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IMAGE SUPER RESOLUTION USING NON SUB-SAMPLE CONTOURLET TRANSFORM WITH LOCAL TERNARY PATTERN

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Abstract: In this paper, we propose a new technique for feature preserving spatial resolution enhancement of an image captured at low spatial resolution. We use a training database containing low resolution (LR) images and their high resolution (HR) versions. In an image, different features like edges, corners, curves and junctions are important to convey its local geometry.

We use Local Ternary Pattern (LTP) operator to represent texture of an image. The missing high resolution details of the low resolution observation are learnt in form of Non-subsampled Contourlet Transform (NSCT) coefficients of the high resolution images in the training database. We demonstrate the effectiveness of the proposed technique by conducting experiments on real world gray scale images. The results are compared with existing learning-based approaches. The proposed technique can be used in applications such as medical imaging, remote surveillance, wildlife sensor networks where the transmission bandwidth, the camera cost and the memory are main constraints.

Keywords: Non-Subsampled Contourlet Transform(NSCT), Local Ternary Pattern (LTP), Super-Resolution (SR)

I. INTRODUCTION

In the field of photogrammetry, high resolution (HR) images are often desired. HR imaging offers more details that can be useful for better analysis, interpretation and classification of information in an image. One way to obtain HR images depends on hardware solution. High precision optics and charge coupled devices (CCDs) can be used to obtain HR images directly from the camera. But, this solution is not appropriate for general purpose commercial applications due to application specific limitations such as cost, memory, sensor dimensions and shot noise, transmission bandwidth etc. Therefore, many algorithmic approaches are designed to obtain HR images. Super-Resolution (SR) methods attempt to recover a high resolution image from one or more low resolution (LR) images. Methods for SR can be classified into two main categories: (i) Classical Multi-image SR and (ii) Example-based SR. We use a non-subsampled contourlet transform (NSCT) to learn its coefficients for the missing high frequency

details from the detailed sub-bands of high resolution training images in the database. NSCT is a flexible and efficient transform. This fully shift-invariant, multiscale, and multidirection expansion transform is effective for images with smooth contours which allows different angular resolution at different scale and direction. NSCT is efficient in image denoising and image enhancement. In the proposed approach, NSCT is used as the multiscale transform (MST) tool to provide a better representation of the contours and overcome limitations of DWT and DCT.

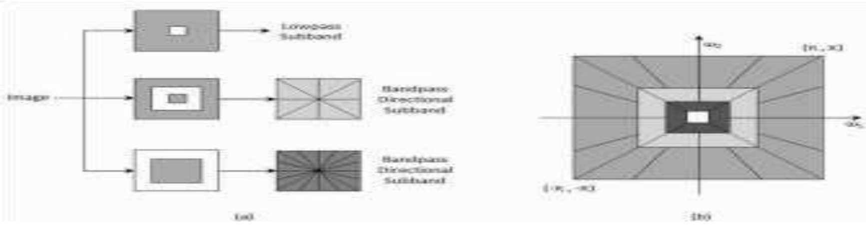

Fig.1. Non-subsampled contourlet transform. (a)NSFB structure that implements the NSCT.(b)Idealized frequency partitioning obtained with the NSCT.

The remainder of the paper is organized as follows.

We briefly describe non-subsampled contourlet transform (NSCT) and filter banks used in it in section II. We then discuss about local Ternary pattern (LTP) operator in section III. We describe different steps of the proposed algorithm in Section IV. It is followed by Section V, where we describe our experimental setup, training database and present our results for real world images. We finally conclude the paper in Section VI with a summary of the obtained results.

II. NON-SUBSAMPLED CONTOURLET TRANSFORM

The non-subsampled contourlet transform (NSCT) is a shiftinvariant version of contourlet transform. NSCT has excellent properties in the process of image decomposition including shift invariance, multiscale and multidirection [25]. This efficient and flexible transform is effective for images with smooth contours which allows different angular resolution at different scales and directions [8]. Fig. 1(a) displays an overview of the NSCT. Fig. 1(b) illustrates the structure consisting of a bank of filters which splits the 2-D frequency plane in the subbands. The NSCT is divided into two shiftinvariant parts: 1) a non-subsampled pyramid structure that gives the multiscale property and 2) a non-subsampled DFB structure that ensures directionality.

A. Non-subsampled Pyramid (NSP)

The multiscale property of the NSCT is obtained by NSP that achieves a sub-band decomposition similar to that of the Laplacian pyramid. It uses two-channel non-subsampled 2-D filter banks. Fig. 2(a) illustrates the non-subsampled pyramid (NSP) decomposition. For each subsequent stage, the filters are obtained by upsampling the filters of the first stage. The multiscale property is achieved without using additional filter design. A similar decomposition can be obtained by removing the downsamplers and upsamplers in the Laplacian pyramid and then upsampling the filters accordingly. Thus, certain parts of the noise spectrum in the processed pyramid coefficients has been filtered [9], [10].

B. Non-subsampled Directional Filter Bank (NSDFB)

The critically-sampled two-channel fan filter banks and resampling operations have been combined to construct NSDFB. This results in a tree-structured filter bank that splits the 2D

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frequency plane into directional wedges. A nonsubsampled DFB (NSDFB) obtains a shift-invariant directional expansion.

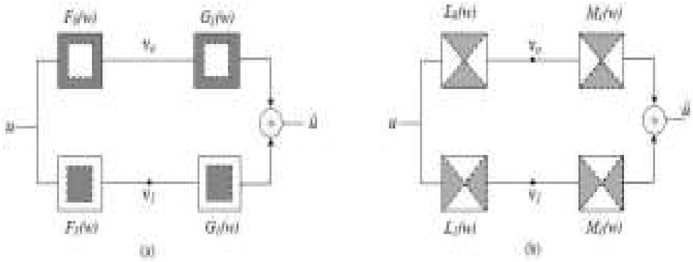

Fig. 2. Non-subsampled contourlets and filter banks (a) Pyramid NSFB.(b) Directional NSFB

The NSDFB is constructed by eliminating the downsamplers and upsamplers in the DFB. This is done by switching off the downsamplers/upsamplers in each two-channel filter bank in the DFB tree structure and upsampling the filters accordingly. Thus, a tree composed of two-channel non-subsampled filter banks (NSFBs) is obtained. Fig. 2(b) illustrates the on subsampled DFB decomposition [11].

The NSCT is constructed by combining the NSP and the NSDFB as shown in Fig. 1(a). The frame elements are localized in space and oriented along a discrete set of directions. The NSCT offers flexibility because it allows any number of directions in each scale. We observe that there are three classes of pixels in the transform coefficients: strong edges, weak edges and noise. The strong edges correspond to the pixels having large magnitude coefficients in all sub-bands. The weak edges correspond to the pixels having large magnitude coefficients in some directional sub-bands but small magnitude coefficients in other directional sub-bands within the same scale.

II. LOCAL TERNARY PATTERN

The Local Ternary Pattern (LTP) at a point c is defined by:

$$\mathrm{LTP(C)} = \sum_{k=0}^{7} 3^k s(I_k - I_c) \qquad (3)$$

$$\mathrm{h(u\ ,\ i)} = \begin{cases} -1\ , & (u-i) < -t \\ 1\ , & (u-i) > t \\ 0\ , & else \end{cases} \qquad (4)$$

The LTP encoding process is illustrated in fig.2(b).However, in LTP, calculations becomes huge. So LTP can be converted into two Local Binary Patterns,namely Up LTP and Down LTP. Mathematically, let:

$$LTP(C) = \sum_{k=0}^{7} 2^k s(I_k - I_c) \qquad (5)$$

$$\mathrm{h_{up}(u\ ,\ i)} = \begin{cases} 1\ , (u-i) > t \\ 0\ , \quad else \end{cases} \qquad (6)$$

$$\mathrm{h_{dw}(u\ ,\ i)} = \begin{cases} 1\ , (u-i) < -t \\ 0\ , \quad else \end{cases} \qquad (7)$$

Then, the LTP vector is the vector of these ternary values over a given neighborhood (fig.2(b)). Thus, the ith bit of the LTP vector for the point c is given by:

$$\mathrm{LTP_C(i) = h(I_{ki}, I_c)} \qquad (8)$$

Where ki is the ith neighborhood point for c.Tan and Triggs[14] create ternary patterns in the above way but while matching, they split the pattern into two binary codes, combining −1 with 0 (termed as Up LTP code (fig.2(c(1))))and 1 with 0 and -1 with 1(termed as Down LTP code fig.2(c(2))) in the two binary patterns (Fig. 2 (c)). This gives some robustness as most of the error in LBP is due to homogenous regions.

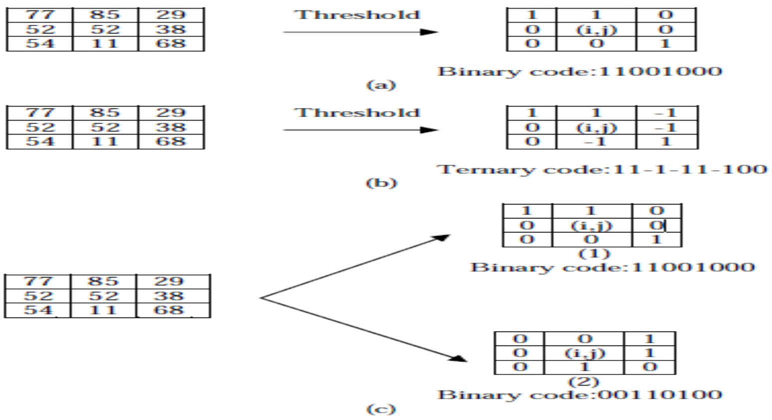

Fig. 3. (a) The LBP operator, (b) LTP operator, and (c) TheTan and Triggs LTP operator.

III. THE PROPOSED APPROACH

The block diagram of the proposed approach is shown in Fig.5.1. The training database consists of low resolution training images and their high resolution versions all captured using a real camera. These images in the database cover a wide range of scenes. Low resolution training images are captured with 1x zoom setting and high resolution training images are captured with 2x zoom setting of camera.

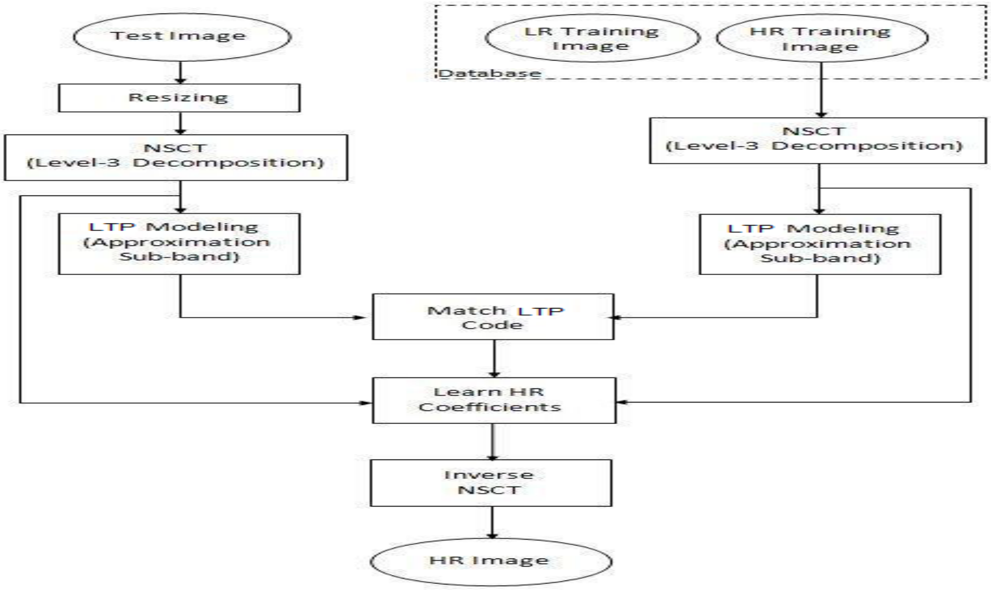

Fig.5.1 Flow of proposed approach

Flow of the algorithm goes through four main steps. Initially, we upsample a test image using bicubic interpolation method with a factor of 2. Then we decompose the test image and HR training images by a non-subsampled contourlet transform(NSCT). In the second step, we model the image features present in the sub-band *0* of the test image and HR training images using LTP operator. The third step searches HR training images with identical LTP code at each pixel in sub-band *0* to that of the test image. In the last step, we learn the missing high frequency details in the form of NSCT coefficients. Finally, we reconstruct the super-resolved image by applying inverse NSCT. The following subsections give detailed description of the proposed approach.

A. Image Feature Modeling Using LTP

The local structural variations of an image are represented by various image features in terms of edges, corners, curves and junctions. The second step of the proposed algorithm is to represent those features using local ternary pattern (LTP).The local ternary patterns can represent fundamental properties of texture, providing the vast majority of 3x3 patterns present in images. This 8-neighborhood system allows us to represent each feature with an 8-bit LTP code. The LTP is a highly discriminative operator in the sense that it uniquely records the influence of neighbouring pixels on the center pixel and the occurrences of various patterns in the neighbourhood of each pixel. This helps us to model different features such as edges, corners, curves, and junctions in an image. We apply LTP coding to the sub-band *0* of NSCT decomposition of bicubic version of the test image and HR training images.

B. **Searching Matched HR Training Images**

. To find the best matching HR training image from the group of all matched HR training images, we need to compare NSCT coefficients as described in
the next section.

We then search for the HR training image that has the best match with the test image by comparing coefficients in the sub-band *0-II* in the minimum absolute difference (MAD) sense. For a given location *(i, j)* the best matching HR image is found by using the following equation for MAD:

$$a(i\ ,j) = argmin\ [|X_0(i,j) - X_0{}^{(m)}(i,j)| + \ |X_1(i,j) - X_1{}^{(m)}(i,j)| \\ + \ |X_2(i,j) - X_2{}^{(m)}(i,j)| + \ |X_3(i,j) - X_3{}^{(m)}(i,j)| \\ + \ |X_4(i,j) - X_4{}^{(m)}(i,j)| + \ |X_5(i,j) - X_5{}^{(m)}(i,j)| \\ + \ |X_6(i,j) - X_6{}^{(m)}(i,j)|\ ]$$

Where, *X0(i, j), X1(i, j)…….X6(i, j)* are contourlet transform coefficients of the test image. *X0 (m)(i, j), X1 (m)(i, j)……..X6 (m)(i, j)* are contourlet transform coefficients of the *m*th R training image (*m*=1,2,3.....) for different sub-bands.

C. Replacing HR Coefficients

This section describes the method to learn NSCT coefficients from the matched HR training images and to map those HR coefficients to sub-band *III* of NSCT decomposition the test image. In order to obtain the best matching HR training image, we refine the matching criterion. This is achieved by comparing all 6 NSCT coefficients in sub-bands *I* and *II* of the test image with the corresponding coefficients of each HR training image included in the group of matched HR training images. Finally, we map the remaining 16 HR coefficients of sub-band *III* from the best matching HR training image to corresponding pixel locations of the test image. Fig. 3 illustrates the representation of NSCT coefficients in various sub-bands and mapping of high frequency coefficients of sub-band *III* from the best matching HR training image to that of the test image.

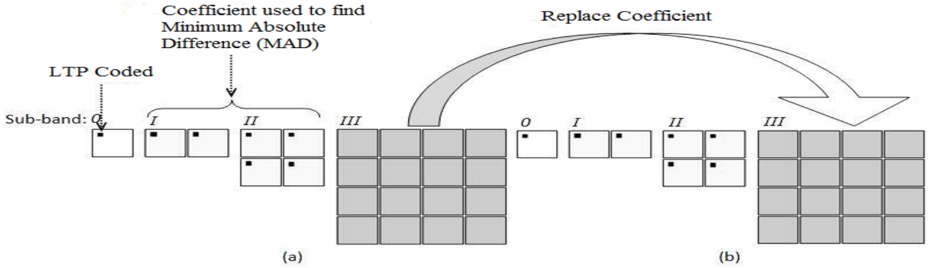

Fig.3 Replacing Coefficient

IV. EXPERIMENTAL RESULTS

In this section, we evaluate the performance of the proposed technique to for the resolution enhancement of a low resolution test image using a database consisting of LR and

HR images. All the experiments are conducted on real world images. The test images are of size 64x64 and the super-resolution is shown for an upsampling factor of 2. The sizes of the super-resolved images are 128x128. All the training images are of real world scenes. A few of the LR training images from the database are selected as test images. LR and HR pairs of the test images are removed from the database. The quantitative comparison of the results is presented using mean squared error (MSE), peak signal to noise ratio (PSNR). The SSIM score of the entire image is computed by averaging the SSIM values of the patches across the image. Higher values of PSNR and SSIM indicate better performance.

TABLE 1 PERFORMANCE ANALYSIS

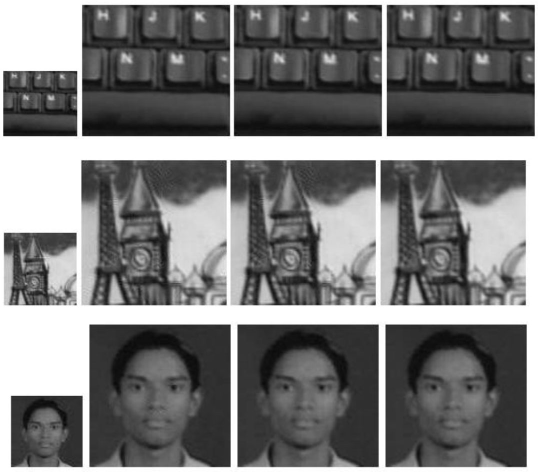

IMAGE NO.	PATEL ET AL. APPROACH [8]	KOLADIA ET. AL Approach[1]	PROPOSED APPROACH
SSIM			
1.	0.8909	0.8916	0.8981
2.	0.8185	0.8227	0.8356
3.	0.9340	0.9364	0.9465
4.	0.8872	0.8897	0.8915
PSNR			
1.	66.8647	66.9145	66.9703
2.	55.8988	55.9091	55.9236
3.	77.1294	77.9424	77.9512
4.	63.4814	63.7623	63.7811

V. CONCLUSION

In this paper, we have presented a new technique for image resolution enhancement. We use non-subsampled contourlet transform (NSCT) coefficients to learn the missing high frequency information of the test image from high resolution training images contained in the database. We use LTP coding to detect the important features and texture of an image so that they can be preserved in the resulting HR image. The experimental results show that proposed algorithm outperforms the other resolution enhancement techniques. The quantitative comparison shows a considerable improvement in PSNR and fairly good SSIM scores. The super resolved images are better in terms of quantity and appearance because local geometric structure information like directional edge details and contour like structures are reconstructed well. The use of NSCT in the proposed algorithm helps to describe line singularities and different directional information more accurately. The use of LTP helps in image modeling to preserve geometric structures of an image when it is reconstructed with higher resolution with a scale factor of 2.

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