1 Optical Flow

Note: These notes are very rough. This section has not been covered to an acceptable level.

1.1 Overview

1.1.1 Motivation

- Object segmentation (using motion)
- Structure recognition
- Image alignment
- Feature extraction
- Video compression

1.1.2 Problem definition

- Compute the pixel movement between frames
- Given a pixel at t, look for nearby pixes of the same colour in $t + 1$
- Describe the optical flow, not the motion field (think of a barber's pole)

1.1.3 Assumptions

- Colour constancy: Colour remains constant for a object as it moves
- Small motion: In small time increments (frame) only small motion can occur

1.2 Horne and Shunck

1.2.1 Solve as optimising an error

$$Error(x, y) = (f_x u + f_y v + f_t)^2 + \lambda(u_x^2 + u_y^2 + v_x^2 + Vy^2)$$

Seek to find the minimum of this: the first term corresponds to the OF equation and should be zero for the true OF. The second term represents a 'smoothness' constraint i.e. real objects motion should be smooth.

1.2.2 The Aperture Problem

- If a object is moving, the H and S algorithm can't detect movement of the smooth regions of an object, nor at the edges in the direction parallel to the edge.

1.3 Lucas Kanade Algorithm

- Solves the aperture problem however it fails in areas of large motion
- Solve the failure by computing a pyramid (e.g. successive downsampling and iterative compute)

1.4 FlowNet: Deep Learning Approach

1.4.1 Overview

- OF needs precise per-pixel localisation
- Requires finding correspondance between 2 pixels
- Use a CNN in a sliding window; yet has a problem (compute, per patch nature and ignores global properties)

1.4.2 Architecture

- Two channels
- Two stacked CNN networks: A contracting part takes the input and outputs a small res OF prediction, then an expanding part successively upscales.
- There are U-net like skip connections between each halve.
- Has an update to handle disparity (think left and right eye) and scene flow
- Benchmark on synthetic data