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Image Resolution Enhancement using Bicubic and Spline Interpolation Techniques

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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 method is used to improve the image resolution for different type of images. In this paper we are comparing different image resolution enhancement techniques those using Wavelet Transform.

In this correspondence, 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— **Image Interpolation, Peak signal-to-noise ratio (PSNR), Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT).**

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I. INTRODUCTION

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 they are applied in: 1) image-domain; and 2) transform-domain. The techniques in image-domain use the statistical and geometric data directly extracted from the input image itself [1], [2],while transform-domain techniques use transformations such as decimated discrete wavelet transform to achieve the image resolution enhancement [3]–[6].

The decimated discrete wavelet transform (DWT) has been widely used for performing image resolution enhancement [3]–[5]. A common assumption of DWT-based image resolution enhancement is that the low-resolution (LR) image is the low-passfiltered subband of the wavelet-transformed high-resolution (HR) image. This type of approach requires the estimation of wavelet coefficients in subbands 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. In [3], [4], only 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 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. Hidden Markov tree (HMT) based method in [5] 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 manifests as ringing in the neighbourhood of discontinuities [6]. In order to combat this drawback in DWT-based image resolution enhancement, cycle-spinning methodology was adopted in [6]. The perceptual and objective quality of the resolution enhanced images by their method compare favorably with recent methods [3], [5] in the field.

Dual-tree complex wavelet transform (DT-CWT) is introduced to alleviate the drawbacks caused by the decimated DWT [7]. 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 high resolution scales is proposed. The initial estimate of the HR image is constructed by applying cycle-spinning methodology [6] in 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.

The letter is organized as follows. Section II gives a brief review of the DT-CWT. Section III describes the proposed DT-CWT domain satellite image resolution enhancement algorithm. Section IV provides some experimental results of the proposed approach and comparisons with the approaches in [1], [2], [4], and [6]. Section V concludes the letter.

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 cubic. Nearest Neighbor result in significant ―Jaggy‖ edge distortion. The Bilinear Interpolation result in smoother edges but somewhat blurred appearance overall. Bicubic Interpolation look’s best with smooth edges and much less blurring than the bilinear result .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.DWT produce four sub bands low-low(LL),low-high(LH),high-low(HL)and high-high(HH).By using these four sub bands we can regenerate original image.

II. IMAGE ENHANCEMENT TECHNIQUES

Denote a two-dimensional digital image of gray-level intensities by I. The image I is ordinarily represented in software accessible form as an M × N matrix containing indexed elements I(i, j), where $0 \leq i \leq M - 1$, $0 \leq j \leq N - 1$. The elements I(i, j) represent samples of the image intensities, usually called pixels (picture elements). For simplicity, we assume that these come from a finite integer-valued range. This is not unreasonable, since a finite wordlength must be used to represent the intensities. Typically, the pixels represent optical intensity, but they may also represent other attributes of sensed radiation, such as radar, electron micrographs, x rays, or thermal imagery.

III. POINT OPERATIONS

Often, images obtained via photography, digital photography, flatbed scanning, or other sensors can be of low quality due to a poor image contrast or, more generally, from a poor usage of the available range of possible gray levels. The images may suffer from overexposure or from underexposure, as in the "mandrill" image in Fig. 1(a). In performing image enhancement, we seek to compute J, an enhanced version of I. The most basic methods of image enhancement involve point operations, where each pixel in the enhanced image is computed as a one-to-one function of the corresponding pixel in the original image: J(i, j) = f[I(i, j)]. The most common point operation is the linear contrast stretching operation, which seeks to maximally utilize the available gray-scale range. If a is the minimum intensity value in image I and b is the maximum, the point operation for linear contrast stretching is defined by

$$J(i,j) = \frac{K-1}{b-a}[I(i,j)-a] \quad (1)$$

assuming that the pixel intensities are bounded by $0 \leq I(i, j) \leq K - 1$, where K is the number of available pixel intensities. The result image J then has maximum gray level K - 1 and minimum gray level 0, with the other gray levels being distributed in-between according to Eq. (1). Figure 1(b)shows the result of linear contrast stretching on Fig. 1(a).

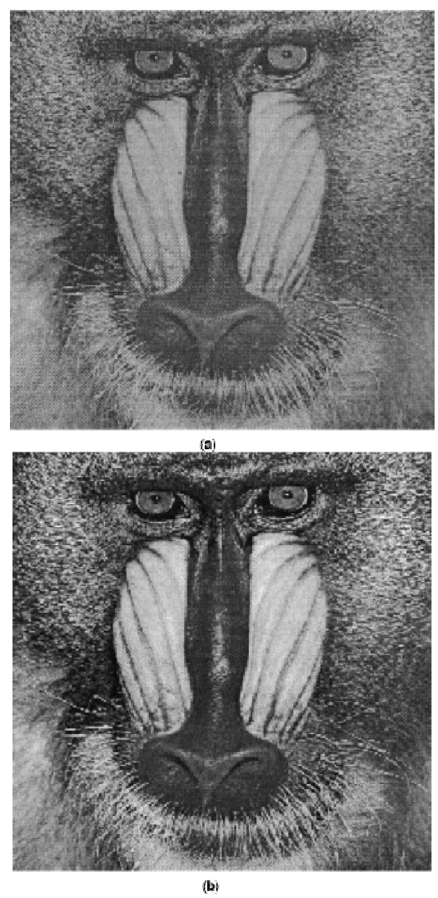

Figure 1. (a) Original "Mandrill" image (low contrast). (b) "Mandrill" enhanced by

linear contrast stretching. (c) "Mandrill"

Several point operations utilize the image histogram, which is a graph of the frequency of occurrence of each gray level in I. The histogram value $H_I(k)$ equals n only if the image I contains exactly n pixels with gray level k. Qualitatively, an image that has a flat or well-distributed histogram may often strike an excellent balance between contrast and preservation of detail. Histogram flattening, also called histogram equalization in Gonzales and Woods (1), may be used to transform an image I into an image J with approximately flat histogram. This transformation can be achieved by assigning

$$J(i,j) = (K-1)P(i,j) \qquad (2)$$

where P(i, j) is a sample cumulative probability formed by using the histogram of I:

$$P(i,j) = \frac{1}{MN}\sum_{k=0}^{I(i,j)} H_1(k) \qquad (3)$$

The image in Fig. 1(c) is a histogram-flattened version of Fig. 1(a).

A third point operation, frame averaging, is useful when it is possible to obtain multiple images G_i, i = 1, . . ., n, of the same scene, each a version of the ideal image I to which deleterious noise has been unintentionally added:

$$\mathbf{G}_i = \mathbf{I} + \mathbf{N}_i \qquad (4)$$

where each noise "image" N_i is an M × N matrix of discrete random variables with zero mean and variance σ^2. The noise may arise as electrical noise, noise in a communications channel, thermal noise, or noise in the sensed radiation. If the noise images are not mutually correlated, then averaging the n frames together will form an effective estimate Î of the uncorrupted image I, which will have a variance of only σ^2/n:

$$\hat{I}(i,j) = \frac{1}{n}\sum_{i=1}^{n} G_i(i,j) \qquad (5)$$

This technique is only useful, of course, when multiple frames are available of the same scene, when the information content between frames remains unchanged (disallowing, for example, motion between frames), and when the noise content does change between frames. Examples arise quite often, however. For example, frame averaging is often used to enhance synthetic aperture radar images, confocal microscope images, and electron micrographs.

IV. WAVELET SHRINKAGE

Recently, wavelet shrinkage has been recognized as a powerful tool for signal estimation and noise reduction or simply de-noising (16). The wavelet transform utilizes scaled and translated versions of a fixed function, which is called a "wavelet," and is localized in both the spatial and frequency domains (17). Such a joint spatial-frequency representation can be naturally adapted to both the global and local features in images. The wavelet shrinkage estimate is computed via thresholding wavelet transform coefficients:

where DWT and IDWT stand for discrete wavelet transform and inverse discrete wavelet transform, respectively (17), and f[ ] is a transform-domain point operator defined by either the hard-thresholding rule or the soft-thresholding rule where the value of the threshold t is usually determined by the variance of the noise and the size of the image. The key idea of wavelet shrinkage derives from the approximation property of wavelet bases. The DWT compresses the image I into a small number of DWT coefficients of large magnitude, and it packs most of the image energy into these coefficients. On the other hand, the DWT coefficients of the noise N have small magnitudes; that is, the noise energy is spread over a large number of coefficients. Therefore, among the DWT coefficients of G, those having large magnitudes correspond to I and those having small magnitudes correspond to N. Apparently, thresholding the DWT coefficients with an appropriate threshold removes a large amount of noise and maintains most image energy. Though the wavelet shrinkage techniques were originally proposed for the attenuation of image-independent white Gaussian noise, they work as well for the suppression of other types of distortion such as the blocking artifacts in JPEG-compressed images (18,19). In this case, the problem of enhancing a compressed image may be viewed as a de-noising problem where we regard the compression error as additive noise. We applied the wavelet shrinkage to enhancing the noisy image shown in Fig. 2(b) and show the de-noised image in Fig. 2(f), from which one can clearly see that a large amount of noise has been removed, and most of the sharp image features were preserved without blurring or ringing effects. This example indicates that wavelet shrinkage can significantly outperform the linear filtering approaches.

Figure 2 illustrates an example of the enhancement of JPEG-compressed images (20). Figure 2(a) shows a part of the original image. Fig. 2(b) shows the same part in the JPEG-compressed image with a compression ratio 32:1, where blocking artifacts are quite severe due to the loss of information in the process of compression. Figure 2(b) reveals the corresponding part in the enhanced version of Fig. 2(b), to which we have applied wavelet shrinkage. One can find that the blocking artifacts are greatly suppressed and the image quality is dramatically improved.

V. LITERATURE SURVAY

PAPER-1 S. SINDHUMOL; A. KUMAR; K. BALAKRISHNAN: A NEW ENHANCEMENT APPROACH FOR ENHANCING IMAGE OF DIGITAL CAMERAS BY CHANGING THE CONTRAST

There are four well-known traditional interpolation techniques namely nearest neighbor, linear, and Lanczos. In [4] using bilinear, bicubic method the PSNR values for Lena's image are 26.34 and 26.86. W. Knox. Carey, Daniel. B. Chuang, and S. S. Hemami in [5] presented the regularity-preserving interpolation technique for image resolution enhancement synthesizes a new wavelet subband based on the known wavelet transform coefficients decay. Which gives PSNR (db) value for Lena's Image as 31.7 [5]. Xin. Li and Michael. T. Orchard in [6] presented a hybrid approach produced by combining bilinear interpolation and covariance-based adaptive interpolation called New Edge-Directed Interpolation Which gives PSNR(db) value for Lena's Image as 28.81 [4]. Alptekin. Temizel and Theo. Vlachos in [7] presented technique named "Wavelet domain image resolution enhancement using cycle-spinning and edge modelling ", which improves PSNR (db) values for Lena's image up to 29.27 [4]. Hasan. Demirel and Gholamreza. Anbarjafari in [8] presented an approach DT- CWT based image resolution enhancement which gives PSNR (db) value for Lena's Image as 33.74 [4]. Gholamreza. Anbarjafari and Hasan. Demirel in [9] presented a method named "Image super resolution based on interpolation of wavelet domain high frequency subbands and the spatial domain input image", whichgives PSNR(db) value for Lena's image up to 34.79 [4]. Hasan. Demirel and Gholamreza.

Anbarjafari in [4] presented new method named "Image Resolution Enhancement by Using Discrete and Stationary Wavelet Decomposition", which give PSNR(db) value for Lena's image as 34.82 [4].

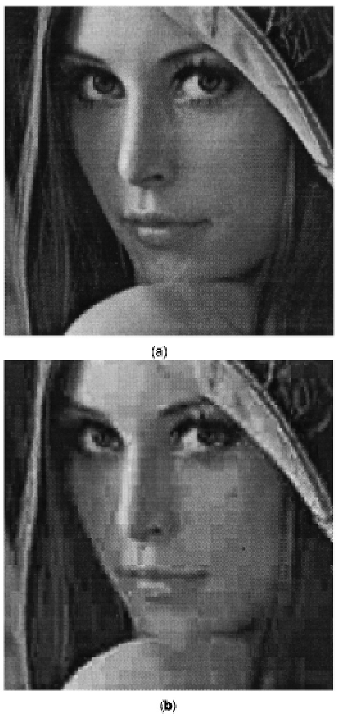

Figure 2. (a) Original "Lena" image. (b) " Lena" JPEG-compressed at 32:1. (c) Wavelet shrinkage applied to Fig. 2b

Regularity-Preserving Image Interpolation

Traditional interpolation methods work in the time domain. As stated in, the regularity-preserving interpolation technique synthesizes a new wavelet sub band 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 sub bands to produce an image interpolated by a factor of two in both directions. The creation of unknown high-frequency sub bands is necessary in the regularity-preserving interpolation strategy.

VI. CONCLUSION AND FUTUREWORK

A method for image resolution enhancement from a single low-resolution image using the dual-tree complex wavelet is presented. The initial rough estimate of the high-resolution image is decomposed to estimate the complex-valued high-pass wavelet coefficients for the input low-resolution image. Estimated complex wavelet coefficients are used together with the input low-resolution image to reconstruct the resultant high-resolution image by employing inverse dual-tree complex wavelet transform. Extensive tests and comparisons with the state-of-the-art methods show the superiority of the method presented in this letter. The proposed resolution enhancement method retains both intensity and geometric features of the low-resolution image. Although the method for image enhancement based on Spline is sufficient but in future efficient methods can be develop for image enhancement which can give more accurate result.

VII. REFERENCES

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