Blind Super Resolution of Real Life Video Sequence

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Abstract— Super resolution (SR) for real-life video sequences is a challenging problem due to complex nature of the motion fields. In this paper, 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 up sample 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.

Keywords: Blind Super Resolution, Video Sequence

I. INTRODUCTION

These Signal processing techniques to augment the visual quality of images and videos are nowadays particularly appealing. 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. The past decade, in fact, 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), and many more -, which present very high-quality pictures with crystal-clear detail at high spatial and temporal resolutions. And the trend does not appear to be declining: only a few months ago, on the occasion of the annual Consumer Electronics Show (CES) held in January 2014, the company Seiki announced new 65-inch 4K TV models, which will be possible to buy at affordable prices. The recently adopted new compression standard HEVC, too, considered 4K videos for the tests, even if only on cropped areas. However, despite the increasing interest towards them, highquality contents are not always available to be displayed. Video source data are unfortunately often at a lower quality than the desired one, because of several possible causes spatial and temporal down-sampling that may be necessary, noise degradation, high compression, etc. Moreover, the new sources of video contents, like the Internet or mobile devices have generally a lower picture quality than conventional TV broadcasting.

II. SUPER RESOLUTION MODEL

Super resolution is technique to reconstruct the high resolution image using low resolution images. The high frequency content lost during the image acquisition process has to be recovered in the super-resolution techniques. From under-sampled low resolution observations the main concern of the super resolution algorithm is to reconstruct high resolution images, it produces high quality images from blurred, noisy and degraded images. The characteristics of the technique overcoming the inherent resolution limitation of low-resolution imaging systems underlines and represents the word 'super'. Some of the advantages of super-resolution approach are

1) Costs less
2) Existing low resolution imaging systems can be still utilized without any additional hardware
3) Offers flexibility.

The Fig.1 illustrates the typical super resolution model.

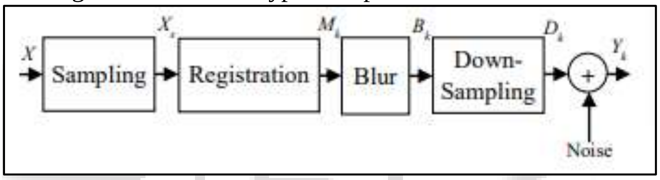

Fig. 1: Super Resolution model

The image restoration problem is closely related to super resolution reconstruction problem. The goal of the image restoration is to recover the image from the degradation such as noise and blur. Hence, for image restoration problem, the size of the restored image and the observed image is the same. Whereas it is different in the image super-resolution since there is a dependency on the decimation factor of the super resolved image. It is necessary to have a detailed understanding of how images are captured and the transformation they undergo in order to apply a super-resolution algorithm. Focusing lens, processor chip, optical sensors, electronic circuits and other mechanical subsystems are usually built in the common digital image acquisition systems (video camera/camcorders/digital cameras). The high resolution image goes through a sequence of degradations such as blur, additive noise and down-sampling when capturing an image of a scene using such camera. There is natural loss of spatial resolution due to optical distortions (out of focus, diffraction limit and insufficient sensor density). Due to causes like relative motion between camera and object, optical aberration, limited shutter speed and atmospheric turbulence the observations could be blurred. The images could also be degraded by various types of noise which occurs during transmission or within the sensor. Due to camera motion like zooming, tilting and panning the frames captured using video camera could be rotated and scaled. Thus due to relative motion between the observations, blur may be introduced. Hence, the observed images account to degraded versions of the high resolution images. A mathematical model that represents the image acquisition process has to be formulated in order to analyze the super-resolution reconstruction problem. The original high resolution (HR) image to be observed low resolution (LR) image(s) is related by this model, known as forward model or observation. The important role in the success of any super-resolution approach is the correct formulation of the observation models. Translation, blur, aliasing and noise in the formulation are the most commonly used forward models for super resolution reconstruction.

III. Literature Review:

1) Qiang. Proposed SR algorithm based on a spatially weighted TV. The information distributed on different regions of image, is added to confine the SR method. This method reduces the artifacts produced in fat regions of the image and preserves the edge information. The approach is tested on aerial image of size 200×200, spot-5 images of size 256×256 and cameraman images of size 200×200 images. The achieved PSNR value for these images is 33.413, 32.636 and 28.65210 respectively.
2) Ren: proposed fractional order total variation (TV) regularization for super-resolution to maintain the texture information. This regularization, image fidelity and TV regularization are included into variational formulation to preserve the discontinuities and image structures. The proposed approach suppresses blocking artifacts. This approach is tested on Lena, Pepper, Parrot and Girl images. The obtained SSIM is 0.8188, 0.8061, 0.8258 and 0.7305 respectively.
3) Deshpande: proposed a Gaussian process regression (GPR) and total variation based framework to superresolve long range captured iris image. Diamond search algorithm is used to calculate the motion vectors which are used in total variation. In GPR linear kernel co-variance function is used to super resolve the images. Further, the super resolved images are used to recognize the person.

IV. Conclusion

A method for blind deconvolution and super resolution from one low-resolution video is introduced in this paper. The complicated nature of motion fields in real-life videos make the frame and blur estimations a challenging problem. To estimate the blur(s), the input frames are first unsampled 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 unsampled frames. After completion of blur estimation, the reconstructed frames are discarded and a non-blind iterative SR process is performed to obtain the final reconstructed frames using the estimated blur(s). A masking operation is applied during each iteration of the final frame reconstruction to successively suppress artifacts resulted by inaccurate motion estimation. Comparison is made with the state of the art and the superior performance of our proposed method is confirmed through different experiments.

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