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IMAGE RESOLUTION ENHANCEMENT BY USING DIFFERENT WAVELET DECOMPOSITIONS

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ABSTRACT: In this paper,the authors propose an image resolution enhancement technique based on interpolation of the high frequency subband images obtained by discrete wavelet transform (DWT) and the input image. The edges are enhanced by introducing an intermediate stage by using stationary wavelet transform (SWT). DWT is applied in order to decompose an input image into different subbands. Then the high frequency subbands as well as the input image are interpolated. The estimated high frequency subbands are being modified by using high frequency subband obtained through SWT. Then all these subbands are combined to generate a new high resolution image by using inverse DWT (IDWT). The quantitative and visual results are showing the superiority of the proposed technique over the conventional and state-of-art image resolution enhancement techniques.

Keywords: *SWT,DWT,IDWT(Inverse discrete wavelet transform).*

1. INTRODUCTION

Resolution has been frequently referred as an important aspect of an image. Images are being processed in order to obtain more enhanced resolution. One of the commonly used techniques for image resolution enhancement is Interpolation. Interpolation has been widely used in many image processing applications such as facial reconstruction, multiple description coding, and super resolution. There are three well known interpolation techniques, namely nearest neighbor interpolation, bilinear interpolation, and bicubic interpolation.

Image resolution enhancement in the wavelet domain is a relatively new research topic and recently many new algorithms have been proposed . Discrete wavelet transform (DWT) is one of the recent wavelet transforms used in image processing. DWT decomposes an image into different subband images, namely low-low (LL), lowhigh (LH), high-low (HL), and high-high (HH). Another recentwavelet transform which has been used in several image processing applications is stationary wavelet transform (SWT). In short, SWT is similar to DWT but it does not use down-sampling, hence the subbands will have the same size as the input image.

In this work, we are proposing an image resolution enhancement technique which generates sharper high resolution image. The proposed technique uses DWT to decompose a low resolution image into different subbands. Then the three high frequency subband images have been interpolated using bicubic interpolation. The high frequency subbands obtained by SWT of the input image are being incremented into the interpolated high frequency subbands in order to correct the estimated coefficients. In parallel, the input image is also interpolated separately.

Finally, corrected interpolated high frequency subbands and interpolated input image are combined by using inverse DWT (IDWT) to achieve a high resolution output image[1]. The proposed technique has been compared with conventional and state-of-art image resolu-tion enhancement techniques. The conventional techniques used are the following:

—interpolation techniques: bilinear interpolation and bicubic interpolation;

—wavelet zero padding (WZP).

The state-of-art techniques used for comparison purposes are the following:

—regularity-preserving image interpolation

—new edge-directed interpolation (NEDI)

—hidden Markov model (HMM)
—HMM-based image super resolution (HMM SR)
—WZP and cycle-spinning (WZP-CS)
—WZP, CS, and edge rectification (WZP-CS-ER)
—DWT based super resolution (DWT SR)
—complex wavelet transform based super resolution (CWT SR)

According to the quantitative and qualitative experimental results, the proposed technique over performs the aforementioned conventional and state-of-art techniques for image resolution enhancement.

2. METHODOLOGY

2.1Interpolation:

One of the commonly used techniques for image resolution enhancement is Interpolation. Interpolation has been widely used in many image processing applications such as facial reconstruction, multiple description coding, and super resolution. There are three well known interpolation techniques, namely nearest neighbor interpolation, bilinear interpolation, and bicubic interpolation. Interpolation is the process of using known data values to estimate unknown data values. Various interpolation techniques are often used in the atmospheric sciences.

2.2Nearest neighbor interpolation:

Nearest-neighbor interpolation (also known as **proximal interpolation** or, in some contexts, **point sampling**) is a simple method of multivariate interpolation in one or more dimensions.Interpolation is the problem of approximating the value for a non-given point in some space when given some colors of points around (neighboring) that point. The nearest neighbor algorithm selects the value of the nearest point and does not consider the values of neighboring points at all, yielding a piecewise-constant interpolant. The algorithm is very simple to implement and is commonly used (usually along with mipmapping) in real-time 3D rendering to select color values for a textured surface[2,4]

2.3Bilinear interpolation:

In computer vision and image processing, bilinear interpolation is one of the basic resampling techniques.In texture mapping, it is also known as bilinear filtering or *bilinear texture mapping*, and it can be used to produce a reasonably realistic image. An algorithm is used to map a screen pixel location to a corresponding point on the texture map. A weighted average of the attributes (color, alpha, etc.) of the four surrounding texels is computed and applied to the screen pixel. This process is repeated for each pixel forming the object being textured.

When an image needs to be scaled up, each pixel of the original image needs to be moved in a certain direction based on the scale constant. However, when scaling up an image by a non-integral scale factor, there are pixels (i.e., *holes*) that are not assigned appropriate pixel values. In this case, those *holes* should be assigned appropriate RGB or grayscale values so that the output image does not have non-valued pixels.

Bilinear interpolation can be used where perfect image transformation with pixel matching is impossible, so that one can calculate and assign appropriate intensity values to pixels. Unlike other interpolation techniques such as nearest neighbor interpolation and bicubic interpolation, bilinear interpolation uses only the 4 nearest pixel values which are located in diagonal directions from a given pixel in order to find the appropriate color intensity values of that pixel.Bilinear interpolation considers the closest 2x2 neighborhood of known pixel values surrounding the unknown pixel's computed location. It then takes a weighted average of these 4 pixels to arrive at its final, interpolated value. The weight on each of the 4 pixel values is based on the computed pixel's distance (in 2D space) from each of the known points[5,6].

2.4Bicupic interpolation:

In mathematics, **bicubic interpolation** is an extension of cubic interpolation for interpolating data points on a two dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear interpolation or nearest-neighbor interpolation. Bicubic interpolation can be accomplished using either Lagrange polynomials, cubic splines, or cubic convolution algorithm.

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In image processing, bicubic interpolation is often chosen over bilinear interpolation or nearest neighbor in image resampling, when speed is not an issue. Images resampled with bicubic interpolation are smoother and have fewer interpolation artifacts.

3.THE WAVELET TRANSFORM:

The Wavelet transform is a transform of this type. It provides the time-frequency representation. (There are other transforms which give this information too, such as short time Fourier transforms, Wigner distributions, etc.)Often times a particular spectral component occurring at any instant can be of particular interest. In these cases it may be very beneficial to know the time intervals these particular spectral components occur. For example, in EEGs, the latency of an event-related potential is of particular interest (Event-related potential is the response of the brain to a specific stimulus like flash-light, the latency of this response is the amount of time elapsed between the onset of the stimulus and the response).Wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. How wavelet transform works is completely a different fun story, and should be explained after short time Fourier Transform (STFT) . The WT was developed as an alternative to the STFT. The STFT will be explained in great detail in the second part of this tutorial. It suffices at this time to say that he WT was developed to overcome some resolution related problems of the STFT, as explained in Part II.

3.1The short term Fourier transform:

There is only a minor difference between STFT and FT. In STFT, the signal is divided into small enough segments, where these segments (portions) of the signal can be assumed to be stationary. For this purpose, a window function "w" is chosen. The width of this window must be equal to the segment of the signal where its stationarity is valid.

This window function is first located to the very beginning of the signal. That is, the window function is located at t=0. Let's suppose that the width of the window is "T" s. At this time instant (t=0), the window function will overlap with the first T/2 seconds (I will assume that all time units are in seconds). The window function and the signal are then multiplied. By doing this, only the first T/2 seconds of the signal is being chosen, with the appropriate weighting of the window (if the window is a rectangle, with amplitude "1", then the product will be equal to the signal). Then this product is assumed to be just another signal, whose FT is to be taken. In other words, FT of this product is taken, just as taking the FT of any signal[2].

The result of this transformation is the FT of the first T/2 seconds of the signal. If this portion of the signal is stationary, as it is assumed, then there will be no problem and the obtained result will be a true frequency representation of the first T/2 seconds of the signal.

The next step, would be shifting this window (for some t1 seconds) to a new location, multiplying with the signal, and taking the FT of the product. This procedure is followed, until the end of the signal is reached by shifting the window with "t1" seconds intervals.

The following definition of the STFT summarizes all the above explanations in one line:

$$STFT_X^{(\omega)}(t,f) = \int_t [x(t) \bullet \omega^*(t-t')] \bullet e^{-j2\pi ft}\, dt$$

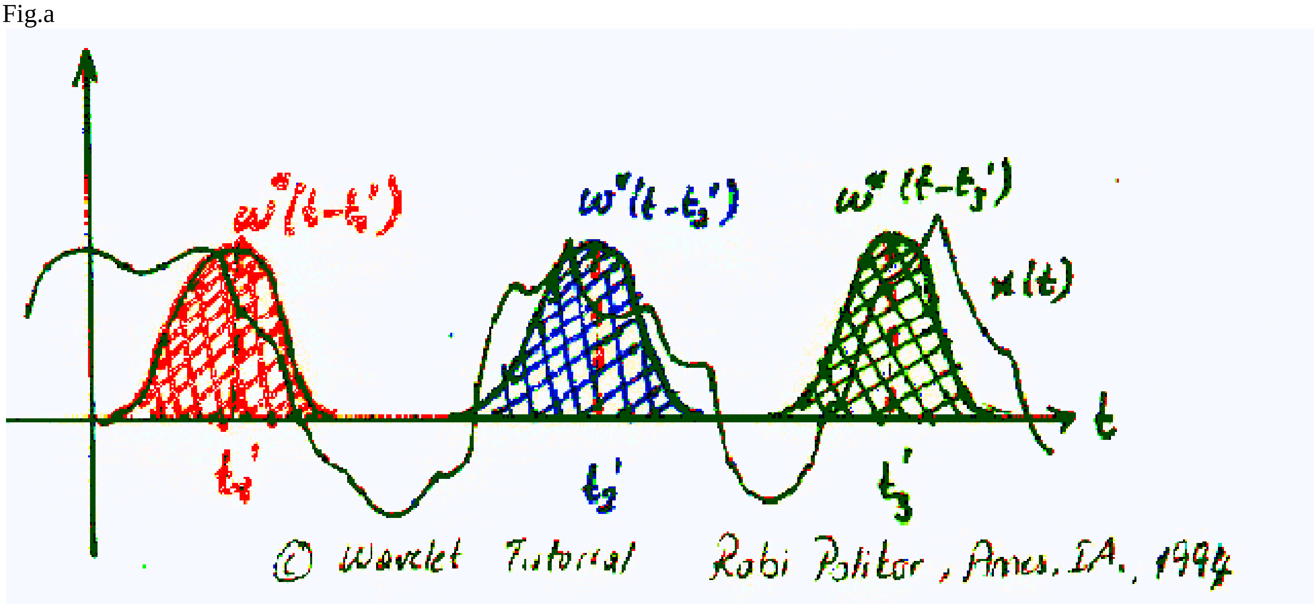
© Wavelet Tutorial Robi Polikar, Ames, IA., 1994 -----(1)

Please look at the above equation carefully. x(t) is the signal itself, w(t) is the window function, and * is the complex conjugate. As you can see from the equation, the STFT of the signal is nothing but the FT of the signal multiplied by a window function.

For every t' and f a new STFT coefficient is computed (Correction: The "t" in the parenthesis of STFT should be "t'". I will correct this soon. I have just noticed that I have mistyped it).

The following figure (fig.a) may help you to understand this a little better:

Fig.a



The Gaussian-like functions in color are the windowing functions. The red one shows the window located at t=t1', the blue shows t=t2', and the green one shows the window located at t=t3'. These will correspond to three different FTs at three different times. Therefore, we will obtain a true time-frequency representation (TFR) of the signal[3].

3.2 The continuous wavelet transform:

The continuous wavelet transform was developed as an alternative approach to the short time Fourier transforms to overcome the resolution problem. The wavelet analysis is done in a similar way to the STFT analysis, in the sense that the signal is multiplied with a function, {\it the wavelet}, similar to the window function in the STFT, and the transform is computed separately for different segments of the time-domain signal. However, there are two main differences between the STFT and the CWT:

1. The Fourier transforms of the windowed signals are not taken, and therefore single peak will be seen corresponding to a sinusoid, i.e., negative frequencies are not computed.

2. The width of the window is changed as the transform is computed for every single spectral component, which is probably the most significant characteristic of the wavelet transform. The continuous wavelet transform is defined as follows

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^*\left(\frac{t-\tau}{s}\right) dt$$

The term wavelet means a small wave. The smallness refers to the condition that this (window) function is of finite length (compactly supported). The wave refers to the condition that this function is oscillatory. The term mother implies that the functions with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet. In other words, the mother wavelet is a prototype for generating the other window functions[5].

The term translation is used in the same sense as it was used in the STFT; it is related to the location of the window, as the window is shifted through the signal. This term, obviously, corresponds to time information in the transform domain. However, we do not have a frequency parameter, as we had before for the STFT. Instead, we have scale parameter which is defined as $1/frequency$. The term frequency is reserved for the STFT.

3.3 The Discrete Wavelet Transform

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The Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. The foundations of DWT go back to 1976 when techniques to decompose discrete time signals were devised[6]. Similar work was done in speech signal coding which was named as sub-band coding. In 1983, a technique similar to sub-band coding was developed which was named pyramidal coding. Later many improvements were made to these coding schemes which resulted in efficient multi-resolution analysis schemes[5]. In CWT, the signals are analyzed using a set of basis functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales.

4.PROPOSED IMAGE RESOLUTION ENHANCEMENT

In image resolution enhancement by using interpolation the main loss is on its high frequency components (i.e., edges), which is due to the smoothing caused by interpolation. In order to increase the quality of the super resolved image, preserving the edges is essential. In this work, DWT has been employed in order to preserve the high frequency components of the image. 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 sub bands (LH, HL, and HH) contain the high frequency components of the input image. In the proposed technique, bicubic interpolation with enlargement factor of 2 is applied to high frequency subband images. Down sampling in each of the DWT sub bands causes information loss in the respective sub bands. That is why SWT is employed to minimize this loss. The interpolated high frequency sub bands and the SWT high frequency sub bands have the same size which means they can be added with each other. The new corrected high frequency sub bands can be interpolated further for higher enlargement. Also it is known that in the wavelet domain, the low resolution image is obtained by low pass filtering of the high 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, we are using the input image for the interpolation of low frequency subband image. Using input image instead of low frequency subband increases the quality of the super resolved image. Fig.4 illustrates the block diagram of the proposed image resolution enhancement technique. By interpolating input image by $\alpha/2$, and high frequency subbands by 2 and α in the intermediate and final interpolation stages respectively, and then by applying IDWT, as illustrated in Fig. 1, 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

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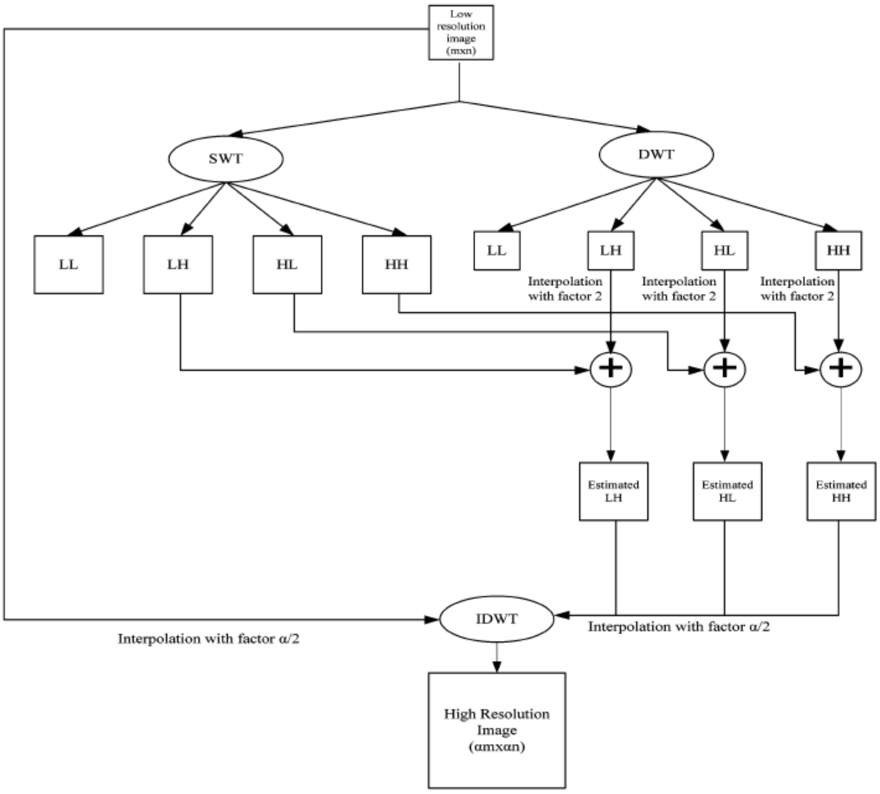

Fig4. Block diagram of the proposed super resolution algorithm.

5. SIMULATION RESULTS

Fig.5.1 shows that super resolved image of Baboon's picture using proposed technique in (d) are much better than the low resolution image in (a), super resolved image by using the interpolation (b), and WZP (c). Note that the input low resolution images have been obtained by down-sampling the original high resolution images. In order to show the effectiveness of the proposed method over the conventional and state-of-art image resolution enhancement techniques, four well-known test images (Lena, Elaine, Baboon, and Peppers) with different features are used for comparison.

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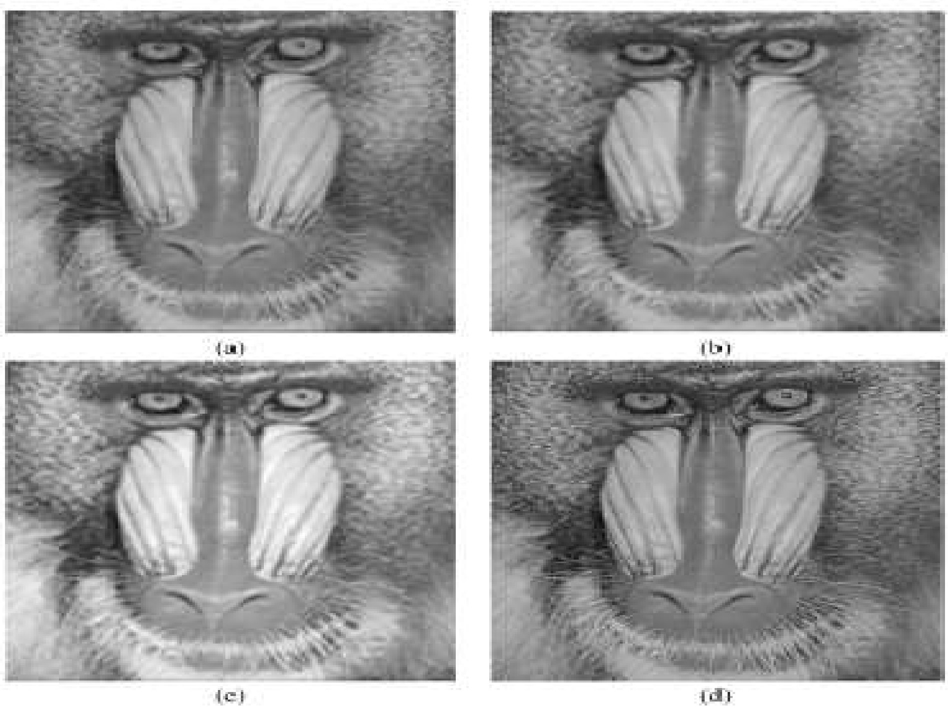

Fig.5.1 (a) Original low resolution Baboon's image. (b) Bicubic interpolated image. (c) Super resolved image using WZP. (d) Proposed technique.

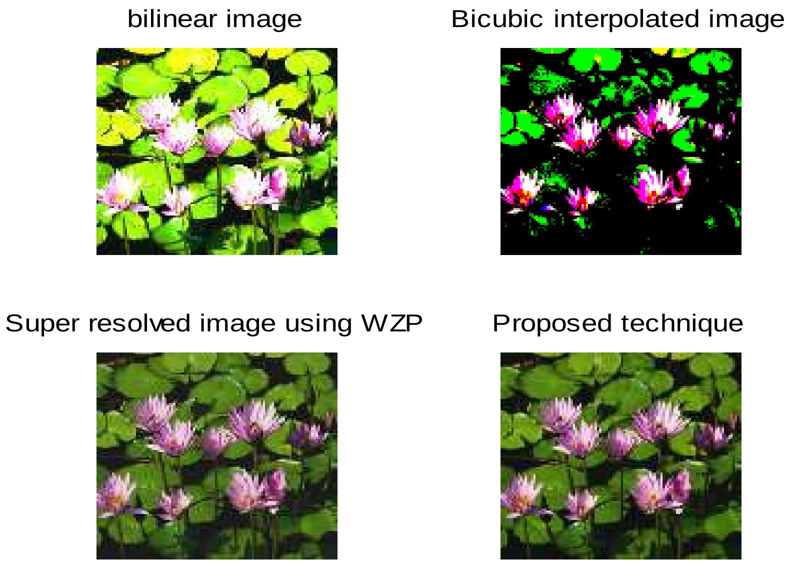

Fig.5.2 (a) Original low resolution Bilinear image. (b) Bicubic interpolated

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image. (c) Super resolved image using WZP. (d) Proposed technique.

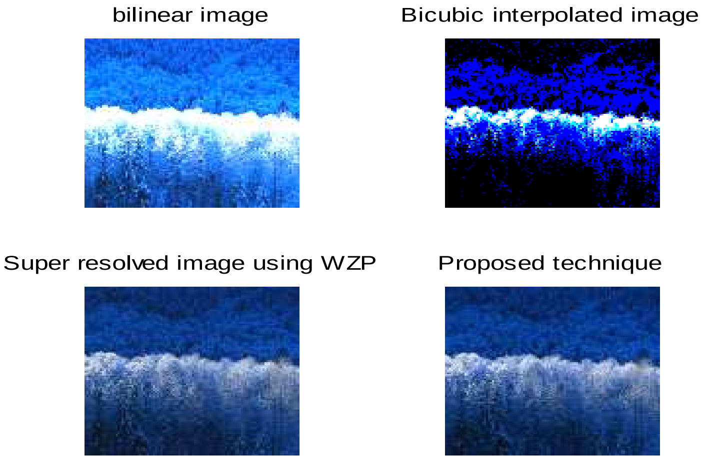

Fig. 5.3 (a) Original low resolution Bilinear image. (b) Bicubic interpolated image. (c) Super resolved image using WZP. (d) Proposed technique

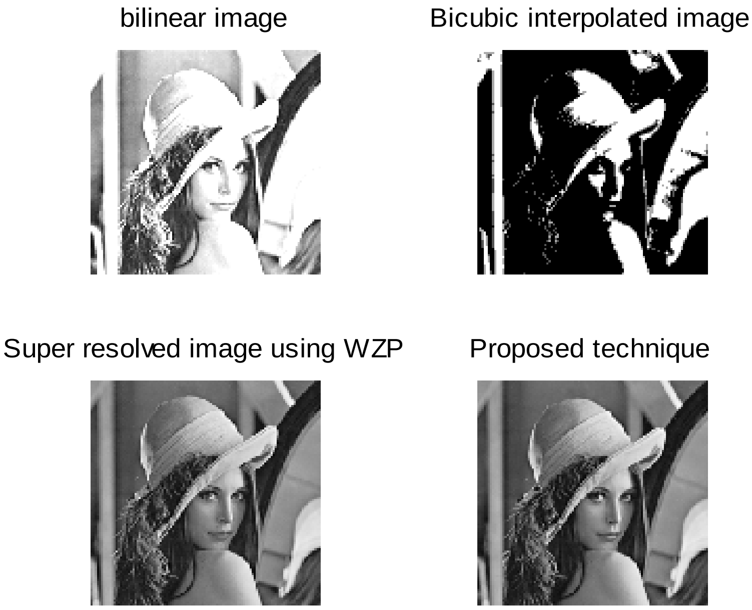

Fig. 5.4 (a) Original low resolution Lena image. (b) Bicubic interpolated image. (c) Super resolved image using WZP. (d) Proposed technique

6. CONCLUSION

This work proposed an image resolution enhancement technique based on the interpolation of the high frequency subbands obtained by DWT, correcting the high frequency subband estimation by usingSWT high frequency subbands, and the input image. The proposed technique uses DWT to decompose an image into different subbands, and then the high frequency subband images have been interpolated. The interpolated high frequency subband coefficients have been corrected by using the high frequency subbands achieved by SWT of the input image. An original image is interpolated with half of the interpolation factor used for interpolation the high frequency subbands. Afterwards all these images have been combined using IDWT to generate a super resolved imaged. The proposed technique has been tested on well-known benchmark images, where their PSNR and visual results show the superiority of proposed technique over the conventional and state-of-art image resolution enhancement techniques.

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