

# Tracking Eye Motion from Retinal Scan Data with a Map Seeking Circuit

Al Parker

Department of Mathematical Sciences  
Montana State University

November 13, 2004

Joint work with

- Austin Roorda and Scott Stevenson, College of Optometry, University of Houston

- Curt Vogel, Department of Mathematical Sciences, Montana State University

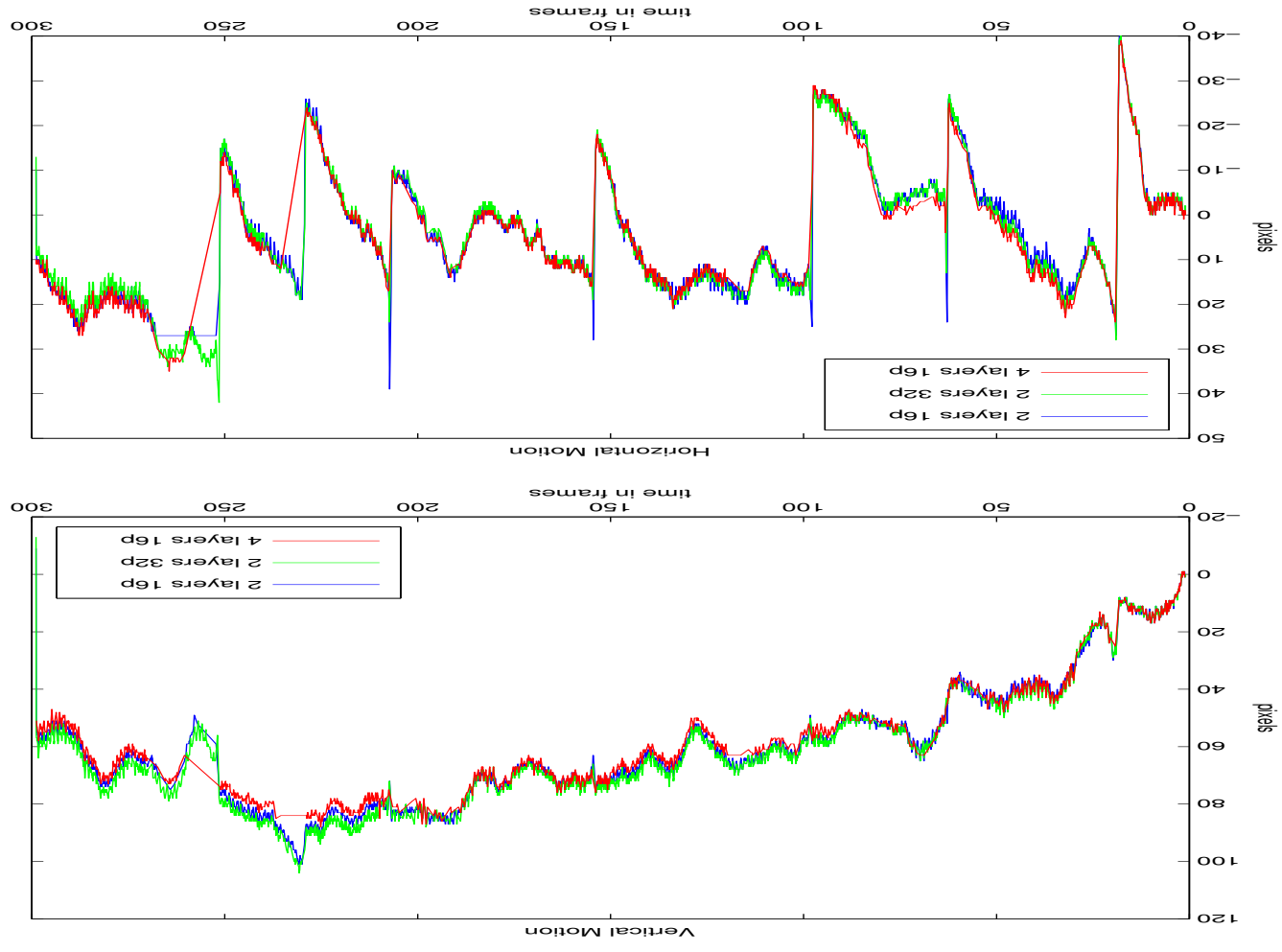
- David Arathorn, Center for Computational Biology, Montana State University

- Tomas Gedeon, Derek Sonderegger and Shaun Harker, MSU Math Dept

## Outline

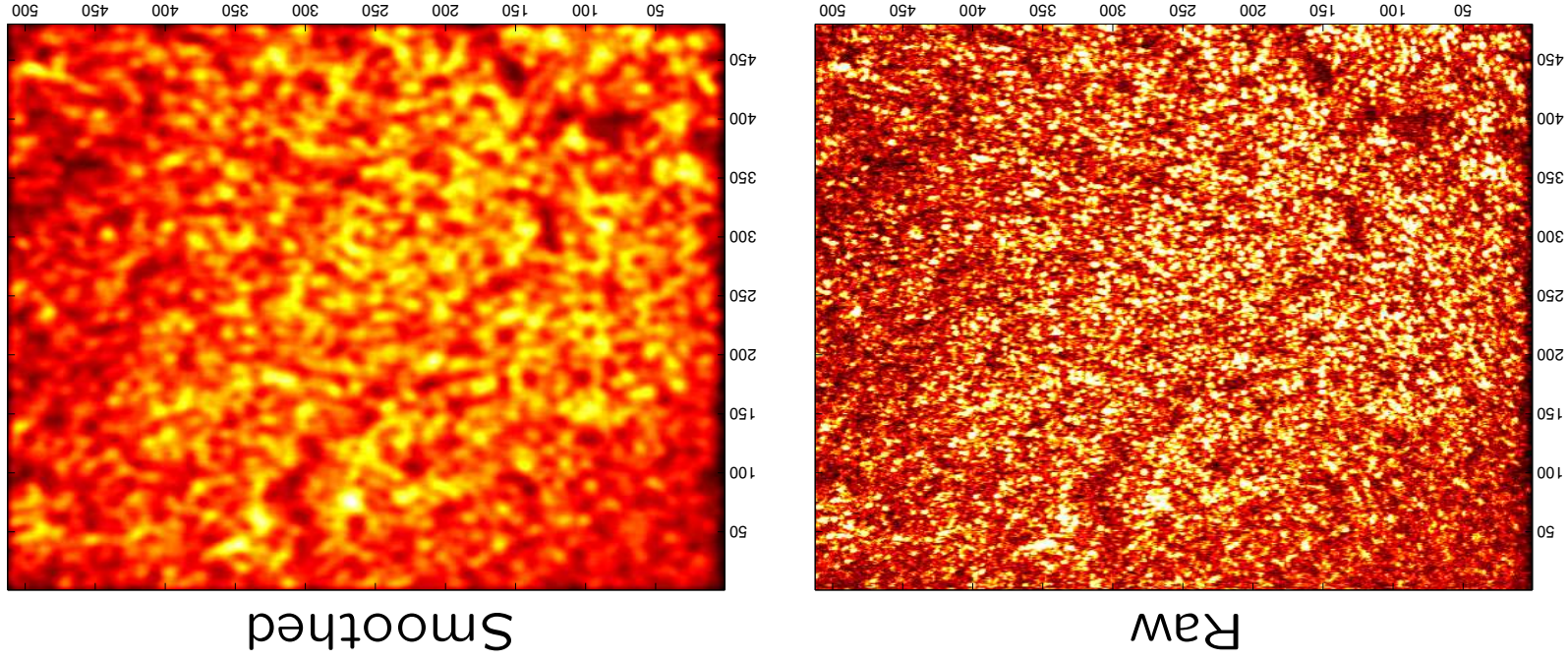
- Show and Tell (Results)
  - Estimating Eye Motion from AOSLO data
  - Image Registration
- The Algorithm which finds the motion: Map-Seeking Circuit (MSC)

# Results: Estimated Motion from AOSLO Data

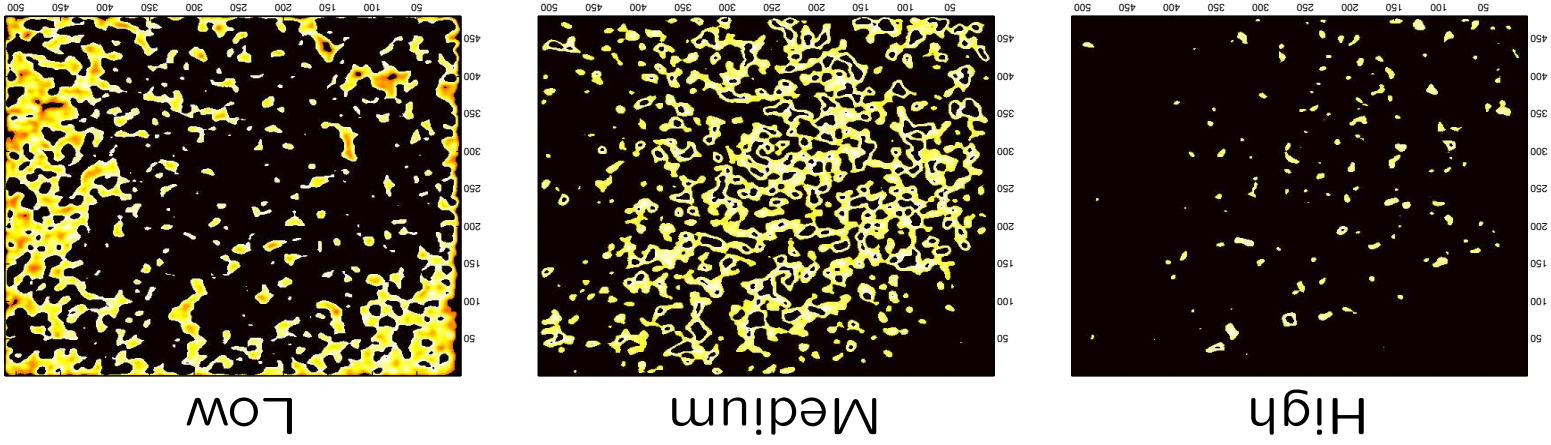


## Image Preprocessing

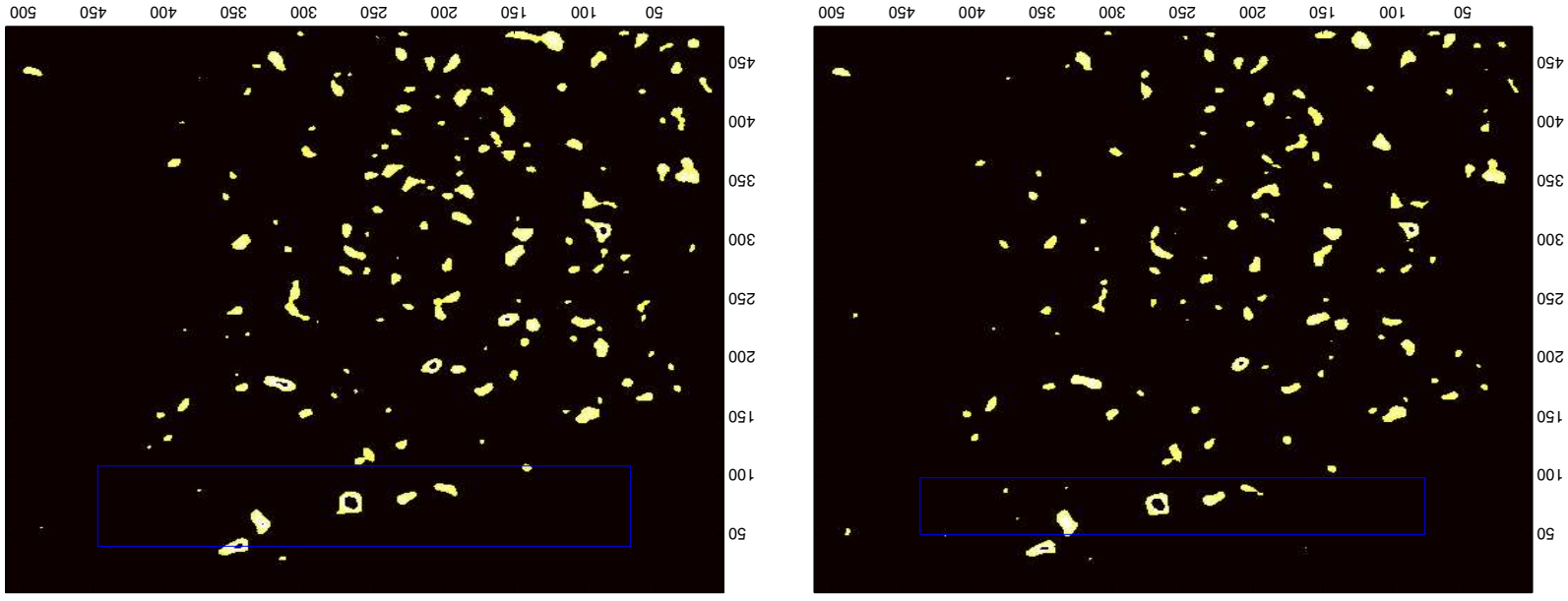
1. Smooth the data with a Gaussian kernel to reduce the effect of noise and amplitude variation.



2. Break the smoothed image into "channels".

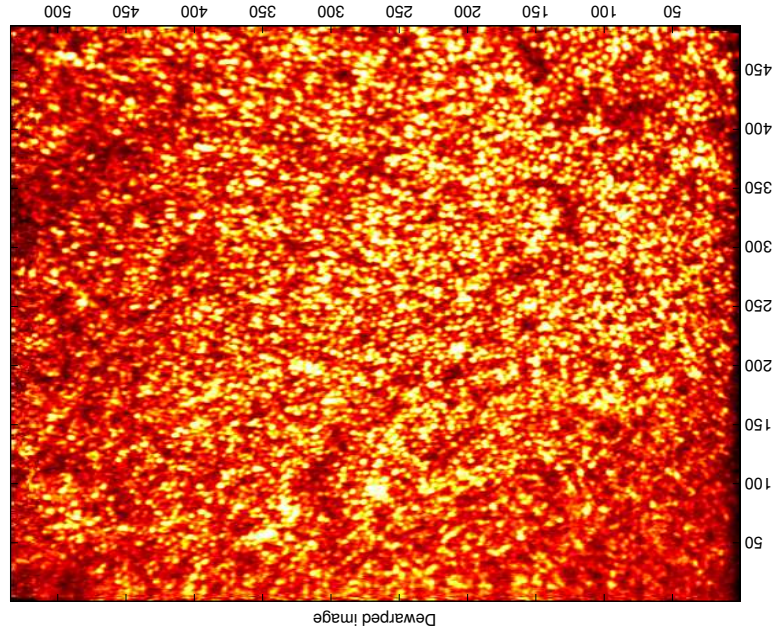


3. Determine the eye motion across "patches".  
This yields HIGH RESOLUTION of the motion: We can calculate 16 - 32 estimates of the motion per frame, which is about 480 - 960 estimates per second.



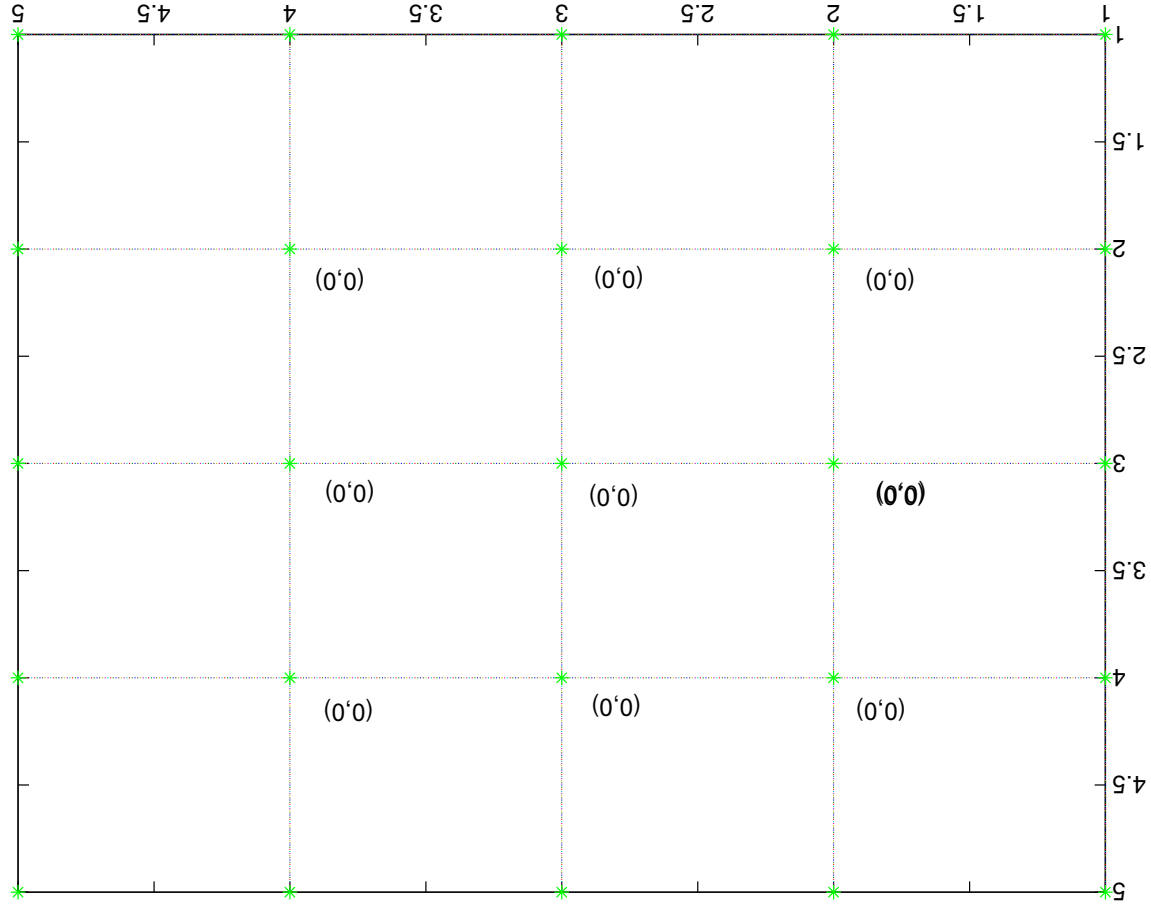
## Image Registration

- Dewarp each frame of the AOSLO video
- Add each dewarped frame to create a mosaic or montage

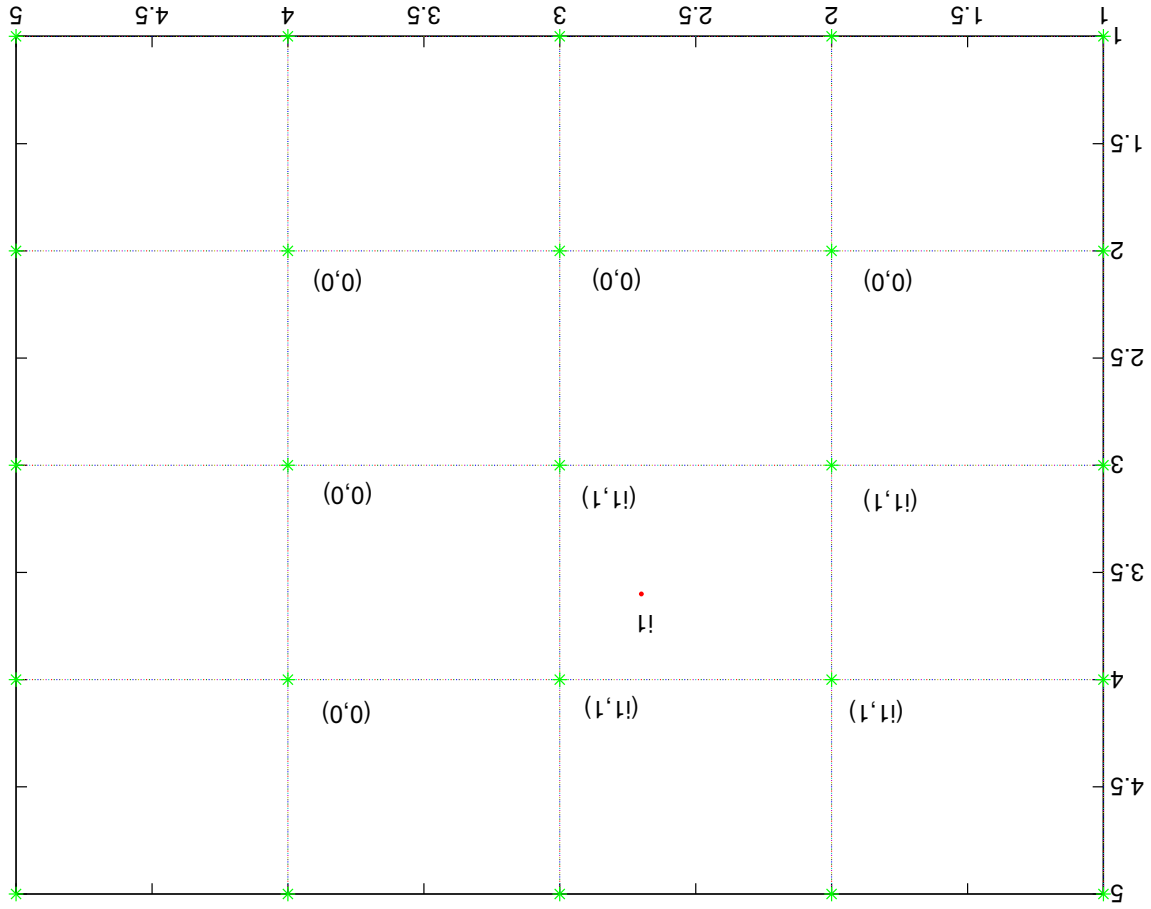




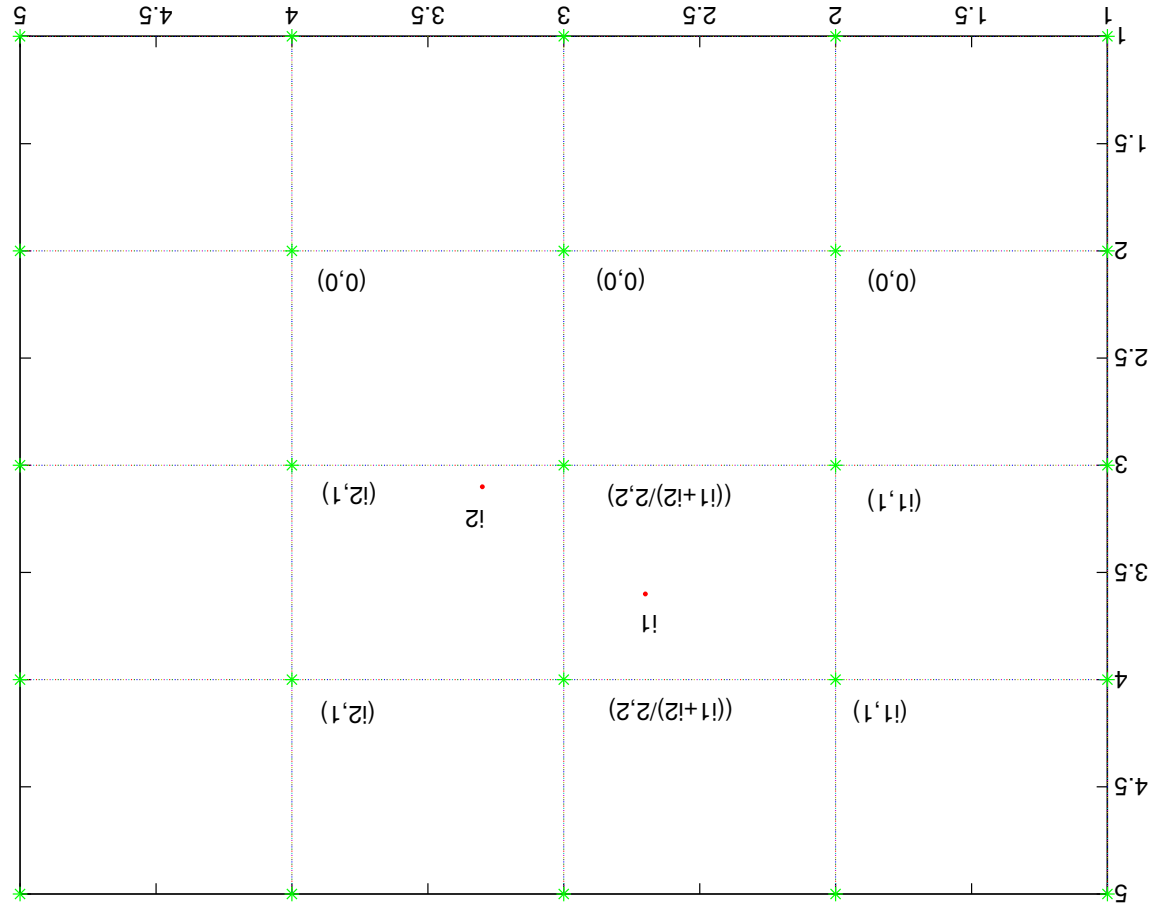
How to add frames: Initialize montage with (intensity=0,weight=0)



How to add frames: Map the first pixel, update the montage



How to add frames: Map the next pixel, update the montage ...



## MAP-SEEKING CIRCUIT ALGORITHM (MSC)

Model images  $E, E'$  as vectors in Hilbert spaces  $\mathcal{H}, \mathcal{H}'$ , respectively. Given transformation  $T : \mathcal{H} \rightarrow \mathcal{H}'$ , define the **correspondence** between  $E$  and  $E'$  associated with the transformation  $T$  to be the inner product

$$\langle T(E), E' \rangle_{\mathcal{H}'}$$

**Goal:** Find  $T$  which **maximizes correspondence** from linear transformations of form

$$T = T_{(T)}^{i_1} \circ \dots \circ T_{(2)}^{i_2} \circ T_{(1)}^{i_1},$$

where for each "layer"  $\ell$  between 1 and  $L$ , we have  $i_\ell \in \{1, 2, \dots, n_\ell\}$ .

For example, we can let  $T_{i_1}$  be some horizontal translation of the image  $E$  and let  $T_{i_2}$  be some vertical translation of the image  $E$ .

ADVANTAGE of MSC over Cross-Correlation: MSC can include other transformations such as rotations, dilations, shear, compression, ...

SYNOPSIS: A Map-Seeking Circuit finds a solution to the discrete optimization problem

$$(\mathcal{I}_*^1, \dots, \mathcal{I}_*^L) = \arg \max_{1 \leq i_1 \leq n_1} \left\langle T_{i_1}^{(1)} \circ T_{i_2}^{(2)} \circ \dots \circ T_{i_L}^{(L)} \right\rangle_{\mathcal{H}}$$

**MSC KEY IDEA** (which makes it fast)

Embed the discrete problem in continuous constrained optimization problem. Maximize multilinear form

$$M(\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(L)}) = \langle T^{(L)\mathbf{x}} \circ \dots \circ T^{(1)\mathbf{x}}(E), E' \rangle_{\mathcal{H}'}$$

where

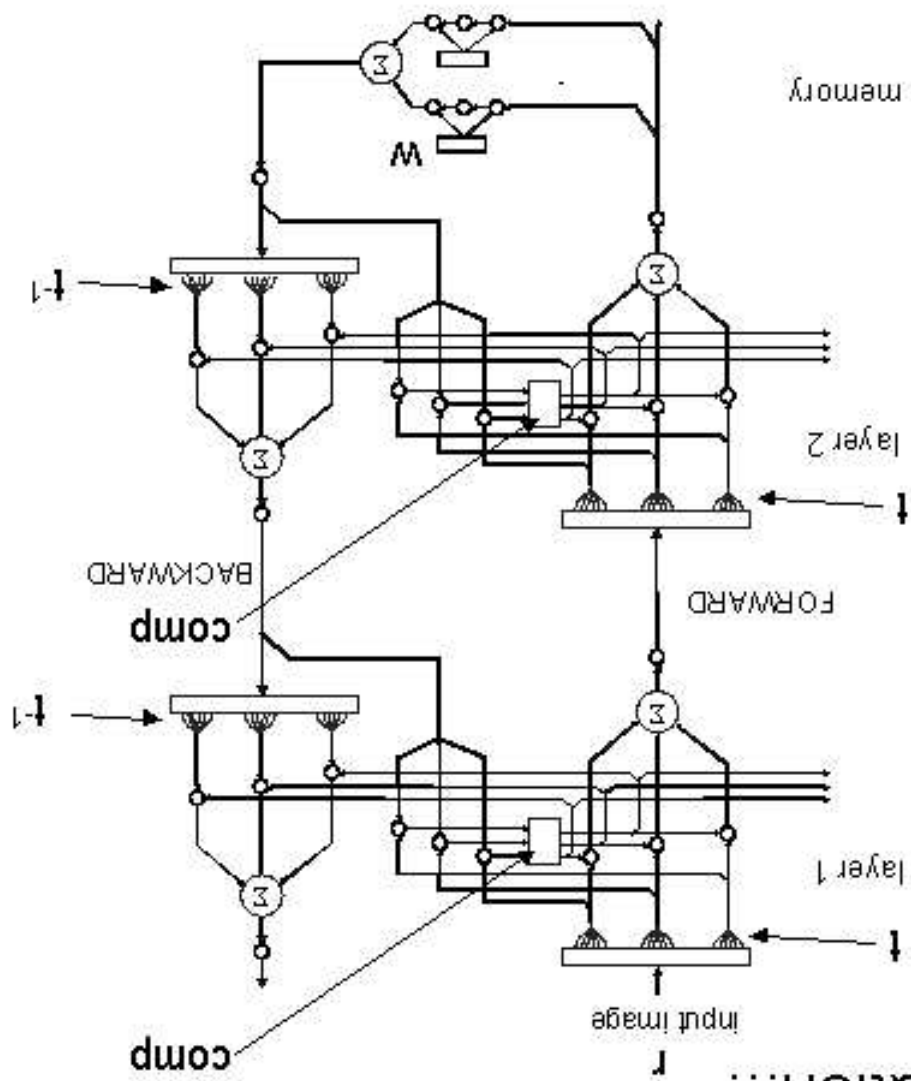
$$T^{(l)\mathbf{x}} = \sum_{n_l=1}^{i_l} T^{(l)\mathbf{x}}_{n_l}$$

**SIMPLIFYING PROPERTY:** Components of gradient of  $M$  can be computed quickly and relatively cheaply via the inner product

$$\langle T^{(l)\mathbf{x}} \circ \dots \circ T^{(l-1)\mathbf{x}} \circ T^{(l+1)\mathbf{x}} \circ \dots \circ T^{(L)\mathbf{x}}(E), E' \rangle_{\mathcal{H}'} = \frac{\partial M}{\partial x^{(l)}} \mathbf{x}^{(l)}$$

where  $T'$  is the adjoint or conjugate transpose of  $T$ .

MSC can be viewed as an iterative algorithm which uses this gradient info to maximize the correspondence.



Implementation...



## COMPUTATIONAL COST

- Computation complexity of each MSC-type iteration is on order of the **sum**

$$n_1 + n_2 + \dots + n_L,$$

where  $n_\ell$  is the number of transformations in layer  $\ell$ , and  $L$  is the number of layers.

- The complexity of an exhaustive search is the **product**

$$n_1 n_2 \dots n_L.$$

Convergence tends to be fast and solutions tend to be robust if the data has a “sparse encoding”. Image data pre-processing can provide such a sparse encoding.

## CONCLUSIONS

Using MSC,

- We can accurately track eye motion from AOSLO videos, even through saccades.
- We can identify very general transformations between AOSLO video frames, including shear and compression.
- Register AOSLO video frames to create a de-noised retinal image