Registration of hyperspectral images of the retina

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Optina Diagnostics

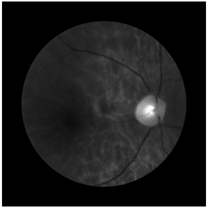
August 10, 2017

Optina diagnostics

Aim: Develop technology to enable early detection of Alzheimers disease.

91 Wavelengths.

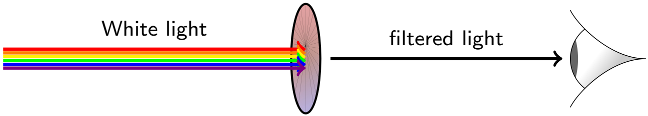
Observe the retina.



[a]

[a] https://isimplifyme.com. Accessed: 10-08-2017. 2014.

The Problem



- The scan produces **91 images** of the retina, for each wavelength.
- The scan takes **1-3 seconds** to complete. In this time the **eye moves** and the blood vessels **deform**.

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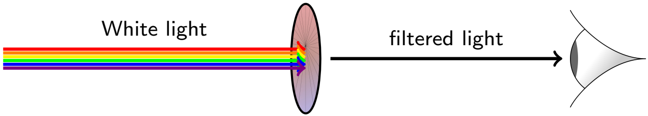

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Undo the transformation of the retinal images to get comparable images for each wavelength.

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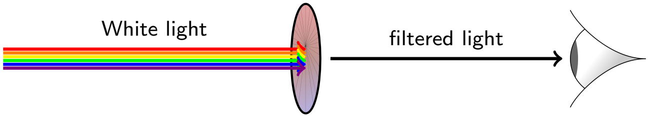

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Problem 1:
Undo the transformation of the retinal images to get comparable images for each wavelength.

Problem 2:
Quantify the accuracy of the corrected images.

Additional Details- Problem 1

- The problem requires **image registration**. Seeking a transformation which aligns one image with another.
- The curved geometry of the eye and the blood vessel deformations result in a non-Euclidean transformation.

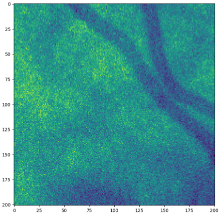

Figure: Section of the eye over different wavelengths

The **intensity** of the images change with wavelength.

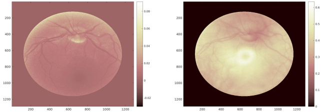

Figure: Intensity Variation between two different wavelengths

The images exhibit non-Gaussian noise from the camera.

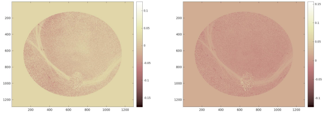

Figure: Noise on a synthetic eye

Literature Review

- Registration of retinal images has been well studied, and there are a number of established techniques.

[1] Charles V Stewart, Chia-Ling Tsai, and Badrinath Roysam. "The dual-bootstrap iterative closest point algorithm with application to retinal image registration". In: *IEEE transactions on medical imaging* 22.11 (2003), pp. 1379–1394.

[2] Lauri Laaksonen et al. "Comparison of image registration methods for composing spectral retinal images". In: *Biomedical Signal Processing and Control* 36 (2017), pp. 234–245.

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- Registration of retinal images has been well studied, and there are a number of established techniques.
- **Local similarities**
  - An intensity-based approach, deforming a grid of points to maximise local similarity.
  - Measures similarity via Correlation Coefficient, Mutual Information, SSD, SAD, etc.
- **Demons**
  - Deforms the source image onto the target by imagining the former as diffusing through membranes (i.e. contours) of the latter, under the influence of Maxwell's demons.

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  - Deforms the source image onto the target by imagining the former as diffusing through membranes (i.e. contours) of the latter, under the influence of Maxwell's demons.
- **Generalized dual-bootstrap iterative closest point**[1]
  - Identifies an initial small "bootstrap" region aligns this region in the source with the target. Gradually increases the size of the bootstrap region, refining the transformation.
- **Comparison of methods**
  - Laaksonen found that Demon methods were inferior to the others, and that the dual-bootstrap method was best. Local similarity methods performed OK.[2]

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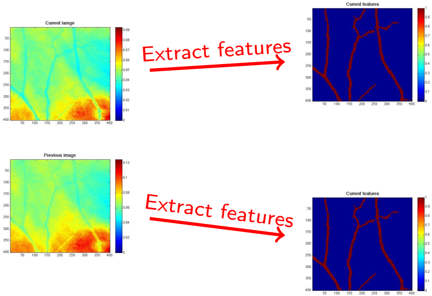
Feature Extraction

The **differences in intensity** make it difficult to compare detailed images.
It is therefore useful to extract the key **features** of the image and compare these.
Optina Diagnostics provided a good feature extraction code.

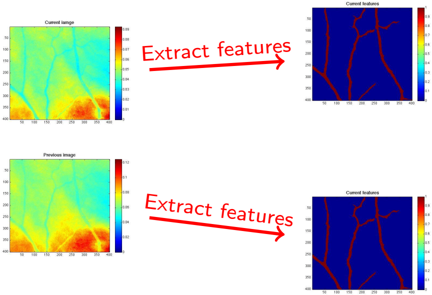
Method Outline

- Extract the features from the detailed image.



Method Outline

- Extract the features from the detailed image.
- **Feature tracking:** fix the key features of the image and their corresponding features in the second image.



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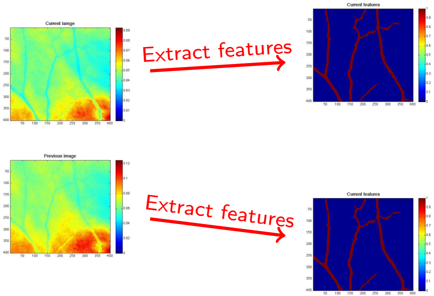

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- Extract the features from the detailed image.
- **Feature tracking:** fix the key features of the image and their corresponding features in the second image.
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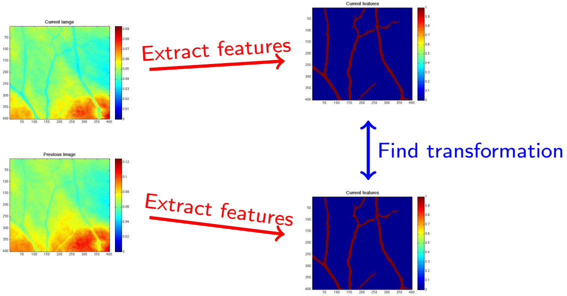
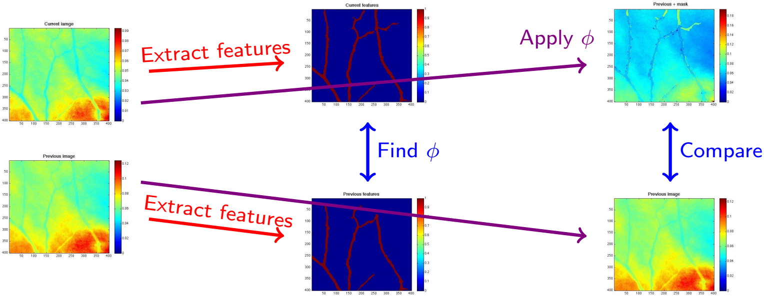


Method Outline

- Extract the features from the detailed image.
- **Feature tracking:** fix the key features of the image and their corresponding features in the second image.
- **Find the transformation** ϕ such that ϕ minimises an objective function $J(\phi)$. Where J is the ℓ^2 between the first feature image and the transformed feature image.
- Compare the registered images.



Variational Approach

Optimisating to find the parameters of a Möbius transformation which minimises the ℓ^2-norm.

Möbius Transformation

$$z \to z + \frac{az + b}{cz + 1}$$

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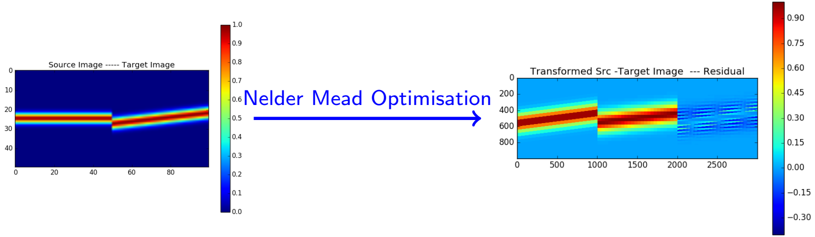
Applied to a test image



Variational Approach

Optimisating to find the parameters of a **Möbius transformation** which minimises the ℓ^2-norm on the residual.

Applied to a **feature image.**

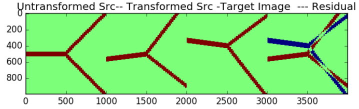


Figure: Fit by Eye

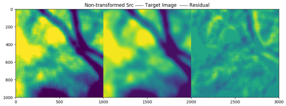


Figure: Source and Target images after smoothing

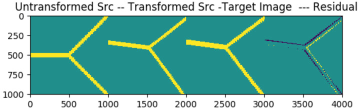


Figure: Nelder Mead Optimisation

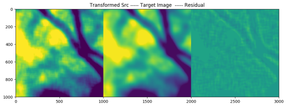
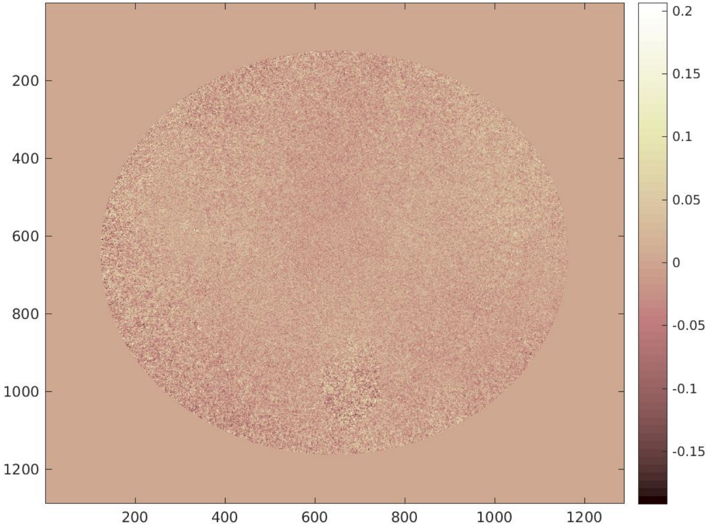


Figure: Optimisation of the transformation on the smoothed images

Observed noise on the phantom



Details and Challenges

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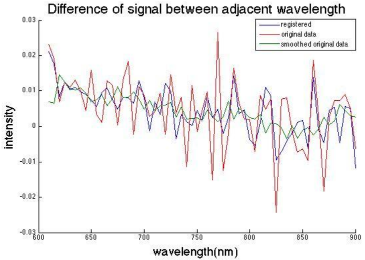
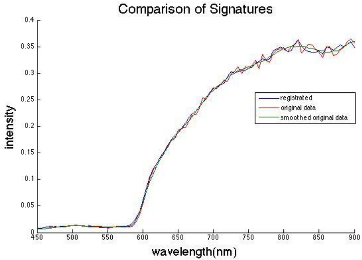
- Features are considered instead of intensity since the intensities have a complicated variation dependent on wavelength.
  - An attempt was made to correct this by normalising about the average intensity but a **non-Gaussian noise** was observed in the images.
  - Evaluating on a phantom eye showed the noise was still apparent. The "rotation" of the noise makes this difficult to model.
- Pairwise comparison of images may lead to accumulating error.

Problem 2: Quality Criterion

- To evaluate the output of the methods in problem 1 it is useful to **quantify the accuracy of the registration**.
- The objective functions in the optimisation (e.g. ℓ^2 or H^1) gives a measure of the error. This error can be low even for low quality registration so further criteria is desired.
- A possible idea is to use spectral criterion, for example the smoothness of the signature.





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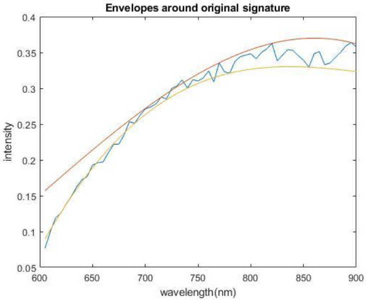
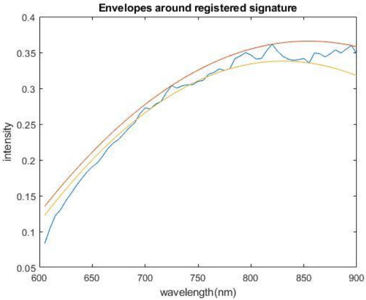




Other Approaches

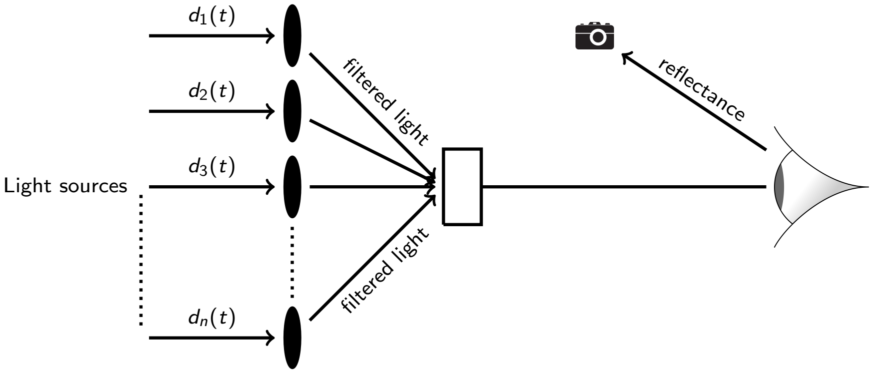
Other approaches to the problem

Adapted Multi-image Registration

To solve this we pick one of our images, I_0, to be a **reference image**. We then seek a set of transformations $\Theta = (\theta_1, ..., \theta_{91})$ where θ_n is a registration of I_n with I_0. We find this by minimising:

$$\mathcal{E}(\Theta) = \sum_{m=1}^{91} p_{m,0} ||\theta_m(I_m) - I_0||^2 \quad + \sum_{(m,n)\in\mathcal{N}} p_{m,n} ||\theta_m(I_m) - \theta_n(\phi_{m,n}(I_m))||^2$$

Hardware Modifications



Optimal Transport

- Consider two (successive) images I_1 and I_2 defined on $\Omega \subset \mathbb{R}^2$.
- Introduce densities $f, g : \Omega \to [0, 1]$ where $f(x_{ij})$ denotes the intensity of I_1 at pixel x_{ij} (and the same for g and I_2).
- Consider the loss function

$$c : (x, y) \in \Omega \times \Omega \mapsto c(x, y) \in \mathbb{R}_+$$

encoding the "energy" needed to **transport** $f(x)$ to $g(y)$. Typically: the euclidian L^2 or the Sobolev H^1 norm.

The aim : solve the problem

$$T \in \min_{\mathcal{M}} \mathcal{J}(T), \quad \text{where} \quad \mathcal{J}(T) = \frac{1}{2} \int_{\mathbb{R}^2} |x - T(x)|^2 f(x) dx.$$

The search space $\mathcal{M}$ is the set of maps of the form $T \sharp f = g$.

Optimal Transport

- The optimal map T is the gradient of some convex potential,i.e. $T = \nabla\Psi$ where $\Psi \in \mathcal{C}^2$ and convex. [Brenier - Only L^2-norm].
- **Monge-Ampère equation**

$$g(\nabla\Psi(x))\det(\nabla^2\Psi) = f(x), \quad \forall x \in \mathbb{R}^2. \tag{1}$$

- Numerically solve this non linear PDE (Newton solver, etc).

Perspectives

- Understand and model the noise: improve preprocessing of the image.
- Divide the optimisation into sub-optimisation problems.
  - Region segmentation into mesh.
  - Circular region increasing.

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Thank you, Questions?