Improved Super-Resolution Algorithm using MAP based on Bayesian Approach

*장재용, **조효문, ***조상복 Jae-Lyong Jang, Hyo-Moon Cho, Sang-Bock Cho

Abstract - Super resolution using stochastic approach which based on the Bayesian approach is to easy modeling for a priori knowledge. Generally, the Bayesian estimation is used when the posterior probability density function of the original image can be established. In this paper, we introduced the improved MAP algorithm based on Bayesian which is stochastic approach in spatial domain. And we presented the observation model between the HR images and LR images applied with MAP reconstruction method which is one of the major in the SR grid construction. Its test results, which are operation speed, chip size and output high resolution image quality, are significantly improved.

Key Words: super-resolution, high-resolution, low-resolution, registration error, Bayesian, maximum a posteriori

1. INTRODUCTION

Recently, HR (High-Resolution) images are desired and often required in the most imaging applications such as surveillance, forensic, scientific, medical, and satellite imaging. One promising approach is to use signal processing techniques to obtain an HR image from observed multiple LR (Low-Resolution) images, and it is called SR (Super-Resolution).

The basic principle of SR is the availability of multiple LR images captured from the same scene. Where, multiple LR images are represented different look at the same scene. That is, LR images are sub-sampled (aliased) as well as shifted with sub-pixel precision. To obtain different looks at the same scene, some relative scene motions must exist from frame to frame via multiple scenes or video sequences. If these scene motions are known or can be estimated within sub-pixel accuracy and we combine these LR images, SR image reconstruction is possible.

Typically, the practical image acquisition and recording devices usually suffer from blur, aliasing effect, and noise. Therefore, the goal of SR techniques is to restore an HR image from several degraded and aliased LR images.

The SR restoration algorithm was first presented by Tsai and Huang. They used the frequency domain approach to obtain one improved resolution image from several down-sampled noise-free version of it, based on the spatial aliasing effect. Most of the super resolution image reconstruction methods which are proposed in the literature consist of the three stages illustrated Figure 1: registration, interpolation, and restoration (i.e., inverse procedure). These steps can be implemented separately or simultaneously according to the reconstruction methods adopted.

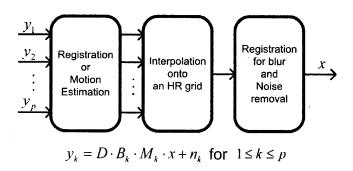


Figure 1.Scheme for super resolution

The estimation of motion information id referred to as registration. And in this stage, the relative shifts between LR images and compared to the reference LR images are estimated with fractional pixel accuracy. Since the shifts between LR images are arbitrary, the registered HR image will not always match up to a uniformly spaced HR grid.

저자 소개

^{*} 장재용: 울산대학교 전기전자정보시스템공학과 석사과정

^{**} 조효문: 울산대학교 전기전자정보시스템공학과 박사과정

^{***} 조상복: 울산대학교 전기전자정보시스템공학과 교수

Thus, non-uniform interpolation is necessary to obtain a uniformly spaced HR image from a non-uniformly spaced composite of LR images. Finally, image restoration is applied to the up-sampled image to remove blurring and noise.

Stochastic SR image reconstruction, typically a Bayesian approach, provides a flexible and convenient way to model a priori knowledge considering the solution.

The SR reconstruction method needs the Priori knowledge considering in sampling process because it is typical ill-posed inverse transform. The stochastic method is used to solve the ill-posed problem and the statistic method is used to solve the reverse problem. Specially, the Bayesian estimation has been come out the best solution for ill-posed reverse problem.

The key development in this paper, which distinguishes it from previous approaches, is the use of maximum a posterior (MAP) based on Bayesian. Additionally, HMRF (Huber Markov Random Field) for the priori term $\ln P(x)$, which is a discontinuity preserving image model allowing edge reconstruction while imposing smoothness constraints on reconstruction, is used.

We construct the system for framework which is composed of three modules, input/output' module, SR reconstruction module, and analysis module. We sampled an image sequence at real time (i.e., 30fps) from CCD camera with 270K pixels. Our algorithm is implemented by Matlab and we verified the performance of our algorithm by using two images which one is 720×480 pixel image (HR image) and 360×240 pixel image (input LR images). And also compare among the previous SR algorithm, traditional interpolation method and proposed algorithm.

This paper describes our proposed algorithm and test and it results.

2. Proposed algorithm

Schults and Stevenson extended their earlier work on the Bayesian image interpolation for improved definition using HMRF prior to the problem of SR image.

Firstly, we assumed three conditions:

The frequency domain approach is based on the following three principles:

- The blur of the measured images is to be simple averaging.
- 2) The measurements of additive noise are to be independent.
- The measurements of additive noise are identically distributed Gaussian vector.

This choice of prior causes the entire problem to be non-quadratic, and it complicates the resulting minimization problem. General observation model is

$$y_L = Hx + n_L \tag{1}$$

and its solution will not be a unique solution for image expansion. MAP method is proposed to compute an estimation of the HR images. MAP approach to estimate x, seeks the estimate x_{MAP} as:

$$\widehat{x_{NAP}} = \operatorname{arg} \max P(x|y_1, y_2, ..., y_k) \tag{2}$$

where the a posteriori PDF $P(x|y_k)$ is in-likelihood function, and this can be calculated using the Bayesian theorem. Thus,

$$P(x|y_t) = \ln P(x|y_t) = P(y_t|x) + \ln P(x) - \ln P(y_t)$$
 (3)

And we can take eq.(4) by applying Bayesian rule

$$\widehat{x_{MAP}} = \operatorname{arg} \max \left[\frac{P(y_k|x)P(x)}{P(y_k)} \right] \tag{4}$$

Since the maximum x_{MAP} is independent of y, we can obtain

$$\widehat{x_{MAP}} = \operatorname{arg} \max \left[P(y_k | x) P(x) \right] \tag{5}$$

Since the logarithm is a monotonic increasing function, eq. (5) is changed to

$$\widehat{x_{MAP}} = \operatorname{arg} \max \left[\ln P(y_k | x) + \ln P(x) \right] \tag{6}$$

where $\ln P(y_k|x)$ is the log-likelihood function and $\ln P(x)$ is the log of the priori density of the noise as $f_N(\cdot)$

$$P(y_k|x) = f_N(y_k - Hx) \tag{7}$$

3. Experiment and Implementation

The video image for testing was recorded by the general CCD camera with 270K pixel on downtown. We sampled an image sequence at 30fps. The video sequence was composed of blurred images.

Four LR images to test were sampled from one video frame which was assumed the original image. An HR image of size 720×480 pixels was reconstructed from an LR image of size 360×240 pixels by the SR reconstruction method.

LR image is separated into R, G, B bands and segmented into a 5×5 images fragment for calculation efficiency. A 5×5 image fragment is reconstructed in to

10×10 image by using MAP SR reconstruction method. All reconstructed image fragments are merged into one reconstructed SR image.

(a) Four 360×240 LR images



(b) 720×480 SR image

4. Result and Conclusion

In the analysis module, using MAP algorithm SR image, based on Bayesian approach, is compare 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 HR image and SR reconstructed HR image are implemented for quantitative analysis. The average values of MAD, MSE, and PSNR are 4.5011, 21.5056, and 34.8143, respectively. These values mean that the SR result image more similar with original image.

Although the test images set was simulated because of poor information about the object, the SR reconstruction

result image provides higher performance and more similar with original HR image.

ACKNOWLEDGMENT

This work was partly sponsored by ETRI SoC Industry Promotion Center, Human Resource Development Project for IT-SoC Architect and NARC (Network-based Automation Research Center) and 2nd level BK21 (EVERDEC(e-Vehicle Research & human Resource Development Center)) in MOE (Ministry of Education & Human Resources Development).

REFERENCES

- [1] S. C. Park, M. K. Park, M. K. Kang, "Super-resolution image reconstruction-A Technical Overview," *IEEE* Signal Processing Magazine, vol. 20, No. 3, pp. 21-36, May 2003.
- [2] H. J. Kwon, B. G. Kim, "Super resolution Image reconstruction using the Maximum A-Posteriori Method," proceedings of Int'l Symposium on remote Sensing 2004, Oct. 2004.
- [3] M. Elad, A. Feuer, "Super-resolution reconstruction of Continuous Image Sequence," in Proc. IEEE Int'l Conference on Image Processing, Dec. 1999.
- [4] M. Elad, A. Feuer, "Restoration of a single Super-resolution Image from Several Blurred, noisy, and Under-sampled Measured Images," *IEEE trans. Image Processing*, vol. 6, No. 12, pp. 646–1658, Dec. 1997.
- [5] 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, Dec. 1994