Seeing Temporal Modulation of Lights from Standard Cameras

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Abstract

In this paper, we propose a novel method for measuring the temporal modulation of lights by using off-the-shelf cameras. In particular, we show that the invisible flicker patterns of various lights such as fluorescent lights can be measured by a simple combination of an off-the-shelf camera and any moving object with specular reflection. Unlike the existing methods, we do not need high speed cameras nor specially designed coded exposure cameras. Based on the extracted flicker patterns of environment lights, we also propose an efficient method for deblurring motion blurs in images. The proposed method enables us to deblur images with better frequency characteristics, which are induced by the flicker patterns of environment lights. The real image experiments show the efficiency of the proposed method.

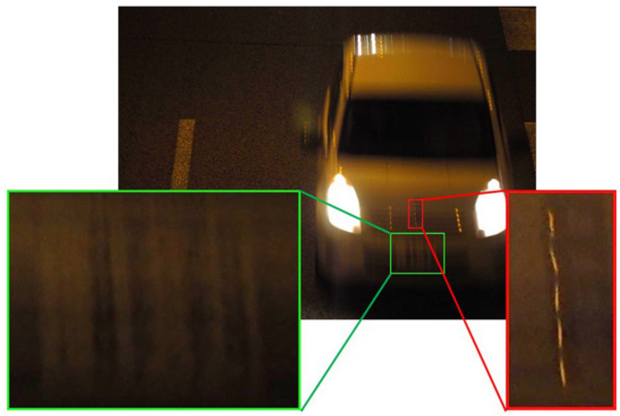


Figure 1. Motion blur of specular reflection is observed as dashed line since light on road was flickering at very high speed.

1. Introduction

Our life environments are brimming over with lights, and these lights seem to illuminate us continuously. However, most artificial lights are blinking at very high speed. For example, fluorescent lights are turning on and off in accordance with the alternating current (AC) of the electric power [20]. Also, many LED lights are controlled to turn on and off for adjusting the intensity and reducing their electric power consumptions. These flicker patterns are very fast, and human vision cannot perceive them.

Usually, these flicker patterns are controlled so that they are invisible to human vision, since visible flicker is a nuisance. However, if we use these flicker patterns efficiently, we may be able to achieve brand new visual measurement methods.

Quite recently, Sheinin et al. [17] have proposed an efficient method for measuring the flicker patterns of various lights and identifying the type of lights from their flicker patterns. They developed a new coded imaging system that observes scene intensity by synchronizing with the AC electric power cycle. By measuring the flicker patterns of light, they showed a new possibility of using them. Unfortunately, their method requires a very special coded imaging system, which controls the input light by using a digital micromirror device (DMD) synchronized with the AC electric power cycle. Since such a very special imaging system is not available for general users, it is not easy to obtain the flicker patterns of lights. Also, their method can only measure periodic light signals, and the change in intensity of non-periodic light signals cannot be captured.

Thus, in this paper, we propose a novel method for measuring the flicker patterns of various lights easily without using special sensors. Our method uses an off-the-shelf camera and a moving object with specular reflection on its surface. Such moving objects can be vehicles on a road, rolling metal balls on desks, etc. The fundamental idea of our method is to decode the temporal flicker pattern of light into a spatial intensity pattern in a single image.

For example, Fig. 1 is an image of a moving vehicle taken by a standard camera with an exposure time of 40 msec. As we can see in this figure, the specular reflections are observed as dashed lines in the image, and these dashed lines are the motion blur of the specular reflections. The motion blur was recorded as dashed lines since the light on the road was flickering at very high speed. In other words, the dashed lines in the image roughly show the temporal flicker patterns of the light. Thus, by eliminating the distortions caused by object properties and sensor properties, we can derive the original flicker patterns of light directly from the static patterns in the image.

Once the temporal flicker patterns are obtained, we can use them for various applications. In this paper, we use the flicker patterns obtained from the image for deblurring motion blurs in the image. As we can see in Fig. 1, the characters on the number plate of the vehicle are heavily blurred because of the high speed motion of the vehicle and are unreadable.

Although many methods have been proposed for deblurring motion blurs up to now [2, 16, 7, 11, 3, 24, 12], image deblurring is an ill-posed problem, and the estimation of unblurred images is unstable in general. In this paper, we show that by using the specular reflections in images, we can recover the point spread functions (PSFs) of motion blurs under flickering light accurately, and hence we can deblur motion blurs stably. Moreover, because of the good frequency characteristics of the flickering light, the motion deblurring becomes more stable than in usual cases. Since our method requires only an off-the-shelf camera, it is very efficient and useful.

2. Related Work

In this paper, we estimate the temporal properties of light sources that illuminate the scene. When we obtain an image with a camera, the imaging device of the camera accumulates the input light within a certain period of time. This is called the exposure time. If the object moves relative to the camera during the exposure time, we will have motion blurs in the observed image. Thus, if the intensity of the input light changes during the exposure time, its effect appears in the motion blur in the observed image. Thus, the measurement of the change in intensity of input light is strongly related to the motion blur and its deblurring.

Many methods have been proposed for deblurring depth and motion blurs [2, 16, 7, 11, 3, 24, 12]. If we know the PSF of the image blur, spectral based methods such as the Wiener filter [22] or optimization-based methods such as the Richardson-Lucy algorithm [14] can often be used for deblurring images. If we do not know the PSF, the problem becomes more difficult since we need to recover PSFs as well as unblurred images. This is called blind deconvolution [2, 16, 7]. In general, blind deconvolution is an ill-posed problem, and we need to combine some additional assumptions and priors. Image priors such as the distribution of natural images are often used [15, 21, 2, 16, 3]. In recent works, the sparseness in deconvolution has also been studied extensively [7, 11, 24]. Although single image blind deconvolution has progressed a great deal, the physical correctness of the deblurred images depends on the conformity of these priors and the assumptions for individual images.

Recently, Queiroz et al. [12] showed an intuitive method for deblurring images without using heavy priors. They showed that the specularity can be used for obtaining PSFs directly from images. Our method is closely related to their method, but it is different in various aspects. In particular, our paper analyzes the relationship between the temporal property of a flickering light and the specularity of a moving object. Based on this analysis, we show that the temporal flicker pattern of light can be recovered from a single static image, and motion blurs in the image can be recovered more accurately.

For recovering more accurate unblurred images, it is important to obtain more information from the scene. For this objective, coded imaging has been developed [13, 6, 19, 1, 18, 25, 5]. Coded apertures [6, 19, 25] and coded exposures [13, 1] enable us to obtain missing information in the standard aperture and exposure, and thus ill-posed problems can be transformed into well-posed problems or less ill-posed problems. Coded imaging can be achieved by using specially designed imaging systems that combine image sensors with some spatial light modulators, such as LCOS and DMD. Coded imaging can also be achieved by coding lights that illuminate the scene [23, 4, 8, 10]. Coded light images can also be obtained by controlling the spatial light modulators put in front of the light sources. Although these coded imaging techniques are very efficient for obtaining physically correct unblurred images, they require accurate high speed control of spatial light modulators.

In this research, we consider coded imaging by using the existing lights in our usual environments, i.e. the flicker of lights, such as fluorescent lights. Since the flicker patterns of lights are generally unknown, we propose a method for estimating the flicker patterns of light. Since the flicker of light is very fast, we need to use high speed cameras to capture the changes in intensity of lights. Quite recently, Sheinin et al. [17] have proposed a new method for capturing flicker patterns by synchronizing the image capture with the AC electric power cycles. They also showed that the scene intensity can be decomposed into single light source intensities. Unfortunately, their method requires synchronizing the image capture with the AC electric power cycles, and hence only periodic lights can be measured. Also, it requires special pieces of equipment to synchronize the image sensing with the AC electric power cycles.

In this paper, we propose a novel method for obtaining arbitrary high speed light flicker patterns in our environments. Unlike Sheinin's method [17], our method does not require synchronization with periodic signals, such as AC electric power cycles. Thus, even non-periodic changes in intensity can be measured and used by using the proposed method. For example, high speed visible light communication among vehicles and traffic signals can be achieved just by using standard cameras. The proposed method is thus quite efficient and can be applied to various fields.

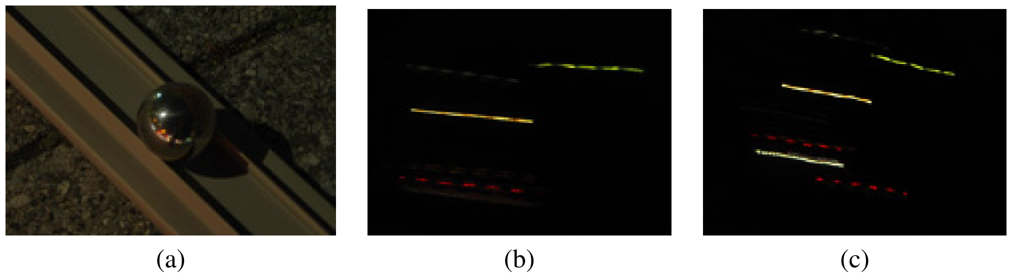


Figure 2. Rolling metal ball (a) and observed images (b) and (c). We use these spatial intensity patterns in a single image for estimating the temporal flicker patterns of light.

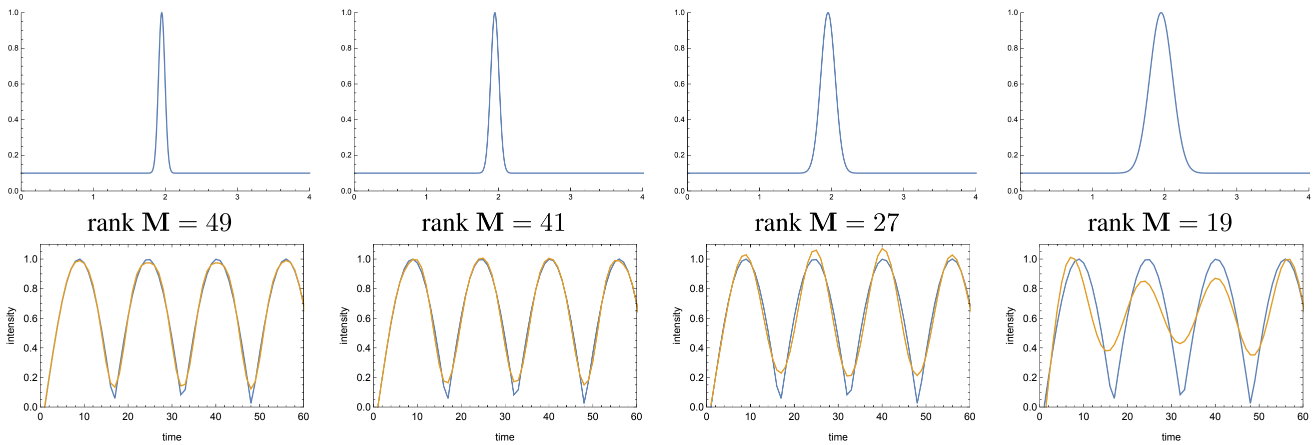


Figure 3. First row shows sharpness of specularities in images, and second row shows rank of matrix $\mathbf{M}$, which changes according to sharpness of specular reflection. Third row shows recovered flicker patterns of light. Red lines show estimated flicker patterns, and blue lines show their ground truth. Note, rank of $\mathbf{M}$ also depends on velocity of object.

3. Estimating Temporal Flicker Patterns of light from Single Image

In this paper, we estimate the temporal flicker patterns of light from spatial intensity patterns in a single image. For this objective, we consider the case where a curved object moves linearly with a constant speed under distant isotropic lights. The rolling ball shown in Fig. 2 (a) is a good example of such an object. If the object has specular reflection, the lights in the environment are reflected on the object surface, and the specular reflections are observed by a camera. Now, if the object moves during a single exposure time of the image, the reflections of light sources are extended in a single image. Then, if the light source is flickering in the single exposure time, its temporal flicker pattern is recorded as a spatial intensity pattern in a single image, as shown in Fig. 2 (b). We use these spatial intensity patterns in a single image for estimating the temporal flicker patterns of light.

Consider a temporal flicker pattern of a light in the scene, which is represented by a function $L(t)$ with respect to time t. We also consider a spatial reflection function $K(\mathbf{x})$ of the scene, which represents the relationship between the input light intensity and the image intensity at an image point $\mathbf{x}$. The spatial reflection function $K(\mathbf{x})$ consists of the sensitivity of the camera and the reflection properties, such as the specular and diffuse reflection coefficients, of an object at an image point $\mathbf{x}$. Then, if the object moves at speed $\mathbf{v}$ in the image, the irradiance $E(\mathbf{x}, t)$ of an image point $\mathbf{x}$ at time t can be described as follows:

$$E(\mathbf{x}, t) = L(t)K(\mathbf{x} - \mathbf{v}t) \tag{1}$$

Since the image sensor accumulates the input light during a single exposure time τ, the image intensity at an image point $\mathbf{x}$ can be described as follows:

$$I(\mathbf{x}) = \int_0^\tau L(t)K(\mathbf{x} - \mathbf{v}t)dt \tag{2}$$

By discretizing Eq. (2), we have:

$$I(\mathbf{x}) = \mathbf{K}^\top \mathbf{L} \tag{3}$$

where $\mathbf{L} = [L_1, \cdots, L_T]^\top$ and $\mathbf{K} = [K_1, \cdots, K_T]^\top$ are the discretized vector of $L(t)$ and $K(\mathbf{x} - \mathbf{v}t)$ along the exposure time $t = 1, \cdots, T$.

Then, if we consider N pixels along the motion blur of a specular reflection in the image, their image intensities $\mathbf{I} = [I_1, \cdots, I_N]^\top$ can be described as follows:

$$\mathbf{I} = \mathbf{M}\mathbf{L} \tag{4}$$

where $\mathbf{M}$ is an $N \times T$ matrix that consists of the reflectance vector $\mathbf{K}_i$ of the ith image pixel as follows:

$$\mathbf{M} = \begin{bmatrix} \mathbf{K}_1 & \cdots & \mathbf{K}_N \end{bmatrix}^\top \tag{5}$$

Thus, if we know $\mathbf{M}$, the temporal flicker pattern $\mathbf{L}$ of the light can be computed from the spatial image intensity $\mathbf{I}$ by using the relationship shown in Eq. (4).

It seems that the temporal flicker pattern $\mathbf{L}$ of the light can be recovered from Eq. (4), if $T \leq N$. However, the rank of $\mathbf{M}$ becomes smaller than T, if the specular reflection is not sharp and has some extent. Thus, we compute $\mathbf{L}$ by adding a regularization term $\mathcal{L}(\mathbf{L})$ and solving the following minimization problem:

$$\hat{\mathbf{L}} = \arg\min_{\mathbf{L}} \|\mathbf{I} - \mathbf{M}\mathbf{L}\|^2 + \alpha\|\mathcal{L}(\mathbf{L})\|^2 \tag{6}$$

where $\mathcal{L}(\cdot)$ denotes the Laplacian for smoothness constraints, and α is its weight. Eq. (6) is a linear problem and can be solved easily by a simple matrix operation.

If the moving object is a sphere, we can observe the flicker patterns of many lights in a single image, as shown in Fig. 2 (c), and the flicker patterns of all these lights can be computed from the single image. Since we only need a standard camera and a moving object for obtaining the flicker patterns of light, the proposed method is very simple and efficient.

4. Sharpness of Specular Reflection

In the previous section, we briefly mentioned the rank deficiency of matrix $\mathbf{M}$. In this section, we consider it in more detail.

The accuracy of decoding of flicker patterns depends on the sharpness of specular reflection on moving objects. The sharpness of specular reflection corresponds to the frequency characteristics of the reflection function K, i.e. a sharp reflection function includes high frequency components, and a spread reflection function consists of low frequency components.

Suppose we have a flat surface with perfect diffuse reflection, i.e. no specular reflection on the surface. Then, the spatial intensity pattern that describes the temporal intensity pattern of light does not appear in a captured image, and hence we cannot recover the flicker pattern of light from the captured images. If we have a weak specularity on the moving object, our method can be used for recovering the flicker patterns. However, because of the limited rank of matrix $\mathbf{M}$, we cannot recover accurate temporal flicker patterns of light.

The degradation of the rank of $\mathbf{M}$ occurs because the matrix $\mathbf{M}$ is a circulant matrix that consists of shifted signals. It is known that the eigen values of a circulant matrix correspond to the Fourier spectrum of a column vector of the circulant matrix. Since a sharp reflection function has flat frequency characteristics, the eigen values of $\mathbf{M}$ are nonzero, and the rank of $\mathbf{M}$ increases. If the reflection function is spread out, the high frequency components are lost, and some eigen values vanish causing rank deficiency in matrix $\mathbf{M}$. Therefore, the rank of $\mathbf{M}$ depends on the sharpness of the reflection function K.

Fig. 3 shows the temporal flicker patterns of light computed from the proposed method under various specularities. As we can see in this figure, if the specularity is not sharp, the recovered flicker pattern is not accurate, but if we have sharp specularities, very accurate flicker patterns can be obtained from the proposed method. The rank of matrix $\mathbf{M}$ in this figure shows the loss of information in spread specularities. Thus, it is desirable in our method to use objects that have strong specular reflections if they are available.

5. Estimating Flicker Patterns and Reflection Functions Simultaneously

Up to now, we have shown a method for estimating the temporal flicker patterns of light from a single image obtained from an off-the-shelf camera. In this method, we assumed that the reflection function K is known. However, in most cases, the reflection function is not known in advance. Thus, in this section, we propose a method for estimating the reflection functions K and the flicker patterns $L(t)$ simultaneously from a single image.

In general, the reflection of a light on an object surface consists of a specular reflection and a diffuse reflection. Although the ideal specular reflection appears at a single point on the curved surface at which the viewpoint direction coincides with the direction of the mirror reflection, the actual specular reflection has some extent because of the surface roughness, etc. The spread of specular reflection is often modeled by a power of the cosine function in the computer graphics field. However, in this paper, we model the spread by using an isotropic 2D Gaussian function, since the cosine function is periodic and is not suitable in this research. We also assume that the diffuse reflection is constant in the observation area. Such an assumption is reasonable when the object surface does not have a texture in the observation area. Based on these assumptions, the reflection function K can be described as follows:

$$K(\mathbf{x}) = G(\mathbf{x}, \mathbf{x}_0, \sigma) + K_d \tag{7}$$

where $G(\mathbf{x}, \mathbf{x}_0, \sigma)$ denotes an isotropic 2D Gaussian function, whose center is at $\mathbf{x}_0$ and standard deviation is σ, and K_d denotes the magnitude of diffuse reflection. Since we have a scale ambiguity between the magnitude of light and the magnitude of the reflection function, the magnitude of the Gaussian function is fixed to 1, and the diffuse reflection K_d is defined relative to the specular reflection in Eq. (7).

By substituting $K(\mathbf{x})$ into Eq. (2), the reflectance matrix $\mathbf{M}$ can be described by $\mathbf{x}_0$, $\mathbf{v}$, σ and K_d, where $\mathbf{x}_0$ is the center of the Gaussian function at time $t = 0$ in the image. Since the position $\mathbf{x}_0$ and the motion $\mathbf{v}$ can be obtained easily from the position and the interval of the specular reflection in the image, our only unknowns in matrix $\mathbf{M}$ are σ and K_d. Therefore, we estimate $\mathbf{L}$, σ and K_d simultaneously by solving the following minimization problem:

$$\{\hat{\mathbf{L}}, \hat{\sigma}, \hat{K_d}\} = \underset{\{\mathbf{L},\sigma,K_d\}}{\arg\min} \|\mathbf{I} - \mathbf{ML}\|^2 + \alpha\|\mathcal{L}(\mathbf{L})\|^2 \qquad (8)$$

Since Eq. (8) is a non-linear problem, we used the Nelder-Mead method [9] for estimating the global minimum. The weight α was chosen empirically in our experiments.

It seems that the flicker pattern $L(t)$ and the reflection function $K(\mathbf{x})$ are inseparable in Eq. (8). However, this is not the case since the flicker pattern $L(t)$ is a 1D signal, while the reflection function $K(\mathbf{x})$ is an isotropic 2D Gaussian function. The distribution of image intensity along the object motion includes both the flicker pattern $L(t)$ and the reflection function $K(\mathbf{x})$. However, the distribution of image intensity across the object motion is affected only by the reflection function $K(\mathbf{x})$, since the flicker pattern $L(t)$ is a 1D signal along the object motion. Therefore, the flicker pattern $L(t)$ and the reflection function $K(\mathbf{x})$ are separable, and they can be estimated from Eq. (8).

In this way, we can estimate the flicker pattern $L(t)$ of light from a single image that observes an unknown moving object.

6. Passive Coded Exposure

We next consider the application of flicker pattern estimation. Here, we consider deblurring of motion blurs by using coded exposure caused by the flicker patterns of light.

Rasker et al. showed that the frequency characteristics of image observation can be improved drastically, if we observe the scene by coding the exposure [13]. Thus, motion blurs in images can be recovered more accurately when we observe the dynamic scene by using coded exposure. For realizing coded exposure, we generally need special imaging systems that can control the temporal exposure patterns in a single image shot. This requires a very fast light modulator such as DMD, and it must be synchronized with the image capture.

Coded exposure can also be realized by controlling the temporal intensity patterns of lights that illuminate the scene. By controlling the temporal intensity patterns of light, the motion blurs in the observed images can be recovered by deconvolution with respect to the temporal coded light patterns. For obtaining better frequency characteristics in images, we need to control the intensity patterns of light in a single image capture.

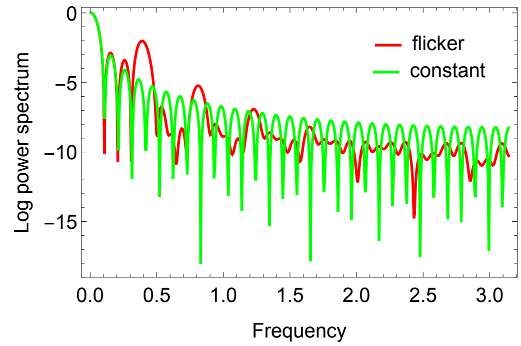


Figure 4. Frequency characteristics of standard constant exposure and coded exposure caused by flicker light shown in Fig. 3. Horizontal axis shows frequency and vertical axis shows log power spectrum of exposure. There are many zero crossings in standard constant exposure, which cause instability in deblurring process. On the contrary, frequency characteristics of flicker light are much more flat and stable.

In this paper, we consider coded exposure imaging by using the existing lights in our environments. As we have seen, a lot of lights in our environment are flickering, and these flickers of light can be considered as natural coded lights in our environments. We call them passive coded exposure. Unlike the existing coded exposure imaging, the coded patterns of the exposure are unknown in the passive coded exposure imaging.

Fig. 4 shows the comparison of the frequency characteristics of the standard constant exposure and the coded exposure caused by the flicker of light. As shown in this figure, the frequency characteristics of the coded exposure are flat, while the standard exposure has many zero crossings that induce instability in deconvolution. Thus, if we know the coded pattern of these environment lights, we can deblur motion blurs more accurately with better frequency characteristics.

Unfortunately, these temporal coded patterns of environment lights are generally unknown. However, as we have seen in this paper, the specular reflection of a moving object provides us with the accurate temporal coded patterns of the environment lights. Thus, the motion blurs in images can be deblurred accurately by using the coded light patterns estimated by the method described in section 5.

If an object moves relative to the camera in a scene, motion blur occurs in the captured images. Suppose we have a blurred image $g(\mathbf{x})$ and its unblurred image $f(\mathbf{x})$. If the motion blur is homogeneous throughout the image, the rela-

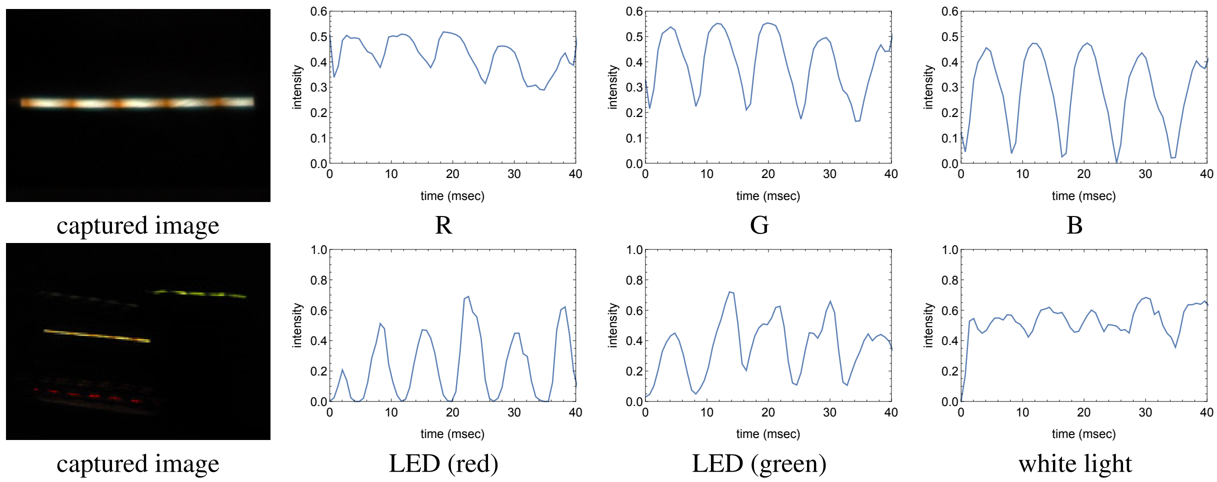


Figure 5. Estimation of flicker patterns of various lights. First row shows results from indoor fluorescent light, in which flicker patterns in R, G and B channels were estimated separately from proposed method. Second row shows results from outdoor scene, where red LED traffic light, green LED traffic light and unknown white road light exist. Second, third and fourth columns show flicker patterns of these lights estimated from proposed method.

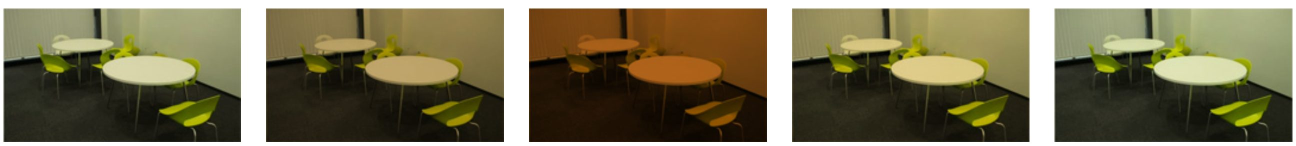


Figure 6. Changes in scene color and intensity in a single flicker of fluorescent light, which were synthesized by using flicker patterns estimated in Fig. 5.

tionship between the blurred image and the unblurred image is described as follows:

$$g(\mathbf{x}) = f(\mathbf{x}) * h(\mathbf{x}) \tag{9}$$

where, $h(\mathbf{x})$ denotes the point spread function (PSF) of the motion blur, and $*$ denotes the convolution.

If we know the PSF $h(\mathbf{x})$ of the motion blur, the unblurred image $f(\mathbf{x})$ can be recovered from the observed image $g(\mathbf{x})$ as follows:

$$f(\mathbf{x}) = g(\mathbf{x}) \oslash h(\mathbf{x}) \tag{10}$$

where, $\oslash$ denotes the deconvolution. It can be executed by using various methods, such as the Wiener filter and Richardson-Lucy algorithm.

In our case, the scene is illuminated by flicker lights, and their flicker patterns can be considered as the PSF of motion blur. Since the flicker patterns can be computed by the method described in section 5, we can recover the unblurred images from Eq. (10). In this research, we used the Richardson-Lucy algorithm [14] for the deconvolution in Eq. (10).

7. Experiments

We next evaluate our method by using real images taken under flickering lights.

We first show the estimation of flicker patterns of light from the proposed method. The upper left image in Fig. 5 shows an image of a rolling metal ball with a specular reflection, which was taken under a fluorescent light. The fluorescent light was flickering at 120 Hz, and the exposure time of the camera was 40 msec. As we can see in this image, the intensity of the specular reflection changes in the locus of specular reflection. Also, we can observe that the color of light changes to reddish at low intensity, which is a known property of fluorescent lights. By using our method, we can visualize not only the change in intensity, but also the change in color of the light in a single flicker cycle. In this experiment, we computed the flicker patterns of R, G and B separately. The flicker patterns estimated from the proposed method are shown in the second, third and fourth columns in Fig. 5 . The estimated result agrees with the result of Sheinin et al. [17], and we find that our method can estimate the flicker patterns of light just from a single image taken by a standard camera.

The second low in Fig. 5 shows the results from an outdoor scene. Again, we used a rolling metal ball as the moving object. The lower left figure shows the captured image,

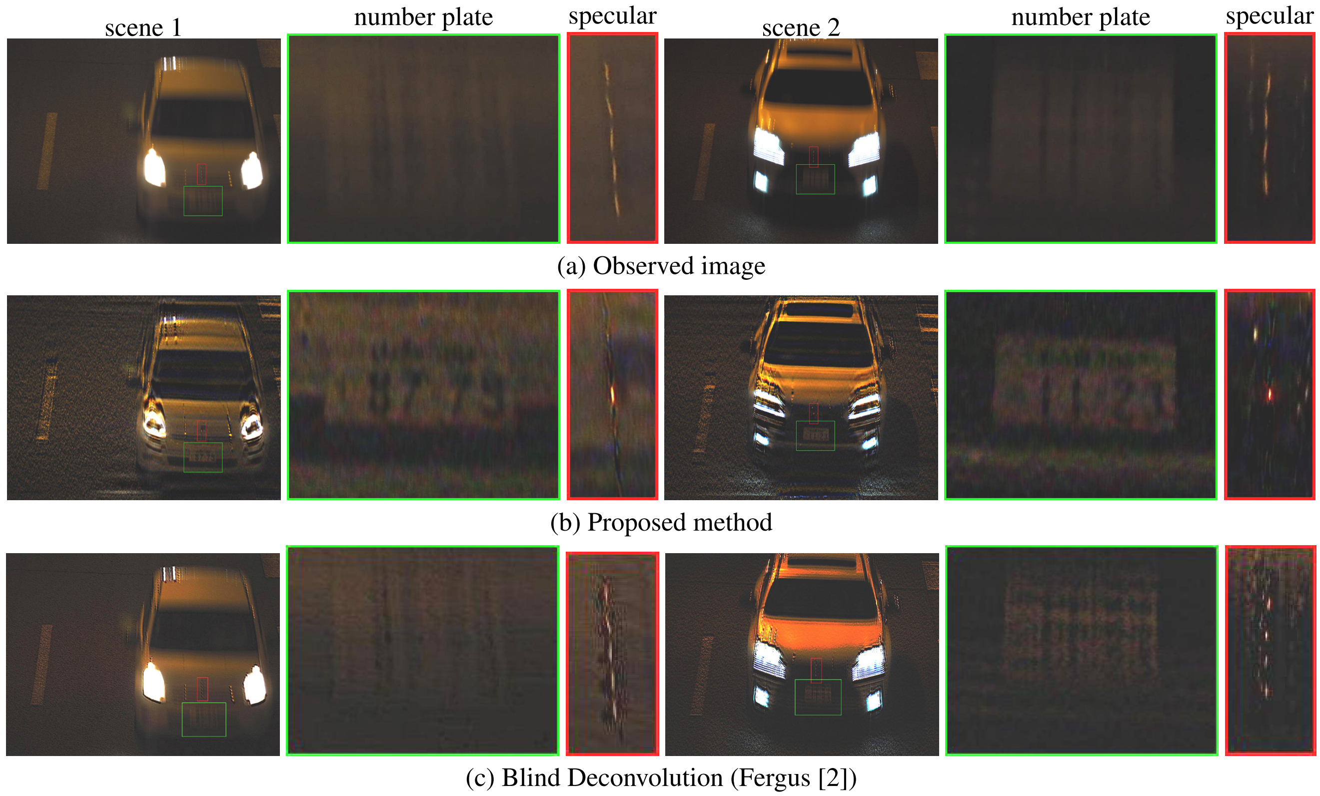


Figure 7. Deblurring motion blurs in images taken under flickering road lights. (a) shows observed images with motion blurs, and (b) shows deblurred images from proposed method. For comparison, (c) shows results from standard blind deconvolution method proposed by Fergus [2]. From left to right, we show image of scene 1, magnified image of number plate and magnified image of specular reflection respectively. Exposure time of scene 1 was 40 msec, and exposure time of scene 2 was 33 msec.

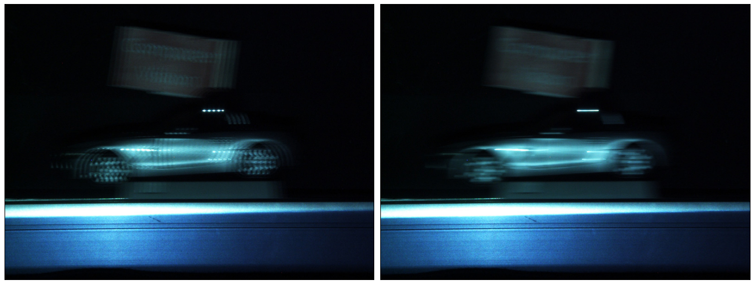
in which we can observe the flicker patterns of a red traffic light, a green traffic light and a white road light. As shown in the second, third and fourth columns, the estimated flicker patterns of these lights are very different, and our method can visualize the difference. From these results, we find that the proposed method is very efficient and useful.

The estimated flicker patters can be used for visualizing the high speed changes of illuminated scenes. For example, the fluorescent light changes its color as well as intensity in each flicker cycle. Since it is very fast, it is invisible to human observers, but we can visualize the change in color and intensity under the fluorescent light by using flicker patters estimated from the proposed method. Fig. 6 shows the changes in color and intensity of a scene in a single flicker of the fluorescent light, which were synthesized by using the flicker patterns estimated in Fig.5. We find that the color of our environment is changing at very high speed.

The estimated flicker patterns can also be used for deblurring images. Fig. 7 (a) shows images of moving vehicles taken at nighttime. The exposure time of the camera was 40 msec in scene 1 and 33 msec in scene 2. The vehicles were illuminated by a sodium light on the road. As we can see in the magnified images of the specular reflection, the sodium light was flickering at 120 Hz. Also, we find that the numbers and characters on the number plates of the vehicles suffer from heavy motion blurs and are unreadable in the observed images in Fig. 7 (a).

We estimated the flicker patterns of light from the specular reflections, and used them for deblurring the images. The unblurred images obtained from the proposed method are shown in Fig. 7 (b). As shown in the magnified images with green frames, we can read the numbers on the number plate in the deblurred images. Also, the specular reflections shown by red frames in Fig. 7 (b) became single points, and we find that the image deblurring was conducted properly in the proposed method. For comparison, we conducted the image deblurring by using the blind deconvolution method proposed by Fergus [2]. As we can see in Fig. 7 (c), we cannot properly deblur the motion blur using that method. These results show that the estimation of blur kernels is very difficult and unstable in the blind deconvolution method. On the contrary, the proposed method uses specular reflections efficiently for estimating blur kernels and deblurring images accurately.

We next show the effect of the light flicker in image de-



(a) image under flickering light (b) image under constant light

(c) deblurred image under flickering light (d) deblurred image under constant light (e) ground truth

Figure 8. Comparison of motion deblurring under a flickering light and a constant light. (a) and (b) show images captured under a flickering light and a constant light respectively. (c) and (d) show deblurred images obtained from (a) and (b) respectively.

convolution. Since the frequency characteristics of the flickering light are better than those of the constant light, we can expect better results in the case of flickering light. Fig. 8 (a) and (b) show images captured under a flickering light and a constant light respectively. The specular reflection on the moving vehicle in Fig. 8 (a) shows that the light is flickering in a single exposure, while it is not flickering in Fig. 8 (b). Fig. 8 (c) and (d) show the deblurred images obtained from (a) and (b). As shown in these images, the result from the flickering light image is much better than the result from the constant light. For example, the characters on the flag are sharp and easy to read in Fig. 8 (c), while they are unreadable in Fig. 8 (d). From these results, we find that passive coded exposure is very useful for image deblurring, and the proposed method is very efficient.

8. Conclusion

In this paper, we proposed a simple and efficient method for measuring the temporal modulation of lights and deblurring motion blurs in images.

We first showed that the invisible flicker patterns of various lights such as fluorescent lights can be measured by a simple combination of an off-the-shelf camera and various moving objects with specular reflections. The basic idea of our method is to decode the temporal modulation of a flickering light into a static pattern in a single image. Unlike the existing methods, we do not need to use high speed cameras nor special devices for synchronizing the periodic light signals. As a result, the proposed method can be applied to non-periodic lights as well as periodic lights.

Based on the extracted flicker patterns of environment lights, we also proposed an efficient method for deblurring motion blurs in images. The proposed method enables us to deblur images with better frequency characteristics by using the flicker patterns of environment lights as the coded lights in coded imaging.

We showed the efficiency of the proposed method by using real images taken under flickering lights in our environment. The experimental results show that our method can estimate flicker patterns of various lights just from a single image taken by an off-the-shelf camera. The results also show that our method is very useful for deburring motion blurs accurately and efficiently.

Our method can also be applied to various other fields. As we increase the image motion of the moving object in a single exposure, we can observe higher frequency components of light modulations in a single static image in our method. Therefore, for example, high speed visible light communication among moving vehicles and traffic signals may be achieved just by using standard cameras mounted on moving vehicles by using our method. Thus, the proposed method has a great impact on various fields.

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