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Aurangabad**

Seminar Report

On

Image Super Resolution

Submitted By

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In partial fulfillment of

Bachelor of Technology

(Computer Science & Engineering)

Guided By

Mrs. Amruta Joshi

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Aurangabad

(2019- 2020)

CERTIFICATE

This is to certify that, the Seminar entitled “**Image Super Resolution**” submitted by **Priti Gajbhare** is a bonafide work completed under my supervision and guidance in partial fulfillment for award of Bachelor of Technology (Computer Science and Engineering) Degree of Dr. Babasaheb Ambedkar Technological University, Lonere.

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Abstract

Super Resolution image reconstruction tries to obtain a high-resolution image from one or more observed low-resolution images of the same scene, using signal processing techniques. Variety of super resolution methods have been proposed in last decades. In this paper, we propose a new super resolution algorithm based on single low-resolution image. As the super resolution reconstruction is an inverse problem, our method consists of three phases up-sampling, deblurring and denoising. Experimental results show the effectiveness of the proposed method. Image super-resolution (SR) reconstruction has been an important research fields due to its wide applications. Although many SR methods have been proposed, there are still some problems remain to be solved, and the quality of the reconstructed high-resolution (HR) image needs to be improved.

Contents

List of Abbreviations

Sr. No	Acronym	Abbreviations
1.	LR	Low Resolution
2.	HR	High Resolution
3.	SR	Super Resolution
4.	POCS	projection onto convex sets
5.	KKR	kernel ridge regression

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1.Introduction

Enlargement of region of interest, is an important application in surveillance, scientific, medical and satellite imaging. For surveillance purposes, it is often needed to magnify objects in the scene such as the face of a criminal or the license plate of a car. In medical imaging such as CT and MRI, high resolution images are very helpful to make a correct diagnosis. As mentioned, having high resolution image is essential while the resolution quality of captured images is not desired due to the limitation of image acquisition systems and imaging environments. The high cost for precision image sensors is also an important concern in many applications regarding high resolution imaging. Super Resolution (SR) provides an inexpensive solution via software approaches to overcome the inherent limitations of image acquisition hardware systems. Process of combining information of one or many input images with low resolution (LR) from the same scene to reconstruct a high resolution (HR) image is called Image Super Resolution. Depending on the number of image frames, SR techniques can be classified into two main approaches: (1) single image SR methods based on one LR image frame which also known as one Input-one Output systems, and (2) SR techniques based on multi image frames which use motion information between different image frames. So algorithms were created that use image reconstruction techniques and motion estimation to produce a HR image from a sequence of LR image frames and also known as multi Input-one Output methods. Multi image SR methods include Bayesian analysis, iterative back projection (IBP), projection onto convex sets (POCS) and bilateral total variation (BTV). On the other hand, various techniques for single frame SR have been developed. Example-based SR such as Markov random field (MRF), locally linear embedding (LLE) and sparse representation can be used for single image SR problem. These algorithms use a training set to learn the fine details of an image at LR. Then, they use those learned relationship to predict fine details in other images.

There is an increasing demand on the images with high pixel density, especially in the fields of military monitoring, public security controlling and medical diagnosis, etc. But sometimes the high-resolution images are difficult to get due to the inherent resolution limitations of low-cost imaging sensors. Therefore the technique of super resolution (SR) reconstruction has been an active area of research. Nowadays various image SR schemes have been developed, which can be roughly divided into three classes: interpolation-based method, reconstruction-based method and machine learning based method.

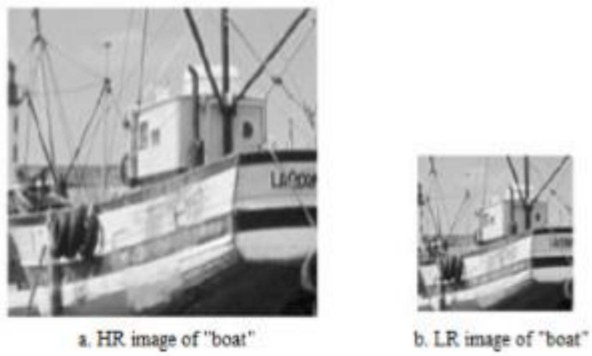

Fig 1.1. The HR and LR image of 'boat'

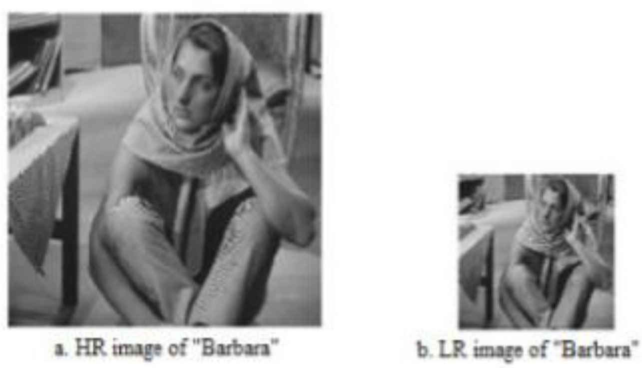

Fig1.2. The HR and LR image of 'Barbara'

2.Literature Survey

Image Super Resolution using multi-surface fitting is a new interpolation-based method of image super-resolution reconstruction. The idea is using multi-surface fitting to take full advantage of spatial structure information. Each site of low-resolution pixels is fitted with one surface, and the final estimation is made by fusing the multisampling values on these surfaces in the maximum a posteriori fashion. With this method, the reconstructed high-resolution images preserve image details effectively without any hypothesis on image prior. An image SR reconstruction framework using multisurface fitting is presented here. It creates one surface for every LR pixel. These surfaces can effectively retain the image details such as image gradients, curvatures, or even higher order information. Each surface has different weights in estimation of the HR intensity values. In the MAP frame, the surfaces with smaller noise and errors tend to have greater contributions. The multi-scale dictionary [2] based hallucination is based upon the following two observations. First, the local structures in a natural image usually tend to repeat themselves many times, both within the same scale and across different scales. The details missing in a local structure at a smaller scale can be estimated from its similar patches at a larger scale.

Secondly, different images prefer different patch sizes for optimal representation. For instance, the major edges prefer a larger scale while the sophisticated details tend to a smaller one. Therefore, it is important to jointly represent an image at different scales. Considering the above cues, this paper introduces a multi-scale dictionary representation to example-based hallucination. Then reformulate it as a hallucination regularization term for the reconstruction- based SR framework to maintain visual details. There are three fundamental stages. Generating training samples from the pyramid images of the LR input, learning multi-scale dictionary, optimizing a unified energy function, in which the HR reconstruction term and finally the local as well as non-local regularization terms, and sparse hallucination regularization term are combined together and the gradient decent method is used to find a local optimal solution to the reconstructed HR image.

Landmark image super-resolution by retrieving web images proposes a new super-resolution scheme for landmark images by retrieving correlated web images. Using correlated web images significantly improves the exemplar-based SR. Given a low-resolution image, we extract local descriptors from its up-sampled version and bundle the descriptors according to their spatial relationship to retrieve correlated high-resolution images from the web. Though similar in content, the retrieved images are usually taken with different illumination, focal lengths, and shot perspectives, resulting in uncertainty for the HR detail approximation. To solve this problem, we first propose aligning these images to the upsampled LR image through a global registration, which identifies the corresponding regions in these images and reduces the mismatching. Second, we propose a structure-aware matching criterion and adaptive block sizes to improve the mapping accuracy between LR and HR patches. Finally, these matched HR patches are blended together by solving an energy minimization problem to recover the desired HR image. Reconstruction and example based Super Resolution (SR) methods [4] are promising for restoring a High Resolution (HR) image from Low Resolution (LR) images. The interpolation-based schemes that do not use extra assisted information, suffer from blurring artifacts because HR details are difficult to infer given only a single LR image. Multi image-based methods fuse multiple LR images of the same scene to provide additional information for extracting details. Methods in this category generally perform better than methods that use only a single LR image, but it is still hard to recover high-frequency details when the magnification factor is large. Exemplar-based methods build a training set of HR/LR pair patches to infer HR patches from LR patches. By using external HR images for additional information, exemplar-based methods are able to introduce new and plausible HR details. However, the training set is generally fixed, thus limiting the SR performance. Image Super-Resolution (SR) has been extensively studied to solve the problem of limited resolution in imaging devices for decades. It has wide applications in video surveillance, remote imaging, medical imaging, etc. The idea of SR is to reconstruct a High-Resolution (HR) image from aliased Low-Resolution (LR) images. There are four main classes of methods to estimate the pixel values in HR grids, i.e., frequency-domain approaches, learning-based approaches, iterative HR image reconstruction techniques and interpolation-based approaches.

Given a generic LR image, to reconstruct a photo-realistic SR image and to suppress artifacts in the reconstructed SR image, in this paper it tells about a multi-scale dictionary to a novel SR method that simultaneously integrates local and non-local priors. The local prior suppresses artifacts by using steering kernel regression to predict the target pixel from a small local area. The non-local prior enriches visual details by taking a weighted average of a large neighborhood as an estimate of the target pixel. Essentially, these two priors are complementary to each other. Experimental results demonstrate that the proposed method can produce high quality SR recovery both quantitatively and perceptually.

The main goal of single image super-resolution is to construct a high resolution (HR) image from a low image. There has many research works done in this field it can be classified into three categories: interpolation-based approaches, learning based approaches and reconstruction-based approaches. More sophisticated interpolation models have also been proposed, like auto regression model, multi-surface fitting model, edge directed models, sparse representation models and ICBI (Interactive Curvature Based Interpolation) algorithm. Interpolation-based approaches always have fast computation speed compared to other methods.HR images are used in many application fields such as remote sensing, biometrics identification, medical imaging, and so on.

A novel edge sharpness metric GPS (gradient profile sharpness) is extracted as the eccentricity of gradient profile description models, which considers both the gradient magnitude and the spatial scattering of a gradient profile. To describe gradient profile shapes here propose two models such as triangle model and mixed Gaussian model [5]. The Triangle Model describes that, when the edges are sharp with small intensities the extracted gradient profiles are always short with no tails. Mixed Gaussian Model describes that, when edges are smooth, gradient profiles become longer and profile shapes become complicated with heavy tails. And these two methods describe gradient profiles with different lengths and complicated asymmetric shapes, which are more flexible to produce better fitting performance. The proposed metric GPS consider both gradient profile's magnitude and spatial scattering, which emphasis the impact of illumination contrast on human visual perception. GPS can represent edge sharpness perceptually well. Experiments are conducted to evaluate the SR approach, and they generate superior HR images with better visual similarity and lower reconstruction error.

The gradient profiles are transformed under the constraint [5] that the sum of gradient magnitude and the shape of gradient profile should be consistent during transformation. Based on these constraints, gradient profiles are enhanced according to their original shapes, which makes the generated HR image more close to ground truth. And also propose a method of merging of two or more images. And in this merging method crop a part from one image and also crop a part from other image and then we can merge these two images into one. For the evaluation of gradient profile fitting performance, for each gradient profile if there is less than eight extracted profile points, the triangular model is used. Else both the triangle model and mixed Gaussian model. GPS is a method that is proposed to estimate the parameter of GPS transformation relationship automatically.

3.Brief on system

3.1 BACKGROUND

Observation Model Image SR reconstruction aims to generate a HR image from its degraded LR image. The first step in analyzing the SR image reconstruction is to formulate a model that relates the original HR image to the observed LR image. As depicted in Fig. 1, SR is an inverse problem and is generally modeled as,

Y=DBX+n

Where D is a down-sampling operator, B is a blurring operator and n is the added noise. Assuming Y is the input image, the problem of SR reconstruction is to produce the SR image X' which is considered as an optimal approximation to the original HR one (X). Due to the ill-posed nature of the reconstruction, the inverse solutions of are generally not unique.

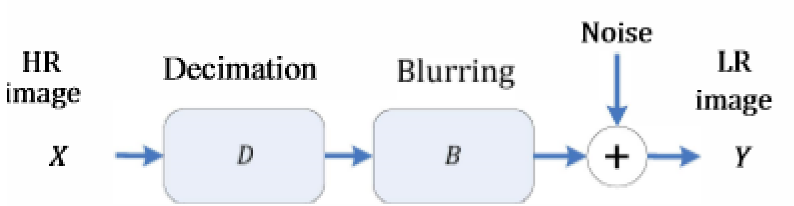

Fig.3.1. Observation model

3.2 Comparison Metrics

To measure how close the output image is to the original input one, MSE and PSNR are used as the image quality comparison metrics which calculated as below:

$$PSNR = 20\log_{10}\left(\frac{255}{\sqrt{MSE}}\right)$$

3.3 PROPOSED METHOD

Our proposed method for single image SR is given in Algorithm 1. As shown in the algorithm, our SR method consists of three phases: up-sampling, deblurring and denoising. The output of each phase is used as the input for next phase. Here are more details of each phase.

3.3.1. Up-Sampling Phase

In SR process, assume up-sampling is done by factor of d, then 100/d2 percent of pixels on the HR grid are original. These pixels only need to be correctly placed on the HR grid with no modification. The rest of pixels are interpolated. For each interpolated pixel, we search an area which is called patch, in the adjacent frames for candidate pixels [9]. This phase is done by applying three interpolation methods with same up-sampling factor for all methods. These methods are nearest neighbor interpolation, bilinear interpolation and bicubic interpolation. Therefore, we have three intermediate up-sampled images. PSNR of these images is calculated. Based on the calculated PSNR a weight is assigned to each intermediate up-sampled image. This weight is used as an impact factor of pixels of intermediate image in calculation of pixels of final up-sampled image. A higher PSNR generally indicates that the reconstruction is of higher quality, but in some cases it may not. So, there is a direct relation between PSNR and impact factor. The value of each pixel in the final up-sampled image is calculated as:

Where P(i,j) is the value of pixel in place (i,j), n is the number of intermediate up-sampled images and Ck is the impact factor of k-th image. Note that sum of impact factor of all up-sampled images should be equal to one.

3.3.2 Deblurring Phase

One of the most important problem in digital photography is motion blur caused by camera shake. In many situations there simply is not enough light to avoid using a long shutter speed, and the inevitable result is that many of our snapshots come out blurry [7]. In general blurring may be caused by optical system (out of focus, diffraction limit or aberrations), relative motion between imaging system and scene and the point spread function (PSF) of the LR sensor, which is modelled as a spatial averaging operator. A lot of works have been done for recovery an un-blurred image from a single, motion blurred one. In most algorithms, the blurring process is assumed to be known, but in many practical situations, it is unknown. For this phase of our SR algorithm, we used the algorithm presented by Q. Shan in [7] which introduces image deconvolution method to remove camera motion blur from a single image. He has performed deblurring by minimizing errors caused by inaccurate blur kernel estimation and image noise. As a result, a high quality deblurred image in low computation time is obtained.

3.3.3 Denoising Phase

Image denoising is an important image processing task, Since noise exists in nearly all digital imaging systems. In image denoising procedure, we try to obtain a noise-free image from a noisy image. Numerous denoising approaches have been developed and in general they can be divided into two categories: transform domain methods are developed under the assumption that the true image can be well approximated by a linear combination of few transform basic elements, while spatial domain methods focuses on different noise suppression approach, which estimates each pixel value as a weighted average of other pixels, where higher weights are assigned to similar pixels.

Fig3.2. Super Resolution

4.Conclusion

4.1 Conclusion

Having high resolution is an important requirement in many applications, but in most situations because of the limitation of imaging hardware system and environmental operators, it is not satisfied. In this paper, we have proposed a new single image super resolution method, which consists of up-sampling, deblurring and denoising. In up-sampling a new algorithm is introduced. Comparison with other super resolution method shows the effectiveness of the proposed method.

4.2Application

The super resolution is widely applied in:

- Remote sensing
- Medical imaging
- Biometric identification
- Satellite imaging
- Video application

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Signature of Student

Name of Student Sign