A Novel Super-resolution Reconstruction Algorithm based on Subspace Projection

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Abstract—Increasing image resolution is a challenging and fundamental image-fusion operation, super-resolution a technique to increase image resolution. However, most of method can not reconstruct image from un-regular sampled data. In this paper, we propose a novel super-resolution reconstruction algorithm based on polynomial bases. This algorithm can be combined with intensity information and structural details in the image. The density of sampled data and local structure decide the certainty function and structural-adaptive applicability function of neighbourhood. Experimental results show that the proposed algorithm can improve denoising effect in the super-resolution reconstruction image, and achieve a state-of-the-art high-resolution visual effect in the edges and detailed features of image.

***Index Terms*—Super-resolution; Subspace projection; Structural-adaptive Applicability Function**

I. INTRODUCTION

Recent technological advances have resulted in the proliferation of imaging devices as well as high-resolution (HR) display units. However, there exists a gap between the resolution of imaging devices and display capabilities. This could be addressed by employing better imaging devices, but this comes at a cost. Several methods for image and video super-resolution (SR) reconstruction methods have been proposed [1,2] to increase the image resolution. This methods can be broadly classified into two families of methods: (1) The classical multi-image SR, and (2) Exampled-based SR. In the classical SR, a set of low-resolution (LR) images are registration to recover the HR image [1]. However, this approach is numerically limited only to small increases in resolution. These limitation have lead to the development of "Example-based SR" also named "image hallucination" [3,4]. In this approach, correspondences between low and high resolution image patches are learned from a database of low and high resolution image pairs and then applied to a new LR image to recover its most likely HR version, but this approach is not guaranteed to provide the true (unknown) HR details. In recent, many studiers have researched in image interpolation and image fusion [5-7]. H. Knutsson and C-F.Westin proposed a normalized and differential convoluted methods for interpolation and filtering uncertain data [8]. K. Andersson and H. Knutsson. proposed a continuous normalized convolution for image fusion [9]. These methods can not be structural-adaptive adjusted by the density of sampled data and local structure, so the weight is inaccurate to over-smooth the SR image. In this paper, we propose a novel method to increase the resolution of a video or an image by subspace projection. In this method, the neighbourhood of a point is viewed as a subspace projection by a set of base functions, the weight of each base function is decided by the certainty and application of this point. This method can adjust shape and scale of neighbour adaptively, preserve edge details and achieve good denoising effect in SR result. The rest of this paper is organized as follows. Section 2 describes the method of signal analysis based on base function projection. Section 3 introduces the proposed novel video sequence SR reconstruction algorithm based on subspace projection. Section 4 presents the experimental results and Section 5 concludes this paper.

II. BASE FUNCTION PROJECTION ON SIGNAL ANALYSIS

Many fields of scientific research benefit or require the analysis of irregularly sampled data. The analysis of irregularly sampled data is more complicated than the analysis of regularly spaced ones. It is often required to reconstruct the irregularly sampled signal or resample it onto a regular grid. A non-direct method which uses interpolation of the irregularly sampled signal in order to obtain a regularly sampled signal. The missing values of

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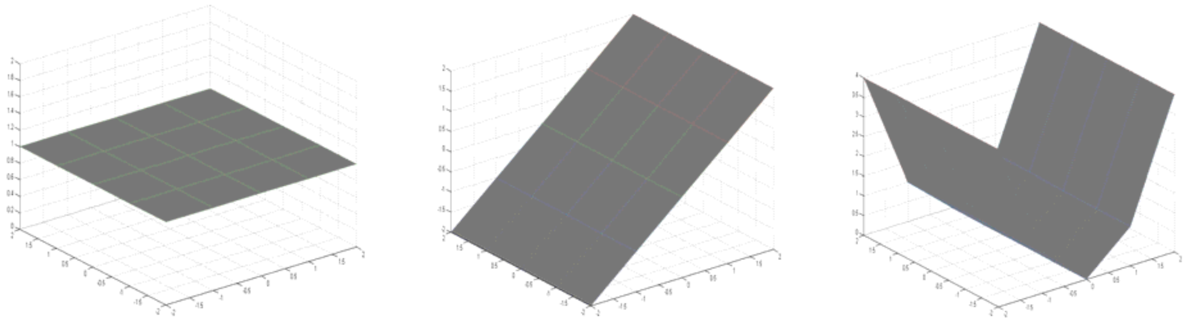
the signal are calculated by this interpolation and then used to process the signal using conventional mathematical tools. This subspace projection is usually done by convolution. The convolution can be made more effective by a normalization operation that takes into account the possibility of missing samples.

This interpolation [10] is a method for local signal modeling from projections onto a set of basis functions. The operation based on polynomial basis function is equivalent to a local Taylor series expansion. A second-order polynomial base is $\{1, x, y, x^2, y^2, xy\}$. In this polynomial bases $1=[1,1,\cdots,1]^T$, $x=[x_1, x_2, \cdots, x_N]^T$, $x^2=[x_1^2, x_2^2, \cdots, x_n^2]^T$, the graphical illustration of these projection coefficients are shown in Fig.1.



(a) 1 (b) X (d) X^2

Figure 1. Projection coefficients of polynomial bases

The polynomial fitting of subspace projection to a signal is decided by the applicability function and certainty function, Usually a Gaussian function is used for applicability function. This polynomial subspace projection can be realized by convolution. For a one-order polynomial projection, it can be described by (1) as follows.

$$\begin{bmatrix} \hat{f} \\ \hat{f}_x \\ \hat{f}_y \end{bmatrix} = \left(\begin{bmatrix} a & ax & ay \\ ax & ax^2 & axy \\ ay & axy & ay^2 \end{bmatrix} \right)^{-1} \bullet \left(\begin{bmatrix} a \\ ax \\ ay \end{bmatrix} \otimes (c \bullet f) \right) \tag{1}$$

$\hat{f}$ is an estimated image (signal), $\hat{f}_x$ and $\hat{f}_y$ is derivative of $\hat{f}$, $\otimes$ represents convolution, a is a applicable matrix, $c \cdot f$ is the product of certainty matrix and image.

A. Estimation of The Certainty Function

For an irregularly sampled signal, the certainty of samples can be estimated by sampling information [11]. The one-order certainty function of each sample is defined by Gaussian function of error $|f - \hat{f}|$ in (2).

$$c(s,s_0) = \exp\left(-\frac{[f(s) - f(\hat{s},s_0)]^2}{2\sigma_r^2}\right) \tag{2}$$

where $f(s)$ is the value of s, $f(\hat{s},s_0)$ is the estimated value of a polynomial in pixel s_0, σ_r is a decayed parameter. When the error is less than $2\sigma_r$, the certainty is close to one; when the error is greater than $2\sigma_r$, the obtained certainty is small.

B. Adaptive Applicable Function

In base function projection, we must select an appropriate applicable function, this selection decides the shape and size of neighbouring window. Adequate samples lead to small size while sparse samples lead to large size of the window. An adaptive applicable function in (3) can adjust the size of neighbourhood according to the density of samples in window.

$$a(s,s_0) = \rho(s-s_0)\exp[-(\frac{x\cos\phi + y\sin\phi}{\sigma_r(s_0)})^2 - (\frac{-x\sin\phi + y\cos\phi}{\sigma_r(s_0)})^2]\cdots \tag{3}$$

where $s_0(x_0, y_0)$ is a central point in the window, $s - s_0 = \{x, y\}$ is a local coordinate of input sample with respect to the central point. ρ is a kernel function [12,13].

III. OUR PROPOSED ALGORITHM

In order to perverse the edge of the SR result, the proposed algorithm based on subspace projection is described as follows. Assuming a LR video sequence is $LR_0, LR_1, \cdots, LR_n$ (Suppose the length of sliding window for SR reconstruction is P=5 and all low-resolution frames are sub-pixel registration).

Step 1:Input the LR video sequence $LR_0, LR_1, \cdots, LR_n$, a frame in the sliding window is selected to be the reference image.

Step 2: The certainty of reference image is initiate to be one, parameter of applicable function and the size of filter are set to be appropriately;
Step 3: The reference image is interpolated to be the initial HR estimation;
Step 4: For all rows of the HR estimation, certainty matrix *C* is computed;
Step 5: For all columns of the HR estimation, applicable matrix *A* is computed;
Step 6: Subspace projection is applied to use base function *B*, $H = B' \cdot diag(C \cdot A) \cdot B$, then *H* is singular value decomposed (SVD) to obtain the updated estimation;
Step 7: This estimation is down-sampled, blurred to a LR image estimation. This LR estimation is subtracted to all LR images in the sliding window, which cause the error of each image subtraction.
Step 8: All error is added up to obtain the sum of error *E*;

If $E \le delta(delta \le 1e-4)$ or the iteration number reaches the maximum number, we can stop the iteration to get the final SR reconstruction result of the reference image in video sequence, or else Step4-Step8 are continued to get a final SR result.

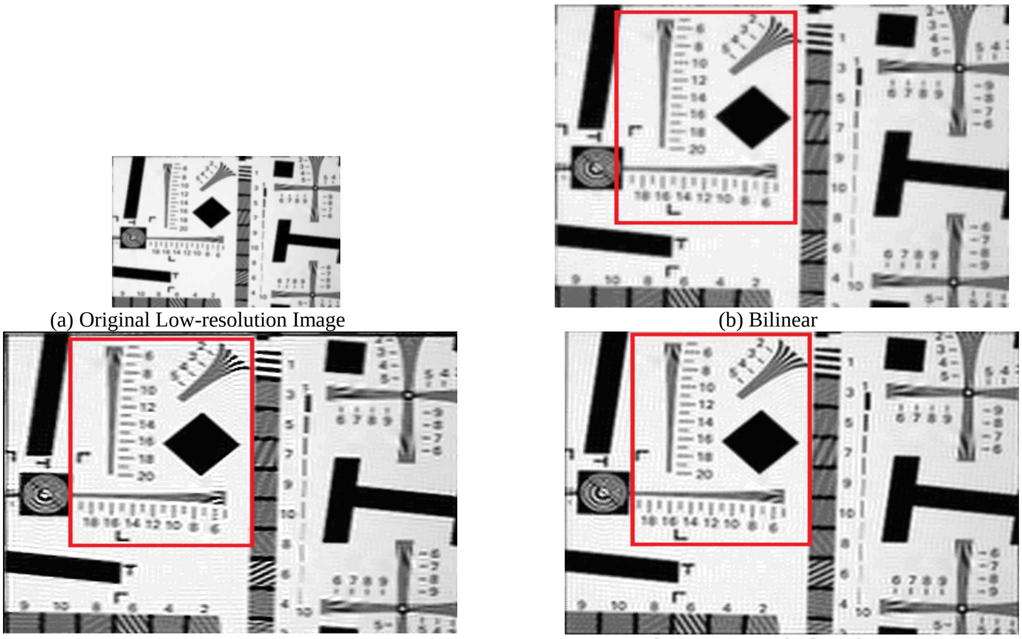
At last, a HR video sequence can be reconstructed by above steps.

IV. Experiments

In this section, we validate the effectiveness of the proposed algorithm in three different cases: (1) a simulated video sequence “Ruler” without additive noise; (2) a real video sequence; (3) a LR video sequence with additive Gaussian noise. The comparison we provided here is the results reconstructed by bilinear interpolation, the maximum A-posterior (MAP) method and our proposed algorithm respectively.

A. Simulated Sequence Without Additive Noise

First, we degrade a HR image “Ruler” with various blurred, down-sampled and shifted to gain a LR image sequence. The image is blurred using a 5×5 Gaussian mask, σ is 0.5, down-sampled with a factor of 2 (in each axis). The SR reconstruction result of this LR simulated video sequence is shown in Fig. 2.



(a) Original Low-resolution Image (b) Bilinear

(c)MAP (d) Our Proposed Algorithm

Figure 2. SR Result of Simulated Video Sequence without Additive Noise

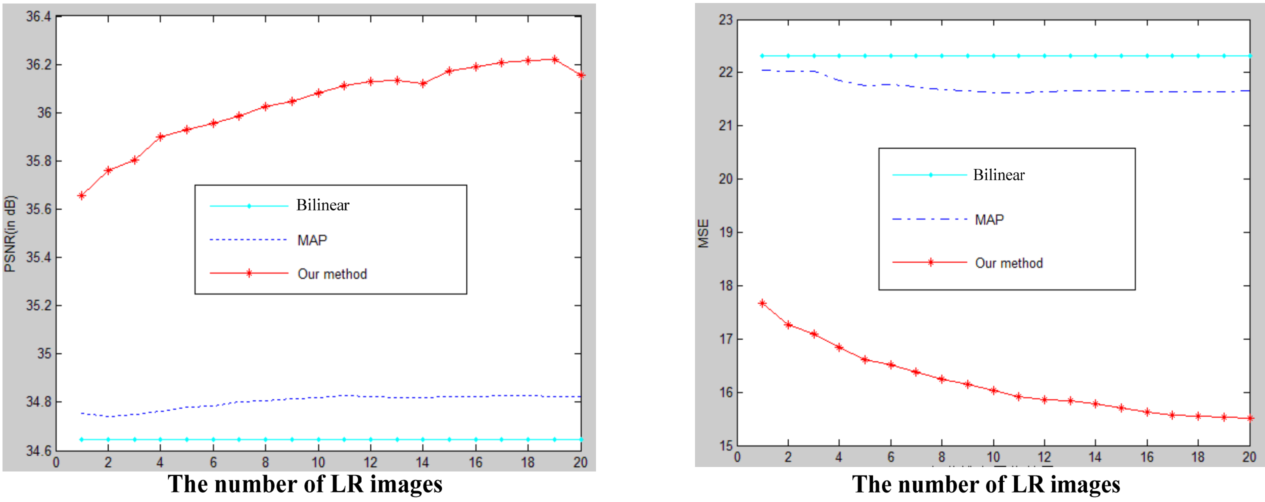
As detailed comparison shown by red rectangle in Fig. 2, we can see that the interpolation result is over-smooth, which implied there is inadequate high frequency information in image. The SR result of MAP method includes artificial edge in the image. The experimental results prove that our proposed algorithm achieves good visual effect and which is superior to several SR reconstruction algorithms.

B. Standard Test Video Sequence

In this experiment, a standard test video sequence “Foreman” is used to validate the proposed algorithm. In Fig. 3(b) we can see that this result is over-smoothing as in the original low-resolution frame. In Fig.3(c), there are edge artifacts in the MAP reconstruction result and the visual effect is too fuzzy. The reconstruction result of our proposed SR reconstruction algorithm is shown in Fig.3 (d).

(a) Origin LR Image (the 6th frame) (b) Bilinear (c) MAP (d) Our Proposed Algorithm

Figure 3. Result of standard test video sequence “Foreman”



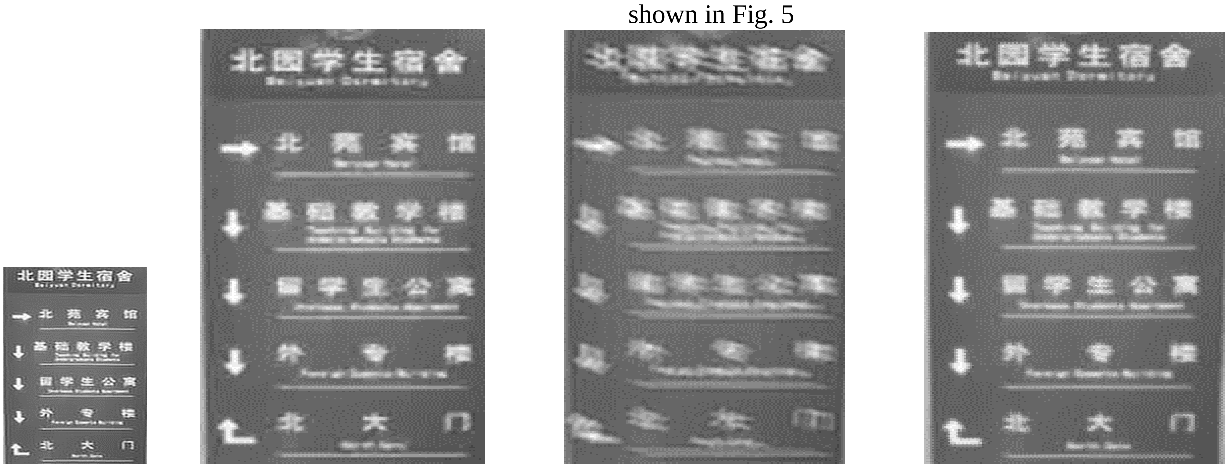
(a) PSNR (b) MSE

Figure 4. The objective comparison of PSNR and MSE for different methods

In order to demonstrate the superiority of the proposed algorithm, an objective comparison of PSNR and MSE is shown in Fig. 4. It is obviously that the proposed method is better than other two methods from these objective and subjective comparisons. The proposed method not only can improve the optical resolution but also achieve a good SR reconstruction result.

C. Simulated video sequence with additive Gaussian noise

In order to verify the proposed SR reconstruction algorithm further, we test on a low-resolution simulated video sequence with additive noise (SNR=40dB). The SR result reconstructed by different method respectively is shown in Fig. 5



(a) A LR image (SNR=30 dB) (b) Bilinear (c) MAP (d) Our Proposed Algorithm

Figure 5. Result of Simulated Video Sequence with Additive Gaussian Noise (SNR=40dB)

In Fig. 5 we can see the reconstruction result of bilinear interpolation is over-smooth, the result reconstructed by MAP method has serious ringing effect and noise. The reconstruction result of our proposed SR algorithm can remove noise effectively, and preserve the details and edge information of image to achieve a best visual effect.

V. CONCLUSIONS

In this paper, a novel video SR reconstruction method based on subspace projection is proposed to solve the un-regular sampled data fusion. This algorithm combines illuminated information and structural details in the original image. Experimental results show that the proposed algorithm improves denoising ability and achieves a state-of-the-art HR reconstruction video. At the same time, we believe that more thorough efforts should be invested in developing the theory and implementation of this method in the future work.

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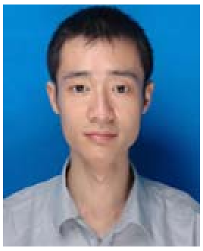

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