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Image Super-Resolution Based on Structure-Modulated Sparse Representation

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Abstract:
The Super Resolution (SR) reconstruction has become a hot research topic in the field of Image Processing. Super resolution is all about generating high-resolution image from low-resolution image. High resolution image provides a high pixel density therefore provides more information about the original image. High resolution images are very much important for computer vision applications for better performance for pattern recognition and analysis of images. It is useful in medical imaging for diagnosis. It is very much useful for processing of satellite images. Also it is useful for other applications. In this paper we have discussed the techniques used for obtaining super resolutions. It is implemented using MATLAB.

Key words: MATLAB, Sparse

I. INTRODUCTION

In most digital image processing applications, high resolution images or videos are very much required for the purpose image processing and analysis. It plays a major role for two application areas such as the improvement of pictorial information for human interpretation and also used for representation for automatic machine perception. The basic reconstruction constraint is that applying the image formation model to the recovered image should produce the same low-resolution images. Image resolution provides the details contained in an image. Higher resolution images provide more image details

1.1 Classification of resolution

The resolution of a digital image can be classified as follows:

- Spatial resolution
- Radiometric resolution
- Temporal resolution
- Spectral resolution
- Pixel resolution

This paper mainly focused on Sparse representation. The basic reconstruction constraint is that applying the image formation model to the recovered image should produce the same low-resolution images. However, because much information is lost in the high-to-low generation process, the reconstruction problem is severely underdetermined, and the solution is not unique. In digital image processing the image is made up of small picture element called pixels. Spatial resolution is the pixel density in an image and measures in pixels per unit area. Another class of super-resolution methods that can overcome this difficulty are learning based approaches, which use a learned co-occurrence prior to predict the correspondence between low-resolution and high-resolution image patches. Nevertheless, the above methods typically require enormous databases of millions of high-resolution and low-resolution patch pairs to make the databases expressive enough. Their algorithm maps the local geometry of the low resolution patch space to the high-resolution patch space, generating high-resolution patch as a linear combination of neighbors. Using this strategy, more patch patterns can be represented using a smaller training database. However, using a fixed number K neighbors for reconstruction often results in blurring effects, due to over- or under-fitting. In this paper, we focus on the problem of recovering the super-resolution version of a given low-resolution image. Although our method can be readily extended to handle multiple input images, we mostly deal with a single input image. Like the aforementioned learning-based methods, we will rely on patches from example images. Our method does not require any learning on the high-resolution patches, instead working directly with the *low-resolution* training patches or their features. Our approach is motivated by recent results in sparse signal representation, which ensure that linear relationships among high-resolution signals can be precisely recovered from their low-dimensional projections.

1.2 Super- Resolution (SR) reconstruction

Super-resolution (SR) are techniques that construct high-resolution (HR) images from several observed low-resolution (LR) images, thereby increasing the high frequency components and removing the degradations caused by the imaging process of the low resolution camera.

1.3 Super-resolution from Sparsity

The single-image super-resolution problem asks: given a low-resolution image Y, recover a higher-resolution image X of the same scene. The fundamental constraint is that the recovered X should be consistent with the input, Y:

1.4 Reconstruction constraint.

The observed low-resolution image Y is a blurred and down sampled version of the solution X:

$Y = D*H*X$

Here, H represents a blurring filter, and D the down sampling operator. Super-resolution remains extremely ill-posed, since for a given low-resolution input Y, infinitely many high resolution images X satisfy the above reconstruction constraint. To address the super-resolution problem using the sparse representation prior, we divide the problem into two steps. First, using the sparse prior, we find the sparse representation for each local patch, respecting spatial compatibility between neighbors. The global model from the reconstruction constraint is then applied to remove possible artifacts from the first step and make the image more consistent and natural.

II. SUPER RESOLUTION APPLICATION AREAS

1. Remote sensing: several images of the same area are provided, and an improved resolution image can be sought.
2. Surveillance video: frame freeze and zoom region of interest (ROI) in video for human perception, resolution enhancement for automatic target recognition (e.g. try to recognize a criminal's face).
3. Video standard conversion, e.g. from NTSC video signal to HDTV signal
4. Medical imaging (CT, MRI, Ultrasound etc): several images limited in resolution quality can be acquired, and SR technique can be applied to enhance the resolution.

2.1 Local Model from Sparse Representation

As in the patch-based methods mentioned previously, we try to infer the high-resolution patch for each low resolution patch from the input. For this local model, we have two dictionaries Dℓ and D~: D~ is composed of high resolution patches and Dℓ is composed of corresponding low-resolution patches. We subtract the mean pixel value for each patch, so that the dictionary represents image textures rather than absolute intensities. For each input low-resolution patch y, we find a sparse representation with respect to Dℓ. The corresponding high resolution patches D~ will be combined according to these coefficients to generate the output high-resolution patch x. The problem of finding the sparsest representation of y can be formulated as:

min II α II 0 s.t. II FD l α− Fy II 2 ≤ €1
where F is a (linear) feature extraction operator. The main role of F in equation is to provide a perceptually meaningful constraint on how closely the coefficient must approximate y. We will discuss the choice of F in Section 3. Although the optimization problem is NP-hard in general, recent results indicate that as long as the desired coefficients α is sufficiently sparse, they can be efficiently recovered by instead minimizing the ℓ1-norm, as follows:
min II α II1 s.t. II FD l α− Fy II 2 ≤ €1
Lagrange multipliers offer an equivalent formulation:
min λ II α II 1 + 1/2 II FD l α− Fy II 2
where the parameter λ balances sparsity of the solution and fidelity of the approximation to y. Notice that this is essentially a linear regression regularized with ℓ1-norm on the coefficients, known in statistical literature as the Lasso. We modify equation so that the super resolution reconstruction Dhα of patch y is constrained to closely agree with the previously computed adjacent high
Resolution patches. The resulting optimization problem is:
min II α II 1st *II FD l α− Fy II 2 ≤ €1*
II *PD l α− w II 2 ≤ €1*
Where the matrix P extracts the region of overlap between current target patch and previously reconstructed high-resolution image, andw contains the values of the previously reconstructed high-resolution image on the overlap.

The constrained optimization can be similarly reformulated as:
min λ II α II 1 +1/2 II FD l α− y II 2
The parameter β controls the trade off between matching the low-resolution input and finding a high-resolution patch that is compatible with its neighbors. In all our experiments, we simply set β = 1. Given the optimal solution **α*** to, the high resolution patch can be reconstructed as
*x = Dhα**

2.2 Enforcing Global Reconstruction Constraint

We eliminate this discrepancy by projecting X0 onto the solution space of
DHX = Y
Computing
X = argmin II X – X0 II s.t. DHX = Y
The solution to this optimization problem can be efficiently computed using the back-projection method, originally developed in computer tomography and applied to super resolution. The update equation for this iterative method is
Xt+1 = Xt + ((Y − DHXt) ↑ s) p, (10)
Where Xt is the estimate of the high-resolution image after the t-th iteration, p is a “back projection” filter, and ↑ s denotes up sampling by a factor of s.

III. ALGORITHM

3.1 Super-resolution via Sparse Representation.

1: **Input:** training dictionaries DH and Dℓ, a low resolution image Y.
2: **for** each 3 × 3 patch y of Y, taken starting from the upper-left corner with 1 pixel overlap in each direction,
• Solve the optimization problem with ˜D and ˜y defined in (8): *min λ II α II 1 + 1/2 II D − y II 2.*
• Generate the high-resolution patch x = Dhα. Put the patch x into a high-resolution image X0. 3: **end**
4: Using back-projection, find the closest image to X0 which satisfies the reconstruction constraint:
X = argmin II X −X0 II s.t. DHX = Y.

5: **Output:** super-resolution image X*.
We take result X_ from back projection as our final estimate of the high-resolution image. This image is as close as possible to the initial super-resolutionX0 given by sparsity, while satisfying the reconstruction constraint. The entire super-resolution process is summarized as Algorithm.

IV. GLOBAL OPTIMIZATION INTERPRETATION

The simple SR algorithm outlined above can be viewed as a special case of a general sparse representation framework for inverse problems in image processing. Related ideas have been profitably applied in image compression, denoising, and restoration. These connections provide context for understanding our work, and also suggest means of further improving the performance, at the cost of increased computational complexity. Given sufficient computational resources, one could in principle solve for the coefficients associated with all patches *simultaneously*.

Moreover, the entire high resolution image X itself can be treated as a variable. Rather than demanding that X be perfectly reproduced by the sparse coefficients, we can penalize the difference between X and the high-resolution image given by these coefficients, allowing solutions that are not perfectly sparse, but better satisfy the reconstruction constraints.

4.1 Experimental settings:

In our experiments, we will mostly magnify the input image by a factor of 3. In the low-resolution images, we always use 3 × 3 low-resolution patches, with overlap of 1 pixel between adjacent patches, corresponding to 9 × 9 patches with overlap of 3 pixels for the high-resolution patches. The features are not extracted directly from the 3×3 low-resolution patch, but rather from an up sampled version produced by bicubic interpolation. For color images, we apply our algorithm to the illuminance component only, since humans are more sensitive to illuminance changes. Our algorithm has only one free parameter λ, which balances sparsity of the solution with fidelity to the reconstruction constraint. In our experience, the reconstruction quality is stable over a large range of λ. The rule of thumb, λ = 50 × dim (patch feature), gives good results for all the test cases in this paper. One advantage of our approach over methods such as Neighbor embedding is that it selects the number of relevant dictionary elements *adaptively* for each patch. Fig demonstrates this for 300 typical patches in one test image. Notice that the recovered coefficients are always sparse (< 35 nonzero entries), but the level of sparsity varies depending on the complexity of each test patch. However, empirically, we find the support of the recovered coefficients typically is neither a superset nor subset of the K nearest neighbors.

4.2 Implementation in MATLAB:

The image is taken for measurement. The following operations are done on the image:

Simulation of a motion blurs Restoration using PSF
Computation of noise spectrum
Simulation of a picture with motion blur and noise
Restoration using ACF
Restoration using NP and ID-ACF

```
I=imread('d:\matlab704\work\jackson.bmp');
figure;imshow(I);
title('I/P:INPUT IMAGE');
%step 2 : Simulate a Motion blur
LEN=31;
THETA=11;
PSF=fspecial('motion',LEN, THETA);
Blurred=imfilter(I,PSF,'circular','conv');
figure;imshow(Blurred);
title('Blurred');
% Step 3 : Restore the Blurred Image
% wnr1=deconvwnr(Blurred,PSF); figure;imshow(wnr1);
% title('Restored, True PSF');
%   Step 6:Use Autocorrelation to improve Image Restoration
noise=0.1*randn(size(I));
BlurredNoisy=imadd(Blurred,im2uint8(noise));
figure;imshow(BlurredNoisy); title('Blurred & Noisy');
NP=abs(fftn(noise)).^2; figure;mesh(NP); title('Noise
Sepctrum'); NPOW=sum(NP(:))/prod(size(noise)); % noise
power
NCORR=fftshift(real(ifftn(NP))); %noise ACF, centered
IP=abs(fftn(im2double(I))).^2;
IPOW=sum(IP(:))/prod(size(I)); % original image power
ICORR=fftshift(real(ifftn(IP))); % Image ACF, cenered
wnr7=deconvwnr(BlurredNoisy,PSF,NCORR,ICORR);
figure;imshow(wnr7);
title('Restored with ACF');
ICORR1=ICORR(:,ceil(size(I,1)/2));
wnr8=deconvwnr(BlurredNoisy,PSF,NPOW,ICORR1);
figure;imshow(wnr8);
title ('Restored with NP & ID-ACF');
```

V. RESULT AND SCREEN SHOTS

Low Resolution Images:

Figure.1. Low resolution images

Main GUI is as below:

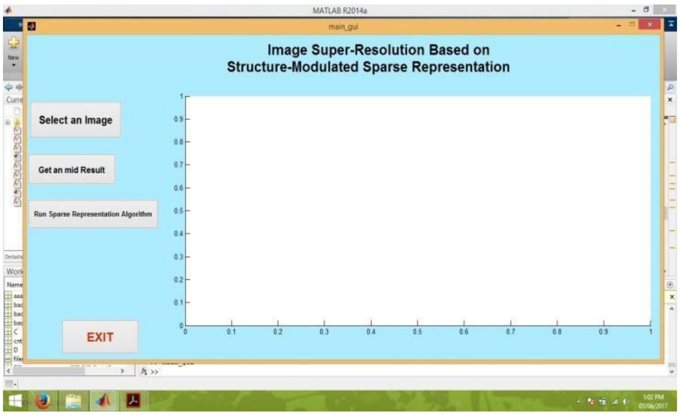

Figure.2. GUI used

Final result of paper

Figure.3. Final result

VI. CONCLUSION

This paper presented an effective approach toward single image super-resolution based on spatial domain. Our progressive deconvolution approach can produce very promising results not only in synthetic experiments, but also in various types of real cases. Our results show our approach outperforms other state-of-the-art techniques and have wide applications in scientific and daily areas. Robotic deblurring is the material removal process used to take burrs, sharp edges, or fins off metal parts. Burrs are almost always left on parts and tools that have been made Deblurring Applications Can Effectively Remove Burrs. Thus our methods are very practical and effective for achieving satisfactory photos in dim light conditions using off-of-shelf hand-held camera.

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