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Image Resolution Enhancement using Adaptive Blind Technique

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Abstract

Image resolution enhancement (IRE) is the process of manipulating a set of low quality images and produce high quality and high resolution images. The two groups of techniques to increase the apparent resolution of the imaging system are Blind deconvolution (BD) and Super-resolution (SR).Most publications on BD/SR are non-blind, i.e., do not explicitly consider blur identification during the reconstruction procedure.This technical paper, we focuses on various methods of superresolution,blind deconvolution and unifying blind approach to the blind deconvolution and superresolution problem i.e., methods that combine blur identification and image restoration into a single procedure, e.g. alternating minimization (AM) .

Keyword: Blind Decovolution (BD),Super Resolution (SR),Alternating Minimization(AM).

Introduction

In the recent years there is increased in the demand for better quality images in the various applications such as medical, astronomy, object recognition. Image resolution enhancement is also widely useful for satellite image applications which include building construction, bridge recognition, in GPS technique. The two approaches used to enhance the resolution are

SuperResolution

Blind Deconvolution.

Super-Resolution, loosely speaking, is the process of recovering a high-resolution image from a set of low resolution input images.The goal of SR is to extract the independent information from each image in that set and combine the information into a single high resolution (HR) image. The only requirement is that each LR image must contain some information that is unique to that image. This means that when these LR images are mapped onto a common reference plane their samples must be subpixel shifted from samples of other images, for SR reconstruction. These samples can be acquired by sub-pixel shifts, by changing scene illumination or, by changing the amount of blur.

The major advantage of the super resolution approach is that it may cost less and the existing LR imaging systems can be still utilized. The SR image reconstruction is proved to be useful in many practical cases where multiple frames of the same scene can be obtained, including Synthetic zooming of region of interest (ROI) is another important application in surveillance, forensic, scientific, medical, and satellite imaging. The SR technique is also useful in medical imaging such as computed tomography (CT) and magnetic resonance imaging,satellite imaging applications such as remote sensing and LANDSAT.

In blind deconvolution one aims to estimate from an input blurred image , a sharp image and an unknown blur kernel .It is categorized into two classes single channel and multichannel deconvolution. For deconvolution method, is the process of estimating the sharp image, it is necessary to rasterize the predicted sharp edge-profile back onto a pixel grid. By rasterizing the subpixel sharp-edge profile onto an up-sampled grid, we can estimate a super-resolved sharp image. In addition, at the actual identified edge location (as before), the pixel color is a weighted average of the minimum and maximum, where the weighting reflects the sub-pixel edge location on the grid.

Deconvolution appears in a wide range of application areas, such as photography, astronomy, medical imaging, and remote sensing. For example, if atmospheric turbulence causes blurring, we can capture several images in a row, and due to the random nature of turbulence, each image is almost surely blurred in a different way. If camera shake causes blurring, continuous shooting with the camera provides several images that are blurred in a different way since our hand moves randomly.

Information hiding is the principle of segregation of the design decisions in a computer program that are most likely to change, thus protecting other parts of the program from extensive modification if the design decision is changed. The protection involves providing a stable interface which protects the remainder of the program from the implementation.The process of encoding messages in such a way that only authorized parties can read it. Encryption doesn't prevent hacking but it reduces the likelihood that the hacker will be able to read the data that is encrypted. In an encryption scheme, the message or information is encrypted using an encryption algorithm, turning it into an unreadable. This is usually done with the use of an key which specifies how the message is to be encoded. Steganography is the art and science of encoding hidden messages in such a way that no one, apart from the sender and intended recipient, suspects the existence of the message.

Super Resolution

Here the input is low resolution frames there followed by subpixel registeration from all available LR images into common reference grid,wrapping of the input LR images into reference grid. Restoration of the LR images to reduce the artifacts due to blurring and sensor noise, Interpolation of the LR images with a predetermined zoom factor to obtain the desired HR image.

The methods are:

Interpolation-based methods: widely used for producing zoom-in images.

Learning-based or example-based methods: the correspondences between LR and HR image patches are first learned from a database of LR and HR image pairs, and then applied to a new LR image to recover its HR version.

Reconstruction-based methods: it requires reconstruction constraint, which requires the down sampling version of the target HR image should be similar to the LR image.

Sophisticated or Edge directed method: estimate the target HR image by enforcing some edge knowledge, it produce pixel accuracies partially there by regularization HR image is derived.

In[3],interpolation based blind super resolution method applied,here the processing time is 40 seconds.

In[5],combined framework of classical + example based SR approaches with the processing time of 250 minutes.

In[14]a self-learning of in scale SVR via Bayesian theorey is applied with the processing time of 160 minutes.

In[26],reconstruction based blind technique is applied,but it resultant processing time is more than 60 minutes.

In[15],a novel seif-learning via contourlet transform with the processing time of 270 seconds

In[13] edge directed SR approaches based on novel adaptive gradient magnitude self interpolation is applied,the resultant processing time is 3 minutes.

Table 1: Comparison Results ofSuperResolution Approaches

Approach	References	Pros	Cons
Non uniform interpolation	[4]	Simultaneous registration & deblurring ,Registration Computational cost is low	Optimality is high
Probablistic method (eg. MAP)	[24,19]	Estimate HR image and motion parameter simultaneously	Not applicable for degradation models
Set theoretic methods (eg.POCS)	[18]	Utilize Spatial domain efficiently	Slow convergence Computation cost is high
Iterative back projection	[10,7]	Back project the image errors	Not applicable for priori constraint
Optimal Filtering Method	[25,17]	Simultaneous restoration & reconstruction	Not applicable for priori constraint

Blind Deconvolution (SIBD & MIBD)

Here in Single Image Blind Deconvolution SIBD, the input is a blurry image where the blur kernel is unknown. This method is conducted by predicting the sharp edges of the image and by gradient thresholding the strong edges get restored from that the blur kernel is estimated, where as in Multi image Deconvolution requires that the input images are properly registered, which first estimates blur kernels and then recovers the original image. The blur kernels are equal to the minimum eigenvector of a special matrix constructed from the blurred input images. Necessary assumptions for perfect recovery of the blurs are noise-free environment and channel coprimeness, i.e., a scalar constant is the only common factor of the blurs.

Fig 1:Blurred Input Images

In[8] IQML algorithm which first estimates the blur function and then recovers the original image by standard non blind methods to recovers blurs.It is limited in case of noise-free environment and channel coprimeness.

In [6],Bezout's based indirect algorithm which finds the restoration filters and by convolving the filters with the observed image,recovers the original image.It is vulnerable to noise and even for moderate noise level restoration.

In[16],Bussgang algorithm which performs well on spatially uncorrelated data such as binary text images and spiky images,It is lack in robustness because it not include any noise assumptions.

In[20],Least square deconvolution based multi channel algorithm ,but it is restricted in case of absence of PSF size and not perfectly registered channels.

In[9],bispectrum based approach is used,it takes the ability to suppress signal independent and Gaussian noise but it is computationally expensive.

In[4],Richardson-lucy algorithm is fairly reduce the noise tolerance,it is restricted in evaluating both the aberration coefficient and object of the image which having unknown amount of aberration in PSF.

In[29],MAP-non Gaussian MRF model based on Huber function,it alleviates the noticeable artifacts in the reconstructed image.

In[11],alpha matte method used to extract a transparency map from that map the blur kernel is estimated,but it is vulnerable to strong edges prediction.

In[12],Edge prior profile method used to predict sharp egdes from that edges the blur kernel is estimated,but it is restricted to use only in multiscale approaches.

In[1],a shock filter and gradient thresholding is applied to restore only strong edges and estimates the blur kernel from that truncated edges,it is limited in case of absence of salient edges in image.

Unified Blind Procedure

Single procedure for single and multi image super resolution,Single and multi image blind Deconvolution.The blur and high resolution image is estimated by regularizing the cost function. Here the input image can be of Color/grey scale image ,by applying the blind procedure the resultant output is High Resolution images.Its performance can be evaluated by means of PSNR,SSIM,NMSE and RMSE values.

In[23]BSR algorithm is used to regularize the energy function with respect to the original image and blur,it is carried out in both the image and blur domains.But it isrestricted to use the minimum or close to minimum number of LR images for the given SR factor.the estimated PSNR value is 24.5 dB

In[3],adaptive BSRalgorithm used in which the cost function is based on Alternating Minimization approach,the regularization for image and blur are Huber Markov Random field Model and Gaussian.The estimated PSNR value is 29 dB.

Fig 2 : Standard Output Of Resolution Enhancement

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Table 2: Comparison Of Resolution Enhancement methods

REFERENCES	PAPER TITLE	SUPER RESOLUTION/ PERFORMANCE ESTIMATED	IMAGE OPTIMIZATION	BLIND DECONVOLUTION/ PERFORMANCE ESTIMATED	REGULARIZATION TERM IMAGE/BLUR	POINT SPREAD FUNCTION
21	Robust Multichannel Blind Deconvolution via Fast Alternating Minimization	-	-	Augmented Lagrangian	Total variation/ MC constraint	PSF 40X40 (estimated)
28	A regularization approach to joint blur identification and image restoration	-	Conjugate gradient method	Generalized cross validation (GCV) method	Space adaptive regularization	PSF 3 x 3
22	Multichannel Blind Iterative Image Restoration	-	Steepest Decent method	MC alternating minimization algorithm /27.2dB(PSNR)	Total variation / Mumford–Shah functional	PSF 20 x 20 (estimated)
2	Image Deblurring and Super-Resolution by Adaptive Sparse Domain Selection and Adaptive Regularization	Adaptive sparse domain selection /27.54 dB(PSNR)	-	Adaptive regularization-iterative shrinkage algorithm/ 29.60(PSNR)	Autoregressive (AR) model	PSF 7 x 7 (estimated)
26	Super-Resolution Based on Blind Deconvolution Using Similarity of Power Spectra	Non uniform interpolation –bicubic /53.71(RMSE)	Precondition Conjugate gradient method	Reinforcement algorithm /1.34(RMSE)	Bilateral total variation/ Fourier power spectra	PSF 8 x8
27	Objective Image Quality Assessment of Multiframe Super-Resolution Methods	Delaunay bicubic non-uniform interpolation /29.02(PSNR)	-	-	-	-
13	Edge-Directed Single-Image Super-Resolution via Adaptive Gradient Magnitude Self-Interpolation	Adaptive gradient magnitude self interpolation /0.696(SSIM)	-	-	-	-
23	A Unified Approach to Superresolution and Multichannel Blind Deconvolution	Nonuniform interpolation –bilinear /24.5(PSNR)	-	Singular value Decomposition	-	PSF 15 x 15
3	Unified Blind Method for Multi-Image Super-Resolution and Single/Multi-Image Blur Deconvolution	Non uniform interpolation –bilinear /29.5(PSNR)	Conjugate gradient method	Cholesky decomposition /31.9(PSNR)	Huber markov random field/L2	PSF 5 x 5

1. $K_B^+ = (n, e); K_B^- = (n, d)$

Suppose Alice wants to send Bob a bit pattern, or number, m such that m < n.

To encrypt the message, Alice uses Bob's public key and determines the cipher text, c as:

$$c = m^e \bmod n$$

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To decrypt the message, Bob uses Bob's private key and determines the plain text, m as:

$m = c^d \bmod n.$

Conclusion

In this paper we investigate the possibility of enhancing the resolution of the image. We use an Blind technique which is for improving clarity of an image with minimum processing time. Our survey result shows that unified Blind technique is efficient to use in the image captured in atmosphere turbulence and continuous capturing of image. In future this method should be extended in several directions, for instance to have space-variant blur identification, study joint image registration and restoration procedures, or consider compression errors in the forward model and video baesd resolution enhancement followed by data hiding in that enhanced image, and so on.

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