

#### Video Based Mice Seizure Detection

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October 1, 2015

#### Content

- Ideas to discuss
  - Dense optical flow is actually good
  - ▶ What are the shadows in the Eulerian magnified video?
  - Flow Difference

This came out from a discussion with Professor Fábio

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- ► The sparse flow computation will solve a minimization problem
- Even though we are computing flow for a small region, we do send the entire image to the algorithm
- Problem: a point inside the area of interest(small region) may be mapped to a point far a way from its previous known position.

▶ I'm looking for 20 points in a 10 km by 10 km square. At time t, point A is at position (0,0). At time  $t+\Delta t$  I see a point that looks like A, but at position (10,10)km. Because I'm only looking for 20 points and I'm a minimization algorithm, I'll say A moved from (0,0) to (10,10) in  $\Delta t$ .

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- Suppose now that I'm looking for 1 million points inside that same square. At time  $t + \Delta t$  it is very unlikely that anyone moved from (0,0) to (10,10). Thus, I'll discard this possibility and say that point A must be near its previous known position. Even though there's a point at (10,10) that looks exactly like A at the previous time, I'll won't consider it to be A, because it is too far away.

#### The point is

We'll have less noise in optical flow computation if we use a dense grid.

For a fixed pixel (i,j) in the image, plot its intensity value as a discrete function  $I_{i,j}(k)$  in the interval of interest of length T. You'll have  $N = \frac{T}{\Delta T}$  points to plot,  $\Delta T$  being the sampling time

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- ➤ This function can be decomposed into a sum of N sinusoidals inside the interval of interest

$$I_{i,j}(k) = \sum_{L=0}^{N-1} a_n \cos(\frac{2\pi}{N} Lk) + b_n \sin(\frac{2\pi}{N} Lk)$$
 (1)

Or, in complex exponential form

$$I_{(i,j)}(k) = \sum_{L=0}^{N-1} d_n e^{j\frac{2\pi}{N}Lk}$$
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- ▶ The  $d_n$  coefficients can be computed with the discrete Fourrier Transform.
- ▶ Part of Eulerian magnification consists in applying a frequency filter the change de  $d_n$  coefficients as a function of n. The idea is to increase those coefficients so high frequency components are more obviously noted.

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- ▶ In openCV, for example, any value of pixel higher than 255 is set to 255. That is, 255 is the value for the brightest white, and nothing can be set brighter than the brightest white.
- Our new function, after the magnification, is thus:

$$E_{i,j}(k) = \min(\sum_{k=0}^{N-1} G(n) d_n e^{j\frac{2\pi}{N}Lk}, 255)$$
 (2)

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- ► Thus, we correct again:

$$E_{i,j}(k) = \max(0, \min(\sum_{L=0}^{N-1} G(n) d_n e^{j\frac{2\pi}{N}Lk}, 255))$$
 (2)

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- When a mouse(white object) moves from A to B, point A became darker because it no longer hold a white pixel and point B hold now something brighter than previously it did. Due to saturation, A becomes black and B becomes white
- ▶ Ideally, only a pixel belonging to the fastest movement in the video should be mapped to 255.

## Solving shadows

#### Solution

Reduce frequency gain in order to avoid saturation.

This is Fábio's approach to study the seizure

- Our previous idea was that the flow field of a seizure event would have a high frequency component.
- ► The new approach is based on that same assumption, we simply use a different way of looking at it
- ► First we compute the vectorial difference between two consecutive flows. This correspond, in some sense I'm sure, to the spatial second derivative of the image.
- Remember that the laplacian operations corresponds to a high pass filter. We're here looking to the effect of the high frequency components
- We now construct an image with magnitude of the flow difference at each point
- ▶ We take the 2 dimensional Fourrier Transform of this image.

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Vidal says that during seizures, it will be easy do detect high frequency by looking at points of the magnitude spectrum distant from the origin.

My comments on the approach:

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- ► The problem of a sparse grid, is that you'll have a flow difference magnitude image with spikes: it can only be different than zero in points where you actually computer the flow.
- Experimentally(and it reminded me of results in one dimensional FFT, and I'm sure this is can be shown for two dimensional) by running FFT on a 2 dimensional image with spikes here and there, you get a FFT that has spikes over the entire spectrum. I feel it is also periodic.

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- ▶ I have not showed Vidal the results so far. More experiments are required before we can drawn any conclusion.

#### Conclusion

Dr. Vidal is proposed a methodology based on the 2 dimensional fourrier transform of the flow difference. The method is terribly heavy and needs more results so we evaluate if it is worth the trouble.