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Multi-Frame Super-Resolution with Quality Self-Assessment for Retinal Fundus Videos

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Background

Fundus video cameras enable the **non-invasive acquisition of fast temporal changes** on the human retina. The low spatial resolution limits their diagnostic applicability.

Contribution: Reconstruction of high-resolution retinal fundus images from low-resolution, low-cost video data by means of **multi-frame super-resolution** to enhance diagnostic usability.

Problem Statement

Generative image model: Each frame $\boldsymbol{y}^{(k)}$ for $k = 1, \ldots, K$ is a low-resolution observation of the high-resolution image $\boldsymbol{x}$:

$$\begin{aligned}\boldsymbol{y}^{(k)} &= \boldsymbol{\gamma}_m^{(k)} \odot \boldsymbol{D}\boldsymbol{B}^{(k)}\boldsymbol{M}^{(k)}\boldsymbol{x} + \gamma_a^{(k)}\mathbf{1} + \boldsymbol{\epsilon}^{(k)} \\ &= \boldsymbol{\gamma}_m^{(k)} \odot \boldsymbol{W}^{(k)}\boldsymbol{x} + \gamma_a^{(k)}\mathbf{1} + \boldsymbol{\epsilon}^{(k)}\end{aligned}$$

- Eye motion modeled by geometric transformation $\boldsymbol{M}^{(k)}$
- Point spread function (PSF) $\boldsymbol{B}^{(k)}$, subsampling $\boldsymbol{D}$, noise $\boldsymbol{\epsilon}^{(k)}$
- Inhomogeneous illumination modeled by $\boldsymbol{\gamma}_m^{(k)}$ and $\gamma_a^{(k)}$

Objective: Given a sequence of K low-resolution frames $\boldsymbol{y}^{(1)}, \ldots, \boldsymbol{y}^{(K)}$, reconstruct unknown high-resolution image $\boldsymbol{x}$

Proposed Super-Resolution Framework

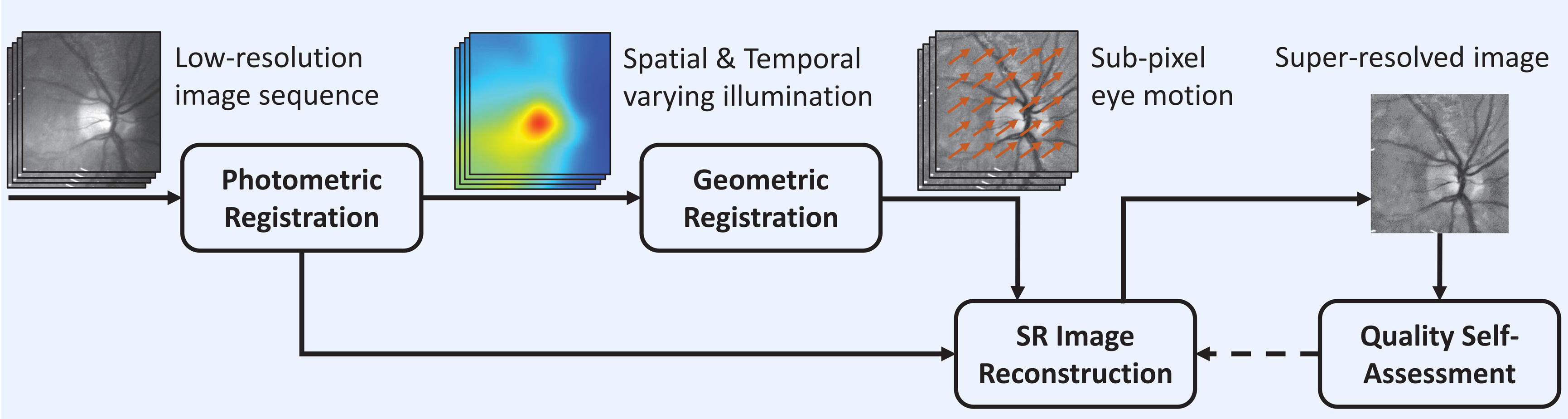


Figure 1: Flowchart of the proposed multi-frame super-resolution framework.

1. **Photometric and geometric registration** for each low-resolution frame $k = 2, \ldots, K$ using $k = 1$ as reference:
   - Estimate photometric parameter $\boldsymbol{\gamma}_m^{(k)}$ using B-spline approximation [1] of the bias field and $\gamma_a^{(k)}$ by the median temporal brightness difference
   - Small, natural eye motion is modeled by $\boldsymbol{M}^{(k)}$ and subpixel motion is estimated by affine registration [2]
2. **Super-resolution image reconstruction:**

   $$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \left\{ \sum_{k=1}^{K} \left\| \boldsymbol{y}^{(k)} - \boldsymbol{\gamma}_m^{(k)} \odot \boldsymbol{W}^{(k)}\boldsymbol{x} - \gamma_a^{(k)}\mathbf{1} \right\|_1 + \lambda R(\boldsymbol{x}) \right\}$$

   $R(\boldsymbol{x})$ is an edge preserving regularizer weighted by λ
   $\rightarrow$ Iterative scaled conjugate gradient (SCG) optimization
3. **Image quality self-assessment:**
   - Quality metric $Q_v(\boldsymbol{x})$ for anisotropic patches $\boldsymbol{p}_i \in \mathcal{P}(\boldsymbol{x})$:

     $$Q_v(\boldsymbol{x}) = \sum_{\boldsymbol{p}_i \in \mathcal{P}(\boldsymbol{x})} \sigma_i \cdot q(\boldsymbol{p}_i)$$

     Local quality score $q(\boldsymbol{p}_i)$ adaptively weighted by local variance σ_i estimated from of the vesselness in $\boldsymbol{p}_i$ [3]
   - Automatic selection of regularization weight λ:

     $$\hat{\lambda} = \arg\max_{\lambda} Q_v(\boldsymbol{x}_\lambda)$$

     $\boldsymbol{x}_\lambda$: super-resolved image reconstructed with weight λ
     $\rightarrow$ Joint super-resolution and parameter selection

Experiments and Results

1. **Experiments for synthetic fundus images:**
   - Ground truth images taken from the DRIVE database
   - Simulation: random translations for eye motion, blurring by a Gaussian PSF, subsampling and Gaussian noise
   - Super-resolution: $K = 16$ frames for $2\times$ magnification

   Evaluation of the peak-signal-to-noise ratio (PSNR) and influence of super-resolution to blood vessel segmentation:

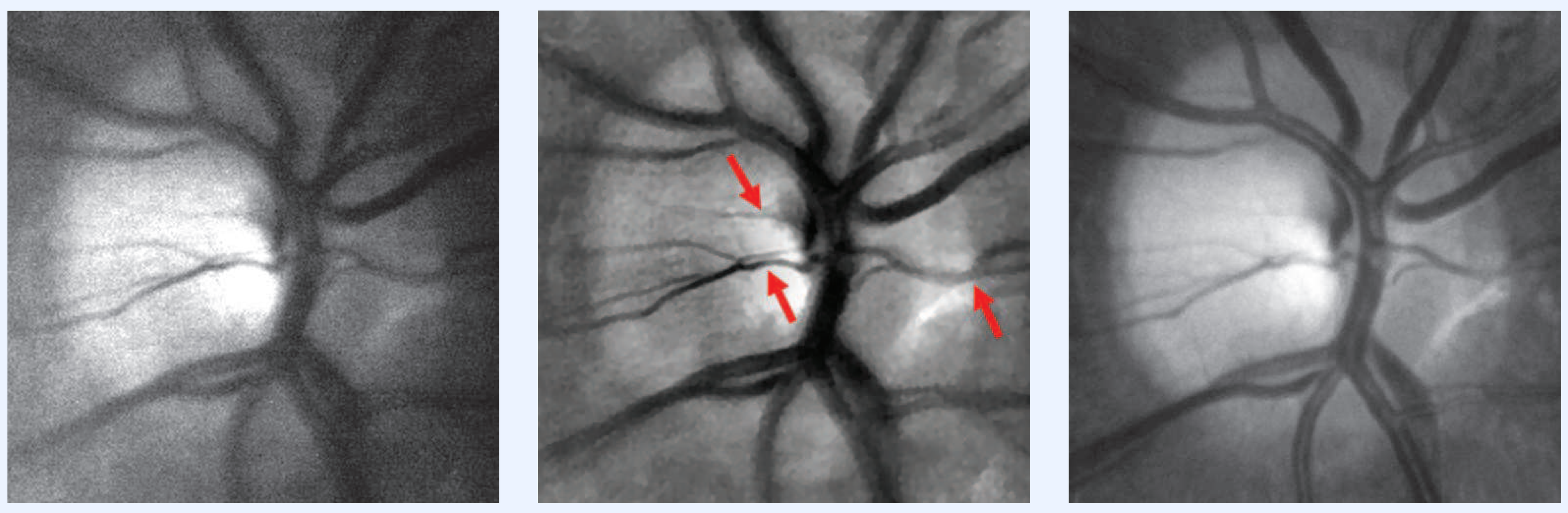
	LR frame	SR image	Ground truth
PSNR (in dB)	31.09 $\pm$ 3.10	**31.92 $\pm$ 3.39**	-
Sensitivity (%)	57.59 $\pm$ 6.01	**70.37 $\pm$ 5.00**	72.85 $\pm$ 6.70
Specificity (%)	94.31 $\pm$ 1.40	**93.99 $\pm$ 1.26**	94.57 $\pm$ 1.34

Figure 2: Peak-signal-to-noise ratio (PSNR) for synthetic images generated from the DRIVE database as well as sensitivity and specificity for automatic vessel segmentation.

   Super-resolution enhanced mean PSNR by 0.8 dB and sensitivity for automatic vessel segmentation by 13 %

2. **Experiments for low-cost fundus video camera:**
   - Videos of 6 healthy subjects ($\approx$ 15 s video per subject)
   - System parameters: CCD camera (640$\times$480 px), 20° field of view (FOV), 12.5 Hz frame rate
   - Super-resolution: $K = 8$ frames for $2\times$ magnification

   Comparison of super-resolved video data to high-resolution Kowa NonMyd images (1600$\times$1216 px, 25° FOV):



(a) Original (low-resolution) frame (b) Super-resolved image (c) Kowa NonMyd image

Figure 3: Low-resolution and super-resolved image (magnification factor: 2) of the optic nerve head in comparison to a high-resolution image acquired with a Kowa NonMyd camera (images contrast enhanced for visual comparison).

   Q_v measure improved by 160 % w.r.t. to low-resolution data (compared to 86 % for temporal median filtering)

Conclusion

Novel super-resolution framework for fundus video imaging:

- **Geometric and photometric registration** to model eye motion and inhomogeneous illumination
- **Image quality self-assessment** for automatic selection of regularization parameter
- Quality of **super-resolved low-cost images** comparable to a high-resolution Kowa NonMyd camera

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References

[1] Radim Kolar, Jan Odstrcilik, Jiri Jan, and Vratislav Harabis. Illumination Correction and Contrast Equalization in Colour Fundus Images. In *Proceedings EUSIPCO 2011*, pages 298–302, 2011.

[2] Georgios D. Evangelidis and Emmanouil Z. Psarakis. Parametric image alignment using enhanced correlation coefficient maximization. *IEEE Transactions on Pattern Analysis Machine Intelligence*, 30(10):1858–65, 2008.

[3] Thomas Köhler, Attila Budai, Martin F. Kraus, Jan Odstrcilik, Georg Michelson, and Joachim Hornegger. Automatic no-reference quality assessment for retinal fundus images using vessel segmentation. In *Proceedings CBMS 2013*, pages 95–100, 2013.