# Supplementary Material for "Semi-Supervised Keypoint Detector and Descriptor for Retinal Image Matching"

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In this supplementary material, we provide more details of our evaluation, which are not included in the paper due to space limit.

**Qualitative comparison between detector-based methods**. Fig. 1 shows that GLAMpoints and R2D2 tend to detect keypoints in non-vascular areas which are not discriminative for retinal image matching. By contrast, the keypoints found by SuperRetina are mostly distributed along the vascular tree, thus more suited for retinal image matching.

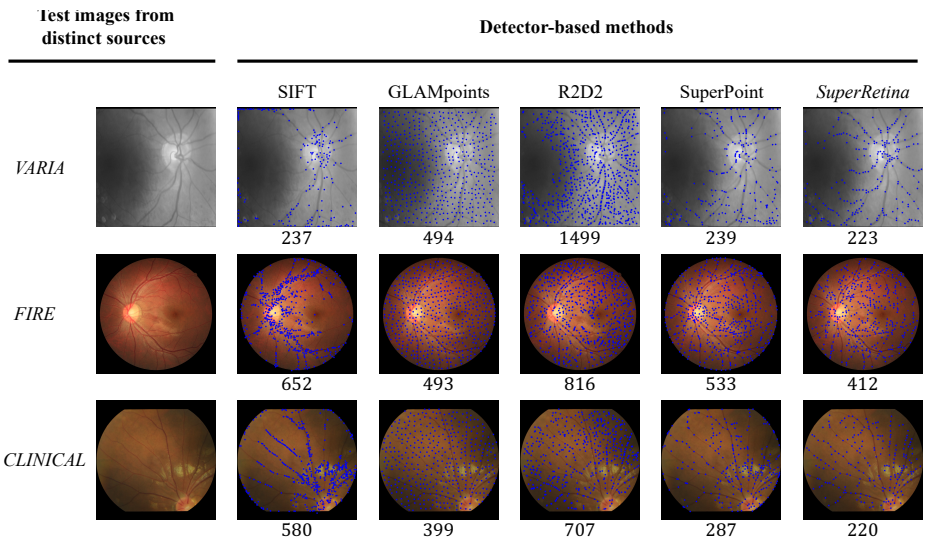
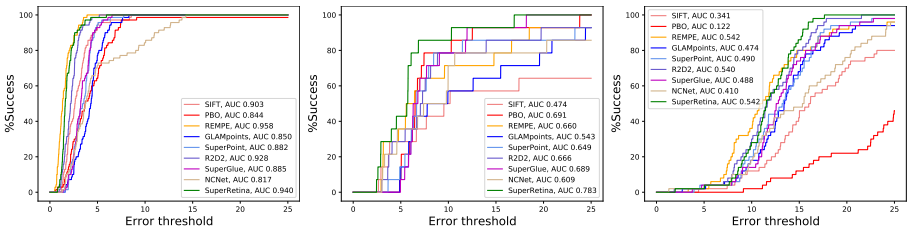



Fig. 1: **Detected keypoints in retinal images from distinct data sources**, *i.e.* VARIA [3], FIRE [2] and CLINICAL, a private dataset collected in clinical scenarios by this paper. Numbers below each image are the amount of keypoints found by a specific method. The proposed SuperRetina detects keypoints that spread over the field-of-view and in the meantime fall on the vascular tree.

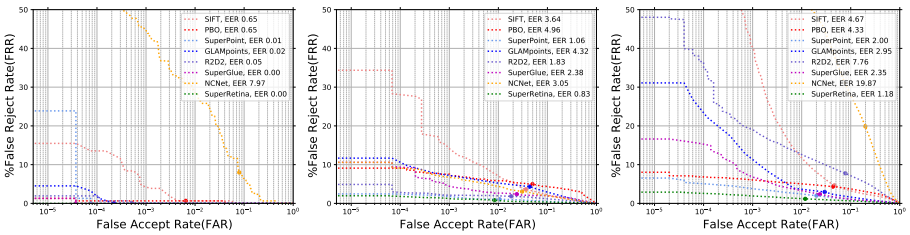
**Performance curves of different methods for retinal image registration**. Fig. 2 shows performance curves of the registration successful rate w.r.t. the error threshold at varied levels in three distinct modes, *i.e.* *Easy*, *Moderate* and *Hard*. We plot the curves using the source code kindly provided by the developers of the FIRE dataset [1, 2] via personal correspondence.




(a) Easy mode (b) Moderate mode (c) Hard mode

Fig. 2: **Performance curves of the image registration successful rate w.r.t. the error threshold**. A curve closer to the top left corner is better. The overall performance is measured by the Area Under the Curve (AUC) scores.

**DET graphs of different methods for retina-based identity verification**. Fig. 3 shows the Detection Error Tradeoff (DET) graphs for the identity verification task.




(a) VARIA (b) CLINICAL (c) BES

Fig. 3: **Detection Error Tradeoff (DET) graphs on three test sets (a) VARIA, (b) CLINICAL and (c) BES for identity verification**. The equal error rate (EER) point per DET graph is shown in solid dots. Lower EER [%] is better.

**Pseudo-code of using a trained SuperRetina model for retinal image matching**. The use of SuperRetina for RIM mentioned in Section 3.3 can be written in just a few lines of Python-style code, see Algorithm 1.

**Other features (lesion / optic disc) for RIM**? We do not consider lesions and optic disc. While lesions are stable in a specific examination session, they can

**Algorithm 1:** SuperRetina for multi-task RIM

```
# q, r: query and reference images
# thresh: acceptance threshold

# Detect and describe keypoints
P_q, D_q = SuperRetina(q)
P_r, D_r = SuperRetina(r)
# NMS to get keypoints
Kp_q = NMS(P_q)
Kp_r = NMS(P_r)
# Sample descriptions
desc_q = sample_desc(D_q, Kp_q)
desc_r = sample_desc(D_r, Kp_r)
# Keypoint match using Brute-force matcher
matches = bfMatch(desc_q, desc_r)
if len(matches) < 4:
   reject and exit  # matching failed
# Compute H for image registration
H = findHomography(Kp_q, Kp_r, matches, cv.LMEDS)
# Remove outlier matches for identity verification
matches = remove_outliers(matches, H)
accept = (len(matches) >= thresh)
```

be unstable across sessions, e.g., reduced after proper treatment or growing due to disease progress. Lesions are not eye-specific, and thus unsuited for identity verification. Moreover, unlike vascular keypoints, labeling lesions requires retinal expertise, making them nontrivial to obtain [4]. The optic disc is not eye-specific also. Moreover, for retinal images of the posterior pole (FoV of 45°), the optic disc possesses a relatively small percentage of the FoV area (1/36), making it less significant for matching. That said, our method is generic and can in principle be used to detect other features by instantiating $Y_0$ with keypoints related to those features.

## References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