





## An Experimental Evaluation of the Accuracy of Keypoints-based Retinal Image Registration

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#### Introduction

**REMPE** Registration framework

- **FIRE Dataset**
- Evaluation

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## What is image registration?

Image registration involves a pair of images: reference and test.

It consists on transforming the **test** image so both images are aligned in the **reference** image **frame**.

This is done by utilizing the **common information** in both images.

Retinal image registration consists on the registration of **retinal images**.









## Why is it important?

#### Analyzing **small vessels** promotes **diagnosis** and **disease monitoring**

The **retina** allows to **directly** observe the microvasculature of the eye

Comparative **analysis** is **facilitated** by retinal image **registration** 

Additionally, registration supports a range of applications









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## REMPE framework

**Geometrical** approach

Simultaneously estimate relative camera pose and eye shape and orientation

Project points from hypothetical cameras to an eye model

**Distance** of points in model should be **0** 

Solution is represented via 12 parameters, divided in 4 groups:

- **R:**  $[r_x, r_y, r_z]$
- **t:**  $[t_x, t_y, t_z]$
- **A:** [*a*, *b*, *c*]
- **Q:**  $[r_a, r_b, r_c]$









#### REMPE framework









## Keypoints









## Keypoints

Keypoints are used to identify common points in the pair of images

Four types of keypoints and their combinations are studied

- **SIFT** [Lowe 2004]: milestone method in extracting characteristic points in images.
- **SURF** [Bay 2008]: is another widely used method to detect and represent keypoints.
- Harris-PIIFD [Chen 2010]: Partial Intensity Invariant Feature Detector on Harris corners. Developed specifically for retinal image registration.
- **Vessel bifurcations**: Bifurcations on the vessel tree are extracted.







## Eye model









Eye model

Two eye models are utilized:

- Sphere [Navarro 1985]: Simplest full eye approximation.
  - A = [a, b, c] = [12, 12, 12]
  - $Q = [r_a, r_b, r_c] = [0, 0, 0]$
  - Only {R, t} are calculated (6 parameters)
- Ellipsoid: The most complex model used.
  - $A = [a, b, c] = [\rho_a, \rho_b, \rho_c]$
  - $Q = [r_a, r_b, r_c] = [\theta_a, \theta_b, \theta_c]$
  - {R, t, A, Q} are calculated (12 parameters)











#### Swarm structure









#### Swarm structure

Initialization:

 Random Sample Consensus (RANSAC) [Fischler 1981]: Estimates the 3D pose of an object given a set of 2D-3D correspondences and the camera projection matrix. Spherical eye model

Optimization

- Attempt to minimize objective function. Sum of the 80% shortest distances of the corresponding points on the eye model
- We look for the solution on a search space with 12 dimensions. 1 for each solution parameter.
- Particle Swarm Optimization (PSO) [Kennedy 1995]:
  - Particles are given random initial position and velocity in the space.
  - Each particle represents a candidate solution (objective function evaluation)
  - Particles evolve through generations.
  - Requires few configuration parameters and no derivatives



$$p(S_h) = \sum_j |q_j - p_{j,h}|$$







#### Multiple swarms









## Multiple swarms

Both RANSAC and PSO non-deterministic

The solution search is executed **multiple parallel** times, denoted as **swarms** 

The parameters of the **best overall** score in the objective function are **selected** as the solution.

This leads to an **increase** on the computational **cost**, but this solution offers **increased accuracy**, **robustness** and **reliability**.









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## Retinal image datasets

Plenty of retinal image datasets for diverse purposes

- Segmentation: CHASEDB1, DRIONS-DB, Drishti-GS, DRIVE, HRF, MESSIDOR, ONHSD and REVIEW
- Diagnosis: DIARETDB0, DIARETDB1, e-ophtha, INSPIRE-AVR, ROC, STARE and VICAVR
- User authentication: VARIA
- Retinal image registration: RODREP

Hard to find datasets suitable for retinal image registration:

- Most datasets have **no image pairs for the same eye**
- No datasets with ground truth to evaluate registration

	Images	FOV	Resolution	Pairs	Large overlap	Small overlap	Anatomical differences	Ground truth
e-ophtha	463	45°	2544x1696	144	Yes	Yes	No	No
RODREP	1120	45°	2000x1312	1400	Yes	Yes	No	No
VARIA	233	20 <sup>o</sup>	768x584	154	Yes	No	No	No







#### FIRE dataset

#### **Fundus Image Registration Dataset:**

- 129 real retinal images acquired with a fundus camera
- 134 image pairs
- 3 categories
- Some image pairs with **anatomical differences**
- Evaluation via manually annotated control points

	Images	FOV	Resolution	Pairs	Large overlap	Small overlap	Anatomical differences	Ground truth
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VARIA	233	20 <sup>0</sup>	768x584	154	Yes	No	No	No
FIRE	129	45°	2912x2912	134	Yes	Yes	Yes	Yes







## S category

- S is for "Similar"
- 71 image pairs
- Significant overlap
- No anatomic changes
- A lot of potential information to use for registration
- Least challenging category for registration
- Image pairs can be used for super resolution









## P category

P is for "Pose difference"

49 image pairs

Minor overlap

No anatomic changes

Little potential information to use for registration

More challenging than previous category

Image pairs can be used for creating mosaics of the retina









## A category

A is for "Anatomic difference"

14 image pairs

Significant overlap

Anatomic changes

Corresponding points may look different due to retinopathy

More challenging than S category

Image pairs can be used for longitudinal studies











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#### Keypoint evaluation









## Competing methods

Method is compared to the previous iteration of the current framework [Hernandez-Matas 2016], as well as GDB-ICP and Harris-PIIFD, which are widely applied in the field.

**Generalized Dual-Bootstrap Iterative Closest Point (GDB-ICP)** [Yang 2007]: a local registration method in the spatial domain that performs quadratic registration of intra- and cross-modal retinal images. Face and corner points are used to iteratively register the image pair.

**Harris-PIIFD** [Chen 2010]: a local registration method in the spatial domain that performs quadratic registration of intra- and cross-modal retinal images. Corner points are selected and PIIFD are extracted. An adaptive transformation is used to register the image pairs.







#### Competing methods



Method	S	Р	Α	FIRE
H-M'17	0.958	0.541	0.660	0.773
H-M'16	0.945	0.443	0.577	0.721
Harris-PIIFD	0.900	0.090	0.443	0.553
GDB-ICP	0.814	0.303	0.303	0.576







#### Registration results S









#### Registration results P









#### Registration results A









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#### Downloads

## REMPE Registration executable <u>http://www.ics.forth.gr/cvrl/rempe</u>

#### FIRE dataset http://www.ics.forth.gr/cvrl/fire







# Thank you for your attention!