The Journal of GIS Association of Korea, Vol. 13, No. 4, pp. 345-354, December 2005

A Study on Super Resolution Image Reconstruction for Effective Spatial Identification

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ABSTRACT

Super resolution image reconstruction method refers to image processing algorithms that produce a high resolution(HR) image from observed several low resolution(LR) images of the same scene. This method has proven to be useful in many practical cases where multiple frames of the same scene can be obtained, such as satellite imaging, video surveillance, video enhancement and restoration, digital mosaicking, and medical imaging. In this paper, we applied the super resolution reconstruction method in spatial domain to video sequences. Test images are adjacently sampled images from continuous video sequences and are overlapped at high rate. We constructed the observation model between the HR images and LR images applied with the Maximum A Posteriori(MAP) reconstruction method which is one of the major methods in the super resolution grid construction. Based on the MAP method, we reconstructed high resolution images from low resolution images and compared the results with those from other known interpolation methods.

Keywords : Super Resolution(SR), Image reconstruction, Resolution enhancement

요 약

초해상도 영상복원은 동일 지역을 촬영한 여러 장의 저해상도 영상을 이용하여 고해상도의 영상으로 재구성하는 영상처리 알고리즘 기법이다. 이 기법은 위성영상, 비디오 감시, 영상 강조 및 복원, 영상 모자이킹, 의료 영상과 같이 여러 장의 프레임 영상을 획득할 수 있는 분야에서 유용하게 사용될 수 있다. 본 연구에서는 지상을 촬영한 비디오 영상 열에 공간영역 초해상도 기법을 적용하였다. 실험에 사용된 영상은

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높은 중복도로 촬영된 연속적인 비디오 영상에서 부표본화되었으며, 저해상도 영상과 고해상도 영상간의 관측 모델을 구성하고 초해상도 영상복원 기법중의 하나인 MAP 알고리즘을 적용하였다. MAP 기법을 이용하여 여러 장의 저해상도 영상에서 고해상도 영상으로 복원하였으며, 그 결과를 기존의 영상보간 방법들과 비교하였다.

주요어 : 초해상도, 영상 복원, 영상 강조

1. Introduction

High resolution images are required in many visual applications, and their demand is steadily increasing. When resolution can not improved by replacing sensors, either because of cost or hardware physical limits, super resolution image reconstruction method can be used.

Recently, the development of resolution enhancement approaches has been one of the most active research areas, and it is referred to as super resolution (SR) image reconstruction or simply, resolution enhancement. Super resolution image reconstruction method uses signal processing for resolution enhancement techniques to obtain an HR image from observed multiple LR image.

We applied the Maximum A Posteriori (MAP) algorithm to a video sequence image. This algorithm is one of the major methods in super resolution construction.

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2. Super Resolution Reconstruction

The super resolution restoration idea was first presented by Tsai and Huang. They used the frequency domain approach to demonstrate the ability to reconstruct one improved resolution image from several down-sampled noise-free version of it, based on the spatial aliasing effect.

The basic principle in super resolution reconstruction method is of the use of multiple LR images captured from the same scene. In super resolution, typically, the LR images represent different looks of the same scene. That is, LR images are subsampled as well as shifted with subpixel precision.

2.1 Observation Model

Digital images usually suffer from aliasing due to undersampling, loss of hig-frequency

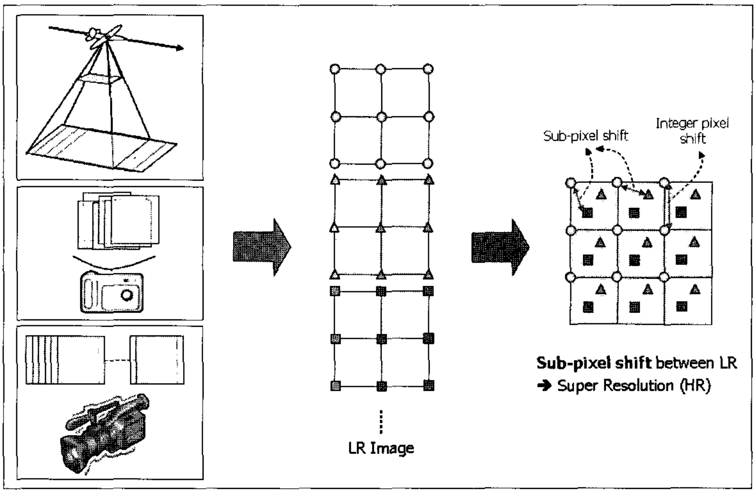


Figure 1. Basic super resolution reconstruction

detail due to low resolution sensor point spread function(PSF), and possible optical blurring due to relative motion or out-of-focus. In the process of recording a digital image, there is a natural loss of spatial resolution caused by optical distortion, motion blur due to shutter speed and additive noise that occurs within the sensor or during transmission.

Given the general super resolution observation model by lexicographical notation,

$$y_k = D\, B_k M_k x + n_k$$

where yk = observation LR images
D = subsampling matrix
Bk = blur matrix

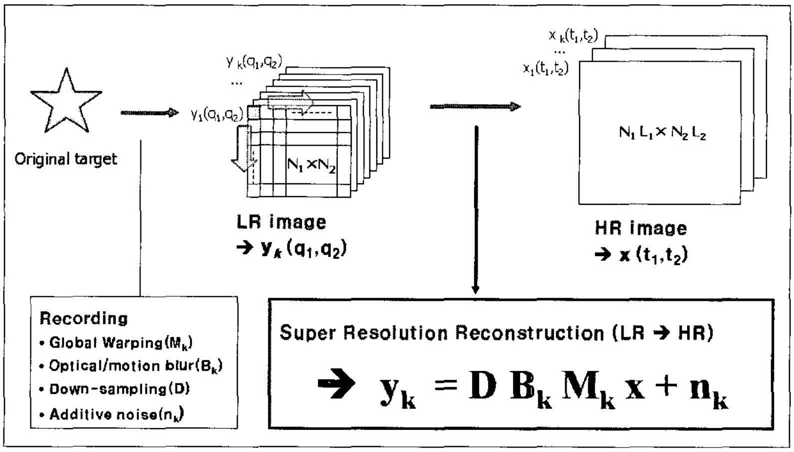


Figure 2. Super resolution observation model

Mk = geometric warping matrix
nk = additive noise
x = observation LR images

The motion that occurs during image acquisition is represented by warp matrix Mk. It may contain global or local translation, rotation, and so on. Since this information is generally unknown, we need to estimate the scene motion for each frame with reference to one particular frame. The warping process performed on HR image x is actually defined in terms of LR pixel spacing when we estimate the motion. Thus, this step requires interpolation when the fractional unit of motion is not equal to the HR sensor grid.

Blurring may be caused by an optical system, relative motion between the imaging system and the original scene, and the point spread function (PSF) of the LR sensor. It can be modeled as a linear space invariant (LSI) or a linear space variant (LSV), and its effects on HR images are represented by the matrix Bk. In single image restoration applications, optical or motion blur is usually considered. In super resolution image reconstruction, however, the finiteness of a physical dimension in LR sensor is an important factor of blur.

The subsampling matrix D generates aliased LR images from the warped and blurred HR image. Although the sizes of LR images are the same here, in more general cases, we can address the different size of LR images by using different subsampling matrices. Although blurring acts more or less as an anti-aliasing filter, in super resolution image reconstruction, it is assumed that aliasing is always present in LR images.

Table 1. Super resolution algorithms(Sean Borman, 2004)

	Frequency Domain	Spatial Domain
Observation model	Frequency domain	Spatial domain
Motion models	Global translation	Almost unlimited
Degradation model	Limited	LSI or LSV
Noise model	Limited	Very flexible Even spatially varying
SR mechanism	Dealiasing	De-aliasing BW extrapolation with a-priori constraints
Simplicity	Very simple	Generally complex
Computational cost	Low	High
A-priori constraints	Limited	Almost unlimited
Regularization	Limited	Excellent
Extensibility	Poor	Excellent
Performance	Good for Specific application	Good

2.2 Super Resolution Algorithms

Super resolution algorithm is divided by specific domain, observation model, the reconstruction method, applied algorithm. Commonly, the super resolution algorithm is classified into the spatial domain type and the frequency domain type. Spatial domain super resolution reconstruction is a pixel value-based method.

There are super resolution methods in the spatial domain non-uniformly interpolation method, stochastic method, set theoretic method and hybrid method. The spatial domain super resolution algorithm is better than frequency domain type with respect to reconstruction performance. In this paper, MAP (Maximum A Posteriori) algorithm, that kinds of stochastic method is applied.

2.3 MAP(Maximum A Posteriori)

Schultz and Stevenson extend their earlier work on Bayesian (MAP) image interpolation for improved definition using the Huber Markov Random Field (HMRF) prior to the problem of super resolution image[3]. The blur of the measured images is assumed to be simple averaging, and the measurements of additive noise are assumed to be independent and identically distributed Gaussian vector. This choice of prior causes the entire problem to be nonquadratic, which complicates the resulting minimization problem.

If the general observation model is yk = Hx + nk, this solution will not be a unique solution for image expansion. MAP method is proposed to compute an estimation of the high resolution images. MAP approach for estimating x seeks the estimate xMAP, for which the a posteriori probability, P(x | yk) is a maximum. Formally, we seek xMAP as,

$$\hat{x}_{MAP} = arg\max_x P(x \mid y_1, y_2 \cdots, y_k)$$

where P(x | yk) is the log-likelihood function, which can be computed using the Bayesian rule.

$$\begin{aligned} P(x \mid y_k) &= logP(x \mid y_k) \\ &= logP(y_k \mid x) + logP(x) - logP(y_k) \end{aligned}$$

Applying the Bayesian rule yields,

$$\hat{x}_{MAP} = arg\max_x \left[\frac{P(x \mid y_k)P(x)}{P(y_k)} \right]$$

And since the maximum xMAP is independent of y we have,

$$\hat{x}_{MAP} = arg\max_x [P(y_k \mid x)P(x)]$$

Since the logarithm is a monotonic increasing function, this equivalent to finding,

$$\hat{x}_{MAP} = arg\max_x [logP(y_k \mid x) + logP(x)]$$

where logP(yk|x) is the log-likelihood function and logP(x) is the log of the a priori density of x. yk = Hx + nk :the likelihood function is determined by the probability density of the noise as fN(·),

$$P(y_k \mid x) = f_N(y_k - Hx)$$

Additionally, it is common to utilize a Markov Random Field prior which has a Gibbs probability density of the form,

$$P(x) = \frac{1}{Z} exp(-\frac{1}{\beta} u(x))$$

where Z is a normalizing constant, β is the density parameter of the density and is the energy of f. The use of the logarithm in the formulation for the MAP solution thus greatly simplifies manipulations in these cases.

Schultz and Stevenson use the Huber Markov Random Field(HMRF) for the priori term log P(x), which is a discontinuity preserving image model allowing edge reconstruction while imposing smoothness constraints on reconstruction.

3. Test

3.1 Test Data

The video image for testing was recorded by the DCR-pc100 (sony) digital video camera on UAV (Unmanned Aerial Vehicle) around Daejeon city. We sampled an image sequence at 30 frames/sec using Pinnalcle Studio 7.0.

The video sequence was composed of blurred images for flighting motion. The estimation of each frame's precise motion is very important in super resolution reconstruction. All the simulations correspond to synthetic data to bypass problems such as motion estimation, which are beyond the scope of this paper. Four LR images for test were sampled from one video frame which was assumed to the original image. An HR image of size 480×720 pixels was reconstructed from an LR image of size 240×360 pixels by the super resolution method.

3.2 Implementation

In the figure 4, the flowchart of implemented software is represented. The super resolution software is composed of three modules, image and some data input/output module, super resolution reconstruction module, and analysis

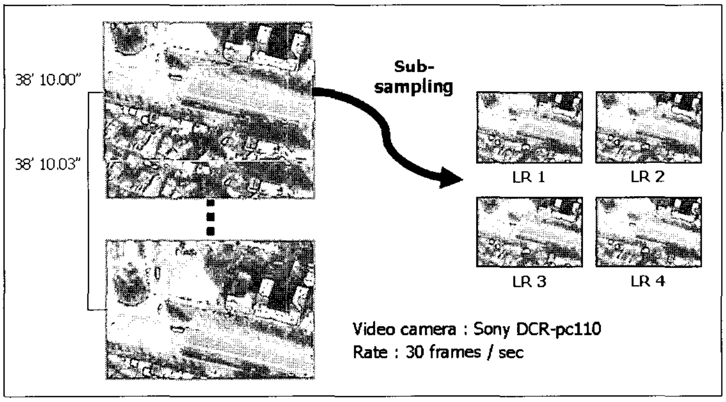


Figure 3. Test images

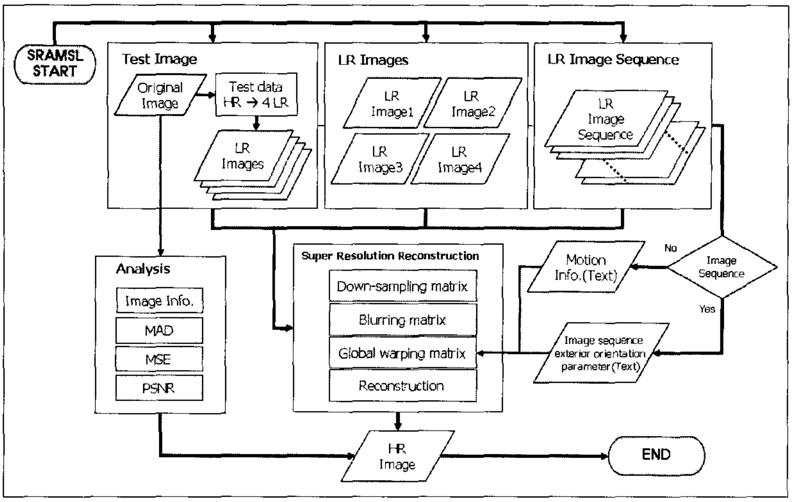


Figure 4. SR implementation - flowchart

module.

In the input module, the original input image is down-sampled to four low resolution images by the subsampling process. Each low resolution image for test is recoded.

In the super resolution reconstruction module, low quality test images are input and then the subsampling matrix, blurring matrix, and global warping matrix are constructed. Because of poor video camera information, sub-pixel precision motion is randomly assumed in this simulation test.

Generally, the images using super resolution such as those from a frame airborne camera, video camera and digital camera have many pixels. Higher resolution image has more pixels, and the dimension of operation matrix is high. In this research, each low resolution image is segmented into smallest fragments. After the process of super resolution reconstruction, each reconstructed high resolution segment is merged into a high resolution image.

A 480×720 color video image is down -sampled into 240×360 4 LR images. Each 240×360 LR image is separated into R, G, B bands and segmented into 5×5 image fragments for calculation efficiency. A 5×5 image fragment is reconstructed into a 10×10 image by using the MAP super resolution reconstruction method. All reconstructed image fragments are merged into one reconstructed super resolution image.

In the analysis module, using the MAP algorithm-reconstructed super resolution image is compared with the original HR image, quantitatively. The calculation method of MAD (Mean Absolute Deviation), MSE (Mean Squared Error) and PSNR (Peak Signal to Noise Ratio) between original image and reconstructed image are implemented for quantitative analysis.

In Figure 5, the executed super resolution implementation software is SRAMSL (Super Resolution Application by Mapping Systems

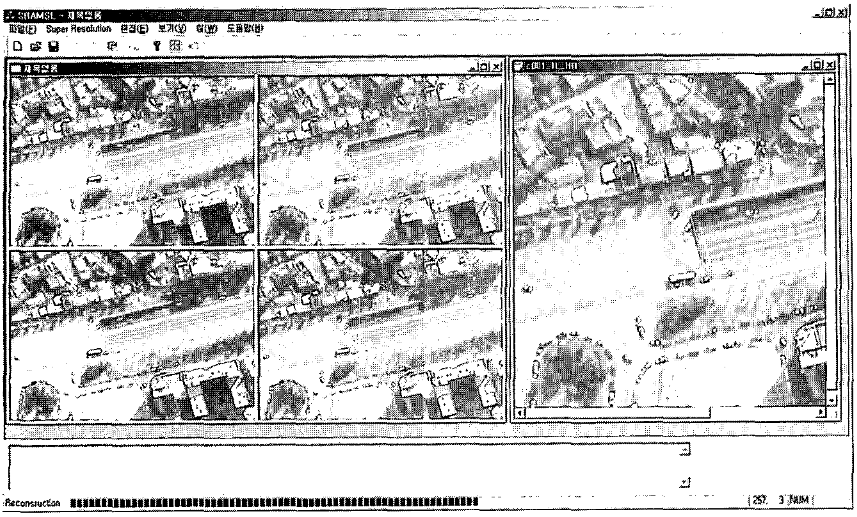


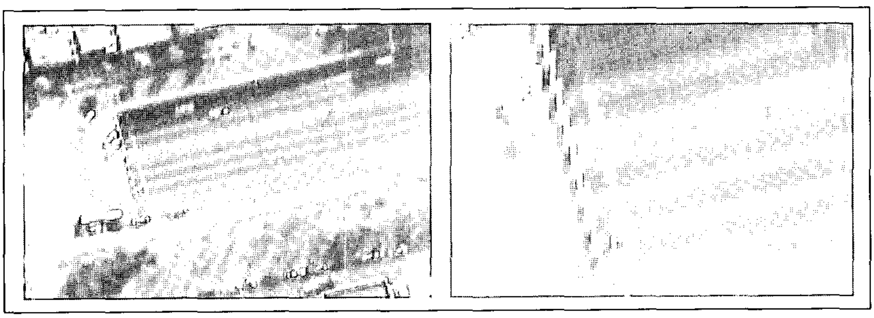
Figure 5. SR implementation - execution

Laboratory), developed by Microsoft visual c++ 6.0 MDI interfaced.

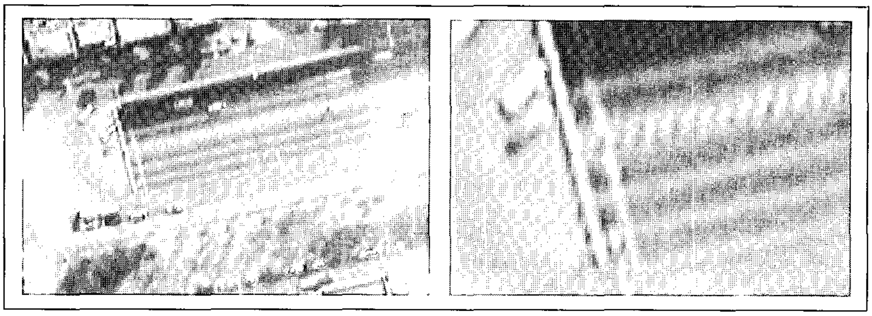
3.3 Result

To give a fair representation of the performance of the super resolution algorithm compared to a general image zooming method, low resolution input images are shown up-sampled to the resolution of the corresponding super resolution results by using nearest neighbor interpolation and bicubic interpolation. Using the MAP algorithm, the result of super resolution shows more improved definition image expansion than those of various methods such as the nearest neighbor interpolation and bicubic interpolation. In the Figure 6, (a) is the nearest neighbor interpolation result, (b) is the bicubic interpolation result and (c) is the SR result.

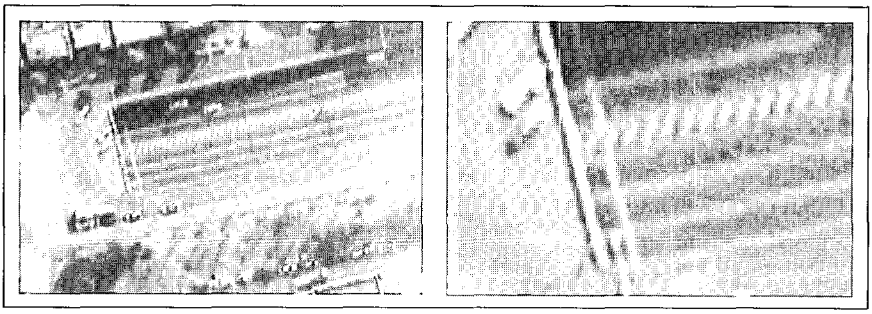
The SR result demonstrates that, despite the shortcomings, it is possible to obtain



(a) Nearest neighbor interpolation



(b) Bicubic interpolation



(c) Super resolution reconstruction

Figure 6. Comparison of result

reconstructions by using MAP, which showed marked improvement in detail over the original low resolution images, even though the levels of pixel zoom were quite modest.

In the quantitative analysis, the SR result also showed the best performance. In the Table 1, MAD, MSE and PSNR values of the SR result image compared with original image were on the average 4.5011, 21.5056, and 34.8143, respectively. These values mean that the SR result image more similar with the original image than those of other interpolations.

Table 1. Comparison with original image

Method		MAD	MSE	PSNR(dB)
SR	R	4.6193	22.7620	34.5587
	G	4.5687	22.1545	34.6762
	B	4.3154	19.6004	35.2081
Nearest Neighbor	R	4.8308	104.3898	27.9442
	G	4.8035	104.4330	27.9424
	B	4.7882	103.7430	27.9825
Binear	R	4.8761	74.4634	29.4114
	G	4.8406	74.3707	29.4168
	B	4.8350	74.1201	29.4314
Bicubic	R	4.7318	70.6398	29.6569
	G	4.6971	70.1905	29.6680
	B	4.6916	69.9499	29.6829

4. Conclusion

Summarizing the obtained results, we applied the super resolution algorithm to video sequence recorded on UAV. We implemented the software for super resolution reconstruction by using visible programming tool and applied the MAP algorithm. Although the test data set was simulated because of poor information about the vehicle, the reconstructed result SR image provides higher performance than those of other interpolation methods with respect to similarity with the original image.

Acknowledgements

This research was supported by the Agency for Defense Development(ADD), Korea, through the Image Information Research Center at Korea Advanced Institute of Science & Technology (KAIST).

REFERENCE

[1] S. C. Park, M. K. Park, M. K. Kang, "Superresolution Image reconstruction - A Technical Overview", IEEE Signal Processing Magazine, Vol. 20, No. 3, pp. 1~36, May 2003.

[2] M. Elad, A. Feuer, "Restoration of a single Superresolution Image from Several Blurred, noisy, and Undersampled Measured Images", IEEE trans. Image Processing, Vol. 6, No. 12, pp. 646~1658, Dec. 1997.

[3] M. Elad, A. Feuer, "Super-resolution Reconstruction of Continuous Image Sequences", In Proc. IEEE Int'l Conference on Image Processing, Dec. 1999.

[4] R. R. Schultz and R. L. Stevenson, "Bayesian approach to image expansion for improved definition", IEEE Trans. Image Processing, Vol. 3, no. 3, pp. 233~242, 1994.

[5] M. Elad, "Super-resolution reconstruction of images", Ph. D. dissertation, Technion, Israel, 1996.

[6] David Peter Capel, "Image Mosaicing and Super-Resolution", Ph. D. dissertation, Univ. of oxford, 2001.

[7] R. C. Gonzalez, R. E. Woods, Digital Image Processing Prentice Hall, 2nd edition, 2002.

[8] Sean Borman, "Topic in Multiframe Super -resolution Restoration", Ph. D. dissertation, Univ. of Notre Dame, Apr. 2004.

[9] H. J. Kown, B. G. Kim, "Super Resolution Image Reconstruction using the Maximum A-Posteriori Method", Proceedings of Int'l Symposium on Remote Sensing 2004, Oct. 2004.

[10] J. M. Park, B. G. Kim, "Super resolution reconstruction from Image Sequence", Proceedings of Int'l Symposium on Remote Sensing 2005, Oct. 2005.