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Analysis on Image Upscaling

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Abstract- Creation of an artifact-free upscaled image should appear like sharp and natural to the human observer. The solution to the problem often referred to also as "single-image super-resolution". It is related to both the statistical relationship between low-resolution and high-resolution image sampling and to the human perception of image quality. The quality of an image should be maintained. Different algorithms are available for super-resolution of an image which is time consuming. To eliminate this time consumption drawback the distributed environment can be used.

Keywords- Image upscaling, image Super Resolution, real-time image upscaling, upscaling approaches.

I. INTRODUCTION

Image upscaling or single-image super resolution has recently become a hot topic in computer vision and computer graphics communities due to the increasing number of practical applications of the algorithms proposed. Image upscaling (and more generally image super-resolution) methods are implemented in a variety of computer tools like printers, digital TV, media players, image processing packages, graphics renderers, and so on. The problem is quite simple to be described: we need to obtain a digital image to be represented on a large bitmap from original data sampled in a smaller grid, and this image should look like it had been acquired with a sensor having the resolution of the upscaled image or, at least, present a "natural" texture [2]. Sometimes we need an upscaled image to be represented from an original image. It should acquire a "natural" texture. The quality of an image should be maintained while upscaling an image. It is related to both statistical relationship between LR and HR image sampling and to the human perception of image quality [1][2].

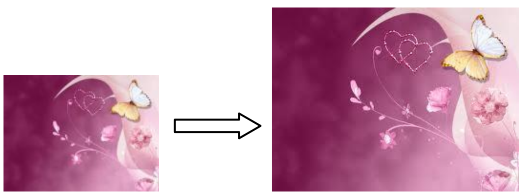

Fig. 1 Example of image upscaling.

Fig.1 gives the example of image upscaling. There are different methods through which the image can be upscaled. There are some other ways through which the image upscaling is possible. Section 2 includes different approaches for super-resolution of an image. Analysis on some existing super-resolution techniques is in section 3. Section 4 concludes this paper.

II. LITERATURE SURVEY

In this section some of the existing techniques in image upscaling are discussed.

A. *Effective Iterative Back Projection Technique*

This technique which was proposed by Bajera and Modi [3] was based on an Iterative back projection (IBP) method. This method is then combined with the Canny Edge Detection and error difference image to recover high frequency information. Using the iteratively back projection it minimizes an error. It uses simple bicubic interpolation to enlarge the image and processes it according to the IBP method. It also back projects high frequency component using Canny Edge Detection and difference images of upsampled LR images to gather more back projecting error.

The initial input LR image was generated from original HR image and apply different algorithms including nearest neighbor (NN) interpolation, bilinear (BL) interpolation, bicubic (BC) interpolation, previous work IBP with LOG as high pass filter [14], IBP with Edge preserving ISEF [15] and proposed method by them, IBP with Canny edge detection and different image on initial input LR image were used, so that resultant image can compared with original HR image.

Advantages: Their proposed technique was fast and robust to noise with edge perseveration. The blurring effect can be greatly reduced in enlarged images after multiple iterations. It also provides sharp edges.

B. Coupled Dictionary Training

This technique proposed by Yang, Wang et al. [4] used novel coupled dictionary training method for single-image SR based on patch wise sparse recovery. The learned couple dictionaries relate the LR and HR image patch spaces via sparse representation. The learning process enforces that the sparse representation of a LR image patch in terms of the LR dictionary. It can well reconstruct its underlying HR image patch with the dictionary in the high-resolution image patch space. The learning problem was modelled as a bi-level optimization problem, where the optimization includes an l^1-norm minimization problem in its constraints. The gradient for stochastic gradient descent was calculated by using implicit differentiation. The coupled dictionary learning method can outperform the existing joint dictionary training method both quantitatively and qualitatively. The algorithm can be speed up approximately 10 times for real applications. It was possible by learning a neural network model for sparse inference. Sampling a large number of training HR/LR image patch pairs from an external database containing clean HR images $\{Xi\}^n_{i=1}$ was used to train the coupled dictionaries. LR image was obtained by blurring and downsampling each HR image Xi. By using “bicubic” interpolation upscale the LR image back to its original size to get the interpolated LR image Yi. From these image pairs $\{Xi , Yi \}^n_{i=1}$, N pairs of HR/LR patches of size pxp, was sampled and extract their patch features using the aforementioned procedures for obtaining training data $\{(xi , yi)\}^N_{i=1}$. The coupled dictionaries Dx and Dy were learnt from the training data which was prepared by eliminating the patches having small variances for avoiding sampling too many smooth patches that were less informative.

Advantages: This coupled learning algorithm is generic, and hence can be potentially applied to many signal recovery and computer vision tasks, e.g., image compression, texture transfer, and SR.

C. Sparse Neighbor Embedding (NE)

This technique suggested by Gao, Zhang et al. [5] used a sparse neighbor selection scheme for SR reconstruction. First predetermine a larger number of neighbors as potential candidates and develop an extended Robust-SL0 algorithm to simultaneously find the neighbors and to solve the reconstruction weights. They suggested that the k-nearest neighbor should have similar local geometric structures based on clustering. For performing such clustering, it employs histograms of oriented gradients (HoG) of LR image patches. The NE-based SR algorithms can represent more patterns even if a relatively smaller training data set was available and thus show much stronger generalization ability for a variety of images.

The main advantage of NE algorithm was that the model was simple and easy to implement. On the contrary, the ASDS method was more complex because of the sparse prior regularization, the non-local similarity regularization, and the local smooth regularization was simultaneously incorporated for the SR problem. The proposed method produces top-level visual quality.

D. Multisurface Fitting

This technique proposed by Zhou, Yang and Liao [6] used a new interpolation-based method of image super-resolution reconstruction. The LR pixels were fitted with one surface and the HR images were obtained by fusing multisampling values of these surfaces in *a posteriori* fashion. They recommended that more LR pixels can effectively contribute to the final estimations through their surfaces.

Advantages: First, it outperforms other interpolation- based approaches with respect to preserving image details, e.g., higher order information can be preserved. Second, unlike the iterative techniques using regularization, it does not need any artificial hypothesis on image prior.

They concluded that the spatial structures in the HR grid should comprise two aspects. *One* was the spatial distributions of LR pixels in the HR grid. *Second* was the local structures of intensity, i.e., edge orientations, curvatures, etc. The first aspect was represented by the positions of LR pixels in the coordinate system of the HR grid, and the second was denoted by intensity derivatives of different orders.

Fit one surface at each site of LR pixels by considering the difference of LR pixels. There was a one-to-one correspondence between fitted surfaces and LR pixels. Then, a series of intensity values was obtained at the location of pixel p_ϕ by sampling all K surfaces.

E. Joint Learning via a Coupled Constraint

This technique suggested by Gao, Zhang et al. [7] mainly contains three parts. *First,* preprocessing was used to construct k-nearest grouping patch pairs (GPPs) by linking the LR and its corresponding HR features together. In the *second* step, joint learning was performed to learn two projection matrices of the nearest GPPs associated with each LR input patch such that the difference between LR and HR was reduced as much as possible. Thereafter, the measurements of LR and HR features in the corresponding GPPs were projected onto a unified feature subspace. Then, the NE algorithm was used to estimate the optimal weights in the learned unified feature subspace and combine linearly the corresponding high-frequency patches with the estimated weights to synthesize the HR image patches. *Finally,* back projection was incorporated into the maximum *a posteriori* (MAP) framework, where the global construction constraint and the prior knowledge (that the final output of the HR image should be as close as possible to the initial SR estimate) were combined to enhance the initial SR image.

The NE for SR reconstruction in the unified feature subspace enforces a much stronger constraint which reduces the ambiguity between the LR image patches and the HR patches. The SSIM scores also suggest the effectiveness of the proposed method.

F. Local Consistency Constrained Adaptive Neighbor Embedding

This technique proposed by Fan, Sun et al. [8] used a robust single image SR method for enlarging low quality text image. Firstly the non-local reconstruction problem was pointed out in neighbor embedding based super-resolution by statistical analysis on an empirical data set. Secondly, introduce a local consistency constraint to explicitly regularize the linear reconstruction process, and adaptively generate the most possible candidates for the HR image patch. Rely on the adjacent overlapping patches for capability verification through a Markov network of the non-consistent candidates.

G. Edge-Preserving using Preconditioning

This technique proposed by Pelletier and Cooperstock [9] increased the priority of LR images' gradient region, learns from other HR images' gradient region, gets horizontal and vertical direction of image gradient map and links the two gradient maps to get the super-resolution image. The shift matrices were determined by the relative displacements between LR frames. The image was blurred using a 5x5 Gaussian kernel. It was then downsampled. Construction & updation of the preconditioner was used after every iteration.

H. Gradient Learning

Based on the traditional magnification methods that learn through training sets, the method proposed by Li and Peng [10] increases the priority of low-frequency images' gradient region and learns from gradient region. Features were extracted from every gradient image fragment, and then find the closest matching fragments to determine the high-frequency of target image. At first, horizontal and vertical gradient images of the input image was obtained then the two images were combined together to get the final HR image. By this way, the target image had sharper edges and higher quality. It was a very flexible technique.

I. Averaged Image and Regularized Deconvolution

In this technique suggested by Park [11], the LR images were downsampled by shifting the original image by sub-pixel distances which was an average light intensity on the corresponding pixel area. The average of multiple LR images with appropriate registration can be considered as a blurred HR image which was based on downsampling. The HR image was obtained by regularizing the deconvoltion method after identifying the point spread function (PSF). The regularization factor was determined by line search of a cost function.

J. Nonparametric Bayesian INLA Approximation

It was a fully automatic SR algorithm which used a nonparametric Bayesian inference method based on numerical integration known in the statistical literature as Integrated Nested Laplace Approximation (INLA) [12]. It uses a statistical inference in Bayesian frameworks. The INLA only can be applied to latent Gaussian models, where the covariance matrix was governed by a few parameters and the latent field was a Gaussian Markov random field (GMRF) with a sparse precision matrix. INLA can be used almost as a black box to analyse latent Gaussian models [13].

III. ANALYSIS OF SOME SUPER-RESOLUTION TECHNIQUES

TABLE I
AN ANALYSIS

Method	***Technique Used***	***Conclusion***
"An Effective Iterative Back Projection" [3]	Iterative back projection method combined with Canny Edge Detection. Uses bicubic Interpolation to enlarge the image	Provides sharp edges. Removes blur effect
"Coupled Dictionary Training"[4]	Sparse representation is used. Optimization employs a stochastic gradient descent procedure.	Computational time decreases as threshold increases. Speeds up the algorithm approximately 10 times by learning a neural network model.
"Sparse Neighbor Embedding" [5]	Sparse neighbor selection scheme is used. Focused on neighbor embedding based method. Robust SL0 algorithm is used to find the neighbor.	Texture similarity can be investigated. To accelerate the speed of SR reconstruction, clustering on histograms of oriented gradients (HoG) features is used to partition the training data set into a set of subsets.
"Multisurface Fitting" [6]	Interpolation based method. i.e fitting one surface for every LR pixel & fusing the multisampling values.	Method is pixel wise & not iterative. It can be accelerated if parallel implementations are adopted.
"Joint Learning via a Coupled Constraint" [7]	It is applied to train two projection matrices simultaneously and to map the original LR and HR feature spaces onto a unified feature	Finds the k-nearest neighbors (k-NNs) for linear embedding in a unified feature subspace spanned by LR-HR image

	subspace.	patches rather than in the original LR feature space alone. Each LR Image patch be super-resolved
"Local Consistency Constrained Adaptive Neighbor Embedding" [8]	Large volume of text primitive patches is extracted from both LR-HR training images. Neighbor embedding is used for local consistent image patches & Markov network by non-consistent image patches.	Used for text image super-resolution
"Preconditioning for Edge-Preserving Image Super Resolution" [9]	The shift matrices are determined by the relative displacements between LR frames. The image was blurred using a 5X5 Gaussian Kernel. It was then downsampled. Construction and updation of the preconditioner is used in every iteration.	Reduces the noise and artifacts from the HR image.
"Gradient Learning" [10]	Horizontal & vertical gradients are extracted from an image. Apply the training data to these gradients. Learning HR Horizontal & vertical gradients & link these for generating SR image.	The observation of image formation is started on the image sensor. The LR images taken by camera with both translational & rotational motions are considered.
"Averaged Image and Regularized Deconvolution" [11]	The LR images are modeled as downsampled images of the original scene shifted by sub-pixel distances. The LR image is blurred by blurring filter. The blurring filter is identified by finding the point spread function.	The observation of image formation is started on the image sensor. The LR images taken by camera with both translational & rotational motions are considered.
"Nonparametric Bayesian INLA Approximation" [12]	It is known in the statistical literature as Integrated Nested Laplace Approximation (INLA). Multiple LR images are obtained from different Gaussian values.	Performs better than other SR algorithms. It gives better results compared to other SR methods.

III. CONCLUSION

Form the literature it is affirms that all the techniques are time consuming. To achieve this drawback of the existing methods, the proposed method is very effective. The PSNR value is also high. Time elapsed between the reconstruction of an image from multiple LR images is also calculated which is in seconds. Not much of the work has been focused on distributed environment to speed up the process of upscaling. So, the proposed work is efficient in all respect of time.

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