



Original research article

# Application of Independent Component Analysis techniques in speckle noise reduction of retinal OCT images

Ahmadreza Baghaie<sup>a,\*</sup>, Roshan M. D'Souza<sup>b</sup>, Zeyun Yu<sup>c</sup><sup>a</sup> Department of Electrical Engineering, University of Wisconsin-Milwaukee, Milwaukee, WI, USA<sup>b</sup> Department of Mechanical Engineering, University of Wisconsin-Milwaukee, Milwaukee, WI, USA<sup>c</sup> Department of Computer Science, University of Wisconsin-Milwaukee, Milwaukee, WI, USA

## ARTICLE INFO

## Article history:

Received 23 July 2015

Received in revised form

17 November 2015

Accepted 29 March 2016

## Keywords:

Independent Component Analysis

Speckle reduction

Optical Coherence Tomography (OCT)

## ABSTRACT

Optical Coherence Tomography (OCT) is an emerging technique in the field of biomedical imaging, with applications in ophthalmology, dermatology, coronary imaging, etc. OCT images usually suffer from a granular pattern, called speckle noise, which restricts the process of interpretation. Therefore the need for speckle noise reduction techniques is of high importance. To the best of our knowledge, use of Independent Component Analysis (ICA) techniques has never been explored for speckle reduction of OCT images. Here, a comparative study of several ICA techniques (InfoMax, JADE, FastICA and SOBI) is provided for noise reduction of retinal OCT images. Having multiple B-scans of the same location, the eye movements are compensated using a rigid registration technique. Then, different ICA techniques are applied to the aggregated set of B-scans for extracting the noise-free image. Signal-to-Noise-Ratio (SNR), Contrast-to-Noise-Ratio (CNR) and Equivalent-Number-of-Looks (ENL), as well as analysis on the computational complexity of the methods, are considered as metrics for comparison. The results show that use of ICA can be beneficial, especially in case of having fewer number of B-scans.

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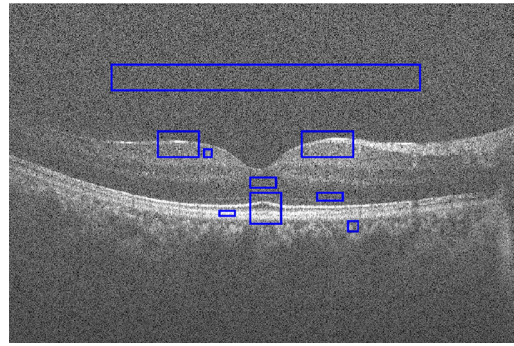
## 1. Introduction

OCT is a powerful imaging system for non-invasive acquisition of 3D volumetric images of tissues [1], with applications in ophthalmology, dermatology, coronary imaging, etc. Due to its underlying physics, which is common in narrow-band detection systems like Synthetic-Aperture Radar (SAR) and ultrasound, OCT images usually suffer from a granular pattern called *speckle*. Not only the optical properties of the system, but also the motion of the subject to be imaged, size and temporal coherence of the light source, multiple scattering, phase deviation of the beam and aperture of the detector can affect the speckle [2]. Fig. 1 shows a sample retinal OCT image, highly degraded by speckle noise.

Speckle is considered to be multiplicative noise, in contrast to the additive Gaussian noise. Limited dynamic range of displays requires us to compress the OCT signals usually by a logarithmic transform, which converts the multiplicative speckle noise to additive noise [3]. Two major classes of speckle noise reduction techniques are: (1) methods of noise reduction during the acquisition time and (2) post-processing techniques. In the first class multiple uncorrelated recordings are averaged. This includes spatial [4], angular [5], polarization [6] and frequency [7] compounding techniques. As for post-processing, anisotropic diffusion-based techniques [3] and multi-scale/multi-resolution geometric representation techniques [8] are of

\* Corresponding author.

E-mail address: [abaghaie@uwm.edu](mailto:abaghaie@uwm.edu) (A. Baghaie).



**Fig. 1.** Sample retinal OCT image degraded by speckle noise; selected ROIs are shown with blue rectangles. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

high interest between scholars. Use of compressive sensing and sparse representation has also been explored in the past few years [9]. For a more complete review on the different image analysis techniques in OCT image processing, including noise reduction, the reader is referred to [10] and references therein.

Post-processing averaging/median filtering is also an interesting method for speckle reduction. In such techniques, multiple B-scans of the same location are acquired and then the average/median is taken. The misalignment between the different B-scans is usually compensated with a parametric image registration technique. Theoretically, having  $N$  B-scans with uncorrelated speckle, SNR can be improved by a factor of  $\sqrt{N}$ . The works presented in [11,12] can be mentioned as examples. Recently the use of sparse and low-rank decomposition based batch image alignment was explored by the authors [13].

When it comes to the question of noise reduction in medical images, there are several issues that one might encounter that are not considered in general purpose image noise reduction techniques. The first is regarding the end user of such techniques. Unlike the common noise reduction techniques, the end users of medical image noise reduction techniques are more concerned about the truthfulness of the result to the actual anatomy rather than image quality metrics, since they need to make clinical decisions regarding the patients' health. This is more critical when dealing with medical images that contain very fine anatomical details, like the cases encountered in OCT images. In such cases, assuming piecewise smoothness constraints that are common in general purpose noise reduction techniques can be very misleading since the scale of different features in these types of images vary drastically within images. Therefore, use of single frame noise reduction techniques is not preferred since the outcome might not be very faithful to the actual anatomy. Having a multi-frame technique, allows for combining information to have a better representation of the imaged anatomy. This is specially very common in OCT community, since image acquisition time is very small with the current imaging devices, with frame rates of several tens or even several hundreds. It is also worth mentioning that unlike white Gaussian noise which is considered as an additive component and is uncorrelated with the image data, speckle is multiplicative and is not completely uncorrelated with the image data. In fact speckle is inherent to imaging systems like SAR and OCT and contains signal-carrying and signal-degrading components [2]. Therefore having several frames with different speckle patterns, which is always the case in retinal OCT since we have involuntary eye movements between frames, provides an uncorrelated representation of signal-degrading part (speckle noise) which will benefit the noise reduction process.

In this paper the use of Independent Component Analysis (ICA) techniques for speckle noise reduction of retinal OCT images is explored, which to the best of our knowledge has never been investigated before. Having multiple B-scans of the same location in retina, the eye movement is compensated by considering a rigid transformation between consecutive B-scans using ImageJ [14]. Having negligible eye motion within each B-scan, the need for deformable registration techniques [15,16] can be eliminated. Then, several ICA techniques are used for extracting the noise-free image from multiple noisy B-scans. SNR, CNR and ENL are considered as metrics for comparing the performance of different methods. Investigating the results reveals interesting facts regarding the impact of using ICA for speckle noise reduction. Especially in case of having a few number of images in which ICA techniques provide better performance in comparison to median filtering. But increasing the number of images causes the ICA techniques to perform poorly, since the main assumption in ICA is having non-Gaussian uncorrelated components which cannot be completely satisfied here.

## 2. Independent Component Analysis (ICA)

ICA is one of the most widely used techniques for Blind Source Separation (BSS) [17]. The problem of BSS consists of having interfering signals from multiple sources recorded and trying to find the individual source signals from these mixed recordings. The very well-known example is a cocktail party, with multiple people talking while there are recorders in different places of the room. This can be mathematically modeled by considering  $s_i(t)$ ,  $i = 1, \dots, N$  as the set of sources and  $x_i(t)$ ,  $i = 1, \dots, N$  as the observations. Therefore:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \quad (1)$$

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