INVESTIGATION OF COMPUTATIONAL COMPOUND-EYE IMAGING SYSTEM WITH SUPER-RESOLUTION RECONSTRUCTION

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ABSTRACT

Despite the emerging architectural designs of compound-eye imaging systems, the post-processing algorithms for the reconstruction of the final image from the multiple sub-images is still not fully developed to maturity, resulting in poor quality or low resolution of the reconstructed images. In this paper, we describe and investigate a practical computational compound-eye imaging system with super-resolution reconstruction. This methodology can enhance the image quality by increasing the resolution of the reconstructed image. A virtual compound-eye camera is built to demonstrate the feasibility of the system. Simulation results which investigate the tolerance of the system to lens diversity, for instance focal length and aberrations, are also presented.

1. INTRODUCTION

Many applications demand the miniaturization of the imaging systems. Direct scaling of the lens elements however would degrade the image quality due to diffraction. Recent development of the multi-lens imaging systems has shown to be a promising solution. Instead of using a single large lens to form a single image of the object, a multi-lens imaging system uses an array of small lenses to form multiple sub-images of the object. The final image of the object is retrieved by post-processing the sub-images. The use of an array of small lenses in the imaging system allows the system to become very compact. An imaging device designed in such a fashion is commonly known as a compound-eye imaging system.

Compound-eye imaging system design has received a lot of attention in recent years. Advantages of compound-eye imaging systems are compactness, lightness and wide field of view. Possibility of parallel signal processing is also considered as a potential of compound-eye camera. Several research groups have designed and constructed novel architectures of compound eye imaging systems [1, 2, 3]. For example, an artificial apposition compound-eye imaging system was designed based on the apposition compound eyes of small invertebrates [1]. Although this design of artificial compound-eye drastically reduces the thickness of an imaging system below 1 mm, both the resolution power and light efficiency of the system is very low as only one sample point of each sub-image is used in the reconstruction of the final image [1]. TOMBO (Thin Observation Module by Bound Optics) is another compound-eye imaging system. This system has the advantage of high sensitivity over the artificial compound-eye imaging system as the entire region of the each of the sub-images are used to retrieve the image of the object [3]. Reconstruction methods based on interpolation of pixel values have been developed, which produce images of fair quality [4].

Resolution is a common problem of compound-eye imaging systems. In this paper, we present how the techniques of super-resolution can be employed in a compound-eye imaging system to enhance the quality and resolution of the reconstructed image, and investigate the performance of super-resolution reconstruction on a practical compound-eye imaging system. In section 2, we describe the compound-eye imaging model of our concern. In section 3, the super-resolution reconstruction algorithm is explained. The simulation results which investigate the tolerance of the system to lens diversity, for instance focal length deviation and aberrations, is discussed in section 4. Finally, concluding remarks are provided in section 5.

2. ARCHITECTURE OF THE COMPUTATIONAL COMPOUND-EYE IMAGING SYSTEM

Fig.1 shows the architecture of the computational compound eye system [3] of our concern. The system consists of an $n \times n$ microlens array, a separation layer, and a photodetector array. In this system, every microlens corresponds to a $\beta \times \beta$ array of photosensitive cells. A microlens together with its array of photosensitive cell form an imaging unit. Each imaging unit gives a $\beta \times \beta$ sub-image of the object on the photodetector array.

The working principle of the computational compound-eye imaging system is shown in Fig.2. The compound-eye imaging system captures an $n \times n$ array of low-resolution sub-images of the target object. Provided that there are sub-pixel displacements in all the sub-images, super-resolution can then

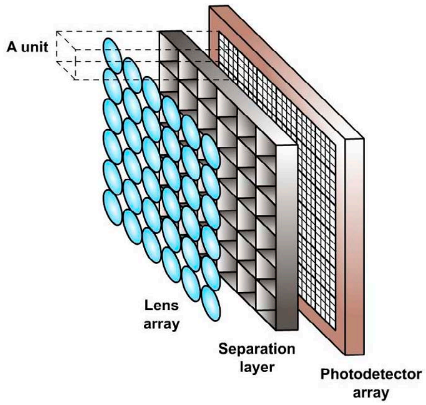


Fig. 1. The computational compound-eye system [3]

be employed to reconstruct a high-resolution image [5]. It should be noted that under this framework, the optics, opto-electronics, and signal processing are taken into account together in the imaging system design.

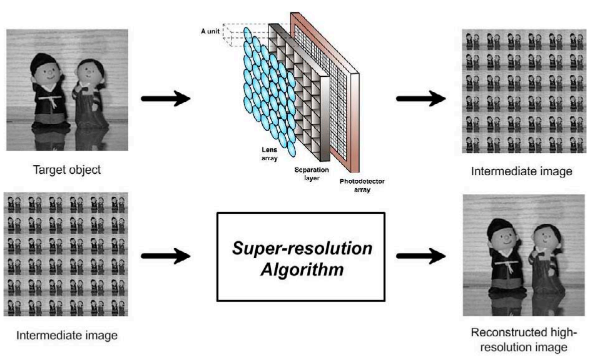


Fig. 2. Diagram showing the workings of the computational compound-eye imaging system.

3. IMAGE RECONSTRUCTION BY SUPER-RESOLUTION

In this section, we describe the super-resolution algorithm we used in the reconstruction process [5]. We can mathematically model the compound-eye imaging system [6]. The block diagram in Fig.3 shows schematically how the formation of a sub-image i_k from a target object f can be represented in a mathematical model. The target object is regarded as the desired high resolution image, on which a series of operations are done. First, as the lenses are displaced from one another, each sub-image formed is shifted away from the reference frame by a corresponding amount. This is referred to as shifting. Second, the light of the high resolution scene passes through the lens and the photosenstive cells collect and average the light intensity of a finite area. This process is

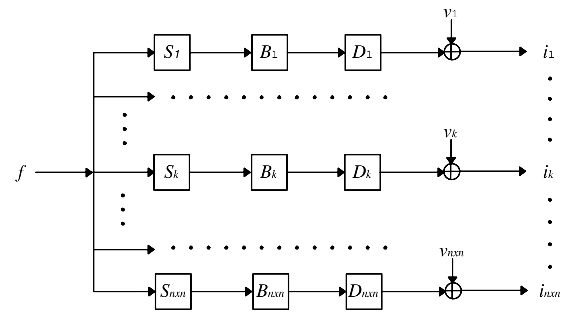


Fig. 3. Block diagram representation of the compound-eye imaging system.

modeled as blurring and downsampling of the high resolution scene. Finally, noise is added to the sub-image due to noise of the photosensitive cells and quantization. Mathematically, we have

$$i_k = D_k B_k S_k f + v_k \tag{1}$$

where S_k, B_k and D_k represent the shifting, blurring and downsampling operator, while v_k is the noise added to the target object. To reconstruct the desired high-resolution image f from the set of low-resolution sub-images $\{i_1, i_2, ..., i_{n \times n}\}$ by super-resolution, the sub-images are first interspersed according to their respective lens displacements to form an image g with $M \times M$ pixels, where $M = n \times \beta$. g is referred to as the observed high resolution image. Then, using column by column ordering for g, we have

$$g = \mathcal{H} f + \eta \tag{2}$$

where $\mathcal{H}$ is the reconstruction operator. f can then be solved by minimization and regularization techniques:

$$\min_f \{\|\mathcal{H} f - g\|^2 + \alpha \|f\|\} \tag{3}$$

where α is the regularization parameter. Cosine transform preconditioners are used to increase the computational speed for the reconstruction process [5].

4. SIMULATION RESULTS

A virtual camera with a 2-by-2 lens-array is built to investigate the performance of a computational compound-eye system with super-resolution reconstruction. Simulations have been done to investigate the performance of our super-resolution algorithm on an ideal compound-eye imaging system and a practical compound-eye imaging system. An assumption in our experiments is that there is no cross talk between sub-images. In this paper, the signal-to-noise ratio (SNR) of an

$N \times N$ image $i(x, y)$ is defined as

$$\text{SNR (dB)} = 10 \log \frac{\sum_{x=1}^{N} \sum_{y=1}^{N} f^2(x, y)}{\sum_{x=1}^{N} \sum_{y=1}^{N} (i(x, y) - f(x, y))^2} \quad (4)$$

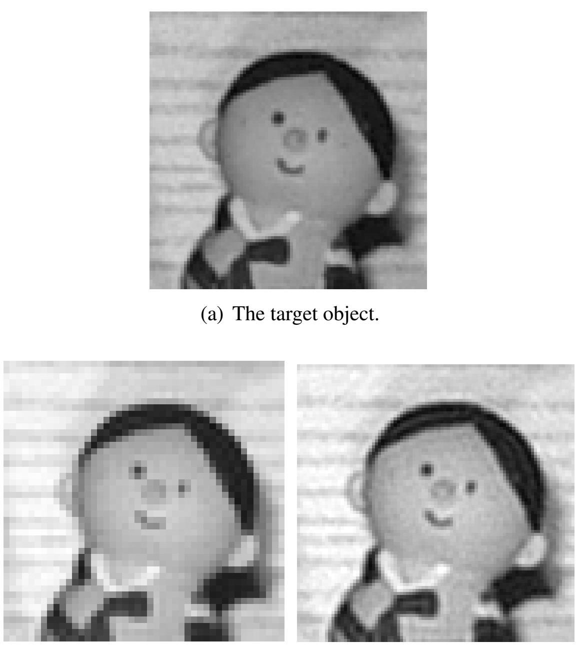
where $f(x, y)$ is the $N \times N$ target object from which $i(x, y)$ is produced. In the case of a sub-image whose dimension is $\frac{N}{2} \times \frac{N}{2}$, we expand it to an $N \times N$ matrix $\tilde{i}(x, y)$ given by

$$\tilde{i}(x, y) = i(x, y) \otimes \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \quad (5)$$

before the SNR is computed.

4.1. An Ideal Compound-eye Imaging System

An ideal compound-eye imaging system is first investigated. By an ideal compound-eye imaging system, we mean all the lenses in the lens array have the exact required value of focal length (thus all four sub-images captured are in-focus) and that there are no aberrations. Fig.4 shows the simulation result, where (a) is the target high-resolution scene, (b) is one of the sub-images, and (c) shows the reconstructed image. It can be observed that the reconstructed image shows good visual quality, and that it is of higher resolution than the sub-image. The SNR of the sub-image is about 22.4 dB while that of the reconstructed image is about 25.3 dB.



(a) The target object.

(b) One of the sub-images. (c) The reconstructed image.

Fig. 4. Simulation results from the virtual camera with super-resolution reconstruction.

Note that we have a choice of the value of regularization parameter α in the super-resolution reconstruction. Fig.5 shows the SNR of the reconstructed image with the sub-images corrupted by different amount of Gaussian noise. It can be observed that with a lower level of noise corruption, a smaller value of α gives a higher SNR of the reconstructed image, while at a higher level of noise corruption, a larger value of α gives a better reconstruction result.

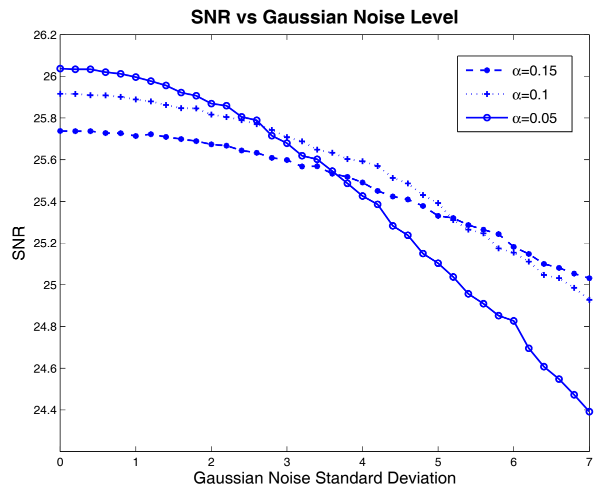


Fig. 5. SNR of the reconstructed image against level of noise corrupting the sub-images.

4.2. A Practical Compound-eye Imaging System

Since it is unlikely that the lenses in a practical compound-eye system all have the exact required focal length and with no aberrations, simulations have been done to investigate the effects of deviation of focal lengths and also of aberrations of the lenses on the quality of the reconstructed image.

In the experiments which study the effects of focal length deviation on the quality of the reconstructed images, the focal lengths of the four lenses of the virtual camera were assigned by generating a random distribution of focal length f with a mean f_m and standard deviation σ (any f generated which deviated from f_m by 2σ were discarded). The percentage of focal length deviation is calculated by

$$\frac{\sigma}{f_m} \times 100\% \quad (6)$$

The four sub-images obtained from the virtual camera were used to reconstruct the high-resolution image by our super-resolution algorithm. The SNR of the reconstructed image was then measured. Simulations were done with different percentage of focal length deviation. The results obtained were plotted and shown in Fig.6. Note that each data point was obtained by averaging the results of 30 data sets.

It can be observed from Fig.6 that the reconstructed image show good SNR of about 25 dB when the focal lengths

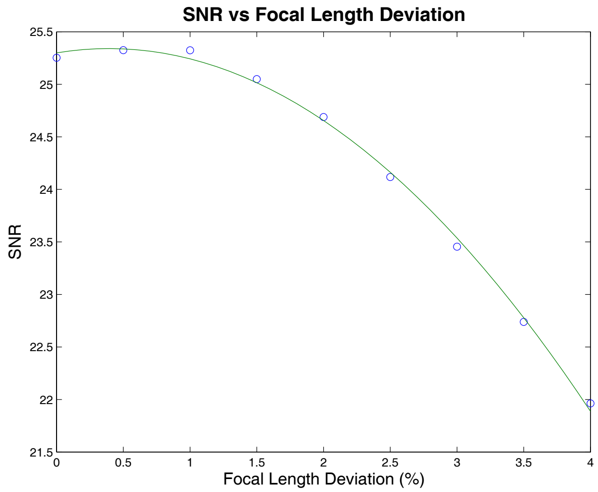


Fig. 6. SNR against variation of focal lengths

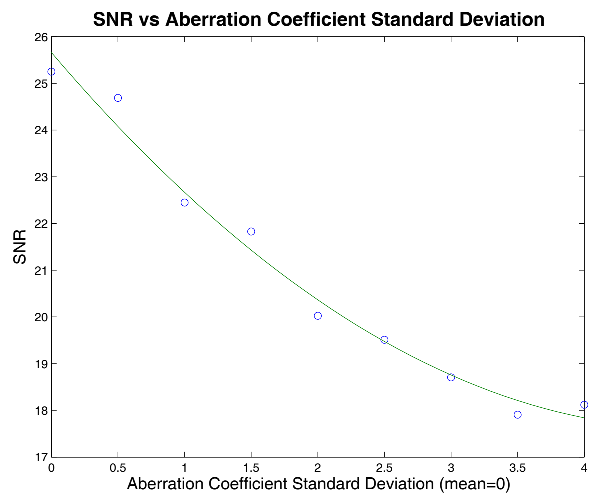


Fig. 7. SNR against aberration coefficient

deviate from desired focal length by less than 1.5%. After that point, the SNR of the reconstructed images falls almost linearly to about 22 dB at a 4% focal length deviation. This shows that the system is to some extent tolerant to focal length deviation.

The methodology in the study of the effects of spherical aberration on the reconstructed image is the same as that of focal length deviation. Random distribution of aberration coefficients with a specific standard deviation were generated and assigned to the four lenses. In Fig.7, the SNR of the reconstructed image decreases quite linearly from about 25.5 dB when there is no aberration to below 20 dB at an aberration coefficient of about 2. This shows our system is quite sensitive to spherical aberrations.

5. CONCLUSION

We have established and investigated a computational compound eye imaging system with super-resolution reconstruction. Simulation results generated by our virtual camera have proved the implementation of our super-resolution algorithm on image reconstruction of the compound-eye imaging system promising. The current system shows tolerance in focal length deviation of the lenses to some extent, but is quite vulnerable to spherical aberration. We believe that the performance of the system can be improved by taking into account the parameters of the optical system, for instance the focal length deviations and aberration coefficients of the lenses, in the post-processing algorithm.

6. REFERENCES

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