Quality-Guided Image Denoising for Low-Cost Fundus Imaging

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Abstract. The restoration of noisy images is an essential pre-processing step in many medical applications to ensure sufficient quality for diagnoses. In this paper we present a new quality guided approach for denoising of eye fundus images that suffer from high noise levels. The denoising is based on image sequences and an adaptive frame averaging approach. The novelty of the method is that it takes an objective image quality criteria to assess the different frames and tries to maximize the quality of the resulting image. It can be implemented in an incremental manner which allows real-time denoising. We evaluated our approach on real image sequences captured by a low-cost fundus camera and obtained competitive results to a state-of-the-art method in terms of signal-to-noise ratio whereas our method performs denoising about four times faster.

1 Introduction

Fundus imaging provides high-resolution photographs with good signal-to-noise ratio (SNR) of the human eye fundus. It is a common modality used by ophthalmologists to diagnose eye diseases. In contrast to high-end cameras, a low-cost fundus device is a mobile solution which suffers from high noise levels in the captured images. Denoising is an essential pre-processing step to analyze such images and to recognize structures like blood vessels. In this work we focus on temporal filtering based on image sequences to acquire a denoised image.

Most approaches for temporal filtering are based on frame averaging [1] where an average image of a sequence of frames showing the same scene is calculated. The average image is an estimation for the ideal image of this scene. A common goal is to make this average more robust and adaptive to the frames of the sequence [2,3]. One potential error source is imperfect alignment of the frames which causes blur in the denoised image. An adaptive approach proposed by Dudek et al. [4] uses optical flow to compensate motion and errors in the motion field are detected to avoid blur in the result image. However, optical flow is sensitive to varying illumination which is a main limitation for fundus images. Multiframe wavelet denoising as described by Borsdorf et al. [5] and Mayer et al. [6] are robust denoising methods. Here noise is identified by analyzing wavelet coefficients and deriving different kind of weights e. g. by correlation analysis. A good SNR gain can be achieved, but this approach has a higher asymptotic run time of $O(n^2)$ for n images. We propose a frame averaging method due to its simplicity and low computational effort. This makes it suitable for a real-time application in a low-cost fundus camera system.

2 Materials and Methods

2.1 Adaptive and Incremental Frame Averaging

The proposed denoising method works in an incremental manner and consists of two stages (Fig. 1). First, a new frame is aligned with the denoised image estimated in the previous time step. Afterwards, an adaptive average between both frames is calculated. This average takes the relative quality of the two images into account and avoids motion blur caused by inaccurate registration.

Frame Averaging Let $\mathbf{Y}^{(1)} \ldots \mathbf{Y}^{(n)} \in \mathbb{R}^{M \times N}$ be a sequence of n images of dimension $M \times N$ which show the same content. Frame averaging calculates a denoised image $\mathbf{X}^{(n)} \in \mathbb{R}^{M \times N}$ according to

$$x_{ij}^{(n)} = \sum_{k=0}^{n} v_{ij}^{(k)} y_{ij}^{(k)} \tag{1}$$

with adpative weights $v_{ij}^{(k)}$ for each pixel (i, j) in each frame $\mathbf{Y}^{(k)}$. For $v_{ij}^{(k)} = 1/n$ and additive white Gaussian noise this provides an unbiased estimate for the ideal image. Motion during image acquisition must be compensated using image registration to avoid motion blur. It is well known that the average is sensitive to outliers, e. g. due to varying and inhomogeneous illumination. One possible solution is the application of robust estimators like median or RANSAC [7]. Unfortunately, these approaches have higher computational effort. Instead we modify equation 1 and provide an incremental solution for image denoising.

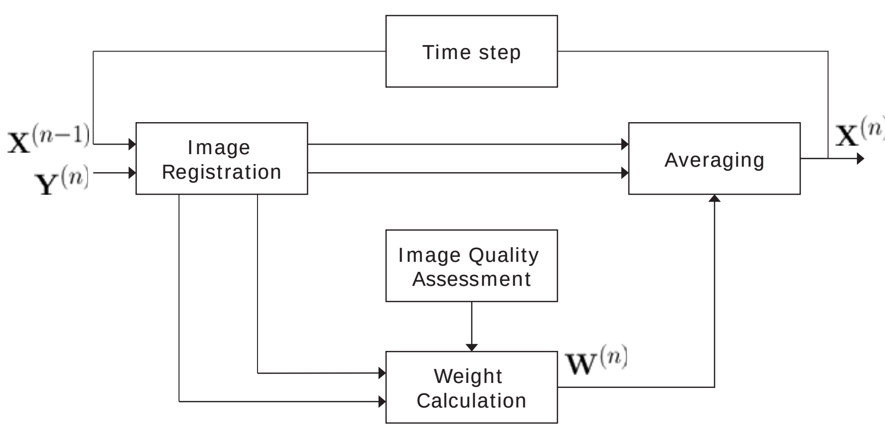

Fig. 1. The flowchart of the proposed denoising algorithm for $n > 1$.

Incremental Frame Averaging A recursive formulation of frame averaging with adaptive weights $w_{ij}^{(n)}$ for each pixel (i, j) is given by

$$x_{ij}^{(n)} = w_{ij}^{(n)} x_{ij}^{(n-1)} + \left(1 - w_{ij}^{(n)}\right) y_{ij}^{(n)}. \tag{2}$$

A new frame $\mathbf{Y}^{(n)}$ at the current time step n refines the previous estimation $\mathbf{X}^{(n-1)}$ based on the frames 1 to $n-1$ to the new estimation $\mathbf{X}^{(n)}$. The weight factors $w_{ij}^{(n)}$ are adjusted such that $\mathbf{X}^{(n)}$ is a usable estimation in terms of an objective quality criteria and outliers are suppressed. This allows an incremental refinement of the denoised image over time as shown in Fig. 1.

Weight Matrix Calculation The weight matrix $\mathbf{W}^{(n)} \in \mathbb{R}^{M \times N}$ in equation 2 is composed as a multiplication $w_{ij}^{(n)} = b_{ij}^{(n)} e_{ij}^{(n)}$. First, we use temporal weights for corresponding pixels of $\mathbf{X}^{(n-1)}$ and $\mathbf{Y}^{(n)}$ to suppress outliers in homogeneous regions or blurring caused by inaccurate registration on edges. Using a Gaussian filter kernel G_σ the first weight matrix $\mathbf{B}^{(n)}$ is calculated as follows:

$$b_{ij}^{(n)} = \frac{1}{1 + \mathrm{G}_\sigma \left(x_{ij}^{(n-1)} - y_{ij}^{(n)}\right)} \tag{3}$$

For $n > 1$ the denoised image $\mathbf{X}^{(1)}$ is initialized with a slightly smoothed version of $\mathbf{Y}^{(1)}$ using a bilateral filter [8]. The standard deviation σ of G_σ has to be adjusted to the noise level, since a large σ filters noise effectively whereas a small σ suppresses motion blur.

The second weight matrix $\mathbf{E}^{(n)}$ is calculated in order to maximize the image quality of $\mathbf{X}^{(n)}$. The image quality is evaluated by using an objective non-reference image quality index $\mathrm{Q}(\mathbf{I})$. In this paper it is assumed that larger values $\mathrm{Q}(\mathbf{I})$ indicates a better quality for image $\mathbf{I}$. The first step is to find a global weight factor α^* according to

$$\alpha^* = \arg\max_{\alpha} \mathrm{Q}\left(\alpha \mathbf{X}^{(n-1)} + (1-\alpha)\mathbf{Y}^{(n)}\right). \tag{4}$$

To make the quality measurement adaptive to locally varying illumination the images are decomposed to smaller blocks. For each block a local weight is determined. In preliminary tests we found out that this weight factor is usable on edge points to detect blurred edges or image structures with poor contrast whereas in homogeneous regions simple averaging in combination with the weights $\mathbf{B}^{(n)}$ gives accurate results. Based on this assumption a weight matrix $\mathbf{E}^{(n)}$ using an edge strength measurement τ_{ij} for each pixel (i, j) is derived:

$$e_{ij}^{(n)} = \begin{cases} \alpha^* & \text{if } \tau_{ij} > \tau_u \\ m\tau_{ij} + t & \text{if } \tau_l \leq \tau_{ij} \leq \tau_u \\ \frac{n-1}{n} & \text{if } \tau_{ij} < \tau_l \end{cases} \tag{5}$$

The edge strength τ_{ij} is determined using edge detection and the thresholds τ_l and τ_u are used to classify into homogeneous points and strong edge points respectively. Between homogeneous and strong edge pixels linear interpolation is performed which is denoted by the linear term $m\tau_{ij} + t$.

Image Quality Index The function $\mathrm{Q}(\mathbf{I})$ is used to give an objective assessment of the quality of an image $\mathbf{I}$. We choose the so called *edge magnitude distribution*. It was already applied to evaluate the quality of low-cost scanning laser ophthalmoscope images [9]. For an image $\mathbf{I}$ the index $\mathrm{Q}(\mathbf{I})$ is calculated as follows: First, the gradient magnitude image $\mathbf{G}$ is calculated. The quality index $\mathrm{Q}(\mathbf{I})$ is the skewness of the histogram of $\mathbf{G}$. A large positive skewness indicates a right-skewed distribution which means that there is a good separation between sharp and weak edges. In this case for fundus images background and structures like blood vessels or the optic disc can be discriminated, thus the image has a good quality.

2.2 Experiments

The denoising method is evaluated using real image sequences captured by a low-cost fundus camera. We compare our quality guided approach with the state-of-the-art wavelet multiframe denoising described in [6] and simple median estimation. For spatial alignment of the frames we use rigid registration based on mutual information [10]. This compensates the motion between the frames caused by the movement of the human eye during image acquisition. We adjusted the parameters of our algorithm as follows: For the Gaussian kernel to determine $\mathbf{B}^{(n)}$ we use the standard deviation $\sigma = 15$ to compensate slow varying illumination. The edge weights $\mathbf{E}^{(n)}$ are calculated in blocks of size 50×50 pixels whereas the ratio of eigenvalues of the structure tensor is used to determine edge strength. For classification of strong and weak edge points we use $\tau_l = 3\tilde{\tau}$ and $\tau_u = 5\tilde{\tau}$ as thresholds where $\tilde{\tau}$ is the median edge strength. For wavelet denoising we use Haar wavelets and three decomposition levels. We provide qualitative as well as quantitative results for the SNR to measure noise suppression. The different methods were implemented in MATLAB and run times were measured on an Intel Xeon 2.80 GHz Quad Core CPU with 4 GB RAM.

3 Results

The qualitative evaluation of the denoising methods is based on a sequence of eight frames. Denoising results and a comparison between the different methods is shown in Fig. 2. We evaluated the SNR in a homogeneous image region for the different denoising methods. The SNR is determined for varying number of frames taken as input for denoising and plotted in Fig. 3. The edge preservation can be observed by visual inspection of the denoised images shown in Fig. 2.

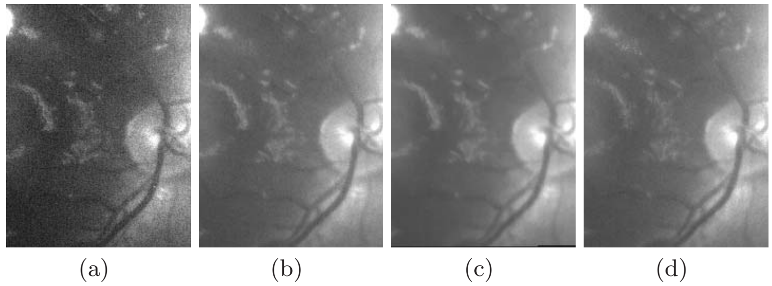

Fig. 2. Results of different denoising methods for a region of interest (ROI) in eight frames after contrast enhancement. (a) A single frame out of the sequence, (b) median method, (c) wavelet multiframe [6] and (d) our quality guided approach.

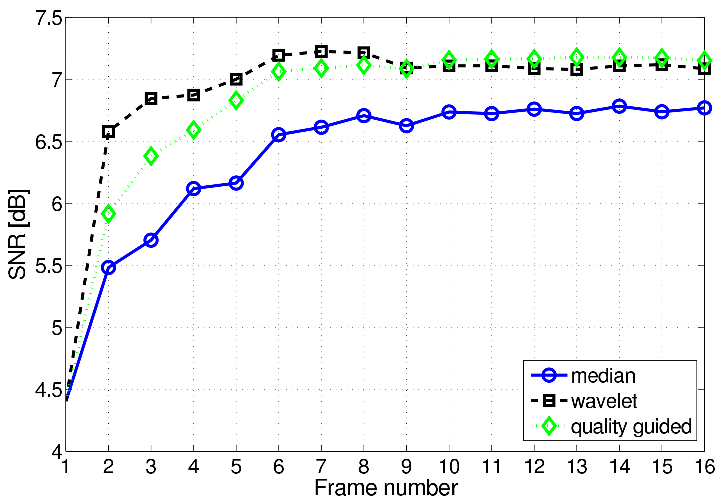

Fig. 3. Evaluation of SNR vs. frame number to be used for denoising.

If we exclude the run time required for image registration, our proposed algorithm needs 23.5 seconds to denoise eight frames of size 296×200. This outperforms the multiframe wavelet approach which takes 96.1 seconds. Compared to the median method that takes 2.5 seconds there is an overhead caused by the assessment of the image quality during each step.

4 Discussion

The SNR evaluation in Fig. 3 shows that our approach outperforms traditional frame averaging although robust median estimation is used. It gives competitive results to the wavelet multiframe method with respect to SNR for longer sequences ($n \geq 5$). If the steady state for the SNR is reached ($n \geq 10$), our approach is slightly better than the multiframe wavelet method whereas the latter one gives better results for short sequences in the present case. Edges are preserved by temporal filtering which can be observed by visual inspection of structures like the optic disc border in Fig. 2. Our proposed method is about four times faster than multiframe wavelet denoising and performs incremental filtering with competitive results. This makes it more feasible to provide real-time denoising. However, there is still a high potential to speed up this method by parallelizing different steps like the weight calculation.

In our future work we plan to evaluate other image quality indices or combinations of them. This should make the image quality assessment more robust and a variety of criteria concerning e. g. contrast or blur can be taken into account.

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