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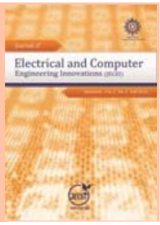


# The Application of Multi-Layer Artificial Neural Networks in Speckle Reduction (Methodology)

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**ABSTRACT**

Optical Coherence Tomography (OCT) uses the spatial and temporal coherence properties of optical waves backscattered from a tissue sample to form an image. An inherent characteristic of coherent imaging is the presence of speckle noise. In this study we use a new ensemble framework which is a combination of several Multi-Layer Perceptron (MLP) neural networks to denoise OCT images. The noise is modeled using Rayleigh distribution with the noise parameter, sigma, estimated by the ensemble framework. The input to the framework is a set of intensity and wavelet statistical features computed from the input image, and the output is the estimated sigma value for the noise model. In this article the methodology of this technique is explained.

## 1. Introduction

Optical Coherence Tomography (OCT) is based on low-coherence interferometry, which uses the spatial and temporal coherence properties of optical waves backscattered from a tissue sample to form an image [1]-[3]. When a spatially coherent source, such as super luminescent diode (SLD), illuminates an object that is of the same scale or smaller than the wavelength of the source, the interference of the partial waves in the reflected light with their random amplitudes and phases produces a phenomenon known as speckle [4], [5]. Speckle is a deterministic interference pattern in an image formed with coherent radiation of a medium containing many sub-resolution scatterers. Speckle reduces the performance of image segmentation and pattern recognition algorithms that are used to extract, analyze, and recognize diagnostically relevant features [6]. Development of successful speckle noise reduction algorithms for OCT is particularly challenging. A number of speckle reduction methods for OCT have been developed using hardware modifications such as frequency compounding [7], shifting the focal plane of the probe beam [8], angular compounding [9], and non-linear anisotropic diffusion [10]. Besides the hardware modifications, a number of image processing algorithms have been reported such as adaptive digital filters [11], [12], filters based on interval type II fuzzy algorithm [13], wavelet transformation with various configurations [14], or the use of median filtering [15]. In this paper, we use a new artificial neural network (ANN) ensemble framework for speckle noise reduction in OCT images which is combined from several multi-layer perceptron (MLP) ANNs. This framework has better results than an individual neural network [7] in sigma estimation.

## 2. Artificial Neural Network

An ANN is an intelligent information processing system which is designed based on a model of the biological nervous systems [16]. ANN is composed of a large amount of small processing units, called neurons and interconnected to each other. The aim of using the ANN is to make a mapping function with which a decision making system with certain inputs and outputs is modeled. Perceptron is the simplest form of a biological neuron. An artificial neural network that is made up from one perceptron called single-layer perceptron that can be used for the classification of patterns that are linearly separable [16].

Therefore multi-layer perceptron as a neural network consists of several perceptron's instead of one perceptron, it was proposed in 1980 for more complex data classification that is not linearly separable. Typically, the multi-layer perceptron neural networks consist of a set of sensory units (source node) that constitute the input layer, one or more hidden layers of computation nodes and an output layer of computation node. The input signal propagates through the network in a forward direction, on layer-by-layer basis [16]. Fig. 1 shows an example of an MLP with one hidden layer. A bias node has no input and always produces one at its output. Since bias nodes can be incorporated in the activation functions, we shall not count them as separate nodes when specifying the ANN structure. So, the ANN in Fig.1 has two input, three hidden, and two output neurons. This ANN configuration can be represented as 2: 3: 2 (input: hidden: output).

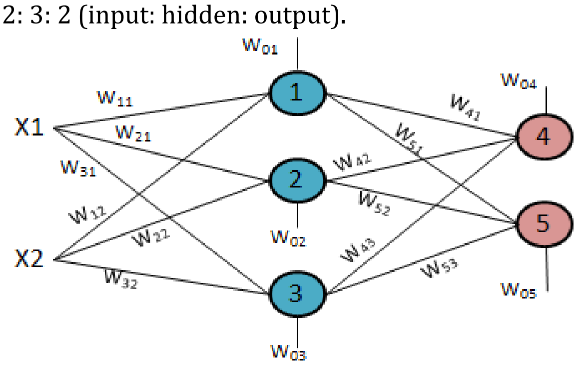



Figure 1: Signal flow graph model of an MLP.

## 3. Speckle Noise Reduction

The stages of the speckle reduction process which is proposed in this paper are as follows: the Rayleigh distribution noise parameter, sigma, is estimated using the ensemble framework as a combination of three MLP neural networks. The inverse Rayleigh distribution function computed using the estimated sigma is then applied to the noisy image to compensate the noise in the signal. Assuming F(m,n) being the image obtained from the OCT system:

$$F(m,n) = s(m,n)n(m,n) + n_a(m,n) \quad (1)$$

where, s(m,n) represents the noise free OCT image, n(m,n) and $n_a(m,n)$ are multiplicative and additive noise components, respectively and (m,n) is the spatial location of a pixel in the OCT image. In eq. (1), the additive noise component is significantly small compared to the multiplicative speckle noise. The process of ensemble framework consists of three stages: pre-processing, feature extraction, and training. In the pre-processing stage, the images are scaled into the same intensity range. Noisy images using eq. (2) are generated by a Rayleigh noise generator.

$$f(x_{i,j}) = \frac{x_{i,j} e^{\frac{-x_{i,j}^2}{2\sigma^2}}}{\sigma^2} \quad (2)$$

where$x_{i,j}$ is an image pixel and sigma ($\sigma$) is the noise variance of the image (the noise parameter). In the next stage, feature extraction, a set of sixteen statistical features are extracted from homogeneous regions of the noisy image, and then averaged. The features consist of the mean (μ), standard deviation ($\sigma$), kurtosis (k), and median, are calculated for the noisy image and its wavelet subband images (vertical, horizontal, and diagonal components). The built-in function, *dwt2*, in MATLAB is used for wavelet transformation. The wavelet mother function used in this study is Daubechies 4 (db4), as the ANN produces a network with a higher reliability with this mother function. The formulae used for mean, standard deviation, and kurtosis are given by the following equations (see eqs. (3) to (5), where *i* and *j* indicate the location of the image pixel, and *M* and *N* are image dimensions.

$$\mu = \frac{1}{MN}\sum_{i=1}^{M} \sum_{j=1}^{N} (xi,j) \quad (3)$$

$$\sigma = \sqrt{\frac{1}{MN}\sum_{i=1}^{M} \sum_{j=1}^{N} (xi,j-\mu)^2} \quad (4)$$

$$K=MN\frac{\sum_{i=1}^{M}\ \sum_{j=1}^{N}\ (xi,j-\mu)4}{(\sum_{i=1}^{M}\ \sum_{j=1}^{N}\ (xi,j-\mu)2)2} \tag{5}$$

The last stage of the algorithm is training the ensemble framework such that to associate a sigma value to the noisy image. The structure of this framework is described in section 4.

## 4. Proposed Ensemble Framework

The proposed ensemble framework is a committee machine combined of several MLP neural networks. The flowchart which is used to estimate the Rayleigh noise parameter is shown in Fig. 2; the dotted circle shows our proposed ensemble framework. Three MLP networks and a combiner which is responsible for averaging process, are the main components of this framework. Each of the MLP networks is composed of 20 neurons in its input layer, 10 neurons in its hidden layer and one output neuron to estimate the sigma parameter. The combiner can be only responsible for averaging or can exploit from another MLP neural network with L (in this paper L=3) neurons in input layer, $L$ neurons in hidden layer and one output neuron which can estimate the sigma parameter in an ensemble fashion. For training purpose, we generated noisy images with a Rayleigh distribution using a built-in MATLAB function.

Sixteen statistical features from each noisy image and its wavelet sub-bands were extracted for training. Using the training image set and the aforementioned functions, the ensemble framework of MLPs was trained and all the weights were updated. The trained framework was then used for estimating the sigma parameter. To show the advantage of ensemble method respect to individual neural networks, we assume that we have $L$ number of trained MLP neural networks with outputs $y_i(\underline{x})$ (where $x$ is input vector) which estimates sigma using the $i^{th}$ MLP neural network and with an error of $e_i$ respect to the desired value of the sigma parameter that is shown by $h(\underline{x})$. In this situation, eq. (6) can be written as follow

$$y_i(\underline{x}) = h(\underline{x}) + e_i \tag{6}$$

Thus, the sum of the square error for the network $y_i$ can be calculated using eq. (7).

$$\mathrm{E}_i = \xi\left[\left(y_i(\underline{x}) - h(\underline{x})\right)^2\right] = \xi[e_i^{\ 2}] \tag{7}$$

where $\xi$ *[.]* denotes the expectation (average or mean value). Thus, the average error for the MLP networks acting individually can be calculated by eq. (8)

$$\mathrm{E}_{AV} = \frac{1}{\mathrm{L}}\sum_{i=1}^{L}\mathrm{E}_i = \frac{1}{\mathrm{L}}\sum_{i=1}^{L}\xi\left[e_i^{\ 2}\right] \tag{8}$$

By averaging the outputs $y_i$, the committee prediction is obtained according to eq. (9).

$$y_{COM}(\underline{x}) = \frac{1}{\mathrm{L}}\sum_{i=1}^{L} y_i(\underline{x}) \tag{9}$$

This estimate will have an error equal to (eq. (9)):

$$E_{COM} = (y_{COM}(\underline{x}) - h(\underline{x}))^2 = \left[\left(\frac{1}{\mathrm{L}}\sum_{i=1}^{L} y_i(\underline{x}) - h(\underline{x})\right)^2\right] = \xi\left[\left(\frac{1}{\mathrm{L}}\sum_{i=1}^{L} e_i\right)^2\right] \tag{10}$$

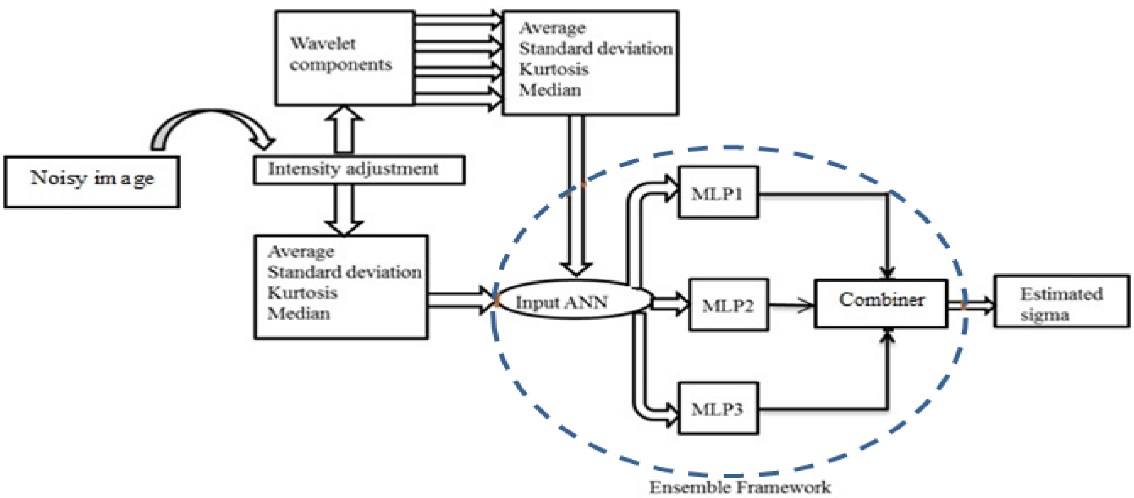



Figure 2: Schematic diagram of the sigma estimator algorithm.

Thus, using the Cauchy's inequality, one can show that $E_{COM} \leq E_{AV}$.

$$E_{COM} = \xi\left[\left(\frac{1}{L}\sum_{i=1}^{L} e_i\right)^2\right] \leq \frac{1}{L}\sum_{i=1}^{L} \xi\left[e_i^{\,2}\right] = E_{AV} \tag{11}$$

As seen in Fig. 3, our proposed framework can estimate the sigma with a negligible error. Using our trained sigma estimator framework, the associated sigma to an OCT image can be estimated and used for denoising. The procedure used for denoising is presented in the block diagram given in Fig. 3. The denoising algorithm consists of a network for sigma estimation, followed by a numerical method to solve the inverse Rayleigh function. Similar to the training stage; the pre-processing was applied to each image. The averaged statistical features were then extracted from each image and used as input for the ensemble framework.

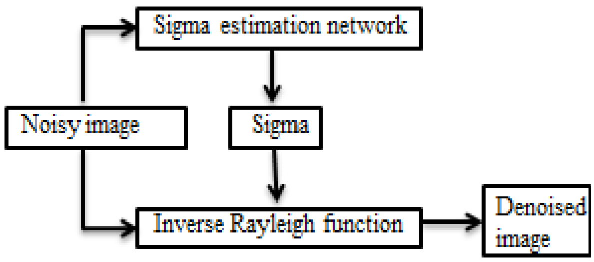


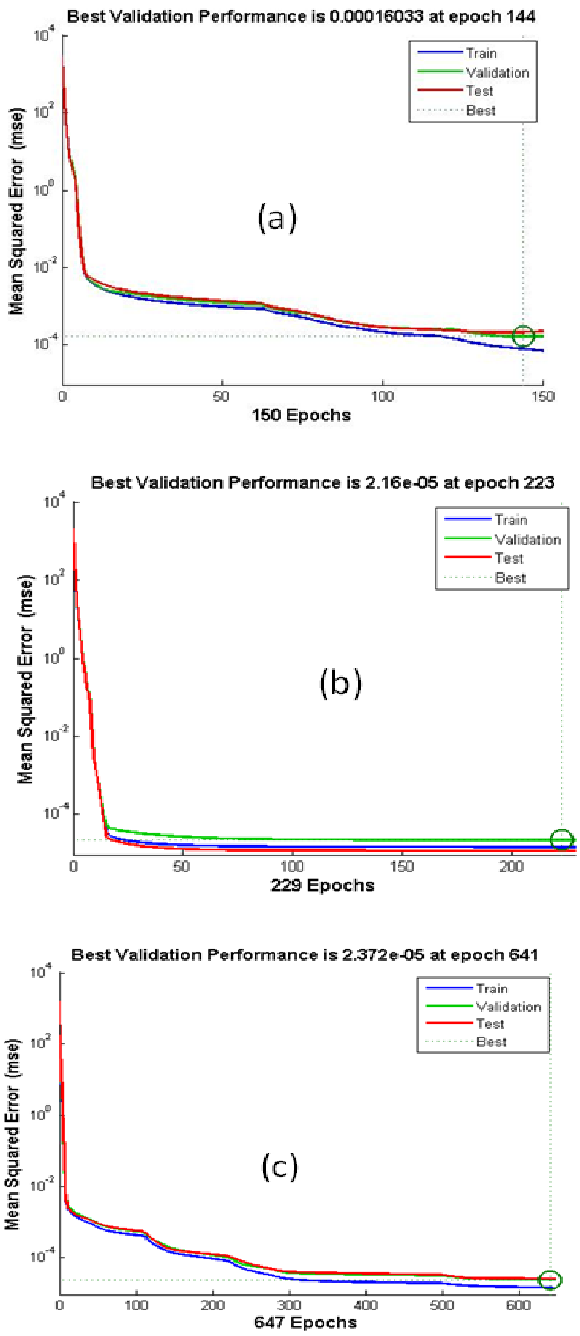

Figure 3: Block-diagram of image denoising using ANN.

The sigma estimator framework estimates the sigma associated to the input image. The inverse Rayleigh function was solved numerically; in eq. (1), 25500 values for *x* (from 0.01 to 255 in steps of 0.01) with combination of various values for sigma were recorded in a lookup table. Fig. 5 shows an overall view of the lookup table. For each pixel of the noisy image, a value from the Rayleigh curve of the estimated sigma was found in the lookup table as the noise value for that pixel. The image constructed with the noise values is a noise model image. Fig. 4 shows the MSE of our proposed framework in different runs. In Fig.5, the MLP error versus the combining error of MLP is demonstrated.

## 5. Conclusion

In this letter, the methodology for a speckle reduction framework was presented based on the approximation that speckle noise has a Rayleigh distribution with a noise parameter, sigma. An ensemble framework was designed to estimate the sigma. The estimated sigma was then used in the denoising algorithm to reduce speckle noise in the noisy images. We expect that our framework reduces the noise while preserving the details of the regions. The speed of convergence in this method is higher than our previous work [6] because our method uses fewer neurons in hidden layer. Moreover, our proposed method is capable to decrease the error of sigma estimation in OCT images about 33 percent in comparison with when an individual MLP network is utilized.

The proposed method can also be used for analyzing other imaging modalities images such as photo-acoustic imaging [17] or in an optical fiber system for optimization [18].



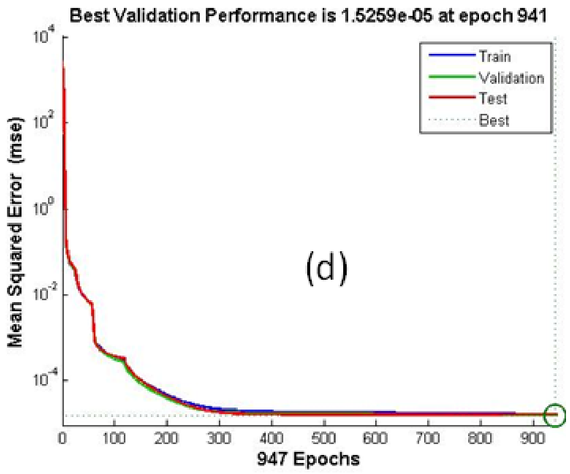



Figure 4:MSE of the proposed method at different runs

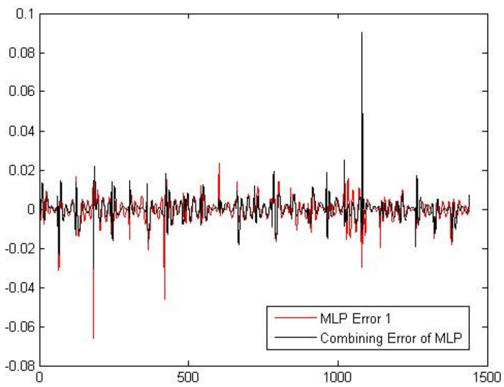



Figure 5: MLP error versus the combining error of MLP

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