Super-resolution Reconstruction Method based on Non-Local Means

1. MOTIVATION

Super resolution images are widely used in many fields [1]. Classic super-resolution techniques generally involve fusing a number of pictures with sub-pixel motion difference and correct estimation of the motion. This kind of accurate estimate, however, is not always available. Incorrect estimation of the motion generally produces artifacts, which is clearly undesirable in most applications [2]. Therefore, various experts and specialists propose super-resolution methods that do not require such estimation. Among the proposed solutions, Non-Local Means-based Super-resolution Reconstruction methods generally give clear high-quality results. In order to study various super-resolution techniques, we decide to implement and compare a few of them in this project.

2. RELATED WORK

2.1 NON-LOCAL PATCH-BASED REGULARIZATION

Zhang et. al [1] proposed a Non-Local Means-based super-resolution reconstruction method to process a sequence of images. In their algorithm, iterative curvature based interpolation is first applied to obtained a raw high-resolution image. Every pixel of the output image is then classified so that the weight matrix for each target is computed based on result of classification. Finally, deconvolution method is applied to obtain the result.

Protter et. al [2] proposed two simple super-resolution reconstruction methods based on non-local means. One of the methods involves fuzzy motion estimation, which gives high flexibility on motion patterns. The other method is a simplified method, which only applies to special cases.

In [3], Mairal et. al proposed a novel image reconstruction model that combines non-local means and sparse coding.
This is achieved by using simultaneous sparse coding to impose that similar patches share the same dictionary elements in their sparse decomposition.

Glasner et. al [4] proposed a new framework using a non-local and non-linear regularization on graphs to solve general inverse problems. This is achieved by iteratively computing an adapted graph and a solution of the inverse problem. Applications to super-resolution and compressive sampling are demonstrated.

In [5], Danielyan et. al proposed a recursive deblurring algorithm based on the novel Block Matching 3-D filtering (BM3D). This algorithm shared the idea introduced by NLM - using similarity between nonlocal blocks to reconstruct image - but proved to outperform the NLM method.

[6] proposes a flexible end-to-end camera image processing system. Rather than breaking down the image processing process into various modules and just building one on the result of the former step, this approach imposes natural priors to optimize the result of image processing.

2.2 PAST SOLUTIONS FOR SUPER-RESOLUTION RECONSTRTION

Glasner et. al [7] proposed a unified computational framework that combines Classical Super Resolution and Example-based Super Resolution to obtain a super-resolution image from a single low-resolution image. Recurrence of patches within the same image scale provides basis for applying Classical Super Resolution constraints. For Example-based Super Resolution, the low-resolution/ high-resolution patch correspondences can be learned from patch recurrence across multiple image scales of a single image, without any additional external information.

In [8], Zhang et. al proposed a maximum a posteriori probability (MAP) Super Resolution framework that incorporates NLM and SKR prior terms to obtain a super-resolution image from a low-resolution image. NLM prior considers redundancy of patches in images and SKR assumes that a target pixel can bee weighted average from its neighbors. Super-resolution image is iteratively optimized using the gradient descent method.

Elad et. al reviewed [9] a class of approaches for this problem, namely, Exampled-based approach. divides this class of approaches further into three sub-classes. First, using examples to fine-tune the parameters of previously defined regularization expressions. Second, using them directly for the reconstruction procedure, and third, combination of approaches in first and second sub-class.

In [10], Danielyan et. al. proposed a framework using an algorithm known as BM3D (discussed in 2.1) to compensate the lack of motion information in super-resolution reconstruction. The proposed framework could be applied to super-resolution reconstruction problem for both video and image reconstruction.

Protter et. al [11] proposed a new algorithm for Super-resolution reconstruction (SRR). It exploits a probabilistic and crude motion estimation based on the classic SRR formulation. Matrix-Vector version and Pixel-Wise version of the algorithm are given. This new approach allows various extensions and re-sampling tasks such as de-interlacing problem is demonstrated.

A another solution of this problem was proposed in[12]. In this approach, the super-resolution videos are produced from a series of images, but without an accurate estimation of the motion. Specifically, the orientation of the video is estimated repeatedly, and the estimations get improved over each iteration. In summary, this approach accommodate a variety of complex motions in the input videos by a two-tiered approach: (i) neutralize large displacements with rough motion compensation using non -local algorithms, and (ii) The fine-scale and details are handled with 3-D ISKR.

3. PROJECT OVERVIEW

In this project, we will implement a few super-resolution image reconstruction methods based on non-local means. Specifically, we are going to implement methods that are proposed in papers [11] and [12] mentioned in previous section. The results will be compared and analyzed. At the end, we might also try to develop an NLM-regularized reconstruction method based on ADMM.

4. MILESTONE & TIMELINE

02/23/2016 – 02/25/2016:

Read papers in Scientific Reference.

02/26/2016 – 03/03/2016

Get original dataset. Implement super-resolution methods described in[11] and [12] in Matlab.

03/04/2016 – 03/06/2016

Compare resulting super-resolution images to those with original motion-based method. In the meantime, compare resulting images using methods in [11] and [12]. Compare of both images and statistics (e.g. MSE and PSNR) will be presented.

03/07/2016 – 03/08/2016

Make project poster and prepare for final presentation.

5. GOALS

The goal of this project is to study and implement various super-resolution reconstruction approaches based on Non-Local Means. We try to effectively eliminate limit in motion-based method and produce similar, or even better results than classic techniques. We will also compare and analyze the result images with different Non-Local Means methods to those with original motion-based method.

6. REFERENCES

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7. TEAM MEMBERS

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