A Novel Approach for Reconstructing Super Resolution Video from Low Resolution Video

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ABSTRACT
Super-resolution is the process of recovering a high-resolution image from multiple low-resolution images of the same scene. Also refers to techniques for overcoming the sampling limits and blurring effect of the digital image. This paper presents a spatiotemporal kernel regression technique for video super resolution, which is computationally efficient and simple in implementation. The objective of image restoration is to restore the visual information of a degraded image. It has wide applications in photographic deblurring, remote sensing, medical imaging, etc. Some web cam captures low resolution images due to low cost sensors or limitation of the hardware. So, the proposed resolution enhancement technique could be used as an inexpensive software alternative. The performance of the proposed algorithm is better when compared to other techniques.

Index terms
kernel regression, Gaussian kernel, Epanichinkov kernel, Enhancement

1. INTRODUCTION
Super resolution is the process of combining multiple low resolution images to form a high resolution image. By aggregating information from multiple correlated images, these methods can overcome the inherent limitations of single frame up-sampling and interpolation. Blurring may be introduced by the imaging device, such as in lens defocusing, or by the medium in which the light propagates, as with atmospheric turbulence. The relative motion of the scene and the camera can also lead to blurring. It has many applications in the consumer products such as cell phone, webcam, high-definition television (HDTV), closed circuit television (CCTV) etc. The resolution of the image taken by a cell phone is very low. Super-resolution technique can be applied to improve the quality of these LR video taken by cell phones. Application of such restoration methods arises in the following areas.

1) Remote sensing: where several images of the same area are given, and an improved resolution image is sought.

2) Frame freeze in video: where typical single frame in video signal is generally of poor quality and is not suitable for hard-copy printout. Enhancement of a freeze image can be done by using several successive images merged together by a super resolution algorithm.

3) Medical imaging (CT, MRI, ultrasound, etc.): these enable the acquisition of several images, yet are limited in resolution quality.

Super-resolution is a process of image enhancement by which low quality, low resolution (LR) images are used to generate a high quality, high resolution (HR) image [1]. For efficient data transmission, these frames are down-sampled at the encoder to achieve higher compression ratio. This reduces the complexity of the encoder at the expense of image quality [2]. In motion detection, numbers of pixel blocks are compared between the previous and current frames [3].To reconstruct an image using fine edge preserving image interpolation algorithm based on local gradient features [4].

This paper proposes a spatiotemporal kernel regression technique for video super resolution which is computationally efficient and simple in implementation. The rest of the paper is organized as follows: In section 2, existing approaches in super resolution is discussed. In section 3, kernel regression based super resolution technique is presented. Simulation results and performance comparison are discussed in section 4. Finally, concluding remarks are presented in section 5.

2. RELATED WORKS
Super resolution techniques can be classified in two categories: single image super-resolution and super resolution from several frames. In the single image super resolution, there is no additional information available to enhance the resolution. So, the algorithms are based on smoothing and interpolation techniques [5]. Support vector regression (SVR) is used to find the mapping function between a low resolution patch and the central pixel of a HR patch [6]. The mathematical model of LR image is expressed in terms of a single HR image [7]. Another approach to super-resolution is iterative back projection (IBP) similar to the projections in computer aided tomography (CAT) [8]. The method starts with an initial guess of the HR image and simulated to generate a set of LR images which are compared with the observed image to update the HR image. A modified IBP algorithm is presented in [9] based on elliptical weighted area (EWA) filter in modeling the spatially-variant point spread functions (PSF).

The total least squares recursive algorithm is done in the wave number domain after transforming the complex data problem to an equivalent real data problem [10]. Contact with the field of nonparametric statistics and present a development and generalization of tools and results for use in image processing and reconstruction [11]. A robust median-based estimator is used to discard measurements which are inconsistent with the imaging model [12]. The paper presents an evaluation in depth of the impact of changing the Full Search (FS) algorithm on a SR environment, for another Fast Block Matching Algorithms (FBMA) of high relevance commonly used for video coding [13]. Another approach is the generalization of kernel regression technique for image de-noising, up-scaling and interpolation in single image.

3. KERNEL REGRESSION BASED SUPER RESOLUTION

Kernel regression is an effective tool for both denoising and interpolation in image processing. Classical parametric image processing methods rely on a specific model of the signal of interest and seek to compute the parameters of this model in the presence of noise.

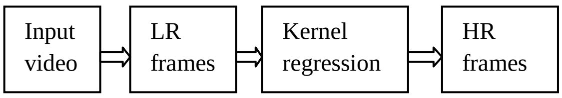

Fig 1: Block diagram of kernel regression

Low resolution video gives as input to the method. This video splitted into N number of Low Resolution(LR) frames. Once the N –th frame is received kernel regression method is applied to construct a HR image. Given N low resolution video frames of size m×n, the problem of super-resolution is to estimate high resolution frame of size rm×rn, where r is the resolution enhancement factor. Assume r=2, (i.e) a 2×2 LR grid is zoomed into a 4×4 HR grid. So, for each 2×2 LR block 12 additional pixel values need to be determined. In order to get super-resolution image with acceptable registration error, use four LR frames. Each LR frame can be considered as a downsampled, degraded version of the desired HR image. These LR frames contribute new information to interpolate sub-pixel values if there are relative motions from frame to frame.

Kernel regression analysis is a nonparametric regression method to estimate the value of an unknown function f (x) at any given point based on the observations. For two dimensional cases, the regression model is

$$Y_i = f(x_i) + \varepsilon_i \text{ , } i = 1,2,...,N \text{ , } x_i=[x_{1i},x_{2i}]T \qquad (3.1)$$

Where {(xi),i = 1,2,...,N} are the design points (pixel position), {(Yi), i = 1,2,...,N} are observations (pixel values) of the response variable Y , f is a regression function and {(εi),i = 1,2,...,N} are independent identically distributed (i.i.d.) random errors and N is the number of samples (number of frames). The generalization of kernel estimate f^(x) is given by solving the following minimization Problem.

$$min_{q_{0,}q_1 \ldots q_l} \sum_{i=1}^{N} \left[Y_i - \left\{ q_0 + q_1(x_i - x) + \cdots + q_l(x_i - x)^l \right\} \right]^2 K\left(\frac{x_i - x}{h}\right)$$
(3.2)

where K(.)is the kernel function with bandwidth h and l is a positive integer which determines the order of the kernel estimator. The parameter h is also known as smoothing parameter since the value of it determines the smoothness of final output. Above equation is solved to determine the unknown regression coefficients q0, q1,q2...,ql . The choice of kernel has only small effect on the accuracy of estimation, so it is preferable to use differentiable kernel with low computational complexity. Commonly used kernel functions include the Epanechnikov kernel, Gaussian kernel etc.

3.1. Epanechnikov Kernel

The function is,

$$K(u) = (12/11)^* (1 - u2) I (-1/2 \le u \le 1/2) \qquad (3.3)$$

Where I(a)=1 if a is “true” and 0 otherwise. Performance of kernel is measured by mean integrated squared error(MISE) or asymptotic MISE(AMISE). Epanechnikov kernel is optimum choice for smoothing because it minimizes asymptotic mean integrated squared error. In fact all other kernels efficiency like gaussian, triangular, uniform is measured against this kernel Epanechnikov kernel vanishes beyond a finite range.

3.2. Gaussian Kernel

The function is,

$$K(u)=0.6171\exp(-u2/2) I (-1/2 \le u \le 1/2) \qquad (3.4)$$

Gaussian functions are widely used in statistics where they describe the normal distributions, in signal processing where they serve to define Gaussian filters, in image processing where two-dimensional Gaussians are used for Gaussian blurs, and in mathematics where they are used to solve heat equations and diffusion equations and to define the Weierstrass transform. The Gaussian smoothing operator is a 2-D convolution operator that is used to `blur' images and remove detail and noise. In this sense it is similar to the mean filter, but it uses a different kernel that represents the shape of a Gaussian (`bell-shaped') hump. Gaussian kernel is differentiable everywhere and it has extended tail and hence improves the quality of reconstruction.

A famous interpolation technique is the Nadaraya-Watson Estimator (NWE).NWE estimates an appropriate pixel value by taking an adaptive weighted average of several nearby samples, and consequently its performance is totally dependent on the choice of weights.

$$f_{NW}(X) = \frac{\sum_{i=1}^{N} YiK\left(\frac{xi - x}{h}\right)}{\sum_{i=1}^{N} K\left(\frac{xi - x}{h}\right)} \qquad (3.5)$$

The estimator is linear in the observations so it called as a linear smoother. Neighborhood pixels can be calculated for increasing resolution of an image.

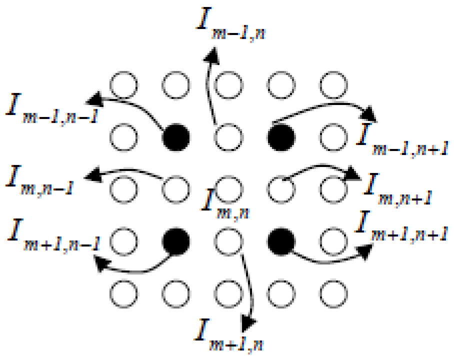

Fig 2: Spatial locations of Neighborhood pixels

Figure shows the LR pixels (black circles) in a HR grid. White circles are the unknown HR pixels which are estimated using kernel regression taking the neighborhood pixels as the sample data point. So, m n I , can be calculated from four of its nearest neighbor Im-1,n-1 , Im-1,n+1 , Im+1,n-1 , Im+1,n+1.

$$f(I_{m,n})=f(I_{m,n}|\ I_{m-1,n-1})+f(I_{m,n}|\ I_{m-1,n+1})+ f(I_{m,n}|I_{m+1,n-1})+f(I_{m,n}|\ I_{m+1,n+1}) \quad (3.6)$$

Similarly,

$$f(I_{m-1,n})=f(I_{m-1,n}|\ I_{m-1,n-1})+f(I_{m-1,n}|\ I_{m-1,n+1})$$

$$f(I_{m,n-1})=f(I_{m,n-1}|\ I_{m-1,n-1})+f(I_{m,n-1}|\ I_{m+1,n-1})$$

$$f(I_{m+1,n})=f(I_{m+1,n}|\ I_{m+1,n-1})+f(I_{m+1,n}|\ I_{m+1,n+1})$$

$$f(I_{m,n+1})=f(I_{m,n+1}|\ I_{m-1,n+1})+f(I_{m,n+1}|\ I_{m+1,n+1}) \quad (3.7)$$

The neighborhood of the pixel $I_{m,n}$, is compared with the neighborhood of the next frame in all directions as indicated. In order to consider the temporal data of N frames, the regression method need to estimate motion between frames. First, the above structure allows for tailoring the estimation problem to the local characteristics of the data, whereas the standard parametric model is intended as a more global fit. Second, in the estimation of the local structure, higher weight is given to the nearby data as compared to samples that are farther away from the center of the analysis window. Meanwhile, this approach does not specifically require that the data follow a regular or periodic sampling structure. More specifically, so long as the samples are near the point x, the non-parametric framework is valid. Again this is in contrast to the general parametric approach which generally either does not directly take the location of the data samples into account, or relies on regular sampling over a grid. Third, and no less important, the approach is useful for both denoising, and equally viable for interpolation of sampled data at points where no actual samples exist. The kernel-based methods appear to be well-studied for a wide class of image processing problems of practical interest. The proposed algorithm is suitable in applications where we can avoid rigorous and computationally expensive motion estimation.

4. EXPERIMENTAL RESULT

The proposed algorithm is tested with several low resolution video sequences. The proposed method generates image with sharp edges with reduced noise. Four consecutive LR frames are used to construct an estimate of HR frame with 2×2 scaling using our kernel regression super resolution technique. The method generates image with sharp edges with reduced noise.

(a)

(b)

Fig 3: Reconstruction of image from successive video frames. (a)Before super resolution of the frame 10, 20, 40, 60 and 80, (b) After super resolution of the respective frames.

Figure 3 presents the experimental results of the image. The Forest video is taken as input and then the video is splitted into several frames. One of the frame is taken as input and process kernel regression and then produce high resolution frame.

(a)

(b)

Fig 4: Reconstruction of an image from successive video frames. (a) original frame, (b)super resolution of the frame.

Figure 4 presents the results of an image. The road video is taken as input. Kernel regression method applied to the frame and produce super resolution image. Kernel regression method gives sharper image than the other methods.

In order to measure performance analysis, this image is downsampled and then reconstructed using this kernel regression method. The restoration quality is measured by PSNR of the image. PSNR (Peak Signal Noise Ratio) can be calculated as,

$$PSNR = 10log_{10} \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} 255^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(f(i,j) - f^\wedge(i,j)\right)^2} \quad (3.8)$$

where f is the original HR image and $f^\wedge$ is the reconstructed image. i and j represents the position of the input frame.

TABLE I

Comparison of PSNR value for varying no of frames

No of frames	PSNR	
	Forest	Road
10	29.36	30.61
20	29.57	30.83
40	30.00	30.97
60	30.01	31.03
80	30.11	31.43

Table I shows the PSNR values of the forest and road video. PSNR value is directly proportional to the number of frames. If no of frames increases then PSNR values also increases.

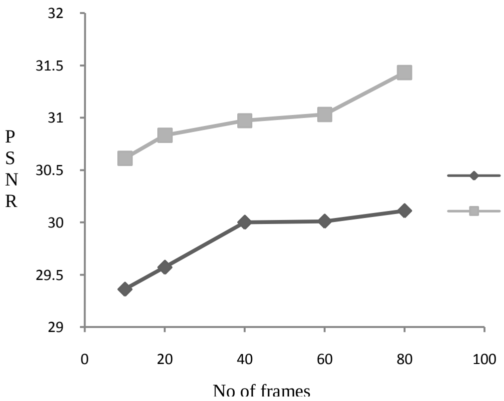

Fig 5: Effects of the number of frames on PSNR

Figure 5 shows a plot of PSNR with the number of frames taken for super-resolution. From the figure, it is evident that increasing the number of frames does not have significant influence on PSNR but causes additional computational cost. The main gain of this algorithm is its sharpness. It is also simple to implement and hence computationally efficient.

5. CONCLUSION AND FUTURE WORK

A method for super resolution of video using kernel regression is presented .In order to achieve super resolution video from low resolution video and dynamic dislocation of object in the video, proposed correlation coefficient based first and second order kernel function selection to reduce edge blurring and stair-case noise. The computational cost of correction coefficient measurements between current frame and next or previous frame is high depending on frame size.

The computational cost of correction coefficient measurements between current frame and next or previous frame is high depending on frame size. For example, one second video 30frame/seconds, 3x30 coefficients are calculated to achieve super resolution video with high psnr value. So that future work of our project could be probable to reduce correlation coefficients computation cost.

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