Image Super Resolution

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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.

Keywords*:* MATLAB, Sparse

I. INTRODUCTION

Signal processing techniques to reconstruct a high quality image from its degraded measurements, named Image Reconstruction (IR), are particularly interesting. A first reason for this assertion is due to the technological progress that has raised the standards and the user expectations when enjoying multimedia contents.

In fact, it has witnessed a revolution in large-size user-end display technology: consumer markets are currently flooded with television and other display systems - liquid crystal displays (LCDs), plasma display panels (PDPs), light emitting diode displays (LEDs), and many more, which present very high-quality pictures with crystal-clear detail at high spatial and temporal resolutions. Despite the increasing interest in large-size user-end display technology, high quality contents are not always available to be displayed. Videos and images are unfortunately often at a lower quality than the desired one, because of several possible causes: spatial and temporal down-sampling, noise degradation, high compression, blurring, etc. Some family of methods belonging to IR can be useful to improve the quality of images and videos, such as: demising, deploring, compressive sensing, and super-resolution. Moreover, the new sources of video and images, like the Internet or mobile devices, have generally a lower picture quality than conventional systems. When we consider only images, things seem to be better than videos. Modern cameras, even the handy and cheap ones, allow any user to easily produce breathtaking high-resolution photos. However, if we consider the old productions, there is an enormous amount of user-produced images collected over the years that are valuable but may be affected by a poor quality. Moreover, there is an enormous amount of images that must be down sampled (or compressed) to use less storage space and facilitate, or even enable, its transmission. The need to improve the image quality can then be remarked also in this case. The other reason for the need of augmenting the resolution of videos and images is related to the applicability of IR in video surveillance and remote sensing, for example. In fact, this kind of applicability requires that the display of images at a considerable resolution, possibly for specific tasks like object recognition or zoom-in operations.

A. Super-Resolution Problems

The main goal of super-resolution is to generate the most feasible High Resolution (HR) image from a given Low Resolution (LR) image assuming both to be representatives of the same scene. HR images hold a higher pixel density and, because of that, an image classified as such holds more details about the original scene. Super-resolution methods play an important role in different areas, such : medical imaging for diagnosis, surveillance, forensics and satellite imaging applications. Also, the need for high resolutions is common in computer vision applications for better performance in pattern recognition and analysis of images. In general, the HR imaging process is very expensive when considering both capture equipments and storage facilities. Also, it may not always be feasible due to the inherent limitations of sensors and optics manufacturing technology. Those problems can be overcome through the use of image processing algorithms, which are relatively inexpensive, giving rise to concept of super-resolution. Super resolution provides an advantage, as it may cost less, but specially because of its applicability to the existing low resolution imaging systems out there. Super-resolution is based on the idea that an LR image (noisy), a combination of LR images or a sequence of images of a scene can be used to generate a HR image or image sequence. Super-resolution attempts to reconstruct a higher resolution image from the original scene from a set of observed images with lower resolutions. The general approach considers the LR image(s) as resulting from the re-sampling of an HR image. The goal is to recover an HR image which, when re-sampled based on the input images and the imaging model, would produce the LR observed images. Thus, it fits the definition of an inverse problem the accuracy of the imaging model is essential for super-resolution and an inaccurate model can degrade the image even further. Super-resolution can be divided into three main domains: single image super resolution, multi-view super resolution, and video super-resolution. In the first case, the observed information could be taken from one image. In the second, the observed information could be taken from multiple cameras. In the third case, The observed information could be sequential frames from a video. The key point to successful super-resolution consists in formulating an accurate and appropriate forward image model.

B. Classification of Super Resolution

The super-resolution approaches can be broadly classified into two major categories: multi-frame super-resolution] and single-image super-resolution.

C. Multi-Frame Super Resolution

There are two basic groups for multi-frame super-resolution methods. One group is static super-resolution , which can be further classified into the frequency domain methods the non-uniform interpolation methods the statistical methods and Projection onto Convex Sets (POCS).POCS is convenient for incorporating any kind of constraints or priors. However, the POCS, whose solution depends on the initial values, has the drawbacks of heavy computation and slow convergence. The other group is dynamic super-resolution which utilizes the previous reconstructed HR frames to estimate the current HR frame.

When multiple degraded LR images are used to generate a single HR image, we refer to it as Multiple-image Single-output (MISO) super-resolution. Some examples of application: license plate recognition from videos streams, astronomical imaging, medical imaging, and text recognition. The multiple LR images can be seen as the different view-points of the same scene and image registration deals with mapping corresponding points in those images to the actual points in original scene and transforming data into one coordinate system. Several types of transformations could be required for the registration of images, like affine transformations, bi-quadratic transformations, or even planar homographic transformations. The posterior alignment involves geometric components as well as photometric components.

D. Single Image Super Resolution

Single-image super-resolution methods can also be further divided into interpolation-based methods reconstruction-based methods and example learning-based methods]. The interpolation based methods usually utilize a base function to construct the unknown data points on the regular grids of HR images. Although they have the advantage of relatively low complexity, the interpolation-based methods tend to produce considerable edge halos, blurring and aliasing artifacts. Therefore, this class of SR methods is often insufficient for practical applications. This family of methods has the ability to recover sharp edges and suppress aliasing artifacts. However, the reconstruction-based methods, whose performance depends heavily on the priors imposed on the HR images, are unable to restore the fine structures when the up scaling factor is larger. The example learning-based methods exploit the information from training images or example images to learn the mapping between the LR and HR image patches for super resolution reconstruction. Usually need a large and representative database of the LR and HR image pairs to encompass various images as much as possible that leads to a heavy computational load in the mapping learning process. Implies that if the structural patterns of the input LR image do not appear in a general image database, the mapping learned from the database may not be able to restore the faithful high-frequency details in the HR image. employed sparse dictionary learning on the LR and HR image patches from a general image database, and then utilized sparse representations of the LR input to generate the output HR image. Proposed a deep learning method that learns an end-to-end mapping between the LR and HR images for single image super-resolution. Introduced the anchored neighborhood regression (ANR) that learns sparse dictionaries and regress anchored to the dictionary atoms for fast super-resolution. Subsequently, they [proposed an improved variant of ANR that achieves substantially less complexity and better performance. Similarly, Perez-Politer *et al.* presented an improved training strategy for SR linear repressors and an inverse-search approach for the speedup of the regression-based SR method. In this paper, we mainly focus on the study of the example learning-based SR methods with multiple image priors for further improvements of single image super-resolution. The optimized example learning-based SR method will build a suitable training set and make full use of image priors to reduce edge halos, blurring and aliasing artifacts effectively.

When a single degraded LR image is used to generate a single HR image, we refer to it as Single-image Single-output (SISO) super-resolution. The problem is, as there can be several HR images generating the same LR image. Single-image super-resolution is the problem of estimating an underlying HR image, given only one observed LR image. In this case, it is assumed that there is no access to the imaging step so that the starting point is a given LR obtained according to some (partially) known or unknown conventional imaging process. The generation process of the LR image from the original HR image that is usually considered can be written as$\mathbf{y} = DH\mathbf{x} + _$ where $\mathbf{y}$ and $\mathbf{x}$ are respectively the LR and HR image, H is a blur kernel original image is convolved with, which is typically modeled as a Gaussian blur[13], and the operator D denotes a down-sampling operation by a scale factor of s. The LR image in then a blurred and down-sampled version of the original HR image.

II. CONCLUSION

This paper presented an effective approach toward image super-resolution. In this paper we discussed classification of super resolution.

III. RESULT

REFERENCES

[1]. Algorithms for Super-resolution of Images based on Sparse Representation and Manifolds by Julio Cesar Ferreira.
[2]. Image Super-Resolution Based on Structure-Modulated Sparse RepresentationYongqin Zhang, Jiaying Liu, Member, IEEE, Wenhan Yang, and Zongming Guo, Member, IEEE Image 3]Super-Resolution via Sparse Representation Jianchao Yang, Student Member, IEEE, John Wright, Student Member, IEEE Thomas Huang, Life Fellow, IEEE and Yi Ma, Senior Member, IEEE.
[3]. P. Milanfar, Ed., Super-resolution imaging (digital imaging and computervision). New York: CRC Press, Sep. 21, 2010.
[4]. R. Y. Tsai and T. S. Huang, Multiple frame image restoration and registration, ser. In Advances in Computer Vision and Image Processing. Greenwich, Conn, USA: JAI Press Inc., 1984, vol. 1.
[5]. W. C. Siu and K. W. Hung, "Review of image interpolation and superresolution," Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, p. 10, 2012.
[6]. M. Irani and S. Peleg, "Improving resolution by image registration," CVGIP-Graphical Models and Image Processing, vol. 53, no. 3, pp. 231–239, 1991.]
[7]. P. Sen and S. Darabi, "Compressive image super-resolution," in 2009 Conference Record of the Forty-Third Asilomar Conference on Signals, Systems and Computers. New Mexico: IEEE, 2009, pp. 1235–1242.
[8]. B. Deka and M. Baruah, "Single-Image Super-Resolution Using Compressive Sensing," International Journal of Image Processing and Visual Communication, vol. 1, no. 4, pp. 8–15, 2013.
[9]. N. Kulkarni, P. Nagesh, R. Gowda, and B. Li, "Understanding compressive sensing and sparse representation-based super-resolution," IEEE Transactions on Circuits and Systems for Video Technology, vol. 22, no. 5, pp.778–789, may 2012.