Inertial Data Based Deblurring for Vision Impaired Navigation

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***Abstract*— Image stabilization is very important in vision based indoor/outdoor navigation systems. Blurring is one main cause of poor image quality, which can be caused by a movement of the camera at the time of taking the image, a movement of objects in front, atmospheric turbulence or out-of-focus. Out of these factors, camera movement is dominant in navigation systems as the camera is continuously moving. This paper presents the preliminary results of deblurring performed using point spread function (PSF) computed using synchronized inertial sensor data. It uses data of the accelerometer and gyroscope to derive a motion vector calculated from the motion of the smartphone during the image capturing period. This motion vector is applied to the captured image so that the effect of motion is reversed during the debrurring process. This work is a part of an indoor navigation project that aims to assist people with vision impairment. Image processing form a significant part of the proposed system and as such clearly defined edges are essential for path and obstruction identification. Different deblurring methods are compared for their performance in reversing the effect of camera movement. Results indicated that deblurring can be successfully performed using the motion vector and that the resulting images can be used as a readily approach to object and path identification in vision based navigation systems, especially for blind and vision impaired indoor/outdoor navigation. The paper also proposes a novel deblurring algorithm that uses PSF computed for different portions of the image to deblur that portion of the image.**

Keywords*— *Image stabilization, deblurring, inertial sensors, vision impaired navigation.

I. INTRODUCTION

Image bluriness is one of the primary causes of poor image quality in image acquisition and can significantly degrade the structure of sharp images. Atmospheric turbulences, out-of-focus and the motion of camera or scene would cause the blur. One of the most common reasons for image discarding is camera shaken blur when the light conditions are poor. The camera shake is high in human way finding application as the movement of the body causes shake in the camera. Although faster shutter speeds would reduce the motion blur, it can increase camera noise and availability of high speed cameras in mobile phones and embedded systems is limited.

Real time object detection and path identification using edge detection is a main part of image processing in way finding systems for vision impaired people [1]. Low resolution images are used for this to reduce the complexity and computational demands as way finding systems have to be implemented as an embedded system. The discontinuity of detected edges will increase if the edges are detected with the blurriness of the image. Blind deconvolution can be used to deblur the image when the point spread function (PSF) is unknown and non-blind deconvolution when PSF in known respectively. In most of the conventional image capturing applications, the PSF is unknown and hence the derivation of the solution is more difficult.

However, the embedded inertial sensors available in latest mobile devices enable the estimation of the PSF by sensor fusion. While the 3-axis accelerometer gives the linear motion, the rotary motion is given by the 3-axis gyroscope. The main challenge in using the accelerometer to compute motion is the noise accumulation when performing integration of the accelerometer signal to compute velocity and displacement [2], [3]. However, as the exposure time is short, calibration and noise filtering can be used to minimize the error caused by sensor drift. The resulting motion that causes the motion blur is a result of both linear and rotary motion of the camera.

This paper proposes a novel image deblurring algorithm that can be used to remove motion blur using synchronized inertial sensor data. This presents initial test results of motion deblurring using existing deblurring algorithms and their Peak Signal-to-Noise Ratio (PSNR) of the result of each method. The work discussed in this paper is a part of the design and development of an indoor/outdoor navigation system for vision impaired people. Previous work related to image deblurring with and without using inertial sensor data are disussed in “Related Work” section and the derivation of the PSF from sensor data and preliminary test results are discussed in “Preliminary Results” section. The proposed algorithm is discussed in the “Proposed Deblurring Algorithm” section of this paper.

II. Related Work

Image de-blurring has recently received significant attention and long lasting problem in the image processing and computer vision fields. Image deblurring can be classified into two types, blind and non-blind deconvolution. Deblurring is more difficult and ill-posed problem when the blur kernel is unknown. When the blur kernel is known all practical solutions can be stronger than when prior information about the kernel is unknown. Image deblurring is the combination of point spread function (PSF) and non-blind deconvolution. For further literature in this area, we refer the survey article by Kundar and Hatzinakos [4].

The majority of the approaches carried out in deblurring require a minimum of two images of the same scene. Rav-Acha and Peleg [5] used the information in two motion blurred images, while Yuan et al. [6] use a pair of images, one blurry and one noisy, to facilitate capture in low light conditions. But capturing two images in the same scene is not suitable in the area of way finding due to the real time constraints.

Fergus et al. [7] discuss a method on removing camera shake using a single image. This solution identifies the camera motion using an initial kernel estimation, which requires a region without saturation effects. Shan, Jia and Agarwala [8] propose a method using a unified probabilistic model of both blur kernel estimation and de-blurred image restoration. Both these methods require complex computational processing which is not suitable for devices with limited processor and memory resources.

Many devices, such as modern smart phones have in-built inertial sensors: gyroscopes and accelerometers. The use of inertial measurement unit (IMU) data to calculate the camera motion may be simpler than the above methods and some of the research already carried out in this area [9]-[13]. Hyeoungho, Fowlkes, and Chou [9] proposed a deblurring method using an integrated depth sensor and IMU sensor with the camera. The joint analysis of these three types of data is used for the better recovery of the real camera motion during the exposure time. This method requires MATLAB® scripts to run on a laptop to control the depth sensor and it cannot be applicable in the area of way finding. Horstmeyer [10], Feng and Tian [11] and Joshi et al. [12] discuss deblurring methods using the accelerometer and gyroscopic sensor data and have used DSLR camera, which is more expensive, and a set of sensors, and used an offline computer for image deblurring process.

Sanketi and Coughlan [13] describe methods of anti-blur feedback for visually impaired users of Smartphone camera using the IMU sensor data. This feedback is primarily used for the camera stabilization and this is also another use of synchronized IMU data, which is useful in the area of image acquisition. Also similar to our work is that of Šindelář and Šroubek [14], who use a smart phone with gyroscope to remove the camera shaken blur. In our work we are using gyroscope and accelerometer to measure the motion blur because there can be linear motion as well as rotation.

Our research is work based on way finding for vision-impaired people. The expected frame rate is in the order of 3-5 frames/sec as the targeted walking speeds are in the order 120 steps/min for normal gait [15]. It is expected that captured images will be of poor quality due to lighting conditions, blur and shadows. Image deblurring is the most important role in this research project due to the fact that edge detection techniques are to be used to detect paths, stairs ways, movable and immovable objects.

III. Preliminary Results

A. Camera Motion Blur

In general photo shooting scenarios, the user tries to keep the camera as steady as possible. In this case the motion blur is minimal and most of debluring techniques are targeting this kind of motion blur. However, in wayfinding applications, there is no control on the movement of the camera, and the result is a heavy motion blur. Therefore, knowing the camera motion is important so that it can be given as an input to the deblurring algorithm.

B. Estimation of PSF

The blurriness of an image may cause due to linear and angular movements of the camera with respect to the scene. The motion is computed in the plane of the scene for the estimation of the PSF. Fig. 1 shows the coordinate frame used for this computation and the definition of each parameter is given in Table 1.

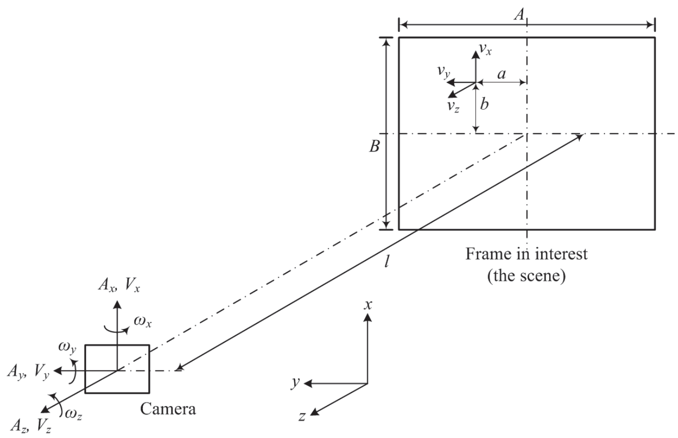

Fig. 1. Illustration of the scene with respect to the camera

TABLE I. MOTION PARAMETERS OF THE CAMERA AND THE FRAME

Parameter	Value
A_x, A_y, A_z	Linear acceleration of camera along x, y and z axis
V_x, V_y, V_z	Linear velocity of camera along x, y and z axis
ω_x, ω_y, ω_z	Angular velocity of camera along x, y and z axis
v_x, v_y, v_z	Linear velocity of frame w.r.t. camera along x, y and z axis

The velocity of the picture frame is given by (1). These velocity components have to be integrated in the time domain to obtain the linear displacement of a particular point in each of the tree directions. This linear displacement is then converted to the pixel displacement using the parameters of the image and the camera. This is then converted to the PSF.

$$
\begin{aligned}
v_x &= -V_x + l\omega_y + a\omega_z \\
v_y &= -V_y - l\omega_x - b\omega_z \qquad (1)\\
v_z &= -V_z - a\omega_x + b\omega_z
\end{aligned}
$$

C. Experimental Results

Fig. 2 shows a sample blurry image with the synchronized inertial sensor data for the period of the image exposure. The image and the sensor data were captured using a Sony Xperia TX smartphone with an application written on Android. The exposure time for this image is 1/16 s.

Fig. 3 shows the PSF computed for the center of the image using the inertial sensor data for the blurry image (center) and the deblurred image using Weiner filter. In addition to the Wiener filter, the original image was deblurred using Blind Deconvolution, Lucy-Richardson method and Regularized filter for comparing the quality of the output. The method proposed by Mittal, Soundararajan and Bovik [16] was used to measure the quality of the original image and each output which are shown in Table 2. The quality score indicated that the Regularized filter gives the best quality.

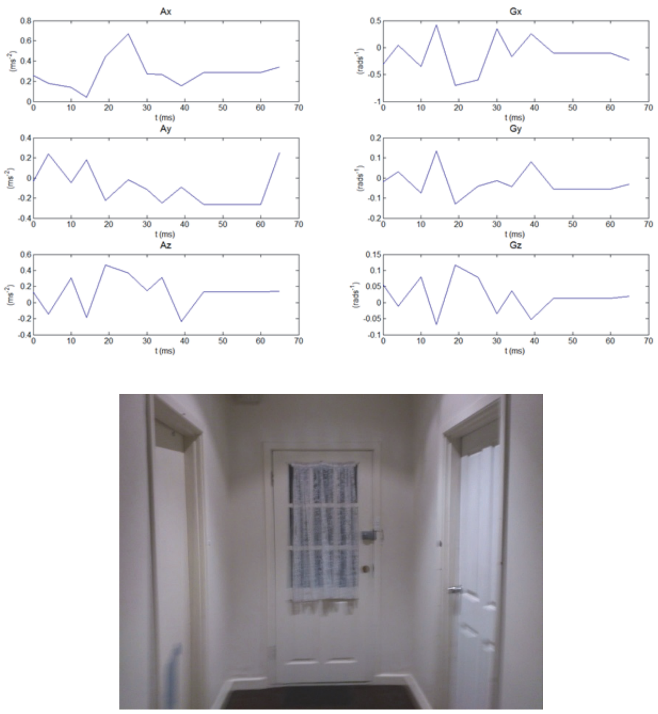

Fig. 2. A sample blurry image with the inertial sensor data

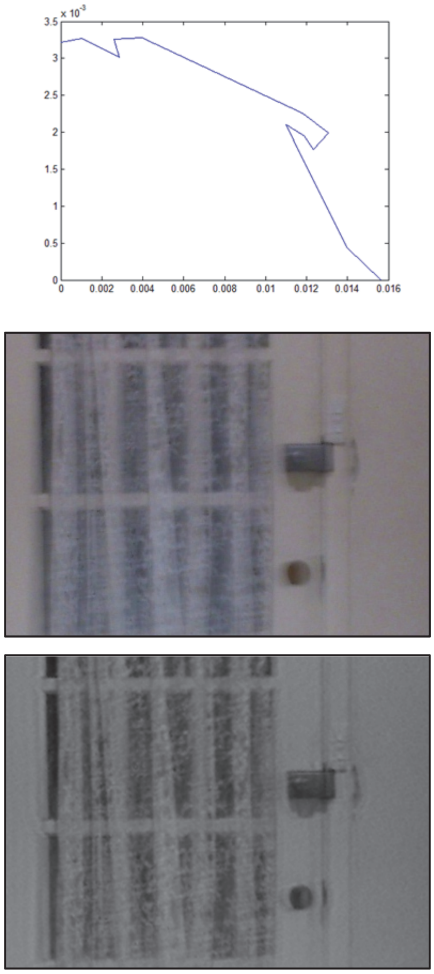

Fig. 3. PSF (top), blurry image (middle) and the deblurred image using Wiener filter (bottom)

With that finding, the next step was to perform the deblurring to a part of the image using the PSF for the center of that part. The image was divided to four quarters and the PSF was estimated for the center of each part and each part was deblurred independently. The quality score, having a value of 18.0008, indicated that the quality is better when deblurring was performed part by part. The best quality score for a part of an image was 17.9256. Fig. 4 shows the original image, output of the Regularized filter using the PSF computed for the center of the image and the output of Regularized filter when deblurring was performed for parts of the image with the PSF computed for the center of each part.

TABLE II. QUALITY OF THE ORIGINAL AND PROCESSED IMAGES

Image	Quality Score
Original	19.8734
Blind deconvolution	19.1981
Wiener filter	19.4946
Lucy-Richardson method	19.2360
Regularized filter	18.3384

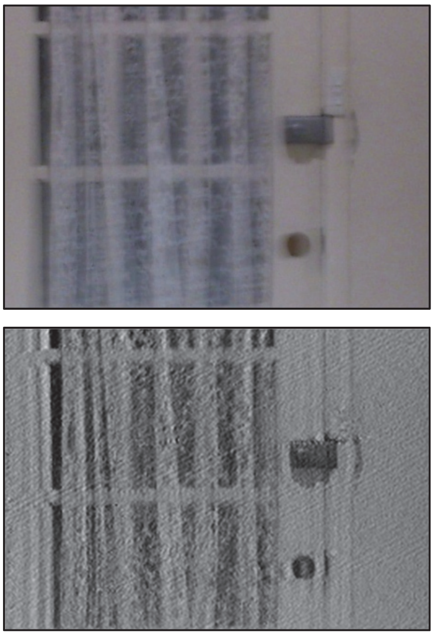

Fig. 4. Original image (top), outputs of Regularized filter with PSF of center (middle) and part wise filtering (bottom)

IV. Proposed Deblurring Algorithm

The above results indicate that none of the existing techniques can deblur the image to achieve a perfect image, especially for motion blur caused by lager movements of the camera, which is usually observed in wayfinding applications.

The proposed algorithm is based on Richardson-Lucy algorithm for image deblurring. We added a new energy preserving of edges term E_{edge}, which is equilibrium on a blurry energy edge function, to the energy (2).

$$I^{*} = argmin_I E(I) \tag{2}$$

where $E(I)$ is the energy of the image. We define E_{edge} as

$$E_{edge} = -|G_{\sigma} * \nabla^2 I|^2 \tag{3}$$

and then the new energy function is given by

$$I^{*} = argmin_I (E(I) + \beta E_{edge}) \tag{4}$$

where β is a constant factor. By minimizing (4), the modified Richardson –Lucy algorithm can be expressed as in (5).

$$I_{deblured}^{t+1} = \frac{I^t}{1+\beta E(I^t)_{edge}} \left[K^{*} \otimes \frac{B}{I^t \otimes K} \right] \tag{5}$$

where K^{*} is adjoint of K (the PSF) and t is time step.

The proposed algorithm is shown in Fig. 5.

V. Conclusion and Future Work

The preliminary results indicated that the synchronized IMU data can be effectively used for deblurring of heavily blurred imaged due to heavy camera motion. Further, it was observed that the output quality is better when deblurring is performed to parts of the image using the PSF computed for the particular part of the image. Hence, the proposed algorithm considers the image part by part using the corresponding PSF.

The authors are working on implementing the algorithm considering different type of sectorising of the image. Further, depending on the results, optimizing the algorithm will be considered to reduce the processing time as our target is to implement this in embedded platform.

Inputs: blurred image, PSF
Output: deblurred image

initiate K^1 from the synchronized IMU data
// *update image*
$\beta \leftarrow 1$
While $\beta \geq 1/16$ ***do***
for $t = 1{:}4$ ***do***
    Solve for E_{edge} using equation (3)
    for $j = 1{:}\beta^{-1}$ ***do***
        Solve for $I_{deblurred}$ using equation (5)
    end
end
// $\beta \leftarrow \beta/2$
Update K using equation (1)
end

Fig. 5. The proposed algorithm

References

[1] Rajakaruna N., Murray I., "Edge detection for Local Navigation System for Vision Impaired People Using Mobile Devices", International Conference on Mathematical Sciences & Computer Engineering, Malaysia, 29-30 Nov. 2012.

[2] K. Abhayasinghe and I. Murray. (2012, Nov.). "A novel approach for indoor localization using human gait analysis with gyroscopic data," in Third International Conference on Indoor Positioning and Indoor Navigation (IPIN2012) [Online], Sydney, Australia, 2012. Available: http://www.surveying.unsw.edu.au/ipin2012/proceedings/submissions/22_Paper.pdf [Mar. 5, 2013].

[3] D. Sachs. Google Tech Talk, Topic: "Sensor Fusion on Android Devices: A Revolution in Motion Processing." [On-Line], Aug. 2, 2010. Available: http://www.youtube.com/watch?v=C7JQ7Rpwn2k [Oct. 27, 2011].

[4] Kundur, D.; Hatzinakos, D., "Blind image deconvolution," Signal Processing Magazine, IEEE , vol.13, no.3, pp.43,64, May 1996

[5] Rav-Acha, A., & Peleg, S. 2005. Two motion blurred images are better than one. Pattern Recognition Letters 26, 311–317.

[6] Yuan, Lu, Sun, Jian, Quan, Long, & Shum Heung-Yeung. (2007). Image deblurring with blurred/noisy image pairs. Paper presented at the ACM SIGGRAPH 2007 papers, San Diego, California.

[7] Fergus, Rob, Singh, Barun, Hertzmann, Aaron, Roweis, Sam T., & Freeman, William T. (2006). Removing camera shake from a single photograph. Paper presented at the ACM SIGGRAPH 2006 Papers, Boston, Massachusetts.

[8] Shan, Qi, Jia, Jiaya, & Agarwala, Aseem. (2008). High-quality motion deblurring from a single image. Paper presented at the ACM SIGGRAPH 2008 papers, Los Angeles, California.

[9] Hyeoungho, Bae, Fowlkes, C. C., & Chou, P. H. (2013, 15-17 Jan. 2013). Accurate motion deblurring using camera motion tracking and scene depth. Paper presented at the Applications of Computer Vision (WACV), 2013 IEEE Workshop on.

[10] Horstmeyer, Roarke, (2010), Camera Motion Tracking for De-blurring and Identification. MIT Media Lab MAS 863 Final Project.

[11] Jin Feng, Li Tian. Digital image stabilization system based on inertial measurement module [J]. Beijing University of Technology English (English interface), 2013,22 (2): 222 ~ 227

[12] Joshi, Neel, Kang, Sing Bing, Zitnick, C. Lawrence, & Szeliski, Richard. (2010). Image deblurring using inertial measurement sensors. Paper presented at the ACM SIGGRAPH 2010 papers, Los Angeles, California.

[13] Sanketi, Pannag R., & Coughlan, James M. (2010). Anti-blur feedback for visually impaired users of smartphone cameras. Paper presented at the Proceedings of the 12th international ACM SIGACCESS conference on Computers and accessibility, Orlando, Florida, USA.

[14] Ondřej Šindelář and Filip Šroubek. "Image deblurring in smartphone devices using built-in inertial measurement sensors", J. Electron. Imaging. 22(1), 011003 (Feb 04, 2013). ; http://dx.doi.org/10.1117/1.JEI.22.1.011003

[15] T. Oberg, A. Karsznia and K. Oberg, “Basic gait parameters: Reference data for normal subjects, 10–79 years of age,” J. Rehabil. Res. Dev., vol.30 no. 2, pp.210–223, 1993.

[16] Mittal, A., Soundararajan, R. & Bovik, A. C. (2013). Making a "Completely Blind" Image Quality Analyzer. IEEE Signal Process. Lett., 20, 209-212.