AN IMPROVED SUPER RESOLUTION RECONSTRUCTION ALGORITHM FOR VIDEO SEQUENCE

Hyo-Moon Cho
School of Electrical, University of Ulsan, 7-524 san29 Muger-dong Nam-gu, Ulsan, South Korea

Sang-Bok Cho
School of Electrical, University of Ulsan, 7-524 san29 Muger-dong Nam-gu, Ulsan, South Korea

Keywords: High resolution, Motion compensation error, Super resolution, Low resolution.

Abstract: In this paper, we introduce the input image selection-method to improve the reconstructed high-resolution (HR) image quality. To obtain ideal super-resolution (SR) reconstruction image, all input images are well-registered. However, the registration is not ideal in practice. By reason of this, the number of input images with low registration error is more important than the number of input images in order to obtain good quality of a HR image. The input image suitability could be evaluated by using statistical and restricted registration properties. Therefore, we propose the input image evaluation-method in automatic manner as pre-processing of SR reconstruction and its architecture. In video sequences, all input images in specified region are allowed to use SR reconstruction as low-resolution (LR) input image and/or the reference image. The evaluation basis is decided by the threshold value and this threshold is calculated by using the maximum motion compensation error (MMCE) of the reference image. If the motion compensation error (MCE) of LR input image is in the range of $0 < MCE < MMCE$ then this LR input image is selected for SR reconstruction, else then LR input image are neglected. The optimal reference LR (ORLR) image is decided by comparing the number of the selected LR input (SLRI) images for each reference LR input (RLRI) image. Finally, we generate a HR image by using optimal reference LR image and selected LR images and by using the Hardie's interpolation method. This proposed algorithm is expected to improve the quality of SR without any user intervention.

1 INTRODUCTION

The super-resolution (SR) algorithms, which produce a high-resolution (HR) image from multiple low-resolution (LR) images, are one of the most promising approaches for image quality enhancement.

The basic framework of SR is to define the reference LR image from given multiple LR images and to generate the HR reconstruction image by fusing the several LR images based on reference LR image.

The various SR algorithms have been proposed by using frequency-domain approach and spatial-domain approach. The SR 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. Usually, it assumed that there is some or small relative motion between the camera and the scene. If there is relative motion between the camera and the scene, then the first step of SR is to register or align the image, i.e., it computes the motion vector from one image to others. The accurate registrations between LR images are very important. To obtain ideal SR reconstruction, the ideal registration is executed among the LR input images and the point spread function (PSF) of camera is accurate estimated. However, in practice, these are not ideal. To overcome such SR constraints, the recognition-based SR algorithms have been proposed and the methods considering the registration error in SR reconstruction process have been tried.

Generally, the improved SR algorithms considering the registration error have been applied by using the restricted input images. However, all input images of the specified region in video

Cho H. and Cho S. (2007).
AN IMPROVED SUPER RESOLUTION RECONSTRUCTION ALGORITHM FOR VIDEO SEQUENCE.
In *Proceedings of the Second International Conference on Signal Processing and Multimedia Applications*, pages 188-191
DOI: 10.5220/0002139601880191

sequence can be used to SR reconstruction. Therefore, to improve SR algorithm, we designed the automatic input image evaluation and selection block as pre-processing in order to solve a registration error problem.

This automatic input image evaluation and selection block designates the reference image arbitrary because all input images are allowed to use super-resolution reconstruction and it selects the suitable LR input images from all LR input (LRI) images for designated reference image. Finally, it selects the optimized reference input LR (RILR) image by using statistical property. All of these processing are executed automatic manner and this method achieves the HR image reconstruction without any user interventions and fast and low computational complexity. And also we design its hardware architecture. This article is organized as follows: in section 2, we describe the importance of the ILR images and RILR image selection; in section 3, we introduce the proposed algorithm and its architecture; experimental results are shown in section 4, and we conclude with section 5.

2 THE LR IMAGE AND RLRI IMAGE SELECTION

The SR reconstruction is achieved when the LR images with sub-pixel distance from reference registered onto the HR image grid. Therefore, the motion estimation and motion compensation are essentially needed.

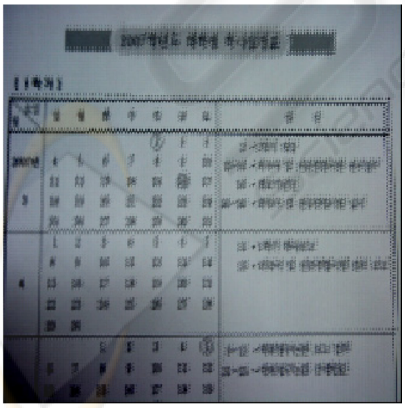

Figure 1: Influence of unsuitable ILR image selection.

The reconstructed HR image is distorted when the sub-pixel motion is estimated inaccurately. In this case, the distortion can be called the registration error (RE) noise. In many conventional approaches, it is assumed that the RE noise is neglected or considered the same for all LR images: i.e., all LR images are ideally confirmed.

In most and practice, ideal registration has constraint by registration model or restricted searching area. As these reasons, the quality of reconstructed HR image is decreased.

Figure 1 shows contaminated HR reconstruction image when the RE is high. Therefore the LR input images with low RE is more important than the number of LR input images.

3 PROPOSED ALGORITHM

We designate a reference LR image arbitrary in specified region of input video since all LR input images are allowed to reference LR input image and we restrict the number of maximum ILR images up to five frames. The reason of this, if many LR input images are used then it is difficult to evaluate the performance of algorithms comparing with others and the SR reconstruction processing time is very long. Therefore, we restricted the number of LR images and make analysis of the influence of a registration error.

To select the suitable LR input images, first, our algorithm decides the threshold value by using designated reference LR input image and its motion compensated image. Secondly, our algorithm evaluates the SAD between a LR input image and reference image is less than the threshold value. Figure 2 shows the flow chart to select the selected LR input (SRLI) images. Therefore, if the LR input image is selected, then it has a low RE noise.

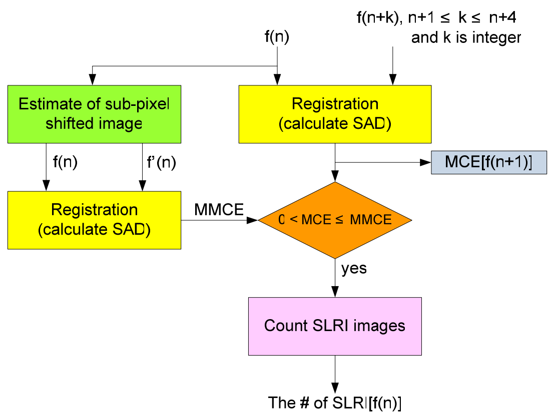

Figure 2: The flowchart of SLRI selection method.

The SAD (Sum of Absolute Difference) computation is used as calculation of the motion compensation error (MCE).The maximum motion compensation error (MMCE) for each reference image is calculated by computing SAD between the reference LR input image and its motion estimated in sequence order.

Generally, the distribution of registration error (RE) for the sub-pixel shifts in practical video, the RE has maximum value when shifting displacement is at (dx, dy)=(0.5, 0.5) as shown figure 3.

To decide optimized reference LR input (ORLRI) image, we count the number of the selected LR input (SLRI) images for each designated reference LR input image and compare the number of SLRI[f(n)] of each designated reference input image in specified region as shown figure 4.

To decrease computation time and complexity, we designed advanced architecture as shown figure 5. As shown figure 5, the duplicated SAD operators on each frame are removed. And the number of selected low resolution input (SLRI) images for one reference image equals to 4 then the remaining the selection of LR input image processes are stopped.

The partial distortion elimination (PDE) method is used to decrease the SAD calculation. The basic concept of PDE is that the motion estimation is more efficient as the larger initial accumulated SAD value is selected.

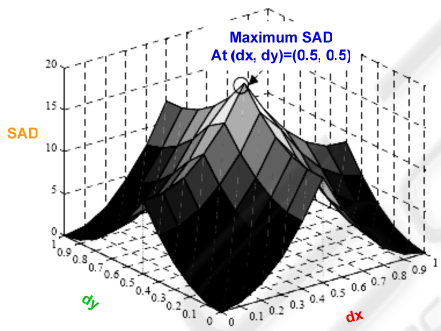

Figure 3: Distribution of RE depending on sub-pixel shift.

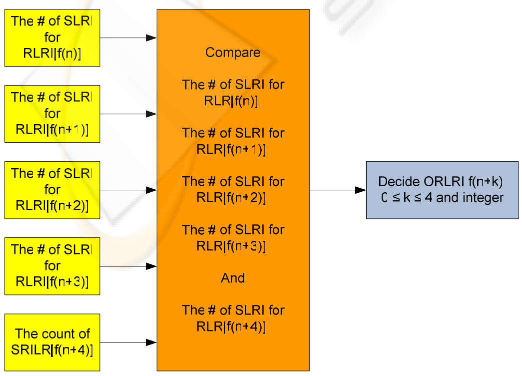

Figure 4: ORLRI block flowchart.

4 EXPERIMENTAL RESULTS

We used the video sequences to experiment by PC camera which is made by China. The camera features are as below:

- CMOS image sensor with 1.3M pixel
- Maximum resolution 1280x960
- 24bit true color video mode
- 640 x 480@30fps
- USB 2.0 interface

We used the Hardie algorithm as interpolation with 16 restricted searching-area and 20 iterations. Figure 7 is shown the sequenced images for experiment.

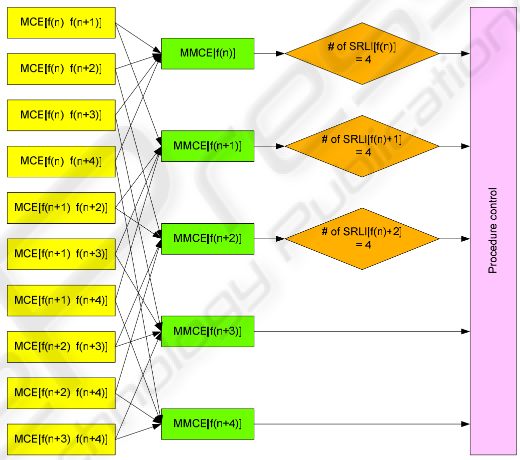

Figure 5: Advanced architecture of the proposed algorithm.

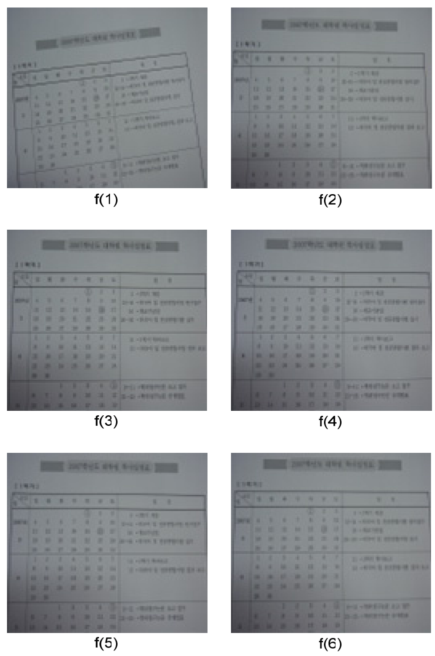

Figure 6: The sample imaged which used to experiment.

We take a picture of the sample object and modified the image size into 128x128 from 512x512 original HR image. The modified images are used as LR images, the f(3) frame is selected as reference image by our algorithm procedure and it takes three selected LR input (SLRI) images and other cases have two or under SLRI images. Figure 8 is shown the result image by using the proposed SR reconstruction method Figure 8 is shown the result image by using conventional SR reconstruction method is shown the result image with bilinear interpolation method. As shown figure 7, 8, figure 7 is better of them..

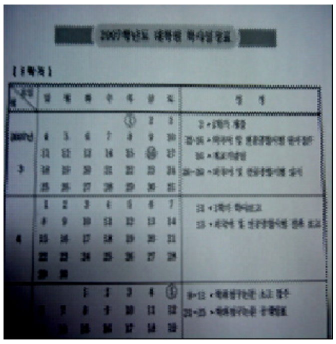

Figure 7: Experimental result image.

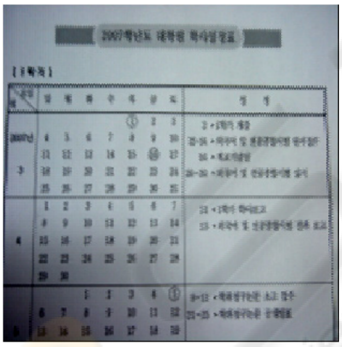

Figure 8: Result image with conventional SR reconstruction method.

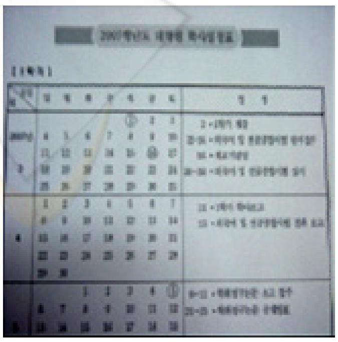

Figure 9: Result image with bilinear interpolation method.

5 CONCLUSIONS

We introduced the improved SR reconstruction algorithm which selects the suitable input images and the optimized reference image in automatic manner. And also we presented its architecture. However, we restrict the maximum input frame number is five, so this is too small. If we increase maximum input frame number then the image quality higher than this. To do this, which restrict the maximum frame number as 5 frames, is only for fast and easy evaluation of our algorithm. This algorithm is used to moving picture like as surveillance systems.

ACKNOWLEDGEMENTS

This research was financially supported by the Ministry of Commerce, Industry and Energy (MOCIE) and Korea Industrial Technology Foundation (KOTEF) through the Human Resource Training Project for Regional Innovation and 2 level BK21 (EVERDEC(e-Vehicle Research & human Resource Development Center)) in MOE (Ministry of Education & Human Resources Development).

REFERENCES

S.C. Park, M.K. Park and M.G. Kang, “Super-resolution image reconstruction: a technical overview,” IEEE Signal Processing magazine, pp. 21-36, May 2003.

E.S. Lee and M. G. Kang, “Regularized adaptive high-resolution image reconstruction considering inaccurate subpixel registration,” IEEE Trans. Image Processing, vol. 12, pp. 826-837, July 2003.

Y. Altunbasak, A.J. Patti, and R.M. Mersereau, “Super-resolution still and video reconstruction from MPEG-coded video,” IEEE Trans. Circuits Syst. Video Technol., Vol. 12, pp. 217-226, April 2002.

S. Baker and T. Kanade, “Limits on sper-resolution and how to break them,” IEEE Trans. Pattern Analysis Machine Intelligence, vol. 24, pp. 1167-1183, Sept. 2002.

R.C. Hardie, K.J. Barnard, and E.E. Armstrong, “Joint MAP registration and high-resolution image estimation using a sequence of undersampled image,” IEEE Trans. Image Processing, vol. 6, pp. 1621-1633, Dec. 1997.

R.R Schultz and R.L. Stevenson, “Extraction of high-resolution frames from video sequences,” IEEE Trans. Image Processing, vol. 5, pp. 996-1011, June 1996.