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Optimum Threshold Decision in Super Resolution using DCT with Local Ternary Pattern Operator

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ABSTRACT

In this paper, I present what should be an ideal value of threshold while reconstructing HR image . I use a new learning based technique to super-resolve a low resolution image using "Local Ternary Pattern Operator" and a database of low resolution (LR) images and corresponding high resolution (HR) versions. The local geometry of an image is conveyed by image features such as edges, corners and curves. We encode these features with local ternary pattern operator. The missing high resolution features of the low resolution observation are learnt in the form of discrete cosine transform coefficients from high resolution images in the training database. Experiments are conducted on real world natural images and results are compared with taking different sizes of database of low resolution (LR) images and corresponding high resolution (HR) versions. The results help us in deciding the best threshold value to achieve good quality HR image.

I. INTRODUCTION

In electronic imaging applications, high quality images with fine details are often desired. Images with high resolution (HR) offer more details. High Resolution means that pixel density within an image is high, and therefore an HR image can offer more details that may be critical in various applications. The learning based super resolution uses a database consisting of high resolution images to learn the missing high frequency details of the super-resolved image. In learning-based SR, correspondences between low and high resolution image patches are learned from a database of low and high resolution image pairs (usually with a relative scale factor of 2), and then applied to a new low-resolution image to recover its most likely high-resolution version. In learning-based SR, this missing high-resolution information is assumed to be available in the high-resolution database patches, and learned from the low-res/high-res pairs of images in the database.. In this paper, we have proposed a super-resolution approach to reconstruct a high resolution image using learning based technique. The missing high frequency details are learned in the form of discrete cosine transform coefficients from the database of LR-HR image pairs. While learning, I reconstruct the local structural information of the image so that the HR image contains sharp edges and corners. Local geometry of the image is captured by modeling the features with local ternary pattern (LTP) operator. The high frequency coefficients in the DCT transform domain are used to reconstruct the fine details pertaining to high resolution information. The rest of the paper is organized as follows. In section II, we describe the proposed approach with four clear steps: Discrete cosine transform, image feature modeling, searching similar features and learning HR feature coefficients. We illustrate the performance of the proposed approach in section III. Finally, I conclude in section IV.

II. THE PROPOSED APPROACH

Threshold can be defined as the maximum possible extent of noise that can be contaminated with the observed intensity, *i*, of a pixel, and can be approximated by certain amount of permissible variation in intensity. When the difference between two neighboring pixel values is within the threshold limits, we consider that the difference is due to noise. In some pixels, the threshold may results in inclusion of orignial texture patterns into the noise band. However, this may not casuse much harm to the classification; rather this helps to distinguish prominent and less prominent patterns, which results in improved classification. the noise characteristics do not remain same for different intensity region. So, how to decide threshold value to achieve high resolved reconstructed image. We have taken three different ways to decide threshold.

a. Fixed Threshold (We decide threshold value between 1 to 15)
b. Take square root of the mean of the image as threshold value
c. Take square root of the intensity observed at the (i , j) pixel of the image as threshold value for that particular pixel. (so, in this case, threshold value for each pixel could be different)
d. Upto certain intensity level, threshold value if fixed ; beyond that level, we take square root of the intensity observed at the (i , j) pixel of the image as threshold value.

The training database consists of 100 low resolution training images and their high resolution versions all captured using a real camera. Low resolution images are captured with 1-x zoom setting and high resolution images are captured with 2-x zoom setting of the camera. The flow of the algorithm goes through four steps. Initially, we upsample the test image and the LR training images with bicubic interpolation method by a factor of 2. Then we take a block based discrete cosine transform of test image and HR training images. In the second step we model image features using LTP. Next we search the training database for similar features that match to the features in the test image. We then learn the high frequency details in the form of discrete cosine transform coefficients and finally obtain the super resolved image by applying inverse DCT. The following subsections give the detailed description of the proposed approach.

A. *Discrete Cosine Transform*

Like other transforms, the Discrete Cosine Transform (DCT) attempts to decorrelate the image data. After decorrelation each transform coefficient can be encoded independently. We use DCT transform domain here as DCT coefficients reflect the pixel intensities of the image into DC coefficients and AC coefficients with low and high frequency regions that can be utilized to recover image details in the region of interest.

B. *Image Feature Representation using LTP*

B..I. *Local Ternary Pattern*

The Local Ternary Pattern (LTP)[14] at a point c is defined by:

$$\mathrm{LTP(C)} = \sum_{k=0}^{7} 3^k s(I_{k-}I_c) \tag{1}$$

$$\mathrm{h(u\,,\,i)} = \begin{cases} -1\,, & (u-i) < -t \\ 1\,, & (u-i) > t \\ 0\,, & else \end{cases} \tag{2}$$

C. Searching similar features

In this step our algorithm searches the training database to find LR training images with similar features to that of the test image. For this we divide the LTP encoded test image and LR training images into 8×8 image patches. We compare 8×8 = 64 pixels in each patch of the test image with the corresponding image patches of all the LR training images in the database and select the LR training image with maximum number of matching pixels in the patch under consideration as the best match for that patch. This indicates that there are maximum matching features such as edges, corners and curves in the patch of the test image and the best matching image patch of the LR training image. Thus we have a matching LR training image with similar features corresponding to all the 8×8 image patches of the test image.

We apply this procedure to each image patch in the test image and find best matching LR training image for the corresponding patch.

D. Learning HR Feature Coefficients

Once we get the best matching LR training image correspond ing to each patch of the test image, we learn the high resolution information in the form of detailed DCT coefficients from the HR training database. Since HR training image in the database is the true high resolution image, we extract the high frequency details from it for improving the resolution of the test image.

III. EXPERIMENTAL RESULTS

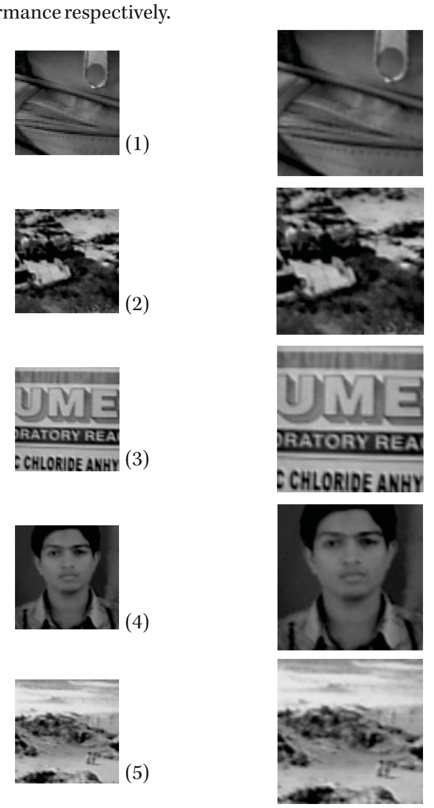
The training database consists of a set of 100 images of various scenes. The LR and HR images are of sizes 64×64 and 128×128, respectively. The test images are of size 64×64 and the super-resolved images are of size 128×128. A few of the LR training images from the database are selected as test images. Thus their true high resolution versions are available for comparison of the reconstructed images. LR-HR pairs of the test images are removed from the database.The quantitative comparison of the results is presented using peak signal to noise ratio (PSNR) & structural similarity (SSIM) efined by,

$$PSNR = 10\log 10\left[\frac{255\times 255}{\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{(f(i,j)-f'(i,j))^2}{M\times N}}\right] \quad (7)$$

where f(i; j) is the original HR version of the reconstructed image $f'(i,j)$ and M×N is the size of the images. The structural similarity (SSIM) index is a method for measuring the similarity between two images. The local similarity S(x; y) between image patches x and y taken from the same locations of the two images under comparison is calculated as,

$$S(x,y) = \left(\frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}\right)\left(\frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}\right)\left(\frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}\right) \quad (8)$$

Where ,μx and μy are local sample means of image patches x and y, respectively. Similarly σ_x and σ_y are the local sample standard deviations of x and y, r espectively. Here σ_{xy} is the sample cross correlation of x and y after removing their means. C1, C2 and C3 are small positive constants preventing the numerical instability. The SSIM score of the entire image is computed by averaging the SSIM values of the patches across the image [5], [6]. Higher value of S(x; y) indicates better performance respectively.



(a) (b)

Fig. 2 (a) Low resolution observations (64 × 64), (b) super-resolved images using 100 images Database (128 × 128),

We did our experiments taking fixed threshold value (as per a)as 10. Then compared its results with (b), (c) and (d). For (d) we kept fixed threshold 5 for the pixels where the intensity level is below 30, where as square root of the intensity observed at the (i , j) pixel of the image as threshold value if the intensity level is above 30. Here are the experimental results. Test images used in experiment are different in terms of picture details.

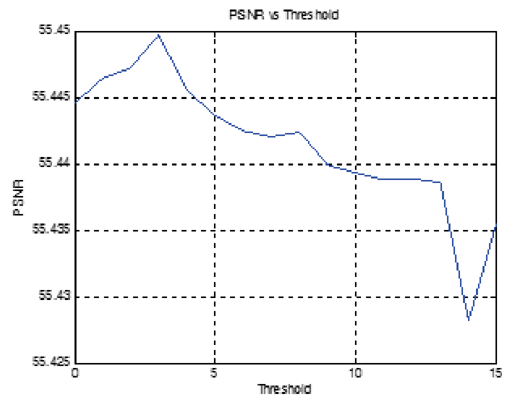
Table I & 2 shows the quantitative performance using PSNR and SSIM as measurement indices.

Table 1 Performance comparision

Image	PSNR			
	a	b	c	d
1	55.4380	55.4416	55.4431	55.4431
2	73.0427	73.0578	73.0667	73.0667
3	57.7989	57.8011	57.8032	57.8032
4	52.5400	52.5410	52.5405	52.5405
5	75.4361	75.4600	75.4690	75.4690

Table 2

Image	SSIM			
	a	b	c	d
1	0.8934	0.8343	0.8343	0.8343
2	0.8917	0.8920	0.8920	0.8920
3	0.8200	0.8202	0.8202	0.8202
4	0.8111	0.8112	0.8112	0.8112
5	0.9290	0.9292	0.9292	0.9292



IV. Conclusion

From the performance comparision , we can see that PSNR and SSIM values are minimum for fixed threshold 10. The results improve with keeping threshold square root of the mean of the image. The results further improve with methods c and d. The results are similar for both methods. We have also implemented the algorithm with keeping threshold 0, then 1, then 2 upto threshold value 15. The resulting PSNR values are shown in the Table 1 . From the table, we can see that upto threshold value 9, PSNR and SSIM values are better than those PSNR and SSIM values getting using NTTP approach . For threshold 3 , we got the best PSNR and SSIM results among all values of thresholds and all the methods of deciding threshold. Above threshold value 10 , the NTTP approach results are better.

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