Multi-camera Imaging System Using Super-Resolution

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Abstract: This work presents a high-resolution image acquisition system by combining a multi-camera imaging system composed of multiple low-resolution digital cameras and a color super-resolution image reconstruction algorithm. Aligned and adjusted multiple mini-cameras and the controlling system consist the multi-camera imaging system. Some of the cameras obtain intensity information and the other ones receive color information. The spatial intensity information is enhanced by the Bayesian super-resolution image reconstruction algorithm. The high-resolution intensity data and the color channel inputs are merged to generate the final color composite high-resolution image. With experimental results, the performance of the proposed system is assessed.

1. Introduction

It is one of the essential methods in reconstructing images with information that is beyond the limit of the existing sensors to obtain several sheets of low-resolution images of the same scene. Unlike the traditional method of taking images sequentially by one imaging sensor, using more than one imaging sensor to take the low-resolution images and use them to overcome the limit of each image from one sensor have been recently proposed by researchers [1] [2] [3].

We propose a new imaging system producing high-resolution images with low-resolution sensors by using super-resolution image reconstruction, instead of using an imaging system with a high-resolution sensor. In order to capture several low-resolution images with minimum local motion, we propose to use several digital cameras attached to each other by an $N \times N$ array fixed frame, and we call this framework a "multi-camera" system. In the proposed multi-camera system, low-resolution images of the same scene and with different sub-pixel displacements from each other are taken simultaneously by frame grabbers and a controlling software within the controlling computer of the multi-camera system. In front of some of the cameras, color filters are attached so that the system can acquire color channel information. The super-resolution image reconstruction algorithm that make a high-resolution image from low-resolution images is performed based on Bayesian multi-channel image estimation. The process of obtaining the final color composite high-resolution image is done by the image fusion based on the color difference domain. In experimental results, the quality of the reconstructed high-resolution images is assessed. The proposed system can be applied to imaging a scene that is relatively away from the imaging system so that there is only global motions between the low-resolution images.

2. Proposed Super-Resolution Image Reconstruction using Multi-camera

The proposed multi-camera system is composed of an $N \times N$ array of grayscale digital cameras attached to one another tightly, the platform and support of the multi-camera, and a control computer. Frame grabbers are ported in the computer and a software is developed and used to help the hardware setting of the multi-camera and take images simultaneously by digital shutter. Figure 1 shows the prototype of the multi-camera system using a 3×3 array composed of 9 digital cameras. We attached red, green, and blue color filters in front of the cameras in the first row of the array. Therefore, the 6 images obtained from the cameras in the lower two rows are used for reconstructing the high-resolution intensity image and the three color channel inputs are used to give color information to the intensity image. The camera used in the prototype is a charge coupled device (CCD) camera VCC-G20E20 made by CIS Corporation, and the lens is FV2020 made by Myutron Co., LTD. We aligned the optical axes of the cameras to be parallel as much as possible. In addition, we adjusted the position of the multi-camera system so that the object plane and the image plane are parallel whenever we take low-resolution images. The multi-camera is placed on a platform designed to take images in a controllable and stable environment. The cameras are linked with the frame grabbers of the controlling computer by cables. The frame grabber used in the experiment is Coreco PC2-Vision.

We developed a software that shows previews and the status of the images and grabs them simultaneously. In order to adjust the lenses for the purpose of intensity and blur uniformity, the intensity and focusing indices are implemented in the software. The low-resolution images are captured by the software, and they go through pre-processing steps. One of the images is selected to be the reference image, and the lightness and contrast of the other images are adjusted with regard to the reference image by histogram specification. The relative global motions of the other images with regard to the reference image are calculated. The integer motions are firstly calculated, and the sub-pixel registration follows.

Then, the super-resolution image reconstruction is performed with the adjusted low-resolution images and the estimated motion information. The super-resolution algorithm is based on Bayesian multi-channel image estimation with the feature of considering local motion errors by local regularization parameters. The basic form of the minimization functional for maximum a posteriori (MAP) based super-resolution using local regularization parameters can be writ-

ten as

$$F(\mathrm{x}) = \sum_{k=1}^{p} ||\mathrm{y}_k - \mathrm{W}_k\mathrm{x}||^2_{\mathrm{A}_k} + ||\mathrm{Cx}||^2 \quad (1)$$

where $||\cdot||^2_{\mathrm{A}_k}$ is a weighted L-2 norm with a weight matrix A_k, and A_k is a diagonal matrix whose elements are the pixel-wise regularization parameters assigned to the data of the k-th fidelity term. The weighted L-2 norm $||\mathrm{y}_k - \mathrm{W}_k\mathrm{x}||^2_{\mathrm{A}_k}$ can be rewritten in the matrix-vector multiplication form as

$$||\mathrm{y}_k - \mathrm{W}_k\mathrm{x}||^2_{\mathrm{A}_k} = (\mathrm{y}_k - \mathrm{W}_k\mathrm{x})^T\mathrm{A}_k(\mathrm{y}_k - \mathrm{W}_k\mathrm{x}). \quad (2)$$

The quality of the solution of super-resolution algorithms can be enhanced with the application of spatially adaptive regularization parameters as A_k in Eq. (1) when the observed images show different statistical characteristics with regard to spatial locations.

The formulation we use in this paper is an extended form of the super-resolution algorithms in [4, 5] to estimate the local accuracy of the motion estimation results and incorporates it in the minimization functional as a local regularization parameter. According to the investigation in [5], the result of inaccurate motion estimation is proportional to the amount of NME and inversely proportional to the partial derivatives of the image, which can be interpreted as the amount of high-frequency data. Using this relation, we can use regularization parameters adaptive to the local NME by applying it to A_k in Eq. (1). The locally adaptive regularization parameter A_k is defined as

$$[\mathrm{A}_k]_{(m,m)} = \mathrm{G}\left(\frac{\sum_{(i,j)\in S_{(i,j)}} ||\mathrm{Cx}||^2_{(i,j)}}{\sum_{(i,j)\in S_{(i,j)}} ||\mathrm{y}_k - \mathrm{W}_k^{\mathrm{est}}\mathrm{x}||^2_{(i,j)}}\right) \quad for\ m = iN_2 + j,\ (i,j) \in R^2, \quad (3)$$

where where $G(\cdot)$ is a monotonically increasing function, and $[\mathrm{A}_k]_{(m,m)}$ is the m-th diagonal element, i.e., the element in the (m,m) position of A_k.

The solution that minimizes the functional (1) can be obtained by adopting the iterative gradient descent method. The gradient descent method is a basic method for obtaining the solution by iterative operations, and there are faster algorithms such as the conjugate gradient method. When the minimization functional is denoted by $F(\mathrm{x})$, the $(n+1)$-th iterative solution $\hat{\mathrm{x}}^{n+1}$ using the n-th estimated solution $\hat{\mathrm{x}}^n$ by the previous n iterations is

$$\hat{\mathrm{x}}^{n+1} = \hat{\mathrm{x}}^n - \beta^n \nabla_{\mathrm{x}} F(\mathrm{x})\Big|_{\mathrm{x}=\hat{\mathrm{x}}^n},\ for\ n = 0, 1, 2, \cdots, \quad (4)$$

where β^n is a parameter controlling the rate of updating the solution in $(n+1)$-th iteration. The initial value of the iterative solution $\hat{\mathrm{x}}^0$ is usually the interpolated reference low-resolution image. $\nabla_{\mathrm{x}} F(\mathrm{x})$ of Eq. (1) is

$$\nabla_{\mathrm{x}} F(\mathrm{x}) = \sum_{k=1}^{p} 2\mathrm{W}_k^T\mathrm{A}_k(\mathrm{W}_k\mathrm{x} - \mathrm{y}_k) + 2\mathrm{C}^{\mathrm{T}}\mathrm{Cx}, \quad (5)$$

respectively. Finally, we replaced the regular zero-padding up-sampler included in the process of inverse warping, i.e. W_k^T with bilinear up-sampler and regularized the resulting image with adaptive regularization parameters considering inaccurateness of the estimated motion information. By these procedures, a high-resolution image whose spatial resolution is beyond the resolution limit of each sensor can be obtained by the proposed multi-camera system.

An image fusion algorithm is applied for merging the high-resolution image reconstructed by the super-resolution algorithm and color channel low-resolution images. By combining image fusion with the color difference domain which is widely used in color interpolation, the proposed image fusion algorithm can produce clearer multi-spectral images even when the spectral low-resolution channels are not perfectly registered to one another.

Let us denote the reconstructed high-resolution intensity by $\hat{\mathrm{x}}$. Let the original high-resolution image of the p-th spectral band be z_p^h, the low-resolution observation of the corresponding band be z_p^l, and let us assume that there are P spectral bands to be used in the multi-camera system. In the normal circumstance that uses three primary color channels, i.e. red, green, and blue, P is equal to 3. We define the color difference between the reconstructed high-resolution panchromatic image $\hat{\mathrm{x}}$ and the p-th high-resolution spectral band z_p^h as

$$\mathrm{k}_p = \hat{\mathrm{x}} - \mathrm{z}_p^h,\ \text{for } l = 0, 1, ..., P, \quad (6)$$

where k_p is the original color difference image of the p-th spectral band. When we know k_p a priori, the high resolution spectral band image can be reconstructed by

$$\hat{\mathrm{z}}_p^h = \hat{\mathrm{x}} - \mathrm{k}_p,\ \text{for } l = 0, 1, ..., P, \quad (7)$$

where $\hat{\mathrm{z}}_p^h$ is the estimated high-resolution image of the p-th spectral band. However, it is impossible to have accurate k_p values in high-resolution since we have only the low-resolution versions of the spectral band images. Therefore, k_p should be estimated with the existing data. When the estimated color difference image of the p-th spectral band is denoted by $\hat{\mathrm{k}}_p$, the estimated high-resolution image of the p-th spectral band becomes

$$\hat{\mathrm{z}}_p^h = \hat{\mathrm{x}} - \hat{\mathrm{k}}_p,\ \text{for } l = 0, 1, ..., P. \quad (8)$$

The estimation of k_p should be performed with the known high-resolution intensity image $\hat{\mathrm{x}}$ and the existing low-resolution data z_p^l. In this paper, we define the intermediate color difference domain $\mathrm{k'}_p$ and utilize it instead of the original k_p for obtaining $\hat{\mathrm{k}}_p$. Specifically, $\mathrm{k'}_p$ is defined as

$$\mathrm{k'}_p = \hat{\mathrm{x}} - \bar{\mathrm{z}}_p^h,\ \text{for } l = 0, 1, ..., P, \quad (9)$$

where $\bar{\mathrm{z}}_p^h$ is the blurred version of z_p^h, which can be approximately obtained by interpolating the low-resolution data z_p^l.

With the basic assumption that the color difference domain is smooth, $\hat{\mathrm{k}}_p$ is obtained by the spatially averaging $\mathrm{k'}_p$ in the neighborhood whose spectral characteristic is similar to that of the centered position. Here, two criteria are proposed for the determination of the spectrally similarity in the neighborhood. With the weighing function $w(m,n)$ based on the

(a) (b)

Figure 1. Multi-camera array system

spectral similarity, the estimated color difference value $\hat{\mathrm{k}}_p$ is calculated as

$$\hat{\mathrm{k}}_p = \frac{1}{\sum_{(m,n)\in R^2(i,j)} w(m,n)} \sum_{(m,n)\in R^2(i,j)} w(m,n)\mathrm{k'}_p(m,n). \tag{10}$$

Then, the final color high-resolution image is estimated by using Eq. (8) throughout the whole image in all the spectral bands. The block diagram of the proposed super-resolution imaging with multi-camera system is shown in Fig. 2.

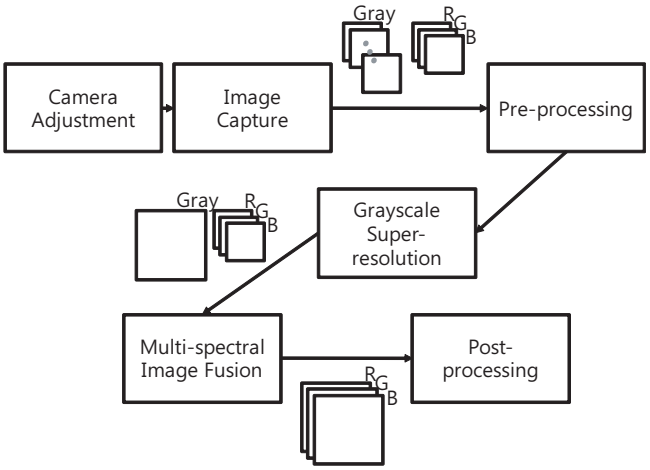
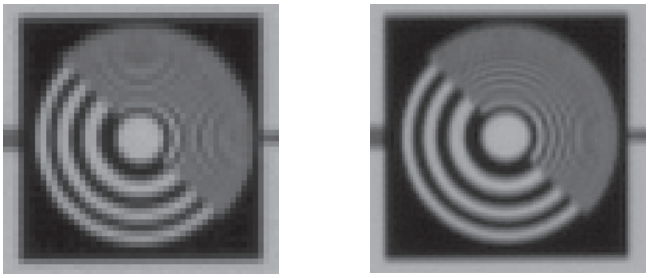


Figure 2. Block diagram of super-resolution imaging with the multi-camera system

3. Experimental Results

For assessing the proposed imaging system, we took nine low-resolution images of a resolution chart located in 2 m distance, using the multi-camera system without color filters in order to assess the maximal performance of regenerating spatial high-frequency of the multi-camera system. The images were intentionally down-sampled by a factor of 2 in both width and height. It is for assessing the quality of the reconstructed high-resolution image by comparing it with the reference image before down-sampling. The down-sampling process includes the simulation of blurring of the observed image. For the blurring process, we used truncated Gaussian blur function with radius 2 and standard deviation 0.5. Then, the high-resolution image enlarged by a factor of 2 in both width and height was reconstructed by the super-resolution algorithm and compared to the reference image before down-sampling. We acquired peak signal to noise ratio (PSNR) values of 34.2 compared to the reference image before down-sampling. For the second experiment, the observed images were directly used for high-resolution image reconstruction in order to check the reconstructed image subjectively. Figure 3 shows the reference frame interpolated with the nearest neighbor algorithm and the reconstructed high-resolution image by super-resolution. The reconstructed image contains sharp details of narrow edges that are not visible in the low-resolution reference image. Finally, we produced results of high-resolution color composite images with color and grayscale low-resolution images simultaneously taken from a color printed image named MulTest. This experiment is for comparing the results with minimized errors in high resolution intensity images and testing the algorithm with images with a colored scene. The results are shown in Fig. 4 In these images, the superiority of the proposed algorithm based on the color difference domain is vivid.



(a) (b)

Figure 3. Reconstructed image comparison with parts of the scene. (a) The reference low-resolution image, and (b) the reconstructed image by super-resolution.

4. Conclusions

We have been introduced a multi-camera imaging system and a color high-resolution image reconstruction algorithm based on the multi-camera system. In the proposed multi-camera system, low-resolution images of the same scene and with different sub-pixel displacements from each other can be taken simultaneously by frame grabbers and a controlling software within the controlling computer of the multi-camera system. The color high-resolution image reconstruction algorithm was composed of the graylevel super-resolution image reconstruction algorithm and the image fusion considering color difference domain. Through the experiments, we found that the combination of the multi-camera system and the proposed super-resolution algorithm could effectively produce high-resolution color images with multiple low-resolution observations from low-resolution cameras.

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(a)

(b)

Figure 4. part of the reconstructed multi-spectral images of MulTest by various image fusion methods (a) bicubic interpolated from low-resolution color composite image (b) using IHS method (c) using SAIF method (d) using the proposed color difference domain based method

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