Image Resolution Enhancement via Multi Surface Fitting

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Abstract: A new method of image resolution enhancement via multi-surface fitting is proposed. Image resolution generally results in loss of image quality. Therefore image resolution requires interpolation to read between the pixels. By the use of spatial structure information, the idea of multi-surface fitting is implemented. The fusion of multi-sampling values on these surfaces in the maximum a posteriori fashion by fitting low resolution pixels on one surface. The reconstructed high-resolution images preserve image details effectively without any hypothesis on image prior. Although the main concern of image resolution algorithm is to reconstruct HR images from under sampled LR images, it covers image restoration techniques that produce high quality images from noisy, blurred images. Therefore, the goal of image resolution techniques is to restore an HR image from several degraded and aliased LR images. The proposed system provides error-free high resolution for real images.

Keywords: Data fusion, Multi surface fitting, Image resolution enhancement, non-uniform interpolation

1. Introduction

Image resolution enhancement 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 image resolution 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.

Frequency - domain approaches make explicit use of the aliasing relation between continuous Fourier transform and discrete Fourier transform. However, this kind of resolution approaches is only restricted to global translational motion and linear space-invariant blur. Learning-based approaches embed more information into LR images from learning examples. The embedded information can be utilized to relate LR and HR image patches, to choose the reconstruction parameters, etc. However, neither of the approaches to represents the image co-occurrence knowledge in an effective way. Thus, their performances largely depend on the learning examples.

The iterative HR image reconstruction techniques, the most popular ones are the projection on convex sets algorithm, the maximum *a posteriori* (MAP) estimation, and their variations. The main advantage of them is that it is convenient to add image priors. To regularize the ill-posed inverse problem, it utilizes the total variation function as the image prior. This prior is conducive to preserve the edge, i.e., image structures of one order. However, the choice of model parameters remains unsolved. A variation approach is proposed to address this problem by using a two-level Bayesian inference.

Interpolation-based approaches generally treat image resolution as a non-uniform interpolation problem. They are usually intuitive and computationally efficient. Interpolation is implemented as a pixel wise average algorithm of the LR measurements. It is proven to be the optimal solution in the maximum-likelihood (ML) sense with Gaussian additive noise. Instead of average operation, a median operation is adopted to seek for a robust ML estimation with a more complex model of noise and error. Meanwhile, regularization of a bilateral filter is introduced for edge preservation.

Consequently, the local spatial structure information is severely lost. The interpolation-based image resolution approach using Delaunay triangulation is first addressed for each triangle patch as a bivariate polynomial. The method suggests a sampling theory framework with an ant aliasing pre filter, where the sampled coefficients are calculated by integrating B-spline polynomials and Delaunay triangles. Although Delaunay triangulation expresses spatial structures implicitly and partially, it does not utilize the structure information effectively. Furthermore, it is expensive to structure the tessellation with respect to both the memory space and computational time.

An interpolation based image resolution enhancement method is proposed using multi surface fitting, i.e., fitting one surface for every LR pixel and fusing the multisampling values. Since the number of LR pixels is more than that of HR pixels in context of the resolution problem, our method represents structure information more elaborately. Moreover, more LR pixels can effectively contribute to the final estimations through their surfaces in our method. In addition, there are another ***two advantages*** of the proposed method. ***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.

The remainder of this correspondence is organized as follows. In Section II, the proposed method is presented in detail. Section III provides the experimental results. Finally, Section IV concludes this correspondence.

1.1. Related works:

In **2001**, Elad & Hel **[5]** provided an adequate mathematical justification for the ***Shift and Add method*** for the simple case of an additive Gaussian noise model. In **2002**, Freeman et.al **[3]** suggested three ***example-based*** approaches for zooming an image. First by a change in the spatial frequency amplitude spectrum associated with image sharpening then by aggregating from multiple frames and then estimating the missing new values by comparing the high – low resolution pairs. Here cubic spline method is used to interpolate the low resolution image. But the performance is affected by the training set and these suits only for images because for moving objects multiple observations of same pixel need to be used as more input data is involved. In **2003,** Farsiu et.al **[6]** suggested **r*obust shift and add approach for image resolution method.*** This method, which have a wide range of complexity, memory and time requirements, are usually very sensitive to their assumed model of data and noise, often limiting their utility. Different implementations of the non-iterative Shift and Add concept have been proposed as very fast and effective resolution .In **2006,** pham et.al **[7]** suggested the ***robust fusion of irregularly sampled data using adaptive normalized convolution.*** The method is based on the framework of normalized convolution, in which the local signal is approximated through a projection onto a subspace. This leads to more samples of the same modality being gathered for the analysis, which in turn improves Signal-to-noise ratio and reduces dilution across discontinuities. A robust signal certainty is also adapted to the sample intensities to minimize the influence of outliers. Again in **2006,** Sheikh Et.al **[9]** adopted ***Image information and visual quality.*** In this, image quality assessment algorithms predict visual quality by comparing a distorted image against a reference image, typically by modeling the Human Visual System (HVS), or by using arbitrary signal fidelity criteria. In this, image information adopts a new paradigm for image quality assessment. Then in **2008**, Kim et al**. [4]** adopted ***example based learning*** for single image super resolution involving a map based on example pairs of input and output images. But here the performance was unpredictable. Again, in **2008,** Jian et.al **[12]** proposed a novel generic image prior - ***gradient profile prior*** for the gradient field of the natural image. But the limitation is that for noisy input low resolution image, estimation of the gradient profile might be inaccurate due to noise. In **2009**, Daniel et.al **[2]** suggested a unified framework for combining ***classical multi-image resolution and example-based super resolution.***

The method is fast and efficient however it is not capable of reproducing fine detailed cluttered region. Next, in **2010,** song et al **[8]** proposed an ***adaptive L1 and L2 hybrid error model*** to super-resolution. In this a hybrid error model with $L1$ and $L2$ norm minimization criteria is proposed for image/video super-resolution. A membership function is defined to adaptively control the tradeoff between the $L1$ and $L2$ norm terms. Therefore, the hybrid error model can have the advantages of both $L1$ norm minimization (i.e. edge preservation) and $L2$ norm minimization (i.e. smoothing noise). In addition, an effective convergence criterion is proposed, which is able to terminate the iterative $L1$ and $L2$ norm minimization process efficiently. Again in **2010,** Yang et.al **[1]** present a method based on the ***sparse association between input and example patches.*** Moreover, the increase in resolution in the learning-based approaches is limited by the resolution of learning examples. So we go for a new algorithm of enhancing the image resolution that consists of estimating the intensity of HR pixels.

2. Proposed Method

This section represents the overall framework and the mathematical notations, and then presents the specific implementation of our algorithm for image resolution.

2.1 System overview

It represents the problem of image resolution enhancement is how to convert arbitrarily sampled data to evenly spaced data. After sub pixel registration, pixels from different observed LR images are positioned in an HR grid, as shown in **Figure 1.**

Suppose that the intensity of the HR pixel pH is the value to be estimated. In the neighborhood ofpH, we have different LR pixels denoted by $pL1 \ldots pLi \ldots pLk$,where k is the number of LR pixels in the neighborhood ofpH.

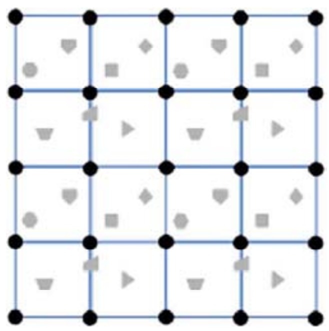

Figure 1: Illustration of the problem of interpolation-based image resolution. The “circles” grid nodes represent the HR pixels to be estimated. The LR pixels are represented by other shapes. Different shapes represent pixels from different LR images.

A conventional idea is to fit a surface with local smoothness from a group of LR pixels ($pL1 \ldots pLi \ldots pLk$). The fitted surface can be regarded as the continuous image. Subsequently, the HR pixel pH is obtained by re-sampling the surface. This process can be formulated as

$$\Gamma = \Gamma\begin{pmatrix} f(pL1), \ldots f(pLi), \ldots f(pLk), xL1, \ldots xLi, \ldots xLk, \\ yL1, \ldots yLi, \ldots yLk \end{pmatrix} \quad \textbf{(1)}$$

$$f(pH) = S(xH, yH, \Gamma) \quad \textbf{(2)}$$

Where Γ represents the fitted surface for multi pixels, $f(p\phi)$ is the intensity of pixel $p\phi, x\phi$ and $y\phi$ indicate the location of pixel $p\phi$ in abscissas and ordinates of the HR grid respectively. $S(x\phi, y\phi, \Gamma)$is an operation of sampling the surface Γ at location $(x\phi, y\phi)$; and ϕ ∊ {H, L1,…Li,…Lk}. In the above formula, all the LR pixels are regarded as equivalent ones with the same noise and error. Moreover, spatial structure information is not sufficiently considered. The spatial structures in the HR grid should comprise two aspects. One is the spatial distributions of LR pixels in the HR grid. The other is the local structures of intensity, i.e., edge orientations, curvatures, etc. The former can be represented by the positions of LR pixels in the coordinate system of the HR grid, and the latter can be denoted by intensity derivatives of different orders.

Each site of LR pixels is fit in one surface and there is a one-to-one correspondence between fitted surfaces and LR pixels. Then, we can obtain a series of intensity values at the location of pixel $p\phi$ by sampling all K surfaces,

i.e., $fLi(p\phi) \triangleq S(x\phi, y\phi, \Gamma Li)$, $1 \le i \le K$ **(3)**

where ΓLi is the fitted surface for pixelpLi. It should be noticed that ΓLi and Γ have different meanings. The final intensity of pH can be calculated by MAP estimation, i.e.

$$\hat{f}(pH) = argmax\ q\left(f(pH)\middle|fL1(pH), \dots, fLK(pH)\right)$$
$$= argmax\ q\left(fL1(pH), \dots, fLK(pH)\middle|f(pH)\right)q\left(f(pH)\right) \quad \textbf{(4)}$$

where $q(\bullet)$ denotes the probability density function.
The idea is illustrated in **Figure 2.**

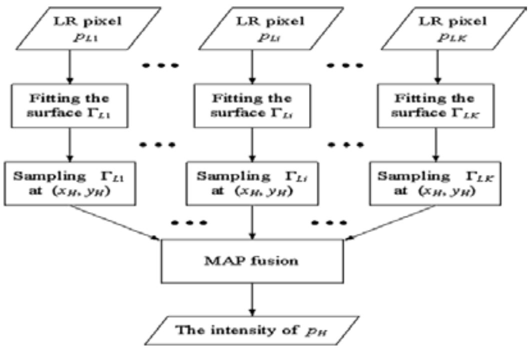

Figure 2: Flowchart for estimating the intensity of HR pixel

2.2. Implementation for enhancement of image resolution

This section describes how to embody the formulas of ΓLi and final intensity of pH. To take advantage of spatial structure information sufficiently and to construct surfaces using 2-D Taylor series,
e.g., surface Li is given by

$$\Gamma Li = \Gamma Li(x, y)$$

$$\Gamma Li = f_{(p_{Li})} + \frac{\partial f(p_{Li})}{\partial x}(x - x_{Li}) + \frac{\partial f(p_{Li})}{\partial x}(y - y_{Li}) + \frac{\partial^2 f(p_{Li})}{2.\partial x^2}(x - x_{Li})^2 + \frac{\partial^2 f(p_{Li})}{2.\partial y^2}(y - y_{Li})^2 + \frac{\partial^2 f(p_{Li})}{\partial x \partial y}(x - x_{Li})(y - y_{Li}) + \dots \quad \textbf{(5)}$$

where x and y are the arguments of function ΓLi, denoting the locations in the HR grid. The intensity derivatives of LR pixel pLi can be considered as the parameters of surface ΓLi. The following equation is utilized to calculate the derivatives for LR images

$$f_{(p_{Lj})} = f_{Li}(p_{Lj}) + \xi_{ij},\ 1 \le i \le K, 1 \le j \le M_i \quad \textbf{(6)}$$

where pLi is an of LR pixels in the neighborhood of pLi , Mi is the number of LR pixels in the neighborhood of pLi and ξij is the error of the surface ΓLi at the location of pixel pLj . Under the smoothness assumption of estimated HR image, ξij $\rightarrow 0$ ideally. Thus, it becomes

$$\begin{bmatrix} \Delta_{x_{1,i}} & \Delta_{y_{1,i}} & \frac{\Delta_{x_{1,i}^2}}{2} & \frac{\Delta_{y_{1,i}^2}}{2} & \Delta_{x_{1,i}}.\Delta_{y_{1,i}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \Delta_{x_{j,i}} & \Delta_{y_{j,i}} & \frac{\Delta_{x_{j,i}^2}}{2} & \frac{\Delta_{y_{j,i}^2}}{2} & \Delta_{x_{j,i}}.\Delta_{y_{j,i}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \Delta_{x_{k,i}} & \Delta_{y_{k,i}} & \frac{\Delta_{x_{k,i}^2}}{2} & \frac{\Delta_{y_{k,i}^2}}{2} & \Delta_{x_{k,i}}.\Delta_{y_{1,i}} \end{bmatrix} \times \begin{bmatrix} \frac{\partial f(p_{Li})}{\partial x} \\ \frac{\partial f(p_{Li})}{\partial y} \\ \frac{\partial^2 f(p_{Li})}{\partial^2 x} \\ \frac{\partial^2 f(p_{Li})}{\partial^2 y} \\ \frac{\partial^2 f(p_{Li})}{\partial x \partial y} \end{bmatrix} = \begin{bmatrix} \Delta f_{1,i} \\ \vdots \\ \Delta f_{j,i} \\ \vdots \\ \Delta f_{k,i} \end{bmatrix} \quad \textbf{(7)}$$

where $1 \le j \le M_i$, $\Delta_{x_{j,i}} = x_{Lj} - x_{Li}$, $\Delta_{y_{j,i}} = x_{Lj} - x_{Li}$,and $\Delta_{f_{j,i}} = f_{(p_{Lj})} - f_{(p_{Li})}$.

In order to obtain reliable and valid solutions, the equation should be over determined. After plugging the least square solutions of explicit surface, it has two important findings. First, spatial structures are retained, including edge orientations (first-order derivatives) and curvatures (second-order derivatives), etc. Second, the levels of retained details depend on the number of LR pixels in the neighborhood. Specifically, first-order derivatives can be retrieved if$Mi > 3$, second-order derivatives can be retrieved if > 6 , etc.Once surface ΓLi is obtained, ξ_{ij} can be calculated from(6).When surface ΓLi is utilized to estimate$f(pH)$, the variance σ_i^2 of fitting errors can be calculated as

$$\sigma_i^2 = \frac{1}{M_i}\sum_{j \ne i}(\xi_{ij})^2 \quad \textbf{(8)}$$

Under Gaussian assumption, the final intensity of pH and the MAP estimation for the intensity of the HR pixel pH becomes

$$\hat{f}(p_H) = \frac{1}{\lambda + \sum_{i=1}^{K}\lambda_i}\left(\lambda f_0(p_H) + \sum_{i=1}^{K}\lambda_i f_{Li}(p_H)\right) \quad \textbf{(9)}$$

where $\lambda_i = 1/\sigma_i^2$. Since the expression of equation has the form of a weighted sum, the proposed method is an interpolation-based approach. Essentially, the weights for the surfaces depend on the agreement of other LR pixels. Generally speaking, the LR pixel with larger registration or acquisition errors corresponds to the surface with smaller weight.

2.3. Algorithm to estimate the intensity of HR pixels

Given registered: LR images
Set the size of neighborhood to 1
For every HR pixel to be estimated
1) Search the LR pixels that are located in the neighborhood of the HR pixel. Count the number of LR pixels, denoted as$K$. If K is equal to zero, increase the size of neighborhood and repeat step 1.
2) According to the value of K, estimate parameters (derivatives of different orders) for every surface (LR pixel).
3) Estimate ξij , using (5), (6) and the derivatives calculated in the previous step.
4) Estimate $\lambda_i = 1/\sigma_i^2$ using (8).
5) Estimate the HR pixel value using (3).
End

3. Experimental Results

To demonstrate the performance of our method, it will compare with some other image resolution approaches like various objects, animals, flowers and buildings. These categories were chosen because they provide a wide range of colors and natural textures. The algorithms are either classic or state-of-art. All the codes are written in MATLAB and performed on a 2.80-GHz Intel(R) Pentium(R) 4 machine.

3.1 An example with real data

This section describes the testing process of a real-world sequence. The sequence was captured with a resolution of 640 $\times$480 pixels and 31 LR frames are used for the experiment. All the proposed HR images reconstructed using different methods have used the identical registration parameters. The visual comparisons are illustrated in **Figure 3.** Compared with the original LR image, the HR patch obtained with our method has significant improvement of image quality. Compared with the other resolution methods, our method removes aliasing artifacts or blurring more successfully.

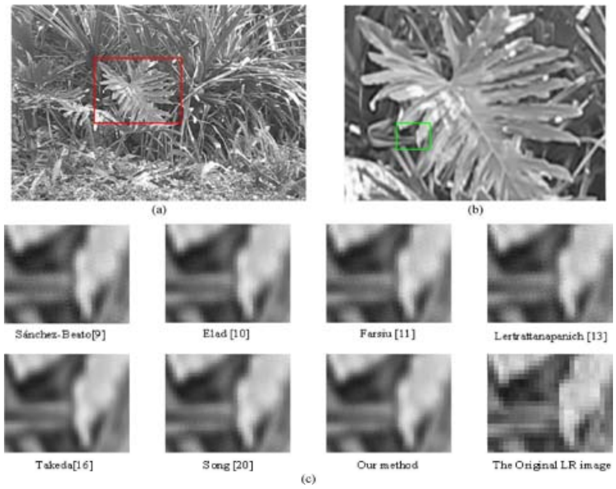

Figure 3: Real data with visual comparisons. (a) One of LR frames from the sequence. (b) Result of our method. (c) Details comparison for the highlighted patch in Fig.3 (b).

Table 1: VISUAL COMPARISONS BASED ON BIQI AND RUN TIME

Methods	BIQI	RUN TIME
Sanchez-Beato [9]	74.6	653.6
Elad [10]	45.0	3.821
Farsiu [11]	51.4	4.226
Lertrattanapanich[13]	76.6	201.4
Takeda [16]	70.5	36.56
Song [20]	57.2	37.19
Our method	77.7	13.64

To quantify the image resolution results, we use a state-of-art image quality assessment method, known as blind image quality index (BIQI). BIQI predicts image quality that correlates with human perception without any knowledge of a reference image. In our case, we do not need the ground truth of the HR image, which is not available in SR for real world sequences. The images with more artifacts, blurring, and noise would have lower values of BIQI. The quantitative comparison based on BIQI and the run time in Table I, which demonstrate the feasibility of the proposed method under real circumstances.

From the experiments on the simulated and real-world data, we can declare that the proposed method is competitive in the reconstruction quality and the run time. The superiority of this method is particularly evident in the case of sufficient LR images since higher order information can be retrieved. In respect of the run time, this method requires no iterative operation. Hence, it is computationally efficient compared with the methods that are in an iterative fashion.

3.2 Snapshots and Experimental Results

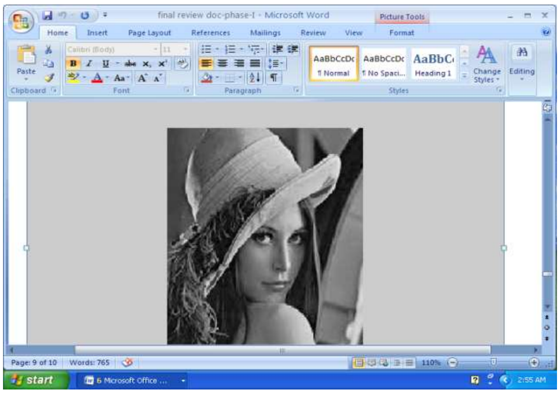

Figure 4: Input image or under sampled LR image

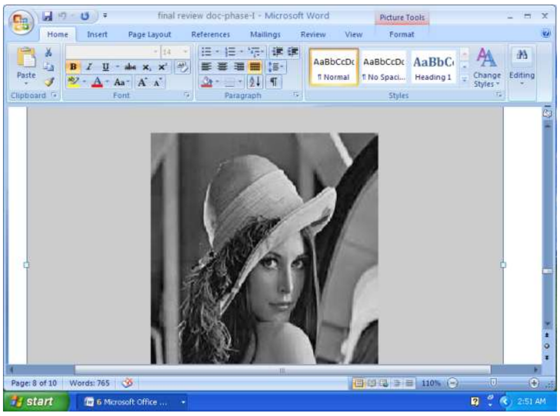

Figure 5: Output for image resolution enhancement (i.e.) High resolution image

4. Conclusion

In this project we discussed several issues related to the problem of creating high resolution images from low resolution original data. It requires an image resolution enhancement reconstruction framework is presented using multi surface fitting. 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. Moreover, this method is pixel wise and non iterative. Hence, it does not suffer from convergence problems and can be accelerated through parallel implementations. Experimental results demonstrate the superiority and potential applications of this method.

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