Accurate Motion Deblurring using Camera Motion Tracking and Scene Depth

Hyeoungho Bae1*, Charless C. Fowlkes2, and Pai H. Chou1
2. Computer Science Dept. University of California, Irvine * hyeoungb@uci.edu

We live in 3D space

The relative motion of the pixel in the scene is dependent on the depth of the point. Basically, constant-depth assumption is not valid for most of the cases in motion deblurring.

Abstract

In this paper, we propose an estimation algorithm for spatially-variant blur due to camera motion. To estimate the most accurate latent image, we integrated depth sensor (Microsoft Kinect) and IMU sensor with the camera. The joint analysis of the blurry image, IMU data and the depth data provide better recovery of the real camera motion during the course of the exposure. The reconstructed camera trajectory along with the depth map is then used to synthesize a spatially-variant blur kernel to estimate the final latent (non-blurry) image. The results show that our algorithm effectively compensates the motion blur from the original image while taking scene geometry into account.

Basic Idea

We wanted to reconstruct the motion of the camera during the exposure time as accurate as possible by combining several hardware components. The camera motion during the exposure time: Rotation, R; Translation, T; and P is a point that is projected on the image plane.

System configuration

Our motion deblurring system is composed of: DSLR camera (Canon EOS450D), IMU (Analog Devices ADIS16350), Depth sensor (Microsoft Kinect), and Control board (Beagleboard-xm).

Deblurring Algorithm

On top of the DSLR+Kinect mount1, we integrated the IMU and control board. Kinect and the board are controlled by a laptop.

Estimated latent image 1: We showed the blur kernel for each rectangle exposure time as accurate as possible by combining several hardware components.

Deblurring Algorithm

The camera motion is reconstructed by compensating the gravity and drift components from the IMU data. The estimated camera motion is combined with the depth map of the scene to estimate the trajectory of each pixel during the exposure time (or spatially-variant blur kernel).

Latent image is estimated by minimizing the following equation:

\[ \hat{I} = \arg \min_{I} \left[ \| \mathbf{w} - \mathbf{R} \mathbf{k} \|^2 + \gamma \| \mathbf{I} \|^2 \right] \]

Compensating Gravity/Drift

Example of naïve gravity assumption and the problem of naïve gravity assumption: simply averaging the acceleration does not give the right direction of the gravity.

Our solution: we estimate the blur kernel of a small image patch using Bae et al.2's algorithm. Then compare the histogram of the blur kernel estimated from the IMU+depth data to compensate the gravity and drift error.

\[ [dx,dy,da] = \text{argmin} \text{Corr} \left( \text{hist}(k_{true}) - \text{hist}(k_{imu}) \right) \]

Results

Estimated latent image 2: Another blurry image by different motion. Bottom images show the original images in the yellow rectangles (top row) and estimated latent images (bottom row).

Acknowledgement

This material is based upon the work supported by the National Science Foundation under Grant No. 0933694, Air Force Office of Scientific Research under Grant No. FA9550-10-1-0538. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.