International Journal of Engineering and Technical Research (IJETR)
ISSN: 2321-0869, Volume-1, Issue-8, October 2013

Wavelet Transform Techniques for Image Resolution Enhancement

Prasanth C.R, Sreeja K.S

Abstract— **Images are being used in many fields of research. One of the major issues of images is their resolution. In this paper we are studying different image resolution enhancement techniques that use Wavelet Transform (WT).**

Basis functions of the WT are small waves located in different times. They are obtained using scaling and translation of a scaling function and wavelet function Therefore, the WT is localized in both time and frequency. In this paper we are comparing different image resolution enhancement techniques those using Wavelet Transform.

***Index Terms*— Image Interpolation, Peak signal-to-noise ratio (PSNR), Wavelet Zero Padding (WZP), Cycle Spanning (CS), Dual-Tree Complex Wavelet Transform (DT-CWT), Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT).**

I. Introduction

Resolution has been frequently referred as an important property of an image. Images are being processed in order to obtain super enhanced resolution. One of the commonly used techniques for image resolution enhancement is Interpolation. Interpolation has been widely used in many image processing applications. Interpolation in image processing is a method to increase the number of pixels in a digital image. Traditionally there are three techniques for image interpolation namely Linear, Nearest Neighbor and Bicubic. Nearest Neighbor result in significant ―Jaggy‖ edge distortion [1]. The Bilinear Interpolation result in smoother edges but somewhat blurred appearance overall [1]. Bicubic Interpolation look's best with smooth edges and much less blurring than the bilinear result [1].

By applying the 1-D discrete wavelet transform (DWT) along the rows of the image first, and then along the columns to produce 2-D decomposition of image[8]. DWT produce four subbands low-low(LL), low- high(LH), high-low(HL)and high-high(HH).By using these four subands we can regenerate original image[8]. Theoretically, a filter bank shown in Fig. 1 should work on the image in order to generate different subband frequency images.

Manuscript received October 15, 2013.

Sreeja K S, currently doing M-Tech in Electronics with specialization in Signal Processing in Govt.College of Engineering Cherthala under Cochin University of Science and Technology,Kerala,India

Prasanth C.R, currently pursing Mtech in Digital signal processing from Govt. Engg college cherthala under Cochin University of science and technology

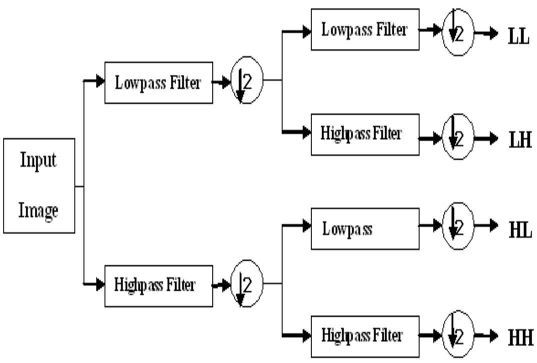

Fig 1. Block diagram of DWT Filter Banks of level 1 [8]

II. Regularity-Preserving Image Interpolation

Traditional interpolation methods work in the time domain. As stated in [2], the regularity-preserving interpolation technique synthesizes a new wavelet subband based on the known wavelet transform coefficients decay. The lowpass output of a wavelet analysis stage can be considered as the image to be interpolated. The original image can given as input to a single wavelet synthesis stage along with the corresponding high frequency subbands to produce an image interpolated by a factor of two in both directions. The creation of unknown high-frequency subbands is necessary in the regularity-preserving interpolation strategy. Two-step process is carried out to obtain the unknown high-frequency subbands separably. In First step, in each row edges with significant correlation across scales are identified.
Then near these edges the rate of decay of the wavelet coefficients is extrapolated to approximate the high-frequency subband required to resynthesize a row of twice the original size. In second step, the same procedure as in first step is then applied to each column of the row-interpolated image. Block diagram of interpolation system for 1-D row and column signals is shown in Fig. 2.

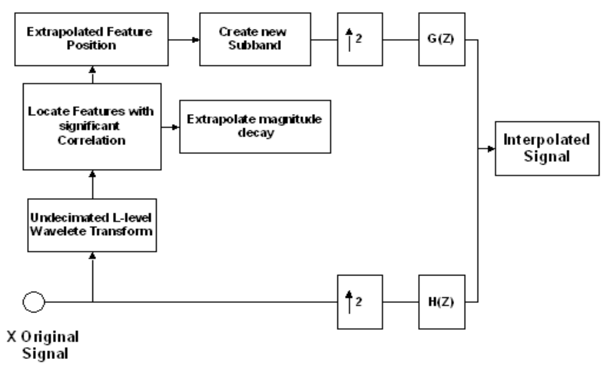

Fig 2. Block diagram of interpolation system for 1-D row and column signals[2].

III. NEW EDGE-DIRECTED INTERPOLATION

A hybrid approach produced by combining bilinear interpolation and covariance-based adaptive interpolation is used in [3] to reduce the overall computational complexity. Traditional linear interpolation schemes (e.g., bilinear and bicubic) based on space-invariant models are not able to capture the fast evolving statistics around edges and consequently produce interpolated images with blurred edges and annoying artifacts. Linear interpolation is good due to it's computational simplicity but not good due to it's the performance issue. Geometric regularity is very much important for the visual quality of a natural image such as the sharpness of edges and the freedom from artifacts. Without the loss of generality, Xin Li & Michael T. Orchard assume that the low-resolution image $X_{i,j}$ of size $H \times W$ directly comes from of size of $2H \times 2W$, i.e. $Y_{2i,2j} = X_{i,j}$.

They use the following basic problem to introduce their new interpolation technique: How do they interpolate the interlacing lattice $Y_{2i+1,2j+1}$ from the lattice $Y_{2i,2j} = X_{i,j}$. They constrain their selves to the fourth-order linear interpolation.

$$Y_{2i+1,2j+1} = \sum_{k=0}^{1}\sum_{l=0}^{1}\alpha_{2k+l}Y_{2(i+k),2(j+l)}$$

The above equation is core part of this algorithm invented in [3]. In order to manage the computational complexity, they used the following hybrid approach: covariance-based adaptive interpolation is only applied to edge pixels (pixels near an edge); for nonedge pixels (pixels in smooth regions), they still use simple bilinear interpolation. Such a hybrid approach is based on the observation that only edge pixels benefit from the covariance-based adaptation and edge pixels often consist of a small fraction of the whole image. A pixel is considered as an edge pixel if an activity measure (e.g., the local variance estimated from the nearest four neighbors) is above a preselected threshold value . Since the computation of the activity measure is typically negligible when compared to that of covariance estimation, dramatic reduction of complexity can be achieved for images containing a small fraction of edge pixels. Xin Li & Michael T. Orchard in [3] have found that the percentage of edge pixels ranges from 5% to 15% for the test images used in their experiments, which implies a speed-up factor of 7–20 [3].

IV. WZP-CS BASED IMAGE RESOLUTION ENHANCEMENT

As stated in[4],[8] this algorithm consists of two main steps as follows: Step **1)** an initial approximation to the unknown high resolution image is generated using wavelet domain zero padding (WZP).Step **2)** The cycle-spinning methodology is adopted to operate the following tasks:

i) Using high resolution image in part (1) a number of low resolution images are generated by spatial shifting, wavelet transforming, and discarding the high frequency subbands.

ii)N high resolution images are obtained by applying the WZP processing to all those low resolution images.

iii) The final high resolution image is reconstructed by re-aligning and averaging these intermediated high resolution images. Fig. 3 shows the block diagram of the WZP- and CS-based image super resolution[4].

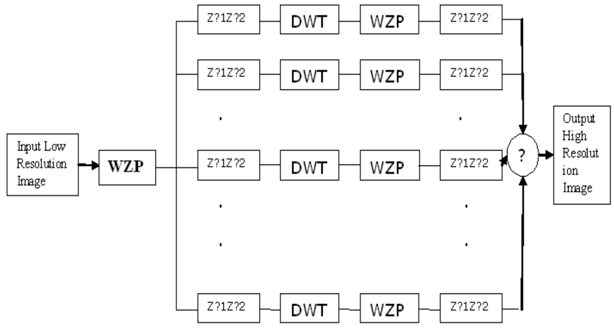

Fig3. Block Diagram of the WZP-and-CS-based image Resolution Enhancement [4].

V. DT-CWT BASED IMAGE RESOLUTION ENHANCEMENT

In this technique, as stated in [5],[8] dual-tree CWT (DT-CWT) is used to decompose an input image into different subband images. DT- CWT is used to decompose an input low-resolution image into different subbands. Then, the high-frequency subband images and the input image are interpolated, followed by combining all these images to generate a new high-resolution image by using inverse DT-CWT. The resolution enhancement is achieved by using directional selectivity provided by the CWT, where the high-frequency subbands in six different directions contribute to the sharpness of the high-frequency details, such as edges. Fig. 4 shows details of this technique, where the enlargement factor through the resolution enhancement is α.

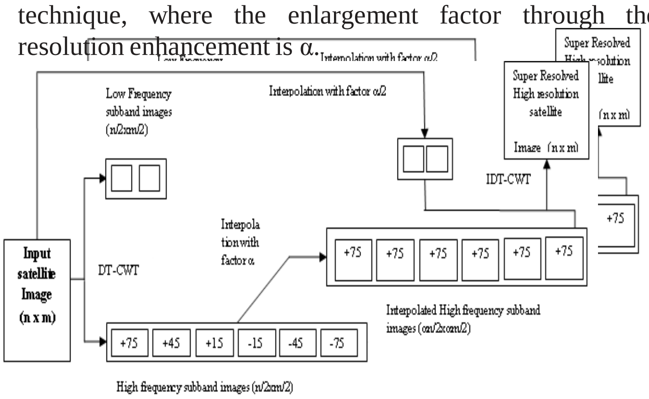

Fig4. Block Diagram of DT-CWT Based Image Resolution Enhancement [5]

The dual-tree complex wavelet transform (CWT) is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties: It is nearly shift invariant and directionally selective in two and higher dimensions. It achieves this with a redundancy factor of only 2d for d-dimensional signals, which is substantially lower than the undecimated DWT. The multidimensional (M-D) dual-tree CWT is nonseparable but is based on a computationally efficient, separable filter bank (FB).A method for image resolution enhancement from a single LR image using the dual-tree complex wavelet. The rough estimate of the HR image is decomposed to estimate the complex-valued high-pass wavelet coefficients for the input LR image. The estimated complex wavelet coefficients are used, together with the input LR image, to reconstruct the resultant HR image by employing IDT-CWT.Image resolution enhancement is a usable preprocess for many satellite image processing applications.

Image resolution enhancement is a usable preprocess for many satellite image processing applications, such as vehicle recognition, bridge recognition, and building recognition to name a few. Image resolution enhancement techniques can be categorized into two major classes according to the domain that they are applied in: 1) image domain and 2) transform domain. The techniques in the image domain use the statistical and geometric data directly extracted from the input image itself while transform-domain techniques use transformations such as decimated discrete wavelet transform (DWT) to achieve the image resolution enhancement. The decimated DWT has been widely used for performing image resolution enhancement. A common assumption of DWT-based image resolution enhancement is that the low-resolution (LR) image is the low-pass-filtered subband of the wavelet-transformed high-resolution (HR) image. This type of approach requires the estimation of wavelet coefficients in sub bands containing high-pass spatial frequency information in order to estimate the HR image from the LR image.

In order to estimate the high-pass spatial frequency information, many different approaches have been introduced.The high-pass coefficients with significant magnitudes are estimated as the evolution of the wavelet coefficients among the scales. The performance is mainly affected from the fact that the signs of the estimated coefficients are copied directly from parent coefficients without any attempt being made to estimate the actual signs. This is contradictory to the fact that there is very little correlation between the signs of the parent coefficients and their descendants. As a result, the signs of the coefficients estimated using extreme evolution techniques cannot be relied upon. A hidden Markov tree (HMT)-based method models the unknown wavelet coefficients as belonging to mixed Gaussian distributions which are symmetrical about the zero mean. HMT models are used to determine the most probable state for the coefficients to be estimated. The performance also suffers mainly from the sign changes between the scales. The decimated DWT is not shift invariant, and as a result, suppression of wavelet coefficients introduces artifacts into the image which manifest as ringing in the neighborhood of discontinuities. In order to combat this drawback in DWTbased image resolution enhancement, a cycle-spinning methodology was adopted. The perceptual and objective quality of the resolution-enhanced images by their method compares favorably with that in recent methods in the field. A dual-tree complex wavelet transform (DT-CWT) is introduced to alleviate the drawbacks caused by the decimated DWT . It is shift invariant and has improved directional resolution when compared with that of the decimated DWT. Such features make it suitable for image resolution enhancement. In this letter, a complex wavelet-domain image resolution enhancement algorithm based on the estimation of wavelet coefficients at HR scales is proposed. The initial estimate of the HR image is constructed by applying a cycle-spinning methodology in the DT-CWT domain. It is then decomposed using the one-level DT-CWT to create a set of high-pass coefficients at the same spatial resolution of the LR image. The high-pass coefficients, together with the LR image, are used to reconstruct the HR image using inverse DT-CWT (IDT-CWT).

The DT-CWT is a combination of two real-valued decimated DWTs. The ordinary decimated DWT is shift variant due to the decimation operation exploited in the transform. As a result, a small shift in the input signal can result in a very different set of wavelet coefficients. For that, Kingsbury introduced a new kind of wavelet transform, called the DT-CWT which exhibits shift-invariant property and improves directional resolution when compared with that of the decimated DWT.

The DT-CWT also yields perfect reconstruction by using two parallel decimated trees with real-valued coefficients generated at each tree. The 1-D DT-CWT decomposes the input signal $f(x)$ by expressing it in terms of a complex shifted and dilated mother wavelet $\Psi(x)$ and a scaling function $\Phi(x)$, i.e.,

$$f(x) = \sum_{l \in Z} s_{j_0,l} \Phi_{j_0,l}(x) + \sum_{j \geq j_0} \sum_{l \in Z} c_{j,l} \Psi_{j,l}(x)$$

where Z is the set of natural numbers, j and l refer to the index of shifts and dilations, respectively, $sj0,l$ is the scaling coefficient, and cj,l is the complex wavelet coefficient with $\Phi j0,l(x) = \Phi rj\ 0,l(x) + \sqrt{-1}\Phi i\ j0,l(x)$ and $\Psi j,l(x) = \Psi r \sqrt{}\ j,l(x) + -1\Psi i\ j,l(x)$, where the superscripts r and i denote the real and imaginary parts, respectively. In the 1-D DT-CWT case, the set $\{\Phi rj\ 0,l,\Phi i\ j0,l,\Psi rj\ 0,l,\Psi i\ j0,l$
$\}$ forms a tight wavelet frame with double redundancy. The real and imaginary parts of the 1-D DT-CWT are computed using separate filter banks with filters $h0$ and $h1$ for the real part and $g0$ and $g1$ for the imaginary part. Similar to the 1-D DT-CWT, the 2-D DT-CWT decomposes a 2-D image $f(x, y)$ through a series of dilations and translations of a complex scaling function and six complex wavelet functions $\Psi\theta\ j,l$,

METHOD

Let us consider the unknown $2H \times 2W$ HR image XH and the known $H \times W$ LR image XL. The aim of the enhancement is to generate an estimated HR image ˆXH of the unknown HR image XH using the known LR image XL. Let us further assume that the one-level DT-CWT decomposition of a $2H \times 2W$ image X results in a matrix of DT-CWT(X) = [LPX HPX], and the IDT-CWT of [LPX HPX] reconstructs the signal X perfectly, i.e., IDT-CWT([LPX HPX]) = X. LPX is a matrix of size $H \times W$ which is the complex-valued low-pass subband resulting
from the one-level DT-CWT decomposition of image X, and HPX is a matrix of size $H \times W \times 6$ which is the collection of all six complex-valued high-pass subbands resulting from the one-level DT-CWT decomposition of image X.

For a given LR image XL, the proposed resolution enhancement method is made up of the following four main steps: 1) Generate the initial estimate (Y) of the HR image; 2) decompose Y using one-level DT-CWT to create a low and high-pass matrix structure [LPY HPY]; 3) formulate a matrix structure [XL HPY] using [LPY HPY] and the input LR image XL; and 4) generate the HR image by employing the IDT-CWT on [XL HPY]. The first step employs the cycle-spinning algorithm in the DT-CWT domain to create an initial estimate of the unknown HR image.

The second step is the estimation of the high-pass coefficients for the input LR signal XL. The initial estimate Y is decomposed using the one-level DT-CWT to create one complex valued low-pass sub band and six complex-valued high-passsubbands with the same spatial resolution as that of XL, i.e.,

DT-CWT(Y) = [LPY HPY].

In the final step, the input LR image, together with the complex-valued high-pass sub bands HPY extracted from the one-level DT-CWT decomposition of Y, is used to create the HR image by employing IDT-CWT, i.e.,

$$\hat{X}_H = \text{IDT-CWT}\left([X_L\ HP_Y]\right).$$

The dual-tree CWT is a valuable enhancement of the traditional real wavelet transform that is nearly shift invariant and, in higher dimensions, directionally selective. Since the real and imaginary parts of the dual-tree CWT are, in fact, conventional real wavelet transforms, the CWT benefits from the vast theoretical, practical, and computational resources that have been developed for the standard DWT. A method for image resolution enhancement from a single LR image using the dual-tree complex wavelet. The initial rough estimate of the HR image is decomposed to estimate the complex-valued high-pass wavelet coefficients for the input LR image. The estimated complex wavelet coefficients are used, together with the input LR image, to reconstruct the resultant HR image by employing IDT-CWT.Thus image resolution enhancement can be effectively achieved by using dual-tree CWT.

VI. IMAGE SUPER RESOLUTION BASED ON INTERPOLATION OF WAVELET DOMAIN HIGH FREQUENCY SUBBANDS AND THE SPATIAL DOMAIN INPUT IMAGE[6]

High-frequency components(i.e. the edges) are main loss of an image after being super-resolved by applying interpolation. This loss occur due to the smoothing caused by interpolation. To increase quality of the super-resolved image, preserving the edges is essential. In [6] work by Hasan Demirel and Gholamreza Anbarjafari, DWT has been employed in order to preserve the high-frequency components of the image. DASR technique uses DWT to decompose an image into different subband images; namely, low-low (LL), low-high (LH), high-low (HL), and high-high (HH).

These subband images contain the high-frequency components of the input image. In the DASR technique, the interpolation is applied to high-frequency subband images.

This technique interpolates the input image as well as the high-frequency subband images obtained through the DWT process. IDWT of the interpolated subband images and the input image produce the final high-resolution output image. In the DASR technique, the employed interpolation method is the same for all subband and the input images. The interpolation technique and the wavelet function are two important factors in determining the quality of the super-resolved images. To measure quality of image PSNR value is used.

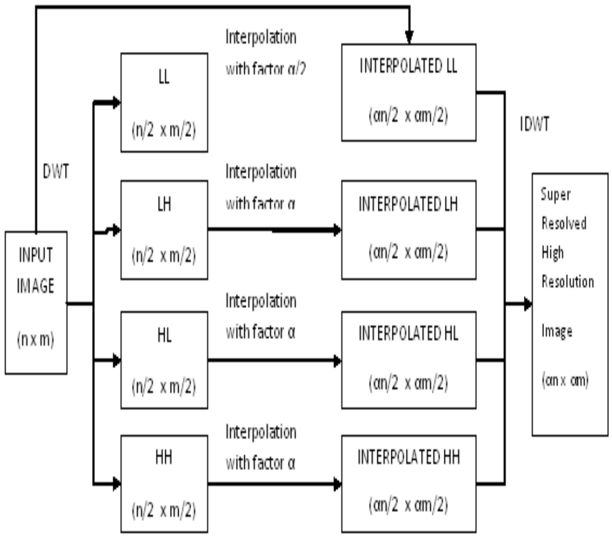

FIG 5. BLOCK DIAGRAM OF IMAGE SUPER RESOLUTION BASED ON INTERPOLATION OF WAVELET DOMAIN HIGH FREQUENCY SUBBANDS AND THE SPATIAL DOMAIN INPUT IMAGE[6]

VII. IMAGE RESOLUTION ENHANCEMENT METHOD USING SWT AND DWT [7]

The main loss in image resolution enhancement by using interpolation is on its high frequency components (i.e., edges), which is due to the smoothing caused by interpolation. Edges plays very important role in image. To increase the quality of the super resolved image, it is essential to preserve all the edges in image. In [7] work, DWT has been employed in order to preserve the high frequency components of the image(i.e. edges). The redundancy and shift invariance of the DWT mean that DWT coefficients are inherently interpolable.In this correspondence, one level DWT (with Daubechies 9/7 as wavelet function) is used to decompose an input image into different sub band images. Three high frequency subbands (LH, HL, and HH) contain the high frequency components of the input image(i.e. edges). In this technique, bicubic interpolation with enlargement factor of 2 is applied to high frequency subband images. Information loss occur due to downsampling in each of the DWT sub bands caused in the respective sub bands. That is why SWT (Stationary Wavelet Transform) is used to minimize this loss.

The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input – so for a decomposition of N levels there is a redundancy of N in the wavelet coefficients. The interpolated high frequency subbands and the SWT high frequency subbands have the same size which means they can be added with each other. The new corrected high frequency subbands can be interpolated further for higher enlargement. Also it is known that in the wavelet domain, lowpass filtering of the high resolution image produce the low resolution image. In other words, low frequency subband is the low resolution of the original image. Therefore, instead of using low frequency subband, which contains less information than the original high resolution image, Hasan Demirel and Gholamreza Anbarjafari [7] are using the input image for the interpolation of low frequency subband image. The quality of the super resolved image increases using input image instead of low frequency subband. Fig. 6 illustrates the block diagram of the used image resolution enhancement technique.

By interpolating input image by 3, and high frequency subbands by 2 and in the intermediate and final interpolation stages respectively, and then by applying IDWT, as illustrated in Fig. 6, the output image will contain sharper edges than the interpolated image obtained by interpolation of the input image directly. This is due to the fact that, the interpolation of isolated high frequency components in high frequency subbands and using the corrections obtained by adding high frequency subbands of SWT of the input image, will preserve more high frequency components after the interpolation than interpolating input image directly.

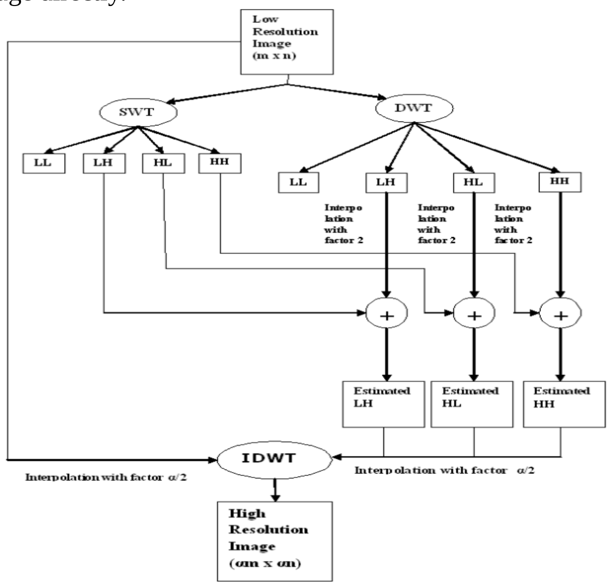

Fig 6. Block diagram of image resolution enhancement method using SWT and DWT [7].

VIII. EXAMPLES AND DISCUSSION

These results are obtained by Hasan Demirel and Gholamreza Anbarjafari as shown in table I from [7]. PSNR and Entropy values are used to measure the quality of an image. Peak signal-to-noise ratio (PSNR) and root mean square error (RMSE) have been implemented in order to obtain some quantitative results for comparison.
PSNR can be obtained by using the following formula :

$$PSNR=10 \log R^2/MSE$$

Where R is the maximum fluctuation in the input image(255 in here as the images are represented by 8 bit , i.e., 8- bit grayscale representation have been used radiometric resolution is 8 bit).

$$MSE=Iavg(i,j)-I—(I,j)/(M*N)$$

Where M and N are the size of the images. *When the two images are identical, the MSE will be zero*.Clearly RMSE is the square root of MSE, hence it is given by

$$RMSE=\sqrt{MSE}$$

And image entropy is a quantity which is used to describe the 'business' of an image. , i.e. the amount of information \which must be coded for by a compression algorithm. Image entropy is calculated with the formula

$$ENTROPY=-\sum P_I \, Log_2 P_I$$

In the above expression, P_i is the probability that the difference between two adjacent pixels is equal to i, and Log_2 is the base 2 logarithms

Techniques	PSNR(dB)
	Lena
Bilinear	26.34
Bicubic	26.86
WZP(db. 9/7)	28.84
Regularity preserving Image Interpolation	28.81
New Edge Directed Interpolation	28.81
HMM	28.86
HMM SR	28.88
WZP-CS	29.27
WZP-CS-ER	29.36
DWT SR	34.79
CWT SR	33.74
SWT SR	32.01
Discrete & Stationary Wavelet Decomposition	34.82

TABLE I
PSNR (DB) VALUES FOR DIFFERENT RESOLUTION ENHANCEMENT TECHNIQUES FROM 128x128 TO 512x5

IX. CONCLUSION

Different image resolution enhancement techniques in wavelet domain are discussed in this paper.WZP , is a simple method we can approach for image resolution enhancement.But efficiency is poor compared to other methods. The DTCWT,DWT,SWT methods gives better image resolution enhancement results.It is cleared from table I values that the image resolution enhancement method using DWT & SWT is giving far better result than any other technique studied in this paper.

APPLICATIONS

The image resolution enhancement techniques discussed in this paper can be apply to noisy images and is mainly applicable to low resolution images.

REFERENCES

[1] Digital Image Processing Using MATLAB (Second Edition) by Rafel C. Gonzalez and Richard E. woods and Steven L. Eddins.
[2] W. Knox. Carey, Daniel. B. Chuang, and S. S. Hemami, ―Regularity Preserving image interpolation,‖ *IEEE Trans. Image Process.*, vol. 8, no. 9, pp. 1295–1297, Sep. 1999.
[3] Xin. Li and Michael. T. Orchard, ―New edge-directed interpolation,‖ *IEEE Trans. Image Process.*, vol. 10, no. 10, pp. 1521–1527, Oct. 2001.
[4] Alptekin. Temizel and Theo. Vlachos, ―Wavelet domain image resolution enhancement using cycle-spinning,‖ *Electron. Lett.*, vol. 41, no. 3, pp. 119–121, Feb. 3, 2005.
[5] Hasan. Demirel and Gholamreza. Anbarjafari, ―Satellite image resolution enhancement using complex wavelet transform,‖ *IEEE Geosci. Remote Sens. Lett.*, vol. 7, no. 1, pp. 123–126, Jan. 2010.
[6] Gholamreza. Anbarjafari and Hasan. Demirel, ―Image super resolution based on interpolation of wavelet domain high frequency subbands and the spatial domain input image,‖ *ETRI J.*, vol. 32, no. 3, pp. 390–394, Jun. 2010.
[7] Hasan. Demirel and Gholamreza. Anbarjafari, ―IMAGE Resolution Enhancement by Using Discrete and Stationary Wavelet Decomposition,‖ *IEEE* IMAGE PROCESSING, VOL. 20, NO. 5, MAY 2011..
[8] Hasan. Demirel and Gholamreza. Anbarjafari, ―Discrete Wavelet Transform-Based Satellite Image Resolution Enhancement,‖ *IEEE Geosciences and Remote Sensing Letter*, VOL. 49, NO. 6, JUNE 2011.Brown, L. D., Hua, H., and Gao, C. 2003. A widget
[9] Dual Tree Complex wavelet Transforms- Ivan W. Selesnick, Richard G. Baraniuk, and Nick G. Kingsbury
[10] Image Resolution Enhancement using Dual Tree Complex Wavelet Transforms- Turgay Celik and Tardi Tjahjadi

Sreeja K S received the B- tech degree from Rajagiri School of Engineering and Technology under Mahatma Gandhi University,Kochi,Kerala,India.She is currently doing M-Tech in Electronics with specialization in Signal Processing in Govt.College of Engineering Cherthala under Cochin University of Science and Technology,Kerala,India

Prasanth C.R Received Diploma in Electronics and Instrumentation from govt. Polytechnic cherthala (first class with distinction, third rank and gold medallist). He passed Btech in Electronics and Communication Engg from M.G university kerala, india.He currently pursing Mtech in Digital signal processing from Govt. Engg college cherthala under Cochin University of science and technology