Image Reconstruction from DVS
The constant battle agains MATLAB
Student Project Report

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Abstract

// TODO - insert abstract

1. Introduction

// TODO - insert introduction here

2. Related Work

// TODO - insert related work here
-Kim *et al.*
-Scaramuzza
-[4]
-vSLAM?

3. Dynamic Vision Sensors

A Dynamic Vision Sensor (DVS) [4], also known as event camera, is a new kind of camera. In contrast to a standard camera id does not output a complete image of the scene, but a series of events. Hereby, an event is generated when the sensed brightness of a pixel changes more than a certain threshold. This happens for each pixel completely independently from all others.

A DVS has several advantages compared to standard cameras. Since there is no need to gather data from all pixels to generate an image, events can be send with an extremely low latency of 15 μs or less [4, **?**]. For the same reason, there is practically no motion blur in the DVS signal. Another benefit of independent pixels is the very high dynamic range. Blooming or smearing as observed when a bright light source is captured with a standard camera is basically nonexistent. Finally, due to the reduction of the camera signal to changes and the resulting neglect of redundant information, the signal bandwith is much smaller than with a standard camera. All these features make DVS a very desirable sensor for motion tracking, especially for mobile robots where the data has to be analyzed on a constraint hardware.

There are, however, several downsides at the current point in time. First of all, currently available DVS, (DVS128 [4], DAVIS [2]) habe a very limited resolution of 128×128 or 240×180 pixels, respectively. This obviously limits the spacial accuracy of the sensed data, but will likely only be a matter of time until sensors with a higher resolution are developed. A more important point is that the computer vision algorithms that have been developed during the last decades can either not be used at all or have to be adapted to the new data representation.

4. Our Work

// TODO - insert section to explain what we did here
-implemented paper (kim) in matlab
-some simplifications
-use particle filter directly with euler angles (ignore corner cases)
-start with first fov in map

5. Core Algorithm

Similar to most SLAM algorithms, an iteration of our program consists of two steps. In the first step we try to estimate the current orientation based on the camera signal, the map and the last orientation. This is then used to write the new data to the map and reconstruct the grayscale image. The iteration is performed every time an event arrives from the camera. Both the tracking and the rotation work on the assumption that the output of the other one is correct.

5.1. Rotation Tracking

// TODO - insert section about tracking
Assumptions:

- event (change in brightness) is caused by camera rotation or noise, but not by movement in the scene ($\rightarrow$

static scene)

- only rotation, no translation and therefore no parallax displacement
- initial FOV is already known and in the map

5.2. Scene Reconstruction

We use Kalman Filters to reconstruct a gradient map from the noisy DVS signal. These gradients are then used to generate a grayscale image by applying a poisson reconstruction algorithm [1] For each pixel in the output image there is a Kalman Filter that keeps track of the color gradient at the pixel position. The input to the Kalman Filter is the event frequency on a line along the current pixel movement. Hereby it is assumed that the pixel's movement was constant since the last event it triggered. While this is obviously not true all the time, it is a good approximation due to the high rate of events. Note that the pixel movement is not necessarily parallel to the camera movement, e.g. if the camera is rotating around its z-axis. The pixel movement is computed with the same formulas as used in the simulationand the map lookup during tracking. Given a camera orientation, the orientation of the ray through the pixel and the camera's focal point is computed. This is then mapped to a pixel in the output image. While we use the exact position in the output image to compute the pixel movement, we do not, however, interpolate between several pixels when writing the signal to the map, but simply round the position in the output image th the closest pixel. Since we do not write the signal directly but use Kalman Filters to reduce the noise, this simplification greatly reduces the complexity of the algorithm compared to dividing the signals between several filters. The exact formulas used for the Kalman Filters can be seen in [3]. In the current state of our program, we assume that the camera's initial field of view is already known and included in the map. With this assumption we do not have to deal with a special initialization procedure but can immediately start with the standard iteration while being relatively sure that the camera movement is tracked correctly.

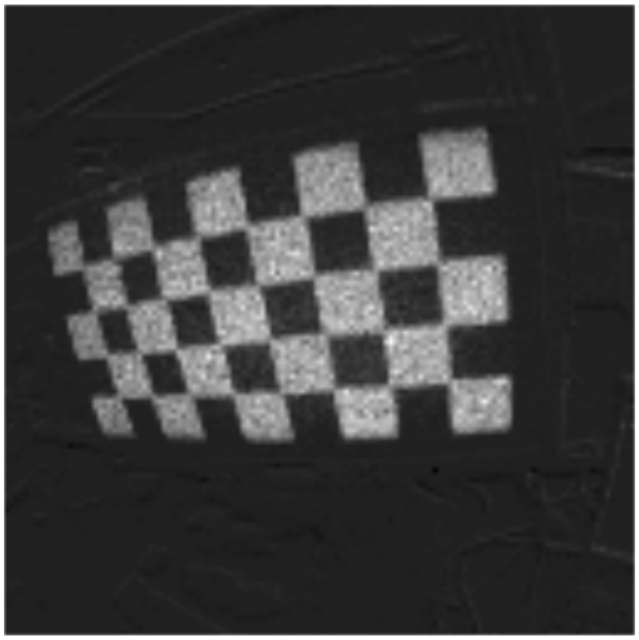
6. Problems

// TODO - insert section about problems
-map initialization
-runtime
$\rightarrow$ couldn't test with camera
-MATLAB

7. Experiments

// TODO - insert section about experiments

- initialization
  - integrate while removing shutter
  - integrate over short interval ($\rightarrow$ outlines)
- camera calibration



7.1. Camera Simulation

// TODO insert section to explain camera simulation

- use image as input
- assume 360 deg view
- compute camera fov for given orientation
- move camera over scene
- sum up differences between patches
- problem: discrete $\rightarrow$ use tiny steps $\rightarrow$ slow

8. Results

References

[1] Matlab code for poisson image reconstruction from image gradients. `http://web.media.mit.edu/~raskar/photo/code.pdf`, 2015. [Online; accessed 07-March-2015].

[2] C. Brandli, R. Berner, M. Yang, S.-C. Liu, and T. Delbruck. A 240 × 180 130 db 3 μs latency global shutter spatiotemporal vision sensor. *Solid-State Circuits, IEEE Journal of*, 49(10):2333–2341, Oct 2014.

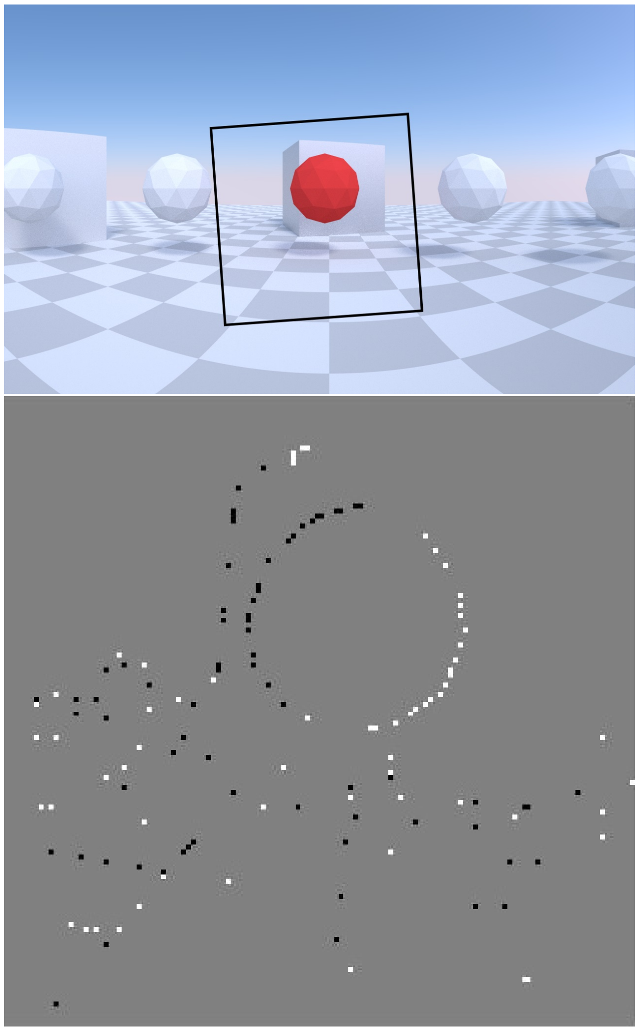


Figure 1. // TODO

[3] H. Kim, A. Handa, R. Benosman, S.-H. Ieng, and A. J. Davison. Simultaneous mosaicing and tracking with an event camera. In *British Machine Vision Conference (BMVC)*. BMVC 2014, 2014.

[4] P. Lichtsteiner, C. Posch, and T. Delbruck. A 128 $\times$ 128 120 db 15 μs latency asynchronous temporal contrast vision sensor. *Solid-State Circuits, IEEE Journal of*, 43(2):566–576, Feb 2008.

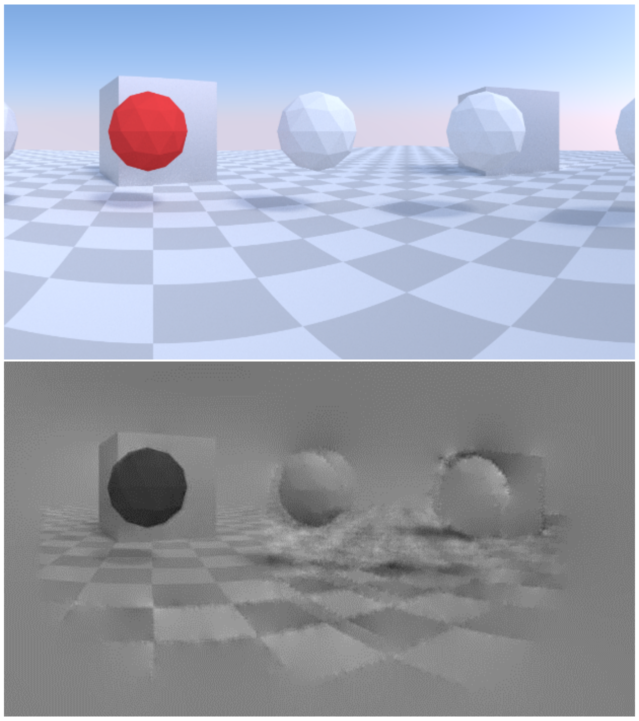


Figure 2. // TODO

Figure 3. // TODO