Motion Deblurring using Coded Exposure for a Wheeled Mobile Robot

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Abstract - We present a motion deblurring framework for a wheeled mobile robot. Motion blur is an inevitable problem in a mobile robot, especially side-view cameras severely suffer from motion blur when a mobile robot moves forward. To handle motion blur in a robot, we develop a fast motion deblurring framework using the concept of coded exposure. We estimate a blur kernel by a simple template matching between adjacent frames with a motion prior and a blind deconvolution algorithm with a Gaussian prior is exploited for fast deblurring. Our system is implemented using an off-the-shelf machine vision camera and enables us to achieve high-quality deblurring results with little computation time. We demonstrate the effectiveness of our system to handle motion blur and validate it is useful for many robot applications such as text recognition and visual structure from motion.

Keywords - Motion Deblurring, Wheeled Mobile Robot

1. Introduction

Motion blur is a common problem of a vision-based mobile robot. Motion blur degrades a performance of vision-based algorithms such as visual path following [7], visual SLAM [20], and visual odometry [9] because of negative effects on feature detectors and tracking algorithms. The goal of motion deblurring is to recover a sharp latent image from a motion blurred image, and there are two approaches for motion deblurring that can handle a blur problem for mobile robots.

The first approach is to utilize dynamics of mobile robots for estimating its blur kernel. Kim and Ueda [11] present a blur kernel estimation method from dynamics of a camera positioning system. Fu *et al.* [6] present an image degradation model for an inspection robot and use a recurrent neural network to restore blurred images captured by an inspection robot. Pretto *et al.* [15] propose a feature detection and tracking algorithm robust to motion blur. They segment an image into several regions and estimate blur kernels for each cluster separately.

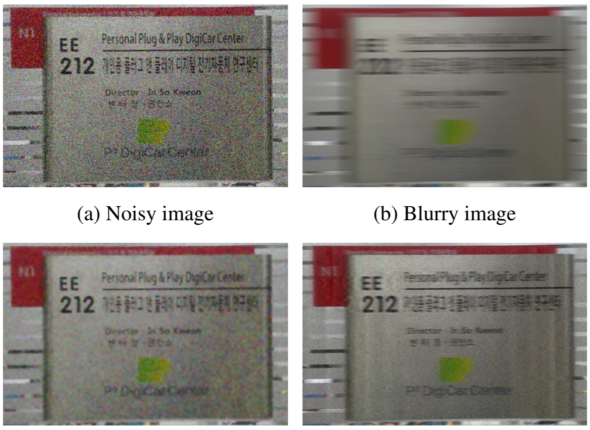
The second approach is an indirect approach that reduces the blur effect. Anati *et al.* [19] present a soft object detection method with a simple object detector and a particle filter for localization. Their method is useful to detect objects with occlusions and a partial blur for a mobile robot. Hornung *et al.* [8] propose a learning framework to determine navigation policy for a mobile robot. They train the trade-off between localization accuracy and the impact of motion blur on observations according to mobile robot velocity. However, this approach has a limitation that can only handle a small amount of blur.

In computer vision, image deblurring is one of the most active research fields. Traditional solutions to the problem include Richardson-Lucy [18], [13] and Wiener filter [24]. Recently, significant progress is accomplished in image deblurring. Fergus *et al.* [5] present a variational Bayesian framework by using a natural image statistics as prior information of a latent image. Shan *et al.* [21] present a unified probabilistic model to estimate a blur kernel and to suppress ringing artifacts in a deblurred image. Xu and Jia [26] handle very large blur by selecting useful edges for kernel estimation and by using an iterative kernel refinement with an adaptive regularization.

There are many studies to use multi-blurred images for deblurring. In [17], Rav-Acha and Peleg show better deblurring performance over single image deblurring methods due to the complementary information. Agrawal *et al.* [2] show that 1-D motion blurred images captured by different exposure times make deblurring to a well-posed problem. Chan *et al.* [3] perform an iterative blur kernel estimation and a dual image deblurring to infer a latent image from complex motion blurred image pairs. Though the multi-image deblurring methods show good performances, computational time for the deblurring task has made it difficult to apply into a mobile robot.

To change the way of image capture is in the limelight to tackle the deblurring problem. In [16], Raskar *et al.* show impressive motion deblurring results by using coded exposure. Coded exposure flutters a camera's shutter open and closed within the exposure time to preserve spatial frequencies in a blurred image. The strength of coded exposure is to achieve high-quality results through simple operations as a matrix inversion. The drawback is that it needs a high computational burden in a blur kernel estimation [1], [14].

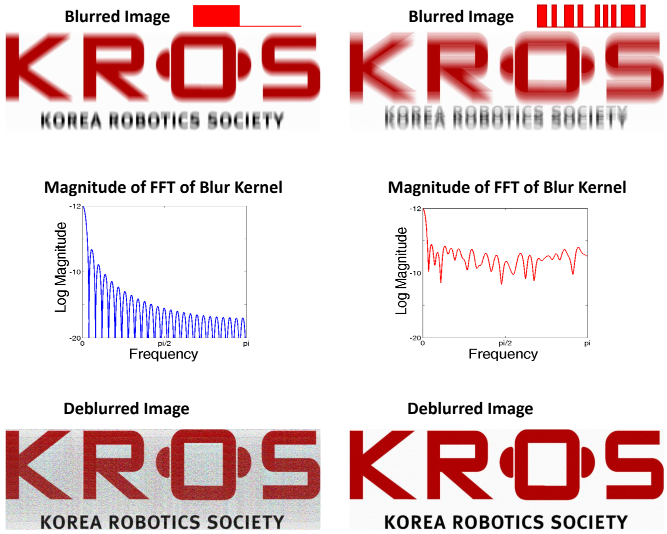
In this paper, we present a motion deblurring method using the concept of coded exposure for a wheeled mobile robot. We calculate an inter-frame motion by matching image patches between adjacent frames and estimate a blur kernel using the inter-frame motion. Our blur kernel estimation is not only able to handle a linear directional motion blur, but a simple projective blur. Our system is implemented using an off-the-shelf machine vision camera and leads us to achieve high-quality deblurring results with little computation time. We validate the effectiveness of our system to handle motion blur and show the proposed method is useful for many robot applications



(a) Noisy image (b) Blurry image

(c) Denoised image (d) Deblurred image

Fig. 1: An example of a motion blur in a mobile robot. Both images (a,b) are captured from a moving mobile robot under low light condition. (a) short exposure time and high ISO sensitivity settings are used to avoid motion blur and it amplify image noise. (b) Long exposure time is used to prevent image noise and it cause severe motion blur. (c) image denoising result of (a) using median filter, (d) image deblurring result of (a) using Wiener deconvolution (MATLAB).



(a) Conventional exposure (b) Coded exposure

Fig. 2: Comparison between conventional exposure and coded exposure. (a) A poor deblurring result due to non-invertible blur kernel, (b) Coded exposure shows a good deblurring result.

such as characters and numbers recognition and visual structure from motion.

2. Motion Blur in a Mobile Robot

Performance of most vision algorithms for a mobile robot is particularly degraded under insufficient light conditions. There are two options for handling such situations: (i) increasing a camera ISO sensitivity, which results in amplification of photon noise, (ii) capturing blurred images with long exposure time, which causes a loss of image's spatial frequencies.

Image restoration such as denoising and deblurring is considered to take a full advantage of vision algorithms. Though image restoration algorithms improve image quality, it can cause another problems. Removing noise destroys useful information as image's edges and a recovered image using deblurring often suffers from ringing artifacts. In robot vision, the problems get worse since it is infeasible to use high performance vision algorithms for handling these problems due to a huge computational complexity. Fig. 1 shows an example of a motion blur problem in a mobile robot.

In a wheeled indoor mobile robot, the robot usually has a camera that is looking forward to the side for vision-based tasks such as room number recognition and moves along a side wall. In the situation, images from the side camera are blurred by a directional motion and the blur problem becomes severe while a robot moves fast. Motion of the robot can be considered as a constant velocity because its camera exposure time is short enough to ignore acceleration. In practice, most vision algorithms for mobile robots such as visual SLAM and motion estimation assumes that velocity of robot motion in a short duration is constant. Accordingly, we assume motion blur in a wheeled mobile robot as a constant directional blur.

Our purpose is to recover a latent image with few ringing artifacts and little computational burden for such a wheeled indoor mobile robot. To achieve this, we apply the concept of coded exposure to a mobile robot platform, and present a blur kernel estimation using template matching between consecutive blurry frames. Our method is not only able to handle 1-D large blur kernels, but cover a simple projective blur, which occur frequently in indoor environments. We will describe details of our solution in the next section.

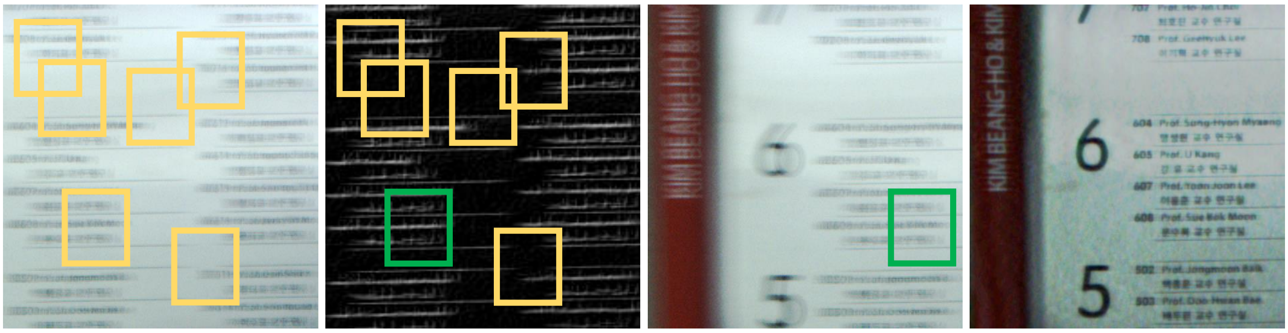
3. Deblurring using Coded Exposure

Let B, K, and I denote a blurred image, a blur kernel, and a latent image. We model motion blur as

$$\mathscr{F}(\mathrm{B}) = \mathscr{F}(\mathrm{I}) \cdot \mathscr{F}(\mathrm{K}) + \mathrm{N}, \quad (1)$$

where $\mathscr{F}$ is Fourier transform operator and N is additive noise. Conventional camera exposure of a wheeled mobile robot has a rectangular point spread function which has many zero-crossing points in the frequency domain. The zero-crossing points results in a loss of spatial frequencies of a blurred image so that deblurring becomes ill-posed as shown in Fig. 2 (a).

Coded exposure is developed by Raskar *et al.* [16] to solve the ill-posed problem. Coded exposure opens and closes a camera shutter during capturing an image. It emulates invertible broadband blur kernels and makes deblurring problem well-posed. As shown in Fig. 2 (b), a deblurred image is robust to ringing artifacts and de-



(a) i *th* frame (b) Gradient image of (a) (c) $i+1$ *th* frame (d) Deblurred result

Fig. 3: Template matching procedure.

convolution noise even though the size of a blur kernel is larger than the conventional capturing method.

3.1 Blur Kernel Estimation

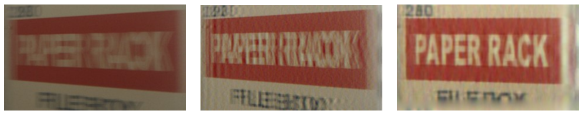
In general, deblurring algorithms consume most of computational time for a blur kernel estimation since the kernel estimation is an iterative process that requires an intensive computation. Such a huge computation is not acceptable to a mobile robot platform in practice. In contrast to a consumer camera setup, mobile robots capture sequential images that have considerable overlaps between adjacent frames. The sequential images give plenty of opportunity to solve the computational issue. In this section, we describe a blur kernel estimation for a wheeled indoor mobile robot.

In the existing coded exposure methods [1], [14], they assume a 1-D linear blur kernel, which is not suitable for mobile robots. We relax the assumption and consider a blur kernel as a 2-D linear directional kernel. With a 2-D linear direction kernel, we can handle various motion blur from mobile robots since motion blur in a wheeled mobile robot can be approximated as a linear direction blur.

We compute a directional blur kernel using template matching between consecutive blurred images. We find a distinctive patch with high texture content in i *th* for robust template matching in Fig. 3 (a). To measure distinctiveness of an image patch, we use the Sobel gradient operation that requires little computational burden. At this step, we select one patch with a maximized sum of magnitude of gradient value in randomly distributed patches in Fig. 3 (b). Then, we perform a template matching based on normalized cross correlation, which finds the most similar patch in $i+1$ *th* frame in Fig. 3 (c). The template matching initially searches into a horizontal direction, and then refines matched point by applying 2-D local search. The final blur kernel is computed by multiplying camera's frame rate and the image-space robot velocity (pixel/ms) obtained by the template matching in Fig. 3 (d).

3.2 Non-uniform Blur in Slanted Scene

We apply image warping to handle non-uniform blur. When the robot moves on the shortest path or avoids an obstacle, side-view camera often faces the corridor wall



(a) (b) (c)

Fig. 4: Handling a simple projective blur. (a) Input image. (b) Deblurred result assuming spatially-invariant blur kernel. (c) Deblurred result using Sec. 3.2

at a slanted angle. In that case, however, blurred image has spatially-variant blur kernel due to depth variation. As shown in Fig. 4 (b) incorrect blur kernel result in severe artifacts. Using the homography, we generate fronto-parallel view of the wall so that the image has uniform blur size in that synthetic view.

The homography matrix H can be represented as follows:

$$\mathbf{H} = \mathbf{KRK}^{-1} \tag{2}$$

where $\mathbf{K}$ is camera intrinsic parameter, and $\mathbf{R}$ is rotation matrix between image plane and the wall. Since indoor mobile robot is our target, we assume only one dimension camera rotation about Y-axis, which is yaw rotation for a robot. Thus the rotation matrix $\mathbf{R}$ can be written:

$$\mathbf{R} = \begin{pmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{pmatrix} \tag{3}$$

To estimate an angle θ, our strategy pass through prediction and verification steps. In the prediction step, a patch is selected by the similar process to deciding a patch for blur kernel estimation. The two patches, however, have a gap in x-axis so that they have different blur size in slanted scene. Then, the patch that we choose in this step is warped by homographies considering the angle of previous frame and constant angular velocity with small variation. In the implementation, the range of small variation is -5° to 5°. In the verification step, we evaluate gradient value of deblurring result for each warped image. Then, the angle which has minimum gradient of

Fig. 5: Our mobile robot which is used for the experiments. The robot captures images sequentially using a side-view camera.

Method	Software	Computational Time (sec)
Cho *et al.* [4]	C++	6.9
Shan *et al.* [21]	C++	15.7
Xu and Jia [26]	C++	49.9
Proposed	C++	0.4

Table 1: Comparison of average computational times. The size of input images is 640×480 and these algorithms are executed on a desktop PC with Intel Core i7 CPU 3.40GHz and 16GB RAM. Compared algorithms are distributed in Executable program based on C++

image is selected since ringing artifacts increase gradient value of an image. If an image has more uniform blur size, then the image gets least ringing artifacts. As shown in Fig. 4 (c), our well-approximated image warping is useful for tackling a simple projective blur, which helps our technique to handle more various indoor situations.

4. Experiments

To validate the effectiveness of our method, we perform experiments on two robot vision tasks: character recognition and structure from motion. Fig. 5 shows our mobile robot, and all the images for experiments are captured from a camera mounted on the mobile robot We set exposure time of the camera to 25ms for all experiments, which gives a good trade-off between image noise and motion blur for general mobile robots. Capturing time of our coded exposure is 50ms due to fluttering of a camera shutter during the exposure time. In presenting experimental results, we begin by describing implementation details.

4.1 Implementation

We implement a coded exposure camera using a machine vision camera, PointGrey Flea3, which is widely used as a machine vision camera. Flea3 camera supports a Trigger mode 5 that enables multiple pulse-width trigger with a single readout. External trigger is generated by an ATMega128 microprocessor. Camera's shutter is opened at 0 to 1 transition and is held until the next 1 to 0 transition is occurred. For fluttering pattern 11001101, for example, three triggers are sent at 0, 5, and 8 ms, and shutter is opened for a duration of 2, 2, and 1 ms, respectively. Each shutter chop is 1 ms long due to the hardware limitation of a Flea3 camera. We use the state-of-the-art fluttering patterns reported in [10] since a fluttering pattern is closely related to the performance of coded exposure deblurring [14].

Our algorithm is implemented using Visual Studio 2010 (C++ language) with Intel OpenCV library. Blurred images are deblurred by using a non-blind deconvolution method with Gaussian prior [12] if there is no statement for a deblurring method. We choose the deconvolution method since it is simple and computationally efficient.

4.2 Results and Discussion

We first compare computational time of our method with other well-known blind deblurring algorithms, [5],[21],[26],[23]. The methods [5],[21] [26] are single image deblurring methods and [23] is a multi-image deblurring method. Computational time of the proposed method includes our PSF estimation and the non-blind motion blurring with Gaussian prior. We calculate the elapsed time for deblurring one VGA resolution image and the result is summarized in Table 1. In the result, we can observe that our method is much faster than other algorithms because we estimate PSF very efficiently while other algorithms spend most computational time on PSF estimations.

To demonstrate the qualitative performance of our method, we show deblurring results in Fig. 6. In the figure, odd rows show captured images and even rows show deblurred results using our method and the state-of-the-art deblurring method [26]. Results from the conventional exposure imaging is displayed in (a,b) and results from the coded exposure imaging is displayed in (c,d). Results in (a,c) are deblurred using the method [26] and results in (b,d) are deblurred using our method.

In Fig. 6, the method [26] fails to accurate PSF estimation in (c) due to large blur. Results using the conventional exposure (b) suffer from deconvolution noise and ringing artifacts comparing to results using the coded exposure (d), since the conventional exposure has a loss of spatial frequencies of a blurred image. Results in (c) that are deblurred using the method [26] have much deconvolution noise and ringing artifacts than results in (d) that are deblurred using our method, since the method [26] fails to estimate accurate blur kernels due to large motion blur. On the other hand, result in (d) shows that the proposed method that utilizes coded exposure with an efficient PSF estimation can recover high-quality images robust to large motion blur.

To verify the effectiveness of our method as a capturing tool for mobile robots, we perform characters and numbers recognition using [22]. We crop text areas from each deblurred results in Fig. 6 and put cropped images into the recognition algorithm. The recognition results are summarized in Table 2 and true positive recognition results are printed as bold strokes in the table. As

(a) Conventional (w/[25]) (b) Conventional(w/Sec.Ⅲ-A) (c) Coded Exposure (w/[25]) (d) Proposed

Fig. 6: Qualitative comparison of deblurring results. (a) Conventional exposure with[26] fails to recover details and to suppress deconvolution noise. (b) Conventional exposure with Sec. 3.1 results in ringing artifacts due to a loss of spatial frequencies of the blurred images. (c) The method[26] fails to estimate accurate blur kernels. (d) The proposed method shows promising deblurring results.

Input	Static	Conventional (Blur)	Conventional (w/ [26])	Coventional (w/Sec. 3.1)	Coded Exposure (w/ [26])	Proposed
illinois	tllinbis	-	-	-	-	-
VGP	VGP	**VGP**	**VGP**	Vt}?	-	**VGP**
768	768	**768**	**768**	**768**	-	**768**
AUG	AUG	-	-	-	xi-1:35	-
Alabama	Alabama	T	-	-	i..::.....: 21	-
61271	61271	**61271**	-	612Z1	-	**61271**
NATIONAL	NATIONAL	-	-	IAHDINL	-	**NATIONAL**
GUARD	GUARD	.	193?+	GUIRI1	-	**GUARD**

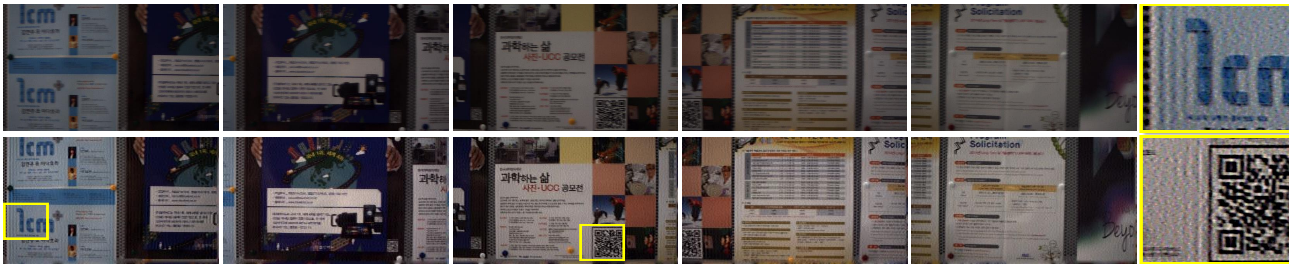
Table 2: Recognition results of characters and numbers from the deblurred images in Fig. 6.

expected, the recognition results from the proposed deblurred images outperform the others. This is because the deblurred images of the others have ringing artifacts and smeared regions that hamper a line finding, features extraction, and classification of the recognition process in [22].

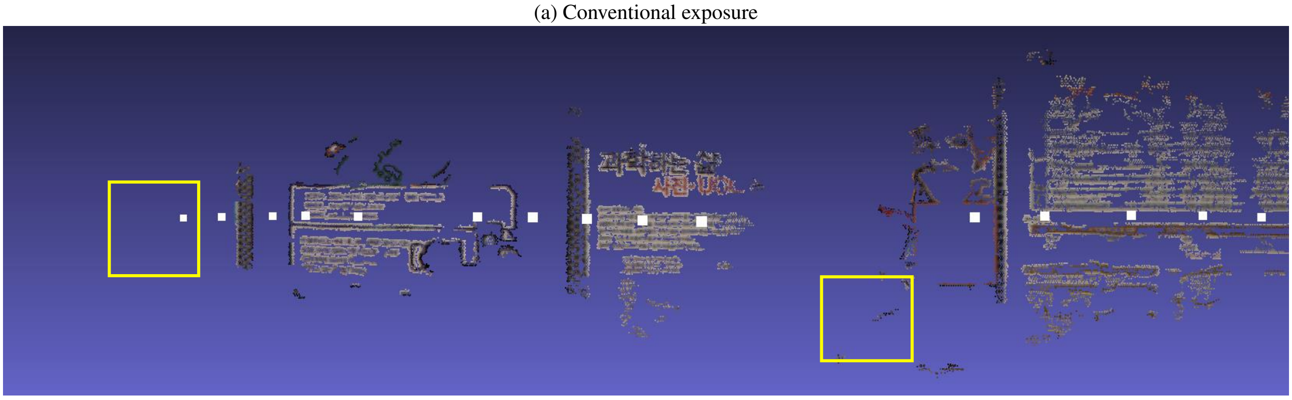
Motion estimation and 3-D scene reconstruction in mobile robots are challenging tasks when consecutive images are blurred since it fails to match image features between blurred images. To show the performance improvement of such tasks using our framework, we perform experiments of structure from motion. Fig. 7 shows reconstruction results. Our mobile robot captures 42 sequential blurred images as moving along a corridor. Since the camera on the robot is looking toward a side-view, the captured images contains large motion blur. We recover images using deblurring, then we perform a well-known visual structure from motion (VisualSFM) to reconstruct the 3D model [25]. In this experiment, we capture images using both our coded exposure and the conventional exposure, and we use ours blur kernel estimation for both captured sequences. The deblurred images in Fig. 7 (a) has ringing artifacts, which result in failures of feature matching. On the other hand, there are few ringing artifacts in the deblurred images from our method in Fig. 7 (c). Due to the difference of deblurred image quality, The result of our method in Fig. 7 (d) shows better reconstruction than the results in Fig. 7 (a).

5. Conclusions

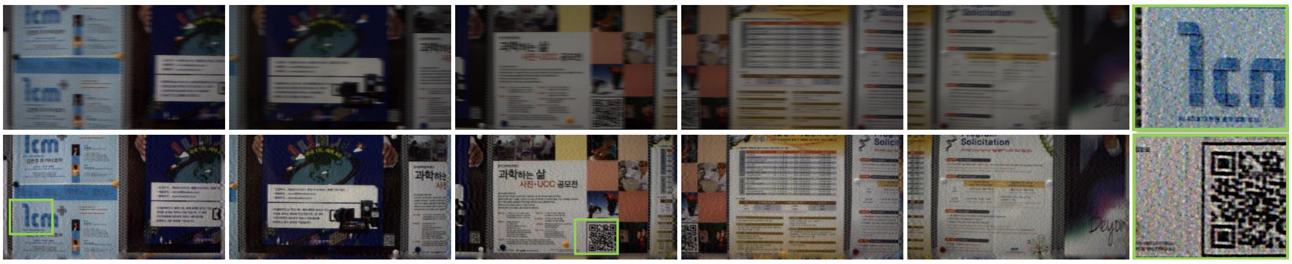
We have presented a motion deblurring framework using coded exposure for a wheeled mobile robot. We have analyzed the characteristics of motion blur in a mobile robot and have designed an efficient deblurring framework that is tailored to a wheeled mobile robot. With our framework, we can recover high-quality images with little computation time, therefore vision-based algorithms become robust to motion blur especially under low light



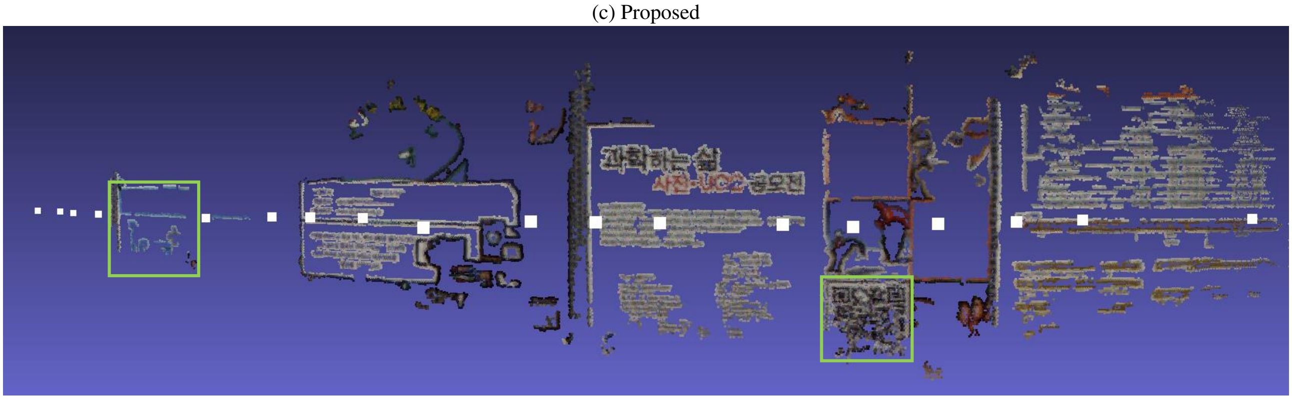
(a) Conventional exposure



(b) Structure from motion result using (a)



(c) Proposed



(d) Structure from motion using (c)

Fig. 7: 3D reconstruction results using structure from motion. First row images of (a,c) are images captured by conventional exposure and the proposed method, respectively. The images contains motion blur due to the motion of the mobile robot. Second row images of (a,c) are deblurred images from consecutive blurred images. (b) and (d) are 3D reconstruction results from the deblurred images in (a,c), respectively. White dots denote camera poses.

condition. The effectiveness of our system is validated on text recognition and feature matching tasks.

In the current implementation, there is a limitation on motion blur from dynamic scene which contains multiple moving objects. The problem requires a huge computational complexity due to multiple blur models and additional weight variables. It can be handled by fusing our system with 3-D depth sensor that can help simplify multiple blur model in the future .

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