Eye Motion Estimation and Image Dewarping using a Map Seeking Circuit

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March 30, 2006

Joint work with:

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Outline

- Show and Tell (Results)
  - Estimating Eye Motion from AOSLO data
  - Image Dewarping and Registration
- A Map-Seeking Circuit (MSC) estimates the mot

Results: Estimated Motion from AOSLO Data

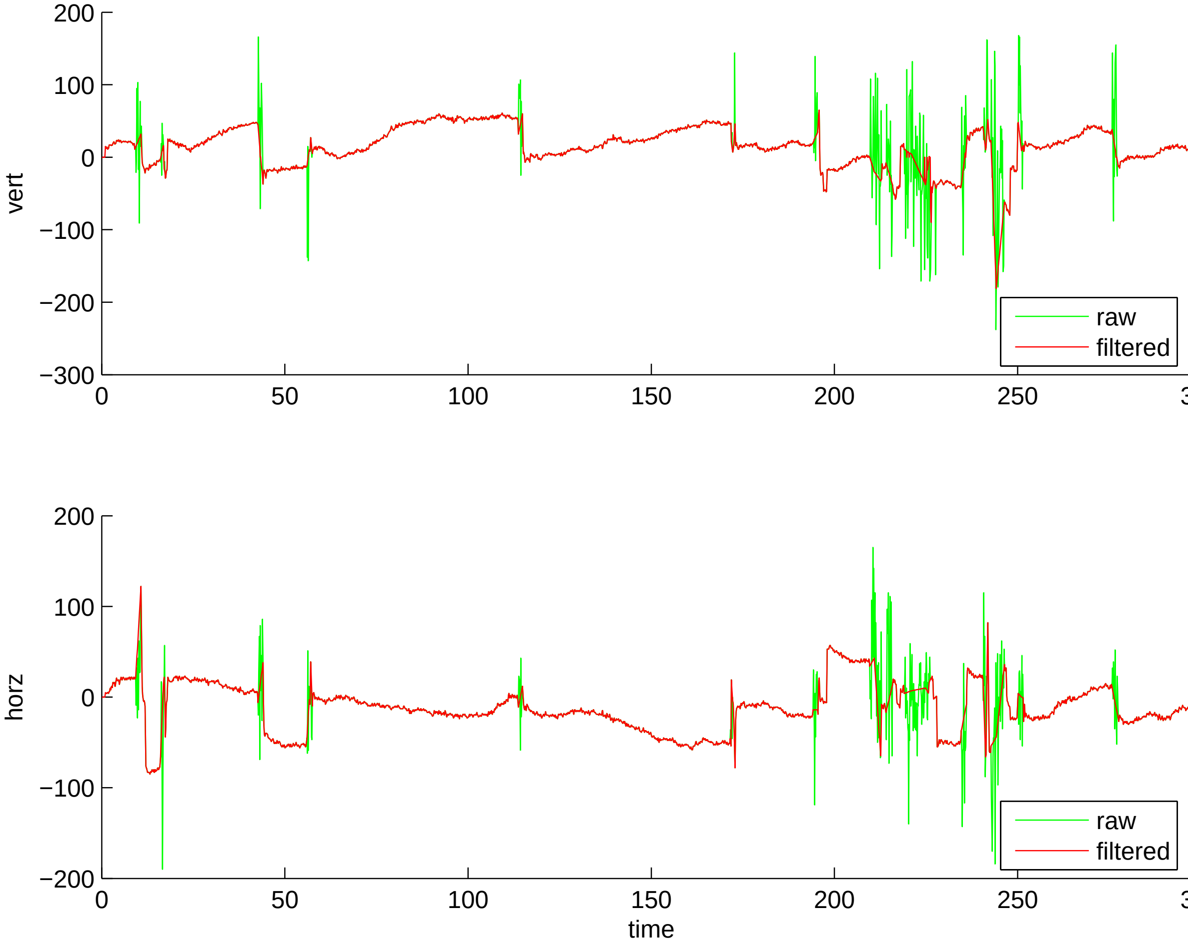
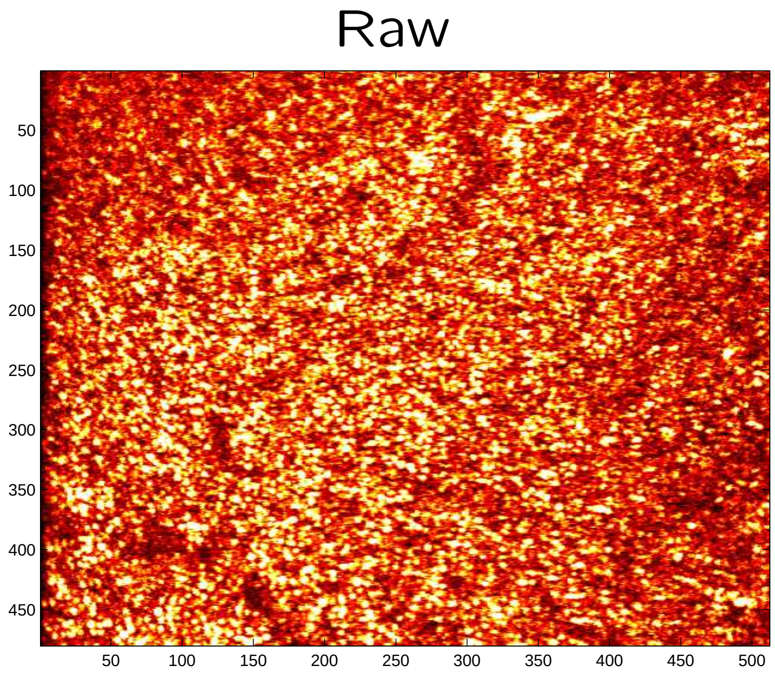
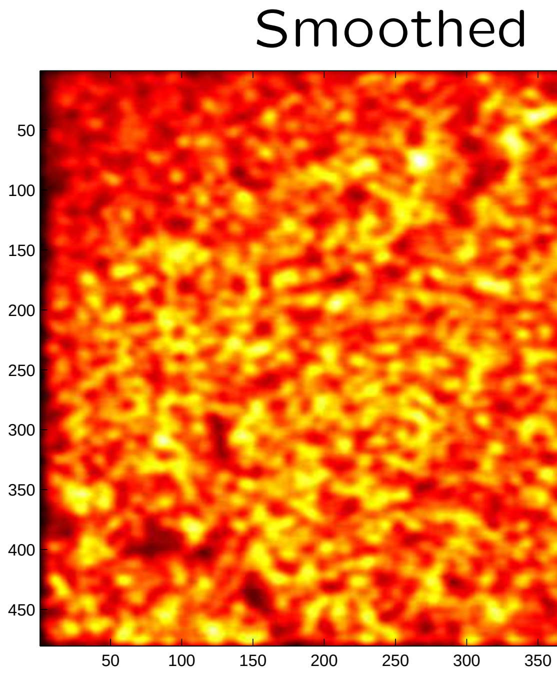


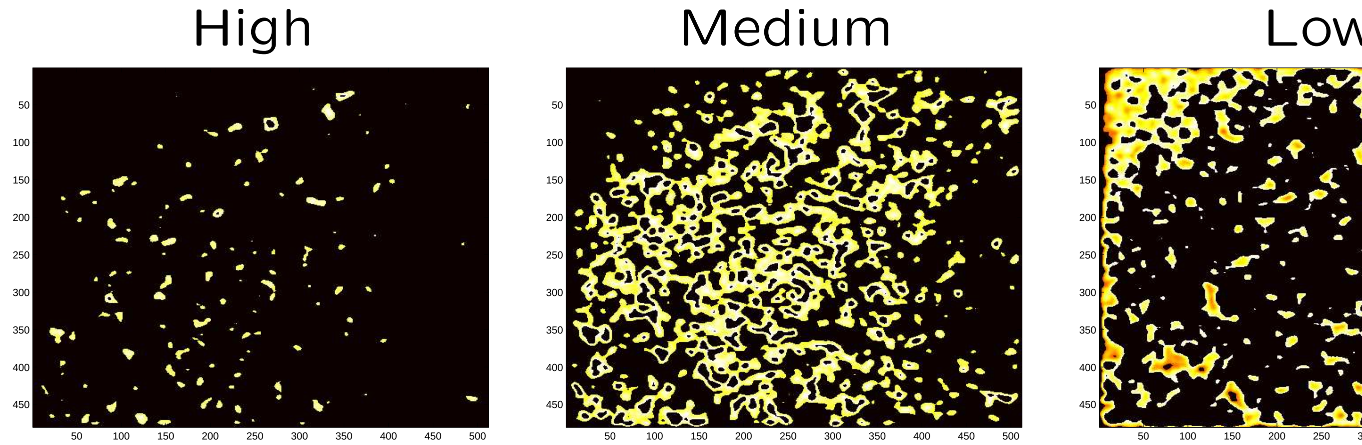
Image Preprocessing

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


Raw


Smoothed

2. Break the smoothed image into one or more “cha


High

Medium

Low

3. Determine the eye motion across “patches”.

We can reliably calculate 16 - 128 motion estimates
which yields 480 - 3840 estimates per second.

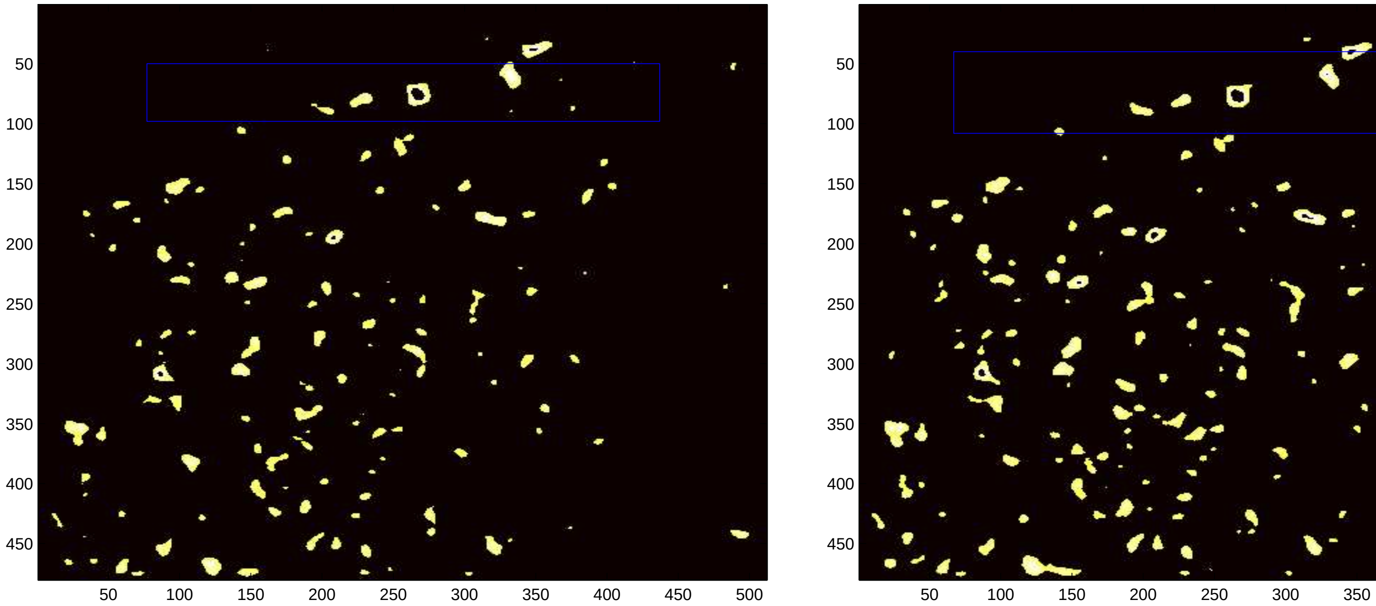


Image Registration

- Dewarp each frame of the AOSLO video
- Add each dewarped frame to create a denoised ret

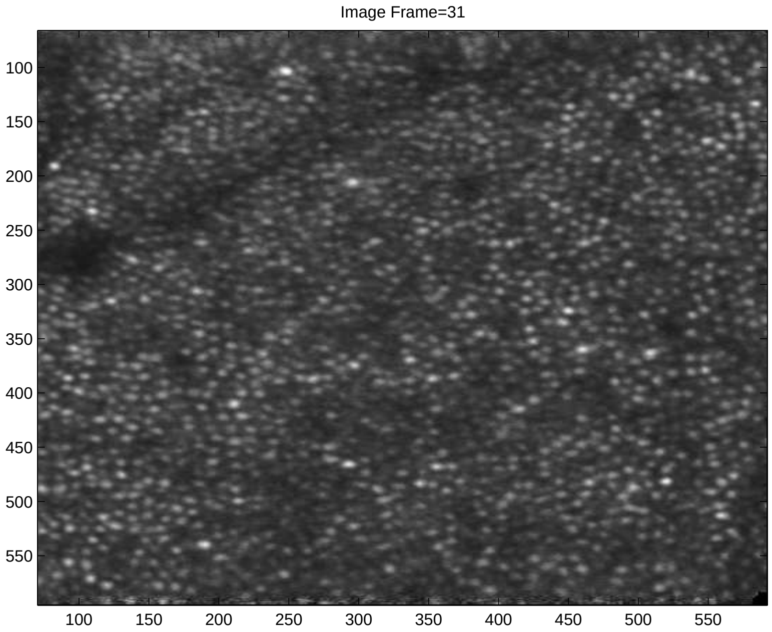
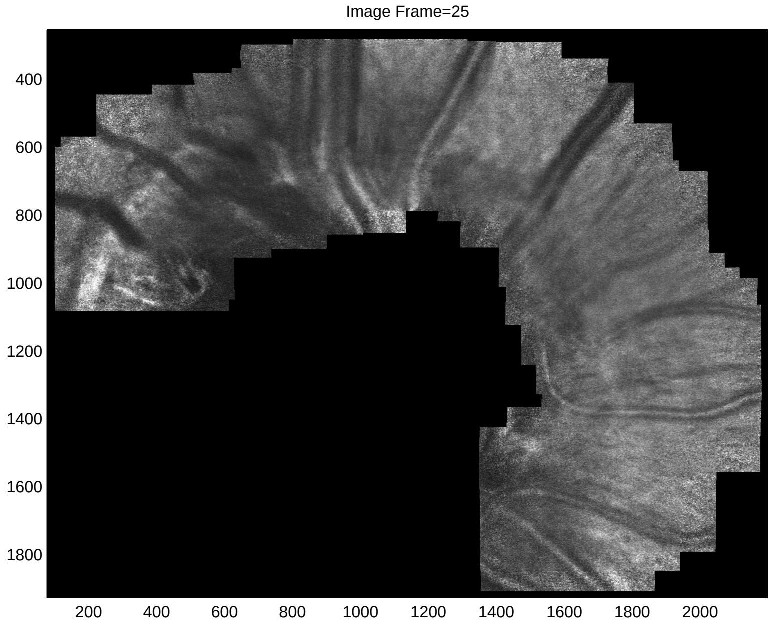


Image Montage

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



MAP-SEEKING CIRCUIT ALGORITHM (MSC)

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

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

Goal: Find T which maximizes correspondence from li
formations of form

$$T = T^{(L)}_{i_L} \circ \cdots \circ T^{(2)}_{i_2} \circ T^{(1)}_{i_1},$$

where for each “layer” ℓ between 1 and L, we have $i_\ell \in$

For example, we can let $T^{(1)}_{i_1}$ be some vertical trans
let $T^{(2)}_{i_2}$ be some horizontal translation of the image

ADVANTAGE of MSC over Cross-Correlation: MSC c
other transformations such as rotations, dilations, sl
pression, ...

SYNOPSIS: A Map-Seeking Circuit finds a solution
crete optimization problem

$$(i_1^*,\ldots,i_L^*) = \text{arg} \max_{1\le i_\ell\le n_\ell} \Big\langle T^{(L)}_{i_L}\circ\cdots\circ T^{(2)}_{i_2}\circ T^{(1)}_{i_1}(E$$

MSC KEY IDEA (which makes it fast)

Imbed the discrete problem in continuous constrained tion problem. Maximize multilinear form

$$M(\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(L)}) \;=\; \langle T_{\mathbf{x}^{(L)}} \circ \cdots \circ T_{\mathbf{x}^{(1)}}(E), E'\rangle$$

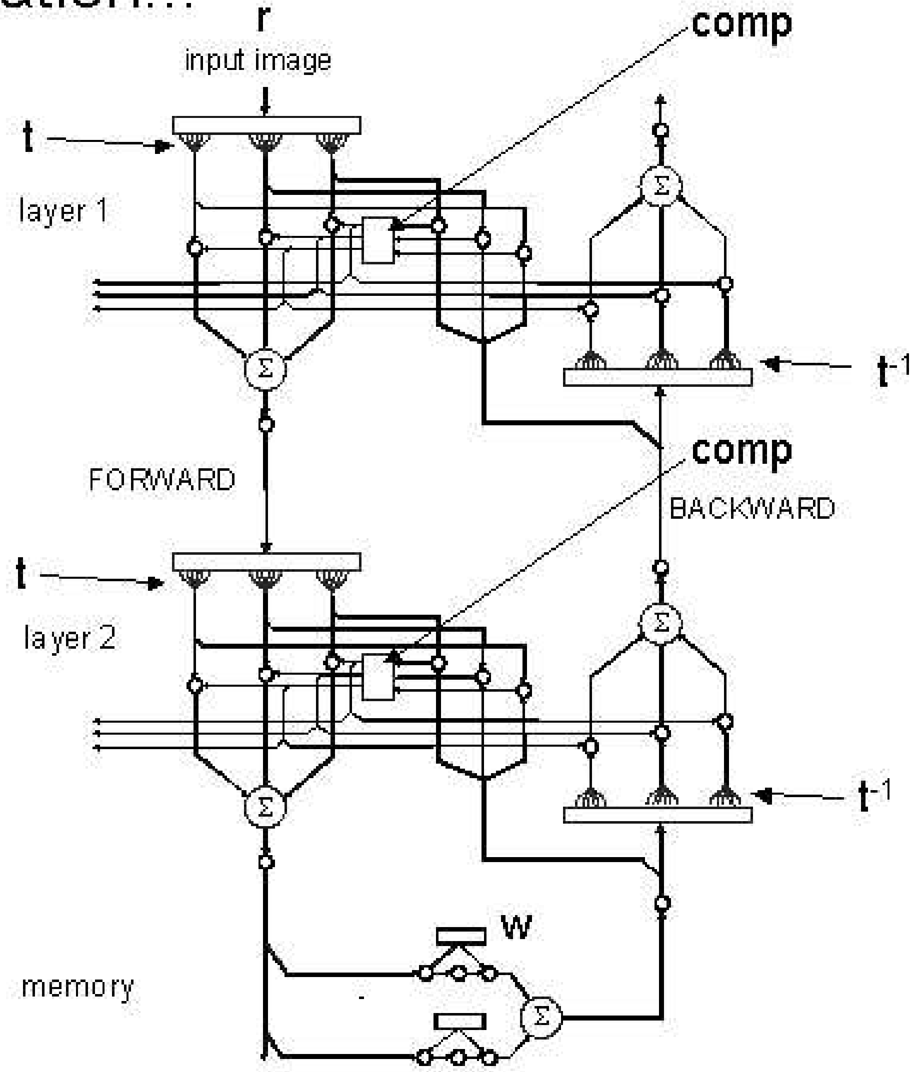
where $T_{\mathbf{x}^{(\ell)}} = \sum_{i=1}^{n_\ell} x_i^{(\ell)} T_i^{(\ell)}$

SIMPLIFYING PROPERTY: Components of $\nabla_{\mathbf{x}} M$ ca puted quickly and relatively cheaply via the inner proc

$$\frac{\partial M}{\partial x_i^{(\ell)}} = \langle T_{i_\ell}^{(\ell)} \circ T_{\mathbf{x}^{(\ell-1)}} \circ \cdots \circ T_{\mathbf{x}^{(1)}}(E), T'_{\mathbf{x}^{(\ell+1)}} \circ \cdots \circ T'_{\mathbf{x}}$$

MSC is an iterative algorithm which uses this gradien cation to maximize the correspondence $\langle T(E), E'\rangle_{\mathcal{H}'}$.

Implementation…



COMPUTATIONAL COST

- Computational complexity of each MSC iteratio
  order of the sum

  $$n_1 + n_2 + \ldots + n_L,$$

  where n_ℓ is the number of transformations in lay
  is the number of layers.

- The complexity of an exhaustive search is the pr

  $$n_1 n_2 \cdots n_L.$$

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

CONCLUSIONS

Using MSC, we can

- Estimate eye motion from AOSLO videos.
- Identify very general transformations between AO
  frames, including translations, rotation, shear an
  sion.
- Register AOSLO video frames to create de-noi
  images and montages