Image Super Resolution from Alignment Errors of Image Sensors and Spatial Light Modulators

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Abstract: In this paper, we propose a novel method for obtaining super resolution images by using alignment errors between an image sensor and a spatial light modulator, such as LCoS device, in the coded imaging systems. Recently, coded imaging systems are often used for obtaining high dynamic range (HDR) images and for deblurring depth and motion blurs. For obtaining accurate HDR images and unblur images, it is very important to setup the spatial light modulators with cameras accurately, so that the one-to-one correspondences hold between light modulator pixels and camera image pixels. However, the accurate alignment of the light modulator and the image sensor is very difficult in reality. In this paper, we do not adjust light modulators and image sensors accurately. Instead, we use the alignment errors between the light modulators and the image sensors for obtaining high resolution images from low resolution observations in the image sensors.

1 INTRODUCTION

Obtaining high resolution images is very important for high quality visualization and for accurate 3D reconstruction. For obtaining high resolution images, sensing devices has been improved in recent yeas, and the number of pixels in image sensors becomes larger and larger. However, the image sensors with large pixel size are very expensive, and are not easy to use.

For obtaining high resolution images without using large image sensors, image super resolution methods have been developed for many years (Tsai and Huang, 1984; Baker and Kanade, 2002; Capel and Zisserman, 2001; Glasner et al., 2009; Huang et al., 2015; Dong et al., 2014). These methods enable us to obtain high resolution images from low resolution image sensors, and thus they are very useful in many applications.

The image super resolution methods can be divided into two classes. The first class of methods is to generate a high resolution image from just a single low resolution image (Glasner et al., 2009; Huang et al., 2015; Dong et al., 2014). The prior knowledge has often been used for generating a plausible high resolution image from a single low resolution image. However, since these methods are based on the prior knowledge, if the prior does not fit the situation, the estimated high resolution images may become very different from the ground truth high resolution images. The second class of methods is based on the multiple observation from low resolution sensors (Tsai and Huang, 1984; Schultz and Stevenson, 1996; Baker and Kanade, 2002; Capel and Zisserman, 2001). In these methods, multiple sensors or single moving sensor are used for obtaining independent low resolution images, and these images are combined for recovering high resolution images. Since these methods are based on the real observations, they can generate physically correct high resolution images. However, these methods require a set of multiple sensors or a single moving sensor for obtaining multiple observations.

In this method, we propose a method for generating high resolution images from a single static image sensor, without using any prior. For obtaining physically correct high resolution images from a static image sensor, we use a spatial light modulator, such as LCoS device, with an image sensor. Recently, coded imaging has been studied extensively, and spatial light modulators, such as LCoS device, have been used with image sensors for obtaining coded images. The coded imaging has been used for generating high dynamic range images from low dynamic range sensors (Mannami et al., 2007; Uda et al., 2016), and for obtaining 4D light fields and debulrring images (Nagahara et al., 2010). In these methods, it is very

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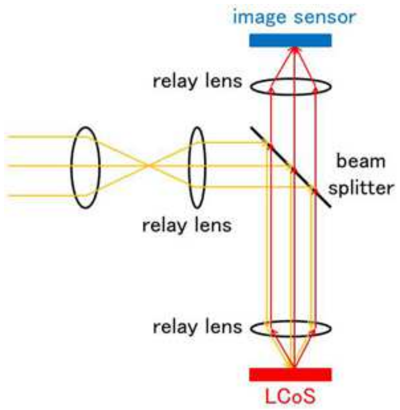


Figure 1: Coded imaging system, which consists of an LCoS device and an image sensor.

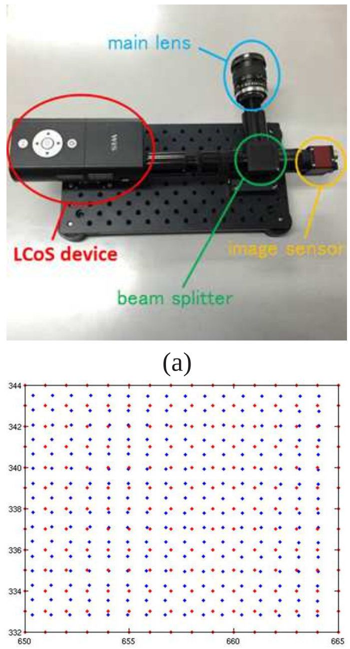
important to setup the spatial light modulators with cameras accurately, so that the one-to-one correspondence between light modulator pixels and camera image pixels hold. However, the accurate alignment of the light modulator and the image sensor is very difficult in reality. In this paper, we do not adjust the light modulators and Image sensors. Instead, we use the alignment errors between the light modulators and the image sensors for obtaining high resolution images from low resolution observations in the image sensors.

2 CODED IMAGING SYSTEM

In general, coded imaging systems combine pixel-wise light modulators, such as LCoS and LCD, with image sensors, so that the input light at each pixel of the image sensor can be controlled. Fig.1 shows an example setup of the coded imaging systems using LCoS device. As shown in this figure, the input light first goes to the LCoS device, and is reflected at the LCoS. Then, the reflected light goes into the image sensor, and is observed. The reflectance of LCoS can be controled pixel by pixel, and thus the input light at the image sensor can be controlled pixel by pixel.

In these systems, it is very important to obtain one-to-one correspondence between image pixels on the image sensor and image pixels on LCoS device. Since the pixel size of the image sensor and LCoS device are different in general, we often use affine transformation or homography to obtain pixel-wise correspondence between them.

However, it is actually impossible to obtain exact one-to-one correspondence between the image sensor and LCoS device, since there exist sub-pixel alignment errors between the image pixels of image sensor and the image pixels of LCoS device. Thus, the input light at each pixel of the image sensor cannot be controlled perfectly in actual systems. Fig. 2 shows an example of real coded imaging systems, and its alignment error of image sensor and LCoS device. As shown in this figure, there exist sub-pixel alignment errors between the image pixels of image sensor and the image pixels of LCoS device.



(a)

(b)

Figure 2: Real coded imaging system and its alignment errors. (a) shows an example of coded imaging system. (b) shows magnified alignment errors between the pixels of image sensor (blue) and the pixels of LCoS device (red).

Although these alignment errors of image pixels are problematic in the sense of point correspondences, it is very good in the sense of image measurement, since these alignment errors enable us to obtain more detail information about the input light distribution. In the following sections, we describe a method for obtaining super resolution images by using the alignment errors between image sensors and LCoS devices. Although we explain our method based on LCoS devices in this paper, our method is not limited to LCoS devices, and it can be applied to any spatial light modulator used in the coded imaging systems.

3 IMAGE OBSERVATION IN CODED IMAGING SYSTEM

We first consider an image observation model of a coded imaging system.

Suppose we have a high resolution image X.

When we observe X by a low resolution image sensor, the observed image Y can be described by using the high resolution image X as follows:

$$Y = DX \tag{1}$$

where, D denotes a degradation matrix, which represents the degradation of resolution caused by the low resolution image sensor. The matrix D represent not only the change in resolution, but also image blur caused by imaging.

Now, suppose we obtain N observations by a coded imaging system changing the coded pattern on the LCoS device. Then, the observed image Y_i $(i = 1,\cdots,N)$ can be described as follows:

$$Y_i = D_i X \tag{2}$$

where D_i denotes the ith degradation matrix generated by the ith coded pattern C_i displayed on the LCoS device, and thus it can be described as follows:

$$D_i = C_i D \tag{3}$$

In this case, the rank of $[D_1^\top,\cdots,D_N^\top]^\top$ is same as the rank of D, and thus the observed images Y_i $(i = 1,\cdots,N)$ are dependent on each other. As a result, we cannot recover the original high resolution image X from low resolution coded images Y_i $(i = 1,\cdots,N)$. Thus, the image super resolution cannot be achieved by the standard coded imaging.

4 IMAGE SUPER RESOLUTION FROM ALIGNMENT ERRORS

We next consider the alignment error between image sensors and LCoS devices. As we described above, the sub-pixel alignment errors between image sensors and LCoS devices is inevitable in real systems. Unlike the existing works, we use these sub-pixel alignment errors positively for obtaining high resolution images from low resolution observations.

Suppose we have alignment errors between an image sensor and an LCoS device as shown in Fig. 3 (a). If we open all the pixels of LCoS device, we observe all the input light. Now, if we open odd rows of LCoS device and close even rows of it, then each pixel of the image sensor observes input light as shown in Fig. 3 (b). We next close odd rows and open even rows of the LCoS device. Then, the observed light at each pixel of the image sensor is as shown in Fig. 3 (c). From Fig. 3 (b) and (c), we find that the observed light is different from each other and we can obtain independent information on the high resolution input light by controlling the LCoS device.

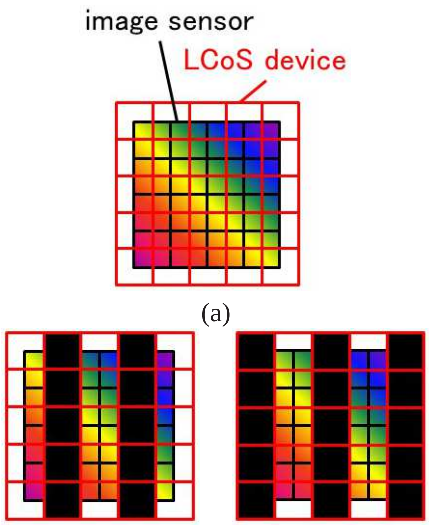


Figure 3: Coded imaging under the existence of alignment errors. The black lines and the red lines in (a) show image pixels of image sensor and LCoS device respectively. (b) shows image observation under an LCoS device control, in which odd rows are open and even rows are closed. (c) shows image observation under another LCoS device control, in which odd rows are closed and even rows are open.

We next consider the degradation matrix D_i of observation under the ith coded pattern of LCoS device assuming that the alignment errors exist. If we consider the sub-pixel alignment errors, the degradation matrix D_i is described as follows:

$$D_i = DA_i \tag{4}$$

where, A_i is a matrix which represents the sub-pixel alignment errors and the ith coded pattern of LCoS device. Unlike the degradation matrix in Eq.(3), we can obtain independent D_i in Eq.(4) by changing the coded pattern of LCoS device. Thus, we can obtain independent information on the high resolution image X from the multiple low resolution observations Y_i $(i = 1,\cdots,N)$ obtained from N different coded patterns of LCoS device. As a result, the image super resolution can be achieved from Y_i $(i = 1,\cdots,N)$ by considering the alignment errors between the image sensor and LCoS device.

The image super resolution can be formalized as a cost minimization problem as follows:

$$X = \arg\min_X \sum_{i=1}^{N} ||Y_i - D_i X||^2 + \alpha|\nabla X|_1 \tag{5}$$

where, the first term in the cost function is a data term, and the second term is a regularization term. ∇ denotes the Laplacian, and $|\cdot|_1$ denotes the L_1-norm. α shows a weight for the regularization term.

By estimating high resolution images X from Eq.(5), we can achieve image super resolution using alignment errors of image sensors and LCoS devices.

5 ESTIMATION OF DEGRADATION MATRIX

In this method, the estimation of the degradation matrix D_i is very important. It seems that if the pixel sizes of the image sensor and the LCoS device are known, we can estimate the degradation matrix. However, this is not the case in the real system, since the degradation matrix depends not only on the geometric relationship between the image sensor and LCoS device, but also on the various photometric properties of LCoS and image sensor. Thus, in our method, we estimate the degradation matrix D_i by using real observations.

Let us consider the case, where we estimate the ith degradation matrix D_i. We first prepare M different high resolution images, X^j $(j = 1, \cdots, M)$, and observe these high resolution images by using the coded imaging system. Then, we obtain M low resolution images, Y_i^j $(j = 1, \cdots, M)$. Then, these image observations can be described as follows:

$$Y_i^j = D_i X^j \tag{6}$$

Thus, we estimate D_i, from X^j and Y_i^j, so that Eq.(6) holds. This is achieved by estimating D_i by solving the following minimization problem:

$$D_i = \arg\min_{D_i} \sum_{j=1}^{M} ||Y_i^j - D_i X^j||^2 + \beta |D_i|_1 \tag{7}$$

where, β denotes a weight for the regularization term. By estimating all the N degradation matrices D_i $(i = 1, \cdots, N)$ from Eq.(7), we obtain N degradation matrices under N coded patterns shown to the LCoS devices.

This method enables us to estimate precise degradation matrices, which represent not only the geometric alignment errors between the image sensor and the LCoS device, but also the photometric distortions caused by the coded imaging system.

By using the derived degradation matrices, we can achieve image super resolution by using the method described in section 4.

6 EXPERIMENTS

In this section, we show the efficiency of the proposed method by using the real coded imaging system shown in Fig. 2 (a). As shown in Fig. 1, the light comes into the main lens is reflected at the beam splitter and goes to the LCoS device. Then the light is reflected by the LCoS device and goes to the image sensor. The reflection at the LCoS can be controlled per pixel. However, there exist alignment errors between the image sensor and the LCoS as shown in Fig. 2 (b).

Figure 4: Examples of high resolution images used for estimating degradation matrices.

6.1 Estimation of Degradation Matrix

We first estimated the degradation matrices of this coded imaging system. For this objective, we showed 480 high resolution images to the coded imaging system, and low resolution images were obtained by the system. Fig. 4 shows some example high resolution images. These images were observed by the low resolution image sensor in the coded imaging system under 100 different coded patterns shown on the LCoS device. Fig. 5 shows two example coded patterns of the LCoS device, and low resolution images observed by the image sensor under these coded patterns. As shown in Fig. 5, we in this experiment used random patterns for coded patterns of the LCoS devise. This is because, we do not know the amount of the alignment errors in the coded imaging system, and specific systematic patterns may cause systematic errors. The degradation matrices under these 100 coded patterns were computed from these images by a method described in section 5. We used $\beta = 1.0$ in this experiment.

For verifying the accuracy of the estimated degradation matrices, we generated 480 low resolution images from a high resolution image by using the estimated degradation matrices, and compared them with real low resolution images observed by the image sensor changing the pattern of LCoS device. The PSNR of the generated low resolution images was 40.35, and thus we find that the degradation matrices were estimated accurately. Fig. 6 shows some examples of generated low resolution images and observed low resolution images.

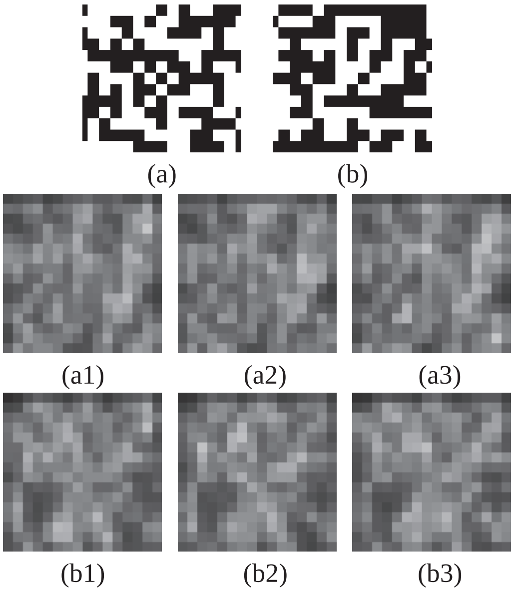


Figure 5: Two example coded patterns for LCoS device, and observed images under these coded patterns. (a) and (b) show two example coded patterns for LCoS device. (a1), (a2) and (a3) show observed low resolution images under the coded pattern (a). These three images are the observed images of three high resolution images in Fig. 4. (b1), (b2) and (b3) show those from the coded pattern (b).

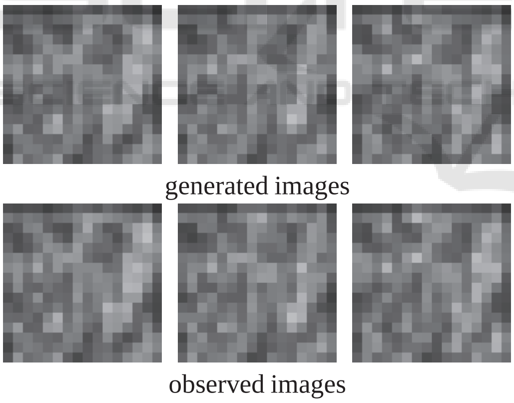


Figure 6: Low resolution images generated from the degradation matrices and low resolution images observed by the image sensor under 3 different high resolution images.

6.2 Image Super Resolution from Alignment Errors

We next show the results of image super resolution from the alignment errors of image sensor and LCoS device.

In this experiment, high resolution images shown in Fig. 7 were observed by the low resolution image sensor with LCoS device, and the observed images were used for recovering the original high resolution images. 100 low resolution images were observed changing the coded patterns shown on the LCoS device. The low resolution images are 32×32, and the high resolution images are 64×64.

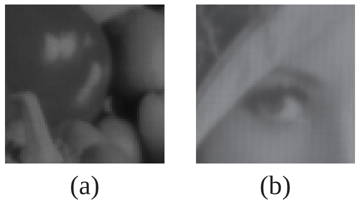


Figure 7: Original high resolution images used in our experiments.

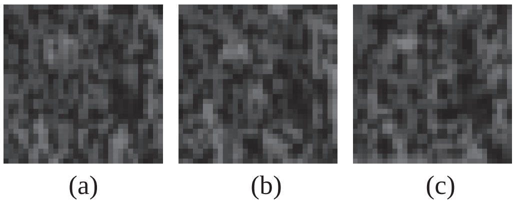


Figure 8: Example low resolution images observed by the image sensor.

Fig. 8 shows some examples of the observed low resolution images. As shown in this figure, the low resolution images are coded by using the LCoS device. The coded patterns of the LCoS device for these images are shown in Fig. 9. From these 100 low resolution images, we estimated a high resolution image by using the proposed method with $\alpha = 1.0$. Fig. 10 shows the estimated high resolution images from the proposed method as well as the high resolution images estimated from the standard bi-cubic method and the original low resolution images. By comparing Fig. 10 with Fig. 7, we find that the proposed method can recover high resolution images much more accurately than the bi-cubic method.

6.3 Accuracy Evaluation

We next evaluate the accuracy of the proposed method by using synthetic image experiments. Since the ac-

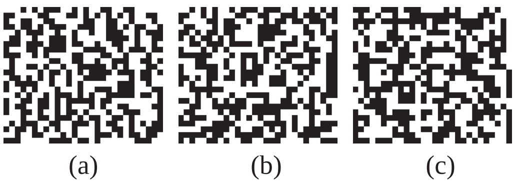


Figure 9: Example coded patterns of the LCoS device. These 3 coded patterns are corresponding to 3 observed images in Fig. 8.

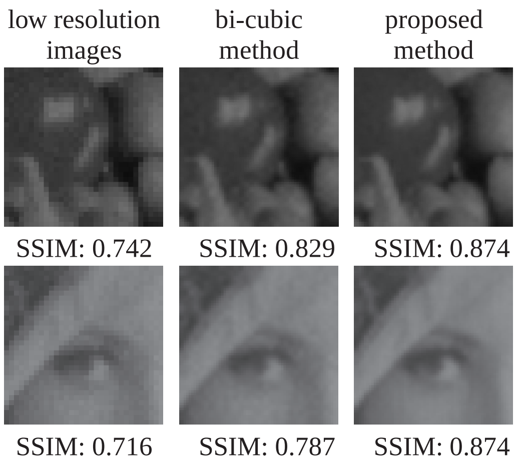


Figure 10: High resolution images estimated by using the proposed method and the bi-cubic method as well as the original low resolution images. SSIMs are also shown.

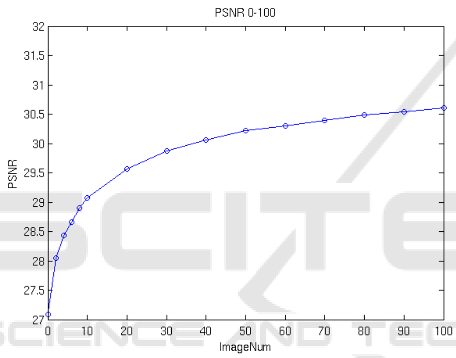


Figure 11: Relationship between the number of coded images and the accuracy of recovered high resolution images.

curacy of the proposed method depends on the number of low resolution images, we evaluated the relationship between the number of coded images and the accuracy of high resolution images recovered from the proposed method. The alignment error of LCoS device and image sensor is simulated in the synthetic images based on the real errors shown in Fig. 2.

Fig. 11 shows the changes in accuracy with respect to the number of coded images. As shown in this figure, the accuracy of the proposed method increases as the number of coded images increases.

7 CONCLUSION

In this paper, we proposed a method for obtaining high resolution images from low resolution observations by using alignment errors between an image sensor and a spatial light modulator, such as LCoS device. In general, accurate alignment of the light modulator and the image sensor is very difficult in coded imaging systems. In this paper, we showed that independent information on high resolution images can be obtained from low resolution observations, if we have alignment errors between the light modulators and the image sensors. Based on this observation, we proposed a method for obtaining high resolution images from low resolution observations in the image sensors. The proposed method is tested by using a real coded imaging system, and the efficiency of the proposed method was shown from the experimental results.

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