An Extensive Survey on Blind Super Resolution of Real-Life Video Sequences

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Abstract - Over the couple of years the field of superresolution has seen a tremendous growth in interest for researchers. A demand for higher resolution is seen in many fields including bio-medical imaging, entertainment (high definition television or HDTV), satellite and astronomical imaging, chemical and biological research (high resolution electron microscopy), military surveillance and remote sensing. Indeed, this demand, in many cases, exceeds the maximum resolution capability of current acquisition systems. A clear, high-quality image of a region of interest in a video sequence may be useful for facial recognition algorithms, car number plate identification, or for producing a "print-quality" picture for the press. This work presents an extensive survey on blind image super resolution.

Keywords- Image Processing, Image Enhancement, Image Super resolution, blur, deconvolution, blind estimation.

I. INTRODUCTION

The term 'resolution' can be defined in the context of digital images as the resolution of a digital image refers to the ability to resolve or distinguish two objects in the image. An image is said to have higher resolution in comparison to another image if it is possible to distinguish smaller/finer objects/features in the former as compared to the latter. The difference between this definition and two other related terms, viz. The resolution of a digital still/video camera and the size of an image are also clearly brought out.

The size of a digital image is given by the Cartesian product of the number of pixels along the vertical and horizontal directions. Since a video is nothing but a sequence of digital images, the size of a digital video is defined as the size of one of its constituent images. The resolution of a digital camera (still or video) is defined as the Cartesian product of the number of CCD (charge coupled device) or CMOS (complementary metal oxide semiconductor) sensing elements along the vertical and horizontal directions. The resolution of the digital camera and the size of the image captured by it are the same since each pixel of the image corresponds to a unique sensing element.

Digital camera takes two steps to provide the observation of the photograph as shown in Fig. 1 (Image acquisition process converts the energy of lights coming from the target scene to measurable value. Image display process shows the digital image using a display device) while Nie´pce's camera directly generated a photo of the scene via one process. First process is image acquisition process. The process receives lights from the scene and then converts the received light as the latent image. For this process, film camera uses photographic film or plate while digital camera uses imaging sensor, e.g., a Charge-Coupled Device (CCD) image sensor or Complementary Metal-Oxide-Semiconductor (CMOS) sensor. Next is image display process. This step transforms the latent image into a visible image. For images saved on the film, follow photographic processing, which is the chemical ways to produce a negative or positive image. On the other hand, digital image has various ways of displaying the photo. One may use printers to make the photo permanent while another may use display devices to see the photo temporarily. Typical display device is computer monitors including Cathode Ray Tubes (CRT) display and Liquid Crystal Display (LCD). Thanks to the recent development of display technologies, bigger and brighter display is available with cheaper cost. In contrast to such monitors, projectors only have light emitting devices. To form an image, projectors require display surface, onto which they emit the light.

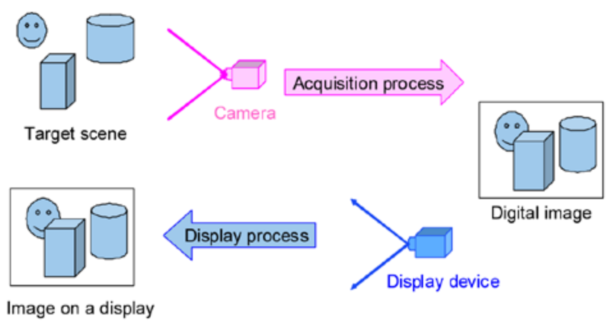

Figure 1.1 Imaging Process of Digital Camera.

The goal of super-resolution (SR) is to increase the resolution of an image or a sequence of images beyond the resolving power of the imaging system. Image processing literature has traditionally used the term 'resolution' to refer to the image size in terms of the number of pixels. However, the conventional unit of pixel count is not an appropriate measure of resolution because increasing the number of pixels in the image may not contribute towards enhancing fine details in the image content. Correspondingly, the hardware-based solution of increasing resolution by reducing the pixel size and increasing the number of pixels per unit area does not always lead to satisfactory results. In digital cameras, a pixel corresponds to the detector sensor which is usually a CCD (charge-coupled device) or CMOS (complementary metal-oxide semiconductor) sensor. These photo-sensitive detectors work by integrating the available light impinging on them for a specified period called the aperture time. When the user presses the camera shutter release, each of these pixels has a ‘photosite’ which is uncovered to collect and store photons in a cavity. Once the exposure finishes, the photosites are closed and an assessment of how many photons fell into each cavity is made..

II. BLIND IMAGE DECONVOLUTION

The process of separating two signals that have been convolved is termed as the de- convolution problem. When both the signals are unknown, it comes under the category of blind technique. The separation of signals using blind deconvolution technique proceeds with some distinguishing characteristics of both the signals that have to be deconvolved. Some signal characteristics must be known and those characteristics has to be kept as nonspecific as possible in order to achieve the solution. There are wide applications of blind deconvolution in seismic, speech, signal processing and ofcourse, in image processing.

The blind deconvolution in image processing first started in the area of astronomical imaging. Due to rapidly changing refractive index of the atmosphere, the ground-based imaging system suffered from blurring. This was first scenerio for applying restoration technique but the various practical applications demand for blind deconvolution still today. The blind deconvolution of images is done by following either of the two approaches.

- The degradation function, psf, is identified and then using any classical restoration technique such as inverse filtering, weiner filtering, pseudoinverse filtering, and the true image is identified. This method is simple and less computation is required. The algorithms in this approach are known as a priori blur identification technique.
- The identification of the psf and the true image is done simultaneously in the restoration algorithm. Hence the algorithms in this approach are complex.

Based on these two approaches, the various existing blind image deconvolution techniques are classified. Lane and Bates approach for multidimensional deconvolution is based on the concept that any degraded image, c, can be deconvolved if the individual convolved components, i_1, i_2, ..., in, have compact support and c has dimension greater than one. Their method exploits the analytical properties of Z-transform for deconvolving the degraded image. The technique is known as zero sheet separation.

III. LITERATURE REVIEW

SR. NO.	TITLE	AUTHOR	YEAR	METHODOLOGY
1	Blind Super Resolution of Real-Life Video Sequences,	E. Faramarzi, D. Rajan, F. C. A. Fernandes and M. P. Christensen,	2016	A novel blind SR method is proposed to improve the spatial resolution of video sequences,
2	Blind super-resolution of sparse spike signals	Y. Chi,	2015	A convex optimization framework based on minimization of the atomic norm for jointly spectrally-sparse ensembles
3	Improved multi-frame super resolution via multiframe blind deblurring using the alternating direction method of multipliers	Qizi Huangpeng, Xiangrong Zeng, Jun Fan, Jing Feng and Quan Sun,	2015	A new MFSR forward model, and reformulate the MFSR problem into a problem of multi-frame blind deblurring (MFDB)
4	A novel total variation optimization method and its application on blind super-resolution	T. Li and P. E. Papamichalis,	2014	A novel TV-based algorithm which can be applied to many inverse problems such as image de-convolution and super-resolution
5	Nonparametric Blind Super-resolution	T. Michaeli and M. Irani,	2013	Propose a general framework for "blind" super resolution. In particular,
6	Blind super-resolution considering a point spread	S. Nakazawa and A. Iwasaki,	2013	It is expected that, using super-resolution framework, high-resolution

	function of a pushbroom sattelite imaging system,			images are obtained from images acquired by two NIR sensors
7	Blind super-resolution using sparse line gradient prior for passive millimeter wave image,	J. Xiong, L. Chen, L. Li and J. Yang,	2012	Aiming at the low resolution problem of Passive Millimeter Wave Image, a blind super-resolution algorithm based on sparse line gradient (SLG)

E. Faramarzi, D. Rajan, F. C. A. Fernandes and M. P. Christensen, [1] Super resolution (SR) for real-life video sequences is a challenging problem due to complex nature of the motion fields. In this work, a novel blind SR method is proposed to improve the spatial resolution of video sequences, while the overall point spread function of the imaging system, motion fields, and noise statistics are unknown. To estimate the blur(s), first, a nonuniform interpolation SR method is utilized to upsample the frames, and then, the blur(s) is(are) estimated through a multiscale process. The blur estimation process is initially performed on a few emphasized edges and gradually on more edges as the iterations continue. Also for faster convergence, the blur is estimated in the filter domain rather than the pixel domain. The high-resolution frames are estimated using a cost function that has the fidelity and regularization terms of type Huber-Markov random field to preserve edges and fine details. The fidelity term is adaptively weighted at each iteration using a masking operation to suppress artifacts due to inaccurate motions. Very promising results are obtained for real-life videos containing detailed structures, complex motions, fast-moving objects, deformable regions, or severe brightness changes. The proposed method outperforms the state of the art in all performed experiments through both subjective and objective evaluations. The results are available online at http://lyle.smu.edu/~rajand/Video_SR/.

Y. Chi, [2] In many applications, the observations can be modeled as a linear combination of a small number of scaled and shifted copies of a bandlimited point spread function, either determined by the nature or designed by the users. Examples include neural spike trains, returns in radar and sonar, images in astronomy and single-molecule microscopy, etc. It is of great interest to resolve the spike signal as accurate as possible from the observation. When the point spread function is assumed unknown, this problem is terribly ill-posed. This work proposes a convex optimization framework based on minimization of the atomic norm for jointly spectrally-sparse ensembles to simultaneously estimate the point spread function as well as the spike signal with provable performance guarantees, by mildly constraining the point spread function lies in a known low-dimensional subspace with an unknown orientation. Numerical examples are provided to validate the effectiveness of the proposed approach.

Qizi Huangpeng, Xiangrong Zeng, Jun Fan, Jing Feng and Quan Sun [3] Multi-frame super resolution (MFSR) aims to estimate a high resolution image from a set of low resolution images. Such task is ill-posed and typically computationally costly. Reported a new MFSR forward model, and reformulate the MFSR problem into a problem of multi-frame blind deblurring (MFDB) which is easier to be addressed than the former. Further efficiently solve the MFBD problem via attacking the resulting sub-problems of alternating minimization using the alternating direction method of multipliers (ADMM). Experiments on synthetic and real images show the effectiveness of the proposed method in terms of speed and image quality.

T. Li and P. E. Papamichalis, [4] The total-variation (TV) regularization is very popular because of its ability to deal with noise while preserving important image features. This work proposes a novel TV-based algorithm which can be applied to many inverse problems such as image de-convolution and super-resolution. The idea is to break the cost function into two parts: a linear part and a nonlinear part containing the TV term, then handling them one after the other in each iteration. This method has overall advantages considering both quality and speed. Then it is applied to blind super-resolution (SR), serving as the solver for both image estimation and the point spread function (PSF) estimation. The PSF estimation is also improved in this work by eliminating boundary pixel values that have not been computed from complete data. Synthetic and real data experiments show the nice performance of the proposed method.

T. Michaeli and M. Irani, [5] Super resolution (SR) algorithms typically assume that the blur kernel is known (either the Point Spread Function 'PSF' of the camera, or some default low-pass filter, e.g. a Gaussian). However, the performance of SR methods significantly deteriorates when the assumed blur kernel deviates from the true one. Propose a general framework for "blind" super resolution. In particular, show that: (i) Unlike the common belief, the PSF of the camera is the wrong blur kernel to use in SR algorithms. (ii) Shows how the correct SR blur kernel can be recovered directly from the low-resolution image. This is done by exploiting the inherent recurrence property of small natural image patches (either internally within the same image, or externally in a collection of other natural images). In particular, shows that recurrence of small patches across scales of the low-res image (which forms the basis for single-image SR), can also be used for estimating the optimal blur kernel. This leads to significant improvement in SR results.

S. Nakazawa and A. Iwasaki,[6] A micro-satellite named “HODOYOSI-1” is a 50-kg-weight small remote sensing satellite. It has a pushbroom imaging system in multi-spectral-band: Red (R), Green (G), Blue (B), and two Near infrared (NIR). It is expected that, using super-resolution framework, high-resolution images are obtained from images acquired by two NIR sensors. In the process of super-resolution, it is necessary to estimate sub-pixel shifts and blur kernels of input images. Although pushbroom systems have different blur properties from normal camera systems, it has always been ignored in super-resolution for satellite images. To improve the results of super-resolution applied to pushbroom images, a new blur model, which is more suitable for pushbroom systems, are proposed. The validity of the new blur model is shown by computer simulations and experiments.

J. Xiong, L. Chen, L. Li and J. Yang [7] Aiming at the low resolution problem of Passive Millimeter Wave Image, a blind super-resolution algorithm based on sparse line gradient (SLG) prior is proposed. Firstly, the line gradient is defined to modeling the specialized prior, which is in line with the characteristics of PMMW image than custom gradient. Then the super-resolution problem under MAP framework is optimized in an alternative iteration progress. Experimental results demonstrate that for the millimeter wave image blind super-resolution, the proposed algorithm is superior to other traditional method.

IV. PROBLEM STATEMENT

The complicated nature of motion fields in real-life videos makes the frame and blur estimations a challenging problem. To estimate the blur(s), the input frames are first upsampled using non-uniform interpolation (NUI) SR method assuming that the blurs are either identical or have slow variations over time. Then the blurs are determined iteratively from some enhanced edges in the upsampled frames [1]. The term ‘superresolution ’ refers to any algorithm which is capable of producing an image with a resolution higher than that of the input image(s). Typically, a superresolu- tion algorithm works with a sequence of low resolution (LR) images (also interchangeably referred to, in this research work, as frames) which are displaced from each other but con- tain a common region of interest. Further, due to various factors, a few among which are imperfections in the optics and other aspects of the acquisition device, limited size and resolution of the physical sensing elements, relative motion between the scene/object and the image capture device, and medium turbulence, the LR images are degraded. Consequently, the superresolved output will not be of high quality, mainly due to the presence of noise and blur. The attribute ‘blind ’ applied to the superresolution problem denotes the lack of information on the function(s) representing the blur in the system. Therefore, a HR reconstruction algorithm/method should include image registration, de- noising and deblurring components in addition to the superresolution module. Though the main focus of this research is on obtaining the highest possible HR image quality from the available LR images

V. CONCLUSION

This work presents an extensive survey on super resolution. The process of image registration with respect to a reference frame results in a matrix with irregularly spaced sampling points. Hence, there is a superresolution algorithm needs to handle irregular sampling. Unfortunately, most algorithms employ some means of approximating the irregularly sampled grid with a regularly sampled one. This induces some error in the process of superresolution which is reflected in the output image quality. It is then reasonable to expect an improvement in performance from a superresolution algorithm which is capable of handling the irregular samples without approximations. Super-resolution algorithms face a number of challenges in parallel with their main super-resolution task. In addition to being able to compute values for all the super- resolution image pixels intensities given the low-resolution image pixel intensities, a super-resolution system must also be able to handle:

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