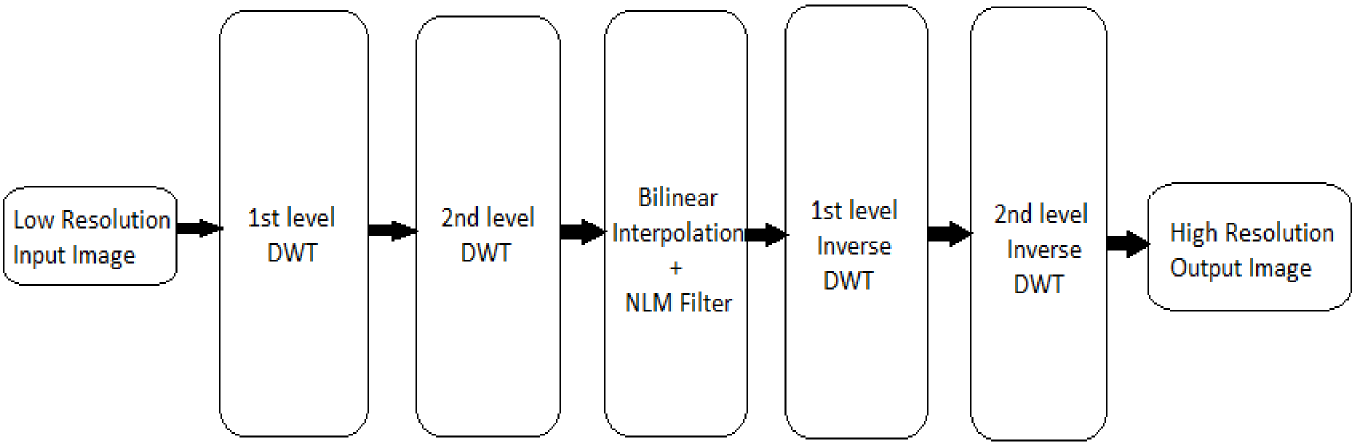

Fig 1. Block diagram of DTCWT-NLM-RE

$$K(r,s) = \exp\left\{-\frac{\|V(p,q)-V\|_2^2}{2\sigma^2}\right\} X\sqrt{(p-r)^2+(q-s)^2+(m-1)^2} \quad (2)$$

where V is centered at Y (p, q) pixel which makes the squared window. Y (r, s) are the pixel values from a geometric neighborhood of pixels Y (p, q) and Y (r, s), σ is the filter coefficient, and f(x) is a geometric distance function, distance between Y (p, q) and Y (r, s) is inversely proportional to the filter weight K.

B. NLM-RE

Resolution enhancement is done by modifying NLM with the following model [17]:

$$L_m = IJQX + n \quad (3)$$

where L_m, is the vectorized low-resolution frame, I denotes decimation operator, J denotes blurring matrix, Q denotes warping matrix, X denotes vectorized high-resolution image, and n is Gaussian white noise. Series of L is formed here and aim is to restore X from it. Penalty function ε is defined as

$$\varepsilon^2 = \frac{1}{2}\sum_{m=1}^{M}\|IJQx - Y_m\|_2^2 + \lambda R(x) \quad (4)$$

where R is a regularization term. λ is the scale coefficient.x isthe target image, and Y_m represents low resolution input image. In [17], thetotal variation kernel is taken to replace R,

which is an image deblurring kernel. To simplify the algorithm, problem in (4) is separated by minimizing

$$\varepsilon_{fusion}^2(Z) = \frac{1}{2}\sum_{m=1}^{M}(IQZ - L_m)^T\, O_m\,(IQZ - L_m) \quad (5)$$

where the blurred version of the target image denoted by Z andO_m is the weight matrix, followed by minimizing a deblurring equation [11], i.e.

$$\epsilon_{RE}^2(X) = \|JX - Z\|_2^2 + \lambda R(Z) \quad (6)$$

A pixel wise solution of equation (5) can be obtained as

$$\hat{z} = \frac{\sum_{m=1}^{M}\sum_{(r,s)\epsilon N(p,q)} Y_m^r(r,s)K_m^r(r,s)}{\sum_{m=1}^{M}\sum_{(r,s)\epsilon N(p,q)} K_m^r(r,s)} \quad (7)$$

where the superscript r refers to the High Resolution (HR) coordinate. Instead of calculating the target pixel position in neighborhood frames, thealgorithm estimateall possible pixel positions; therefore, motion estimation is avoided [11]. Equation (7) apparently resembles (1), but (7) has some differences ascompared with (1). The weight estimation in (2) should bemodified because size of high resolution image andK's corresponding matrix O must have to be ofthe same size. Therefore, before computing K a simple upscaling process is needed for patching V. The totalnumber of pixel Y in (7) should be equal to the number ofweights K.

Thus, a zero-padding interpolation is applied to L before fusing the images [11].

III. PROPOSED TECHNIQUE

In the proposed algorithm (DT-CWT-NLM-RE) [1], decomposition ofthe LR input image in different subbands (i.e., Ci and W_i^j , where i ∈ {A,B,C,D} and j ∈ {1, 2, 3}) by using DT-CWT, as shown in Fig. 1. Ci denotes the image coefficient subbands values, and W_i^j denotes wavelet coefficient subbands values.The subscripts A denotes the even-row and even-column index, B denotes the odd-row and even column index, C denotes the even-row and odd-column index, and D denotes odd-row and odd-column index, whereas h represent the low-pass and g represent the high-pass filters. The superscript e for even and o for odd indices.

W_i^j values are interpolated by factor β using the bicubicinterpolation and combined with the β/2-interpolated low resolution input image. Since Ci contains low-pass-filtered image losing high-frequency information of the LR input image. So for that we have used the low resolution input image instead of Ci.Although the DT-CWT is having the property of shift invariance [14], however, it may produce artifacts after the interpolation of W_i^j Therefore, to reduce these artifacts, NLM filtering is used.

All interpolated W_i^j values are passed through the NLM filter.Then; we apply the inverse DT-CWT decomposition to these filtered subbandsalong with the interpolated low resolution input image to reconstructthe high resolution image. The results will show better performance of proposed DT-CWT-NLM algorithm by comparing PSNR, and MSE [18].

IV. RESULTS

There are majorly two commonly used measures:Mean-Squared Error and Peak Signal-to-Noise Ratio. The mean-squared error (MSE) between two images $g(x,y)$ and $\hat{g}(x,y)$ is given by:

$$e_{MSE} = \frac{1}{MN}\sum_{n=1}^{M}\sum_{m=1}^{N}[\hat{g}(n,m) - g(n,m)]^2 \qquad (8)$$

Peak Signal-to-Noise Ratio (PSNR) is given by:

$$\mathrm{PSNR} = -10\log_{10}\frac{e_{MSE}}{S^2} \qquad (9)$$

where S is the maximum pixel value. PSNR is measured in decibels (dB).
The image of Washington DC Digital Aerial Photography −0.15 mis taken here for comparison with existing RE techniques. Here by down samplingthe original HR image by a factor of 4, the input LR image is obtained. Results are shown in fig. (2)

TABLE I
COMPARISON OF THE EXISTING AND PROPOSED TECHNIQUESFOR THE "WASHINGTON DC" IMAGE

ALGORITHM	MSE	PSNR(dB)
SWT-RE[8]	0.0464	13.3332
DWT-RE[7]	0.0419	13.7802
SWT-DWT-RE[8]	0.0335	14.7527
WIR-PDE-RE[5]	0.0269	15.6970
DT-CWT-RE[9]	0.0242	16.1576

V. CONCLUSION

An RE technique based on DT-CWT, bicubic interpolator and Non Local Mean filter has been modified. In this technique DT-CWT decomposes the input LR image. DT-CWT is used instead of DWT since it is almost shift invariant and produce fewer artifacts than DWT. Bicubic interpolator interpolates wavelet coefficients and the LR input image. NLM filtering here used to overcome the artifacts generated by decomposition due to DT-CWT and for the further enhancement of performance is compared in terms of PSNR, MSE for the proposed technique. Hence this technique will give better results than the conventional algorithms.

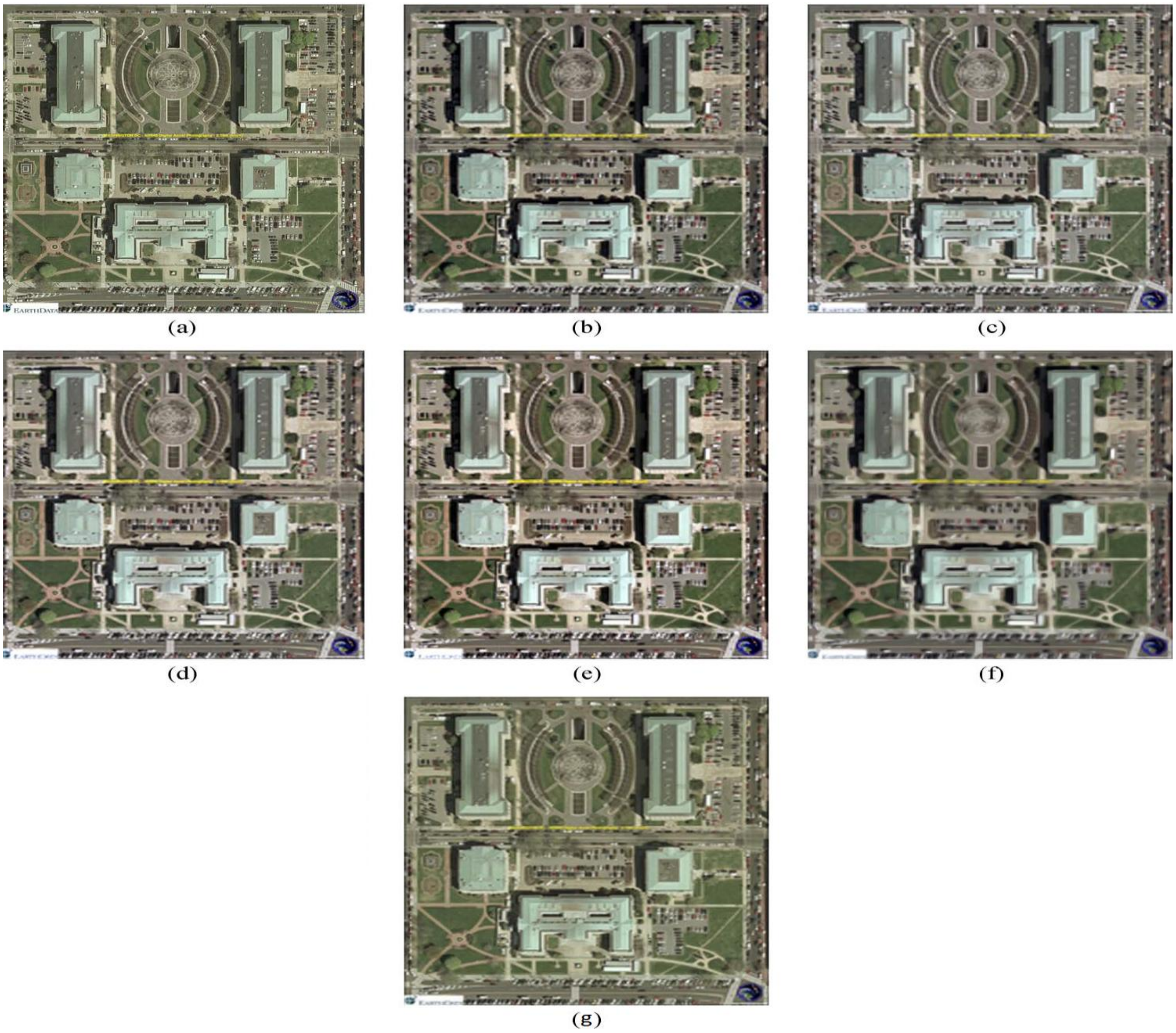

Fig. 2. (a) Original “Washington DC” image. (b) Input image. (c) SWT-RE. (d) DWT-RE. (e) SWT-DWT-RE. (f) VVIR-PDE-RE. (g) DT-CWT-RE

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