Quality Guided Image Denoising for Low-Cost Fundus Imaging

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Quality Guided Denoising Method

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Summary and Conclusion

Introduction – Denoising for (Low-cost) Fundus Imaging

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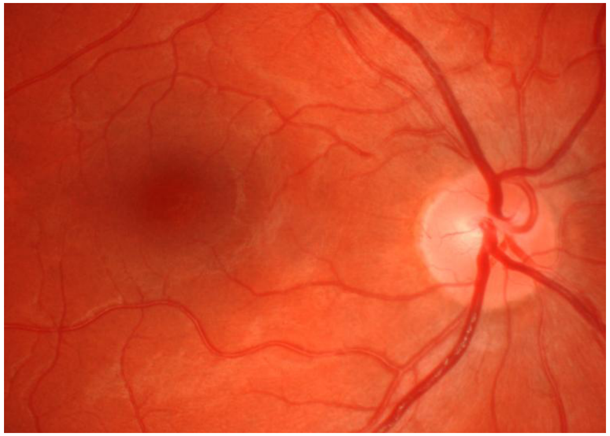
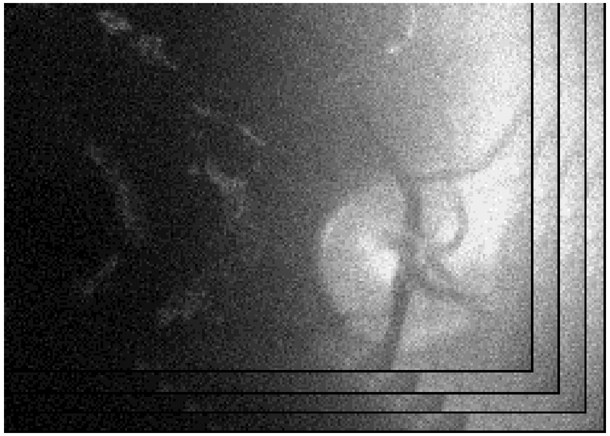
Motivation

- Fundus imaging: modality to capture the human eye fundus
  - High-resolution color image, low noise level
  - Expensive and not mobile

- **Our goal:** low-cost camera system
  - Cheap and mobile
  - Problems: low-resolution grey-scale images, illumination artifacts, **poor noise conditions**
  - Capture **image sequences**

$\Rightarrow$ Denoising as initial preprocessing





Denoising Methods – Overview

- Single-frame denoising: e. g. edge preserving filtering per frame
- Multi-frame denoising: single denoised image from noisy image sequence
  - (Adaptive) frame averaging
  - More robust estimators: temporal median, temporal RANSAC
  - Wavelet multi-frame[1]

Our method: adaptive and incremental averaging

- Average of captured frames $\Rightarrow$ runtime efficient
- Incremental scheme $\Rightarrow$ memory efficient for real-time application
- Adaptive to image quality $\Rightarrow$ weighting of input frames

[1] **Mayer et al., Wavelet denoising of multiframe optical coherence tomography data, Biomedical Optics Express, 2012**

Quality Guided Denoising Method

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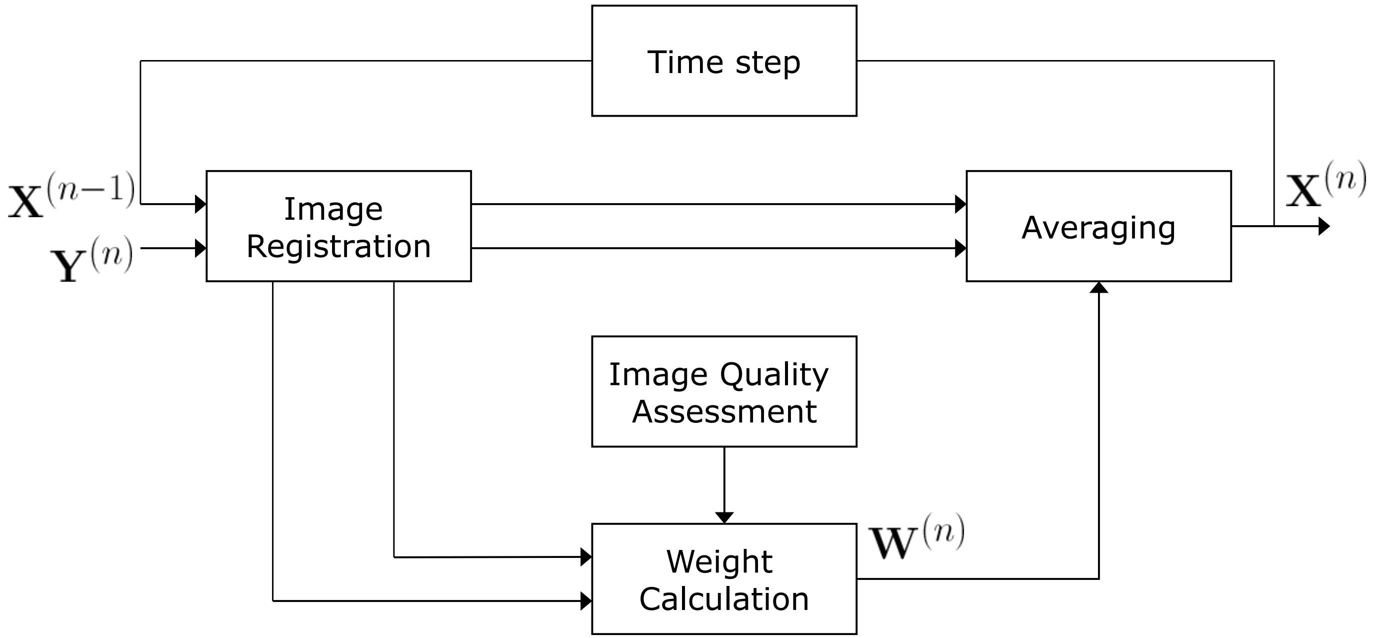
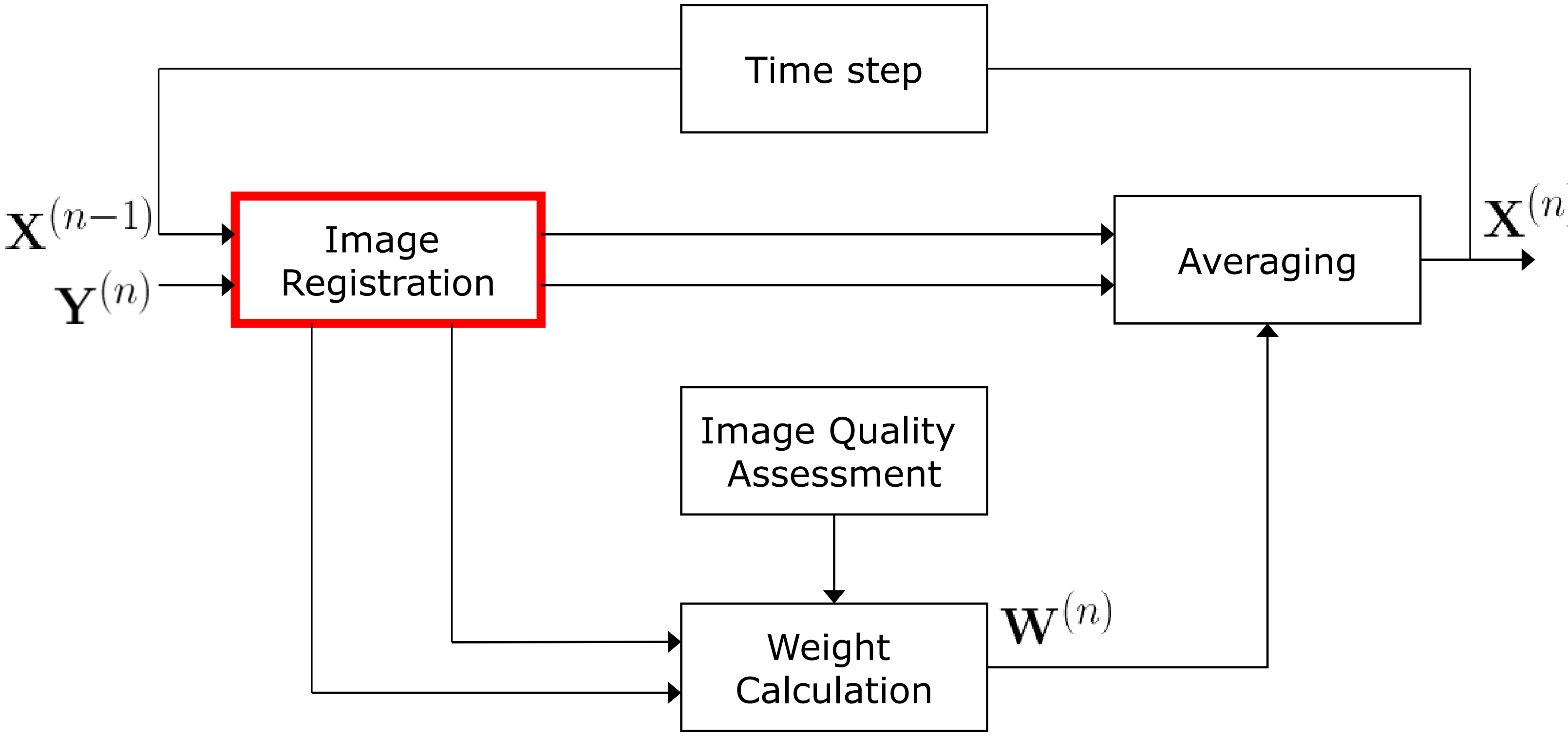
Quality Guided Denoising – Algorithm Overview



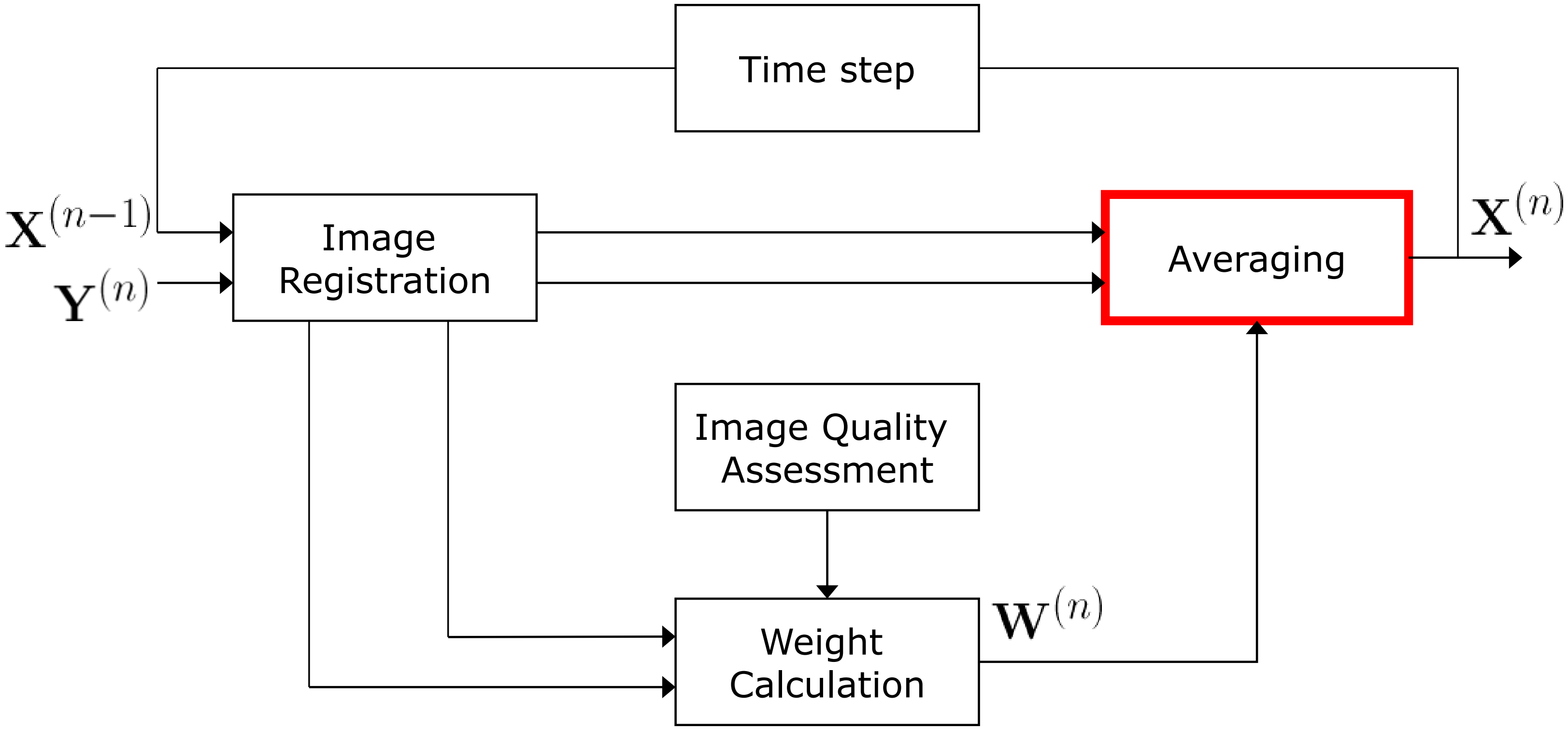
Incremental/recursive refinement:

- **Input:** Noisy frame $\mathbf{Y}^{(n)}$ at time step n
- **Output:** Denoised image $\mathbf{X}^{(n)}$ based on $\mathbf{Y}^{(n)}$ and previous $\mathbf{X}^{(n-1)}$

Image Registration



Averaging


Time step
$\mathbf{X}^{(n-1)}$
$\mathbf{Y}^{(n)}$
Image Registration
Averaging
$\mathbf{X}^{(n)}$
Image Quality Assessment
Weight Calculation
$\mathbf{W}^{(n)}$

Averaging

- Incremental scheme for frame averaging:

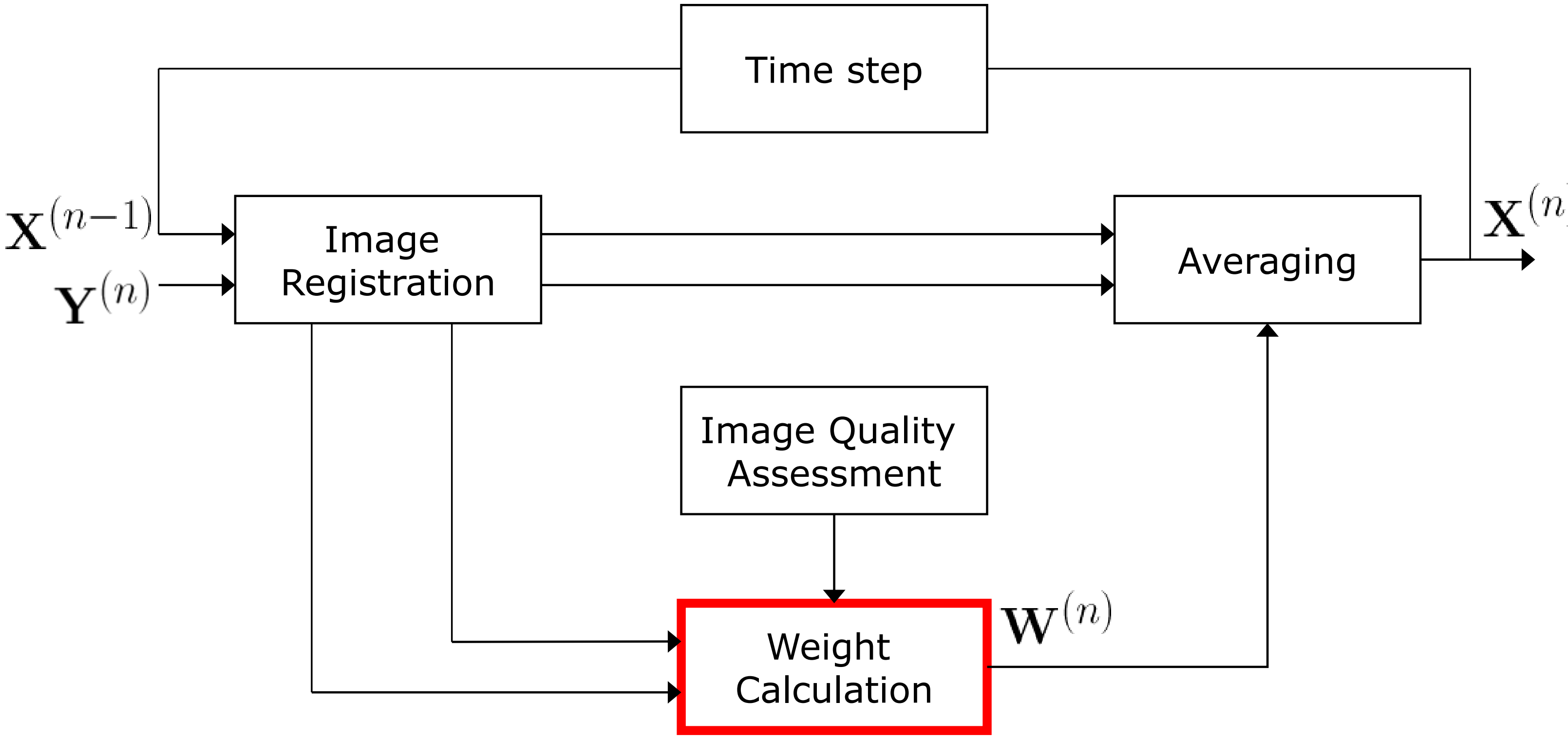
$$\boldsymbol{X}^{(n)} \equiv x_{ij}^{(n)} = \underbrace{w_{ij}^{(n)} x_{ij}^{(n-1)}}_{\text{previous estimation}} + \underbrace{\left(1 - w_{ij}^{(n)}\right) y_{ij}^{(n)}}_{\text{new input}}$$

$\boldsymbol{X}^{(n)}$:	Refined denoised image (based on n frames)
$\boldsymbol{X}^{(n-1)}$:	Previous estimation (based on $n-1$ frames)
$\boldsymbol{Y}^{(n)}$:	n^{th} input image
$\boldsymbol{W}^{(n)}$:	Incremental weight matrix for $\boldsymbol{X}^{(n-1)}$ and $\boldsymbol{Y}^{(n)}$

Goal: Find optimal weights $\boldsymbol{W}^{(n)} \equiv w_{ij}^{(n)}$ for denoising

- Update $\boldsymbol{X}^{(n)}$ at each time step.

Weight Calculation



Weight Calculation

- Weight matrix $\boldsymbol{W}^{(n)}$ (single weights $w_{ij}^{(n)}$) is adaptive with respect to image content.
- Compose two types of weights:

$$w_{ij}^{(n)} = b_{ij}^{(n)} e_{ij}^{(n)}$$

$\boldsymbol{B}^{(n)}$: **Suppress outliers**
$\boldsymbol{E}^{(n)}$: **Edge weights** based on image quality assessment

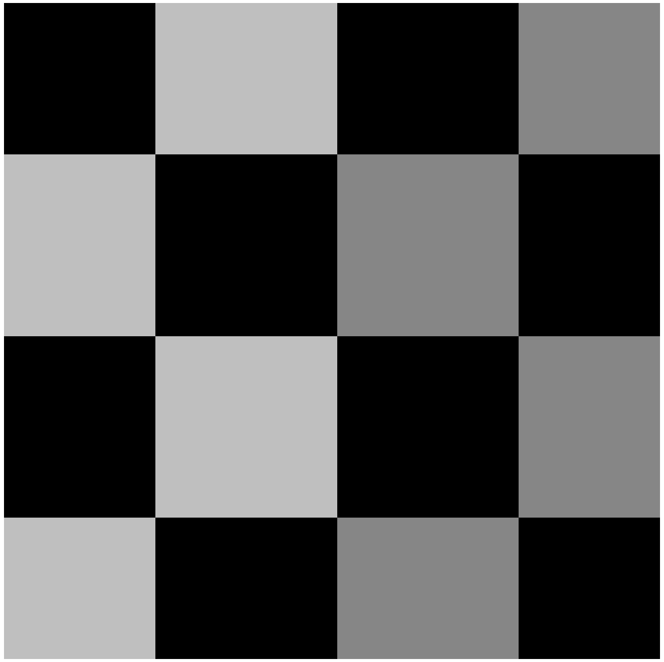
Weight Calculation – Detect Outliers with $b_{ij}^{(n)}$

- Outliers caused by:
  - Inaccurate registration on edges (blur)
  - Salt-and-pepper or illumination artifacts in homogeneous regions
- Use temporal weights for outlier suppression:

$$b_{ij}^{(n)} = \frac{1}{1 + \mathrm{G}_\sigma \left(x_{ij}^{(n-1)} - y_{ij}^{(n)} \right)}$$

G_σ: Gaussian kernel

Reference image



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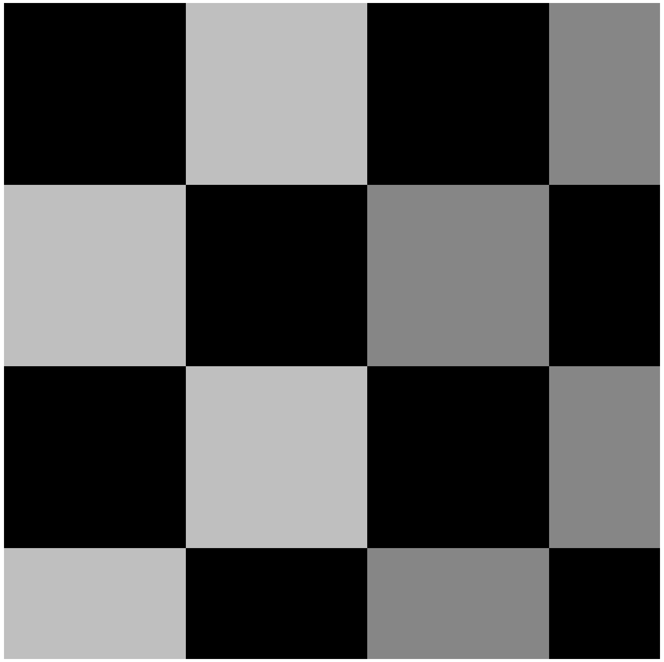
Template image (mis-registered)



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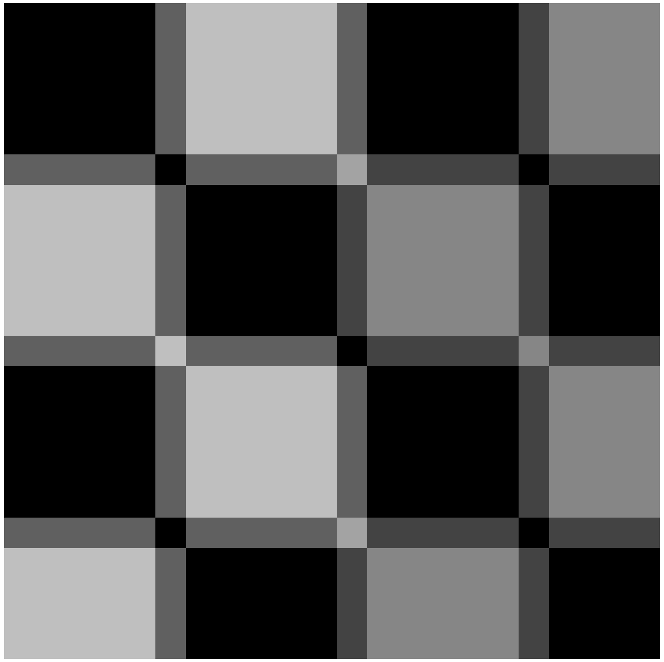
Average image



Weight Calculation – Detect Outliers with $b_{ij}^{(n)}$

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  - Inaccurate registration on edges (blur)
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- Use temporal weights for outlier suppression:

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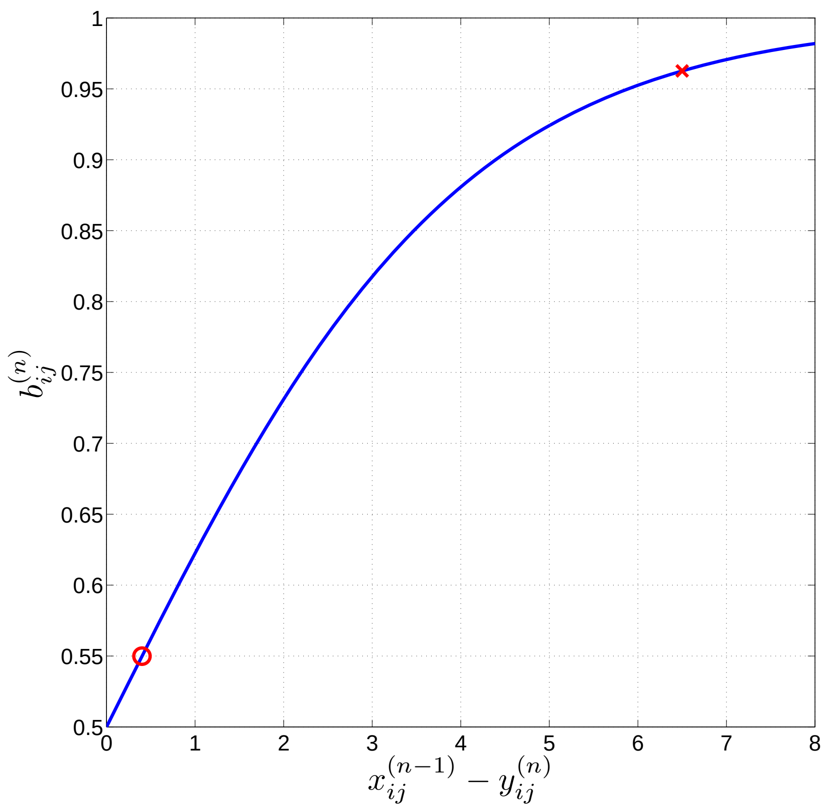
Weights $b_{ij}^{(n)}$



Weight Calculation – Detect Outliers with $b_{ij}^{(n)}$

- Outliers caused by:
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- Use temporal weights for outlier suppression:

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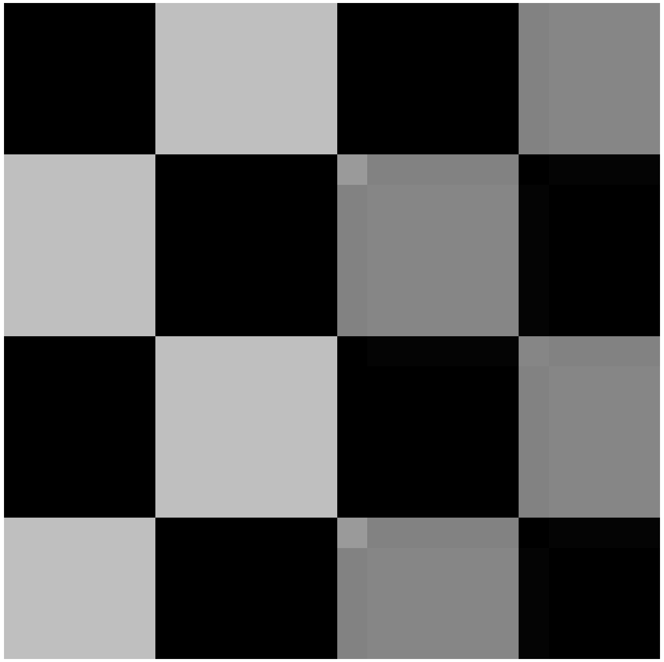
G_σ: Gaussian kernel

Average with $b_{ij}^{(n)}$



Weight Calculation – Edge Weights $e_{ij}^{(n)}$

- Decompose image into blocks
- Peform edge detection $\Rightarrow$ edge strength τ_{ij}
- For each block: classify image points
  - Edge points $\tau_{ij} > \tau_u$: find weights that maximize **image quality index** $\mathrm{Q}(\cdot)$

$$e_{ij}^{(n)} = \alpha^* = \arg\max_{\alpha} \mathrm{Q}\left(\alpha \mathbf{X}^{(n-1)} + (1-\alpha)\mathbf{Y}^{(n)}\right)$$

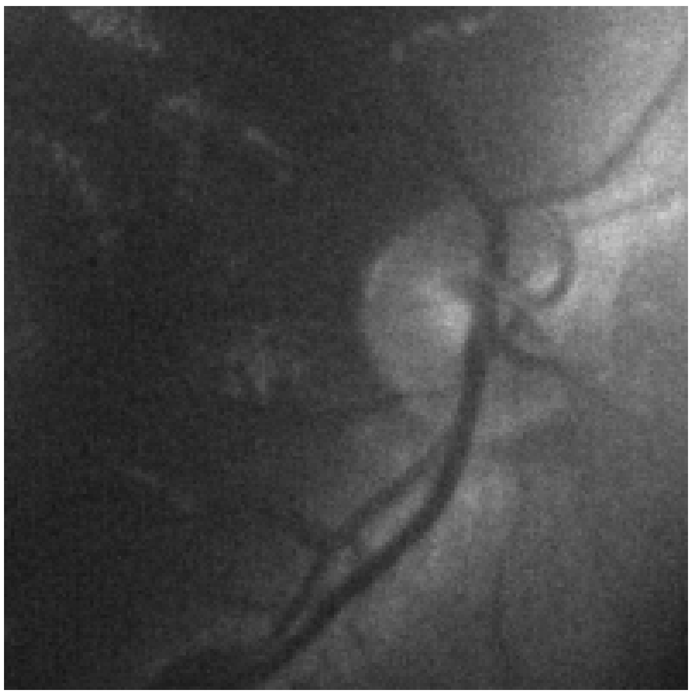
  - Homogeneous points $\tau_{ij} < \tau_l$: simple averaging $e_{ij}^{(n)} = \frac{n-1}{n}$
  - Interpolate weights between homogeneous and strong edge points

$$e_{ij}^{(n)} = \begin{cases} \alpha^* & \text{if } \tau_{ij} > \tau_u \\ m\tau_{ij} + t & \text{if } \tau_l \leq \tau_{ij} \leq \tau_u \\ \frac{n-1}{n} & \text{if } \tau_{ij} < \tau_l \end{cases}$$

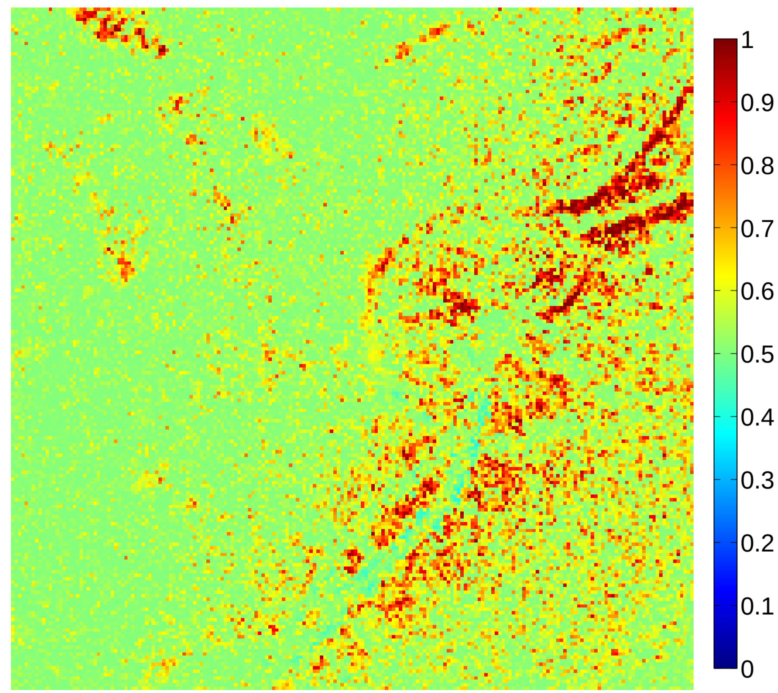
- Smooth over blocks to avoid boundary artifacts

Weight Calculation – Composition to $W^{(n)}$

Compose single weights to weight matrix $W^{(n)}$:



(a) Input fundus image



(b) Weight matrix $\boldsymbol{W}^{(n)}$

Image Quality Assessment

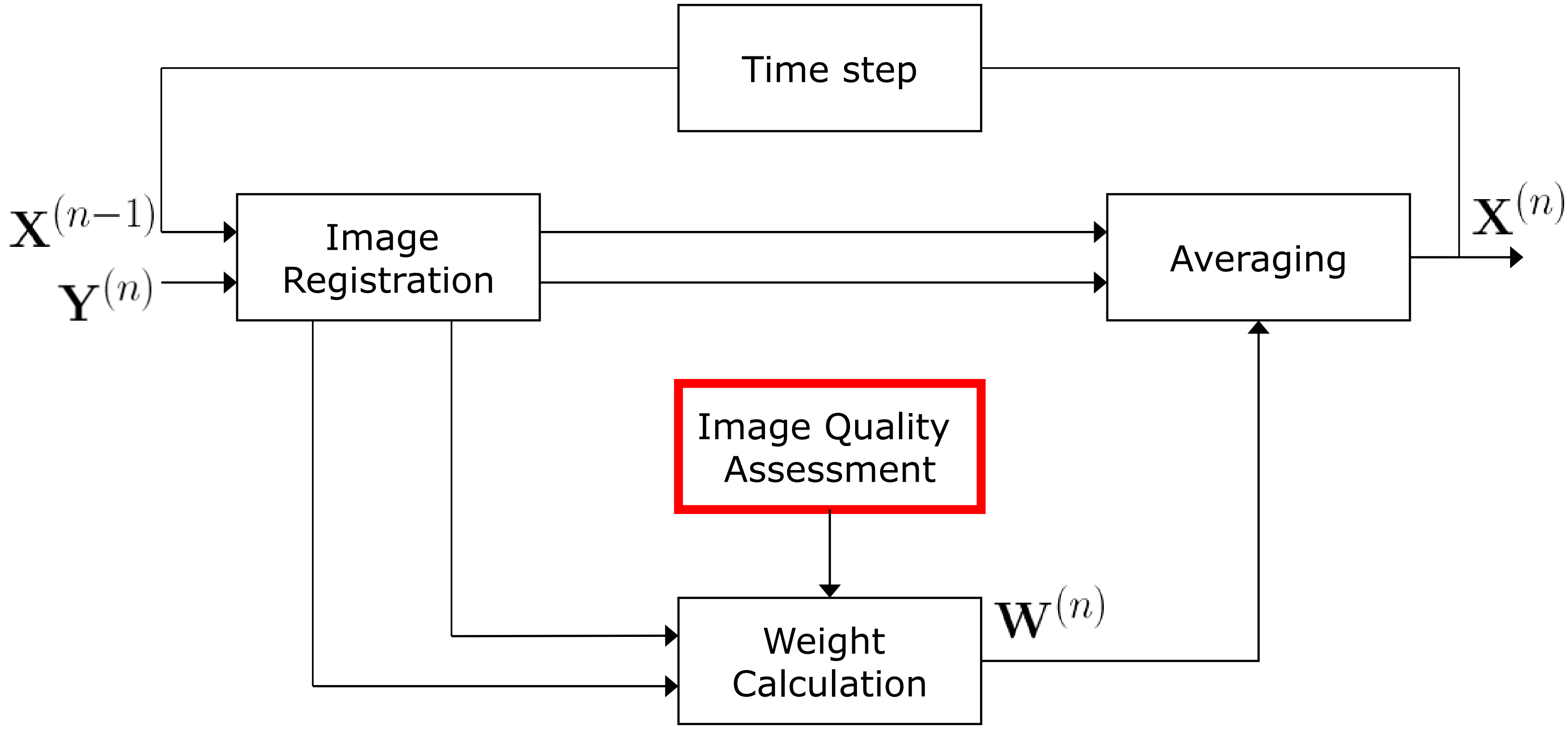


Image Quality Assessment

- Definition of image quality index $Q(\cdot)$
- Different metrics can be used.
- Examples: measurement of blur, contrast, ...
- Here: **edge magnitude distribution**[2]
  1. Calculate gradient magnitude image
  2. Determine histogram of gradient image
  3. Quality index: **skewness** of gradient histogram

Large Skewness $\Rightarrow$ good separation between weak/strong edges $\Rightarrow$ better subjective/objective quality

[2] **Murillo et al., Proc. SPIE, Medical Imaging 2011: Image Processing, 2011**

Algorithm Properties – Run Time/Memory

Time/memory complexity in **incremental mode** vs. number of frames n:

Time complexity:

Method	**Complexity**
Median	$O(n)$
Wavelet	$O(n)$
Quality guided	$O(1)$

Algorithm Properties – Run Time/Memory

Time/memory complexity in **incremental mode** vs. number of frames n:

Time complexity:

Method	**Complexity**
Median	$O(n)$
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Quality guided	$O(1)$

Memory complexity:

Method	**Complexity**
Median	$O(n)$
Wavelet	$O(n^2)$
Quality guided	$O(1)$

Experiments and Results

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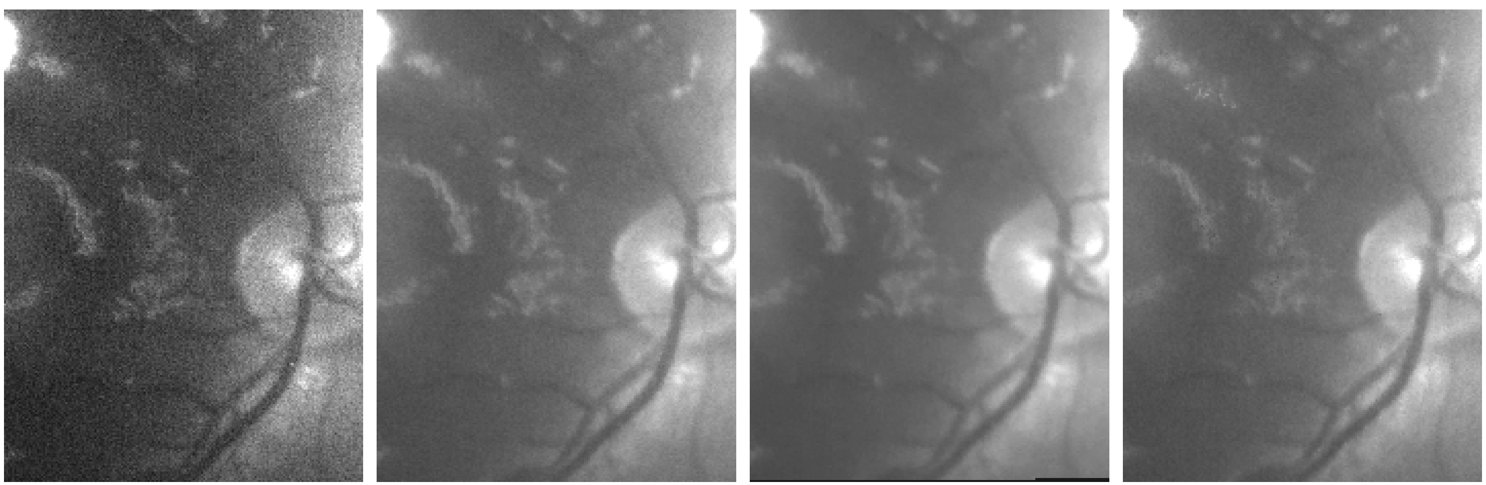
Qualitative Comparison

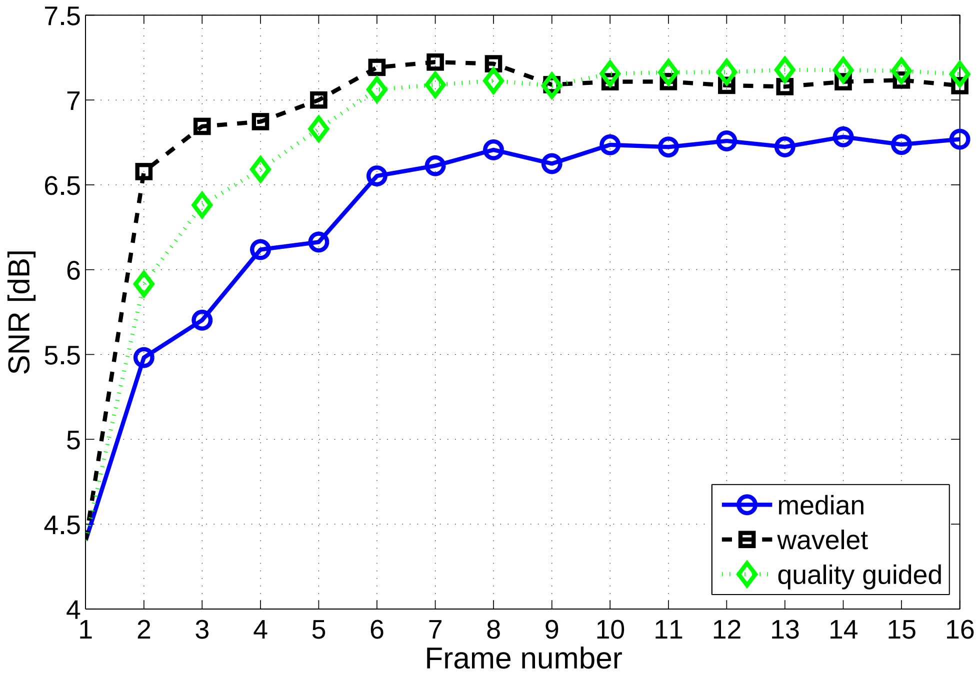
- Denoising based on 8 frames
- Comparison of
  - Temporal median
  - Wavelet multi-frame
  - Our method



(c) Single frame (d) Temporal median (e) Wavelet multi-frame (f) Quality guided

Denoising Performance

Evaluation of **signal-to-noise ratio (SNR)** for varying number of frames:



Quality guided denoising:

- Outperforms non-adaptive median method
- Short sequences ($n < 5$): smaller SNR than wavelet multi-frame method
- Long sequences ($n \geq 5$): competitive SNR

Summary and Conclusion

Summary and Conclusion

- Multi-frame denoising with application to low-cost fundus imaging
- Adaptive and incremental frame averaging
  - Takes objective image quality index into account
  - Using adaptive weighting scheme based on image quality and temporal weights
  - Competitive SNR to state-of-the-art methods
  - But: efficient implementation (run time and memory)

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