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Characterization of layered scattering media using polarized light measurements and neural networks

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Abstract. Measurements of the spatial distributions of polarized light backscattered from a two-layer scattering medium are used to train a neural network. We investigated whether the absorption coefficients and thickness of the layer can be determined when the scattering properties are known. When determining the absorption of the upper layer or the layer's thickness, polarized light measurements provide better performance than unpolarized measurements, demonstrating the sensitivity of polarized light to superficial tissue. Determination of the lower layer's absorption coefficient is not improved by polarized light measurements. Prior knowledge of the tissue under investigation is also beneficial because errors are reduced if the range of absorption or thickness is restricted.
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1 Introduction

There is a great deal of interest in the development of noninvasive optical techniques for tissue diagnosis.[1] The main drawback is that light is heavily scattered within tissue and this leads to uncertainty about the volume from which information is retrieved. Our recent research[2,3] has focused on the use of polarized light to characterize layered media for such applications as measurement of burn and melanoma thicknesses. In burn treatment, thickness is the most important parameter for clinicians diagnosing the need to perform a skin graft;[4] e.g., a deep second-degree burn penetrates into the dermis to a depth on the order of 1 to 2 mm.[5] Thickness is important in melanoma prognosis because the cancer may spread if the epidermis–dermis boundary is broken.[6]

Polarized light techniques[7–12] utilize the property that light depolarizes as it propagates and the initial polarization of incident light is lost within relatively few scattering events. This can be used to localize volumes close to the surface. In addition, it has been observed that there are varying rates of depolarization of different initial polarization states with scattering[13] and it has been demonstrated[2,3] that this has the potential to characterize layered scattering media and make coarse optical sectioning possible. Previously[3] we showed that the spatial distribution of polarized light backscattered from a layered medium is sensitive to variations in optical absorption and thickness of the layer. This represents only part of the problem, and in this work we investigated whether such measurements can be used to determine the absorption coefficients and thickness of a two-layer scattering medium.

Other research groups have investigated methods, to determine the optical properties of layered media. Most notably, Pham et al.[14] fitted a layered diffusion model to obtain the optical properties from frequency-domain measurements. They varied one parameter at a time to determine the accuracy of their approach and then increased the number of variables. This allows the effectiveness of the fitting algorithm at different stages of complexity of the medium to be established. The results are considered quantitatively accurate if the errors are less than 10% and qualitatively useful if they are between 10 and 20%. When three or more parameters are varied, the results become inaccurate. Alexandrakis et al.[15] investigated a similar problem but used a frequency-domain hybrid Monte Carlo diffusion model to obtain the scattering and absorption of both layers and the thickness of the layers simultaneously. It was found that the hybrid model is more accurate than a diffusion model in recovering optical properties of the upper layer and the thickness, but the errors are still fairly large ($>30\%$). However, diffusion theory cannot be used to model polarized light and so we considered using neural networks trained on data obtained from Monte Carlo simulations to recover the optical properties of layered media. Encouraging results have been obtained when neural networks are used to extract the optical coefficients of semi-infinite media,[16,17] but in this work the more difficult problem of layered media was considered.

The following section presents the analysis methods, including details of the Monte Carlo simulation; the samples used; and the neural network applied. Section 3 presents the results of an investigation to determine whether a neural network trained on polarized light measurements can be used to characterize layered scattering media. Discussions and conclusions follow in Secs. 4 and 5, respectively.

2 Theory

2.1 *Monte Carlo Simulation*

The polarization Monte Carlo model simulates illumination with a pencil beam of polarized light perpendicular to the

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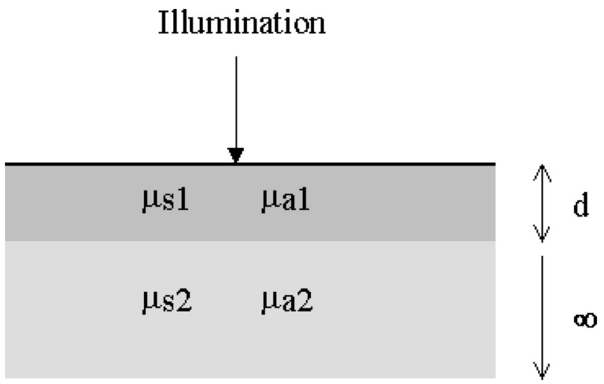

Fig. 1 General geometry of the sample.

surface of the medium and models individual photons (or light packets) propagating through a layered scattering medium composed of Mie scattering particles. The details of this model have been discussed previously[18,19] and therefore are addressed only briefly here. Photons are individually tracked through the medium, and at each photon–particle collision the direction and polarization are modified by adjusting the directional cosines and Stokes parameters. The characteristics of photons backscattered from the medium are recorded. Spatial intensity distributions, $I(r)$, are obtained by measuring the frequency of photons emerging within annuli centered on the source and normalized by the annular area. The Monte Carlo data that are used to train the neural networks in this study are presented elsewhere.[3]

2.2 *Samples and Sample Geometries*

Figure 1 shows the general form of the sample under investigation. The model is capable of simulating multiple layers, each infinite in the $x-y$ plane with a semi-infinite lower layer. However, for simplicity here we consider only a two-layer medium, with an upper planar layer of thickness d and a semi-infinite lower layer. There is a mismatch of 1.4 in the refractive index at the air–tissue interface; at the tissue–tissue interface the layers are index matched. The medium is composed of a monodispersion of Mie scatterers with the mean cosine of the scattering angle, $g=0.92$ and a size parameter $ka=13.9$, which are consistent with typical tissue scatterers.[1,20] Each layer has different scattering (μ_s) and absorption (μ_a) coefficients and absorption is added postsimulation using Lambert-Beer's law, depending on the propagation distance within each layer. The absorption and scattering properties of the media analyzed are stated in mean-free paths (mfp) where $1\ \mathrm{mfp}=1/\mu_s$ so that the results can be easily scaled for a wide range of media.

2.3 *Polarization Analysis*

A four-channel detection scheme is used with different illumination and detection arrangements (Table 1). These channels can be easily measured experimentally using a simple detection scheme.[2,11] The different channels allow various categories of backscattered photons to be detected and these were described in detail previously.[3] The subtraction of the different channels allows light to be separated into its component parts, i.e., light that has maintained its original polarization state or has been multiply scattered.

2.4 *Moments of Distributions*

Moment analysis is a widely used technique for curve analysis and provides a useful method of characterizing the spatial intensity distributions used in this study. In the cases considered, we found that moments are more robust to noise than training the networks with measurements at discrete detector positions. The first-order moment, M_1, and normalized second-order moment, N_2, are defined as

$$M_1=\int_{r=0}^{\infty} P(r)r\,dr \tag{1}$$

$$N_2=\frac{\int_{r=0}^{\infty} P(r)r^2 dr}{M_1^2}, \tag{2}$$

where $P(r)$ is a probability density function estimated by normalizing the area under the photon frequency histogram $I(r)$ to unity [$I(r)$ is obtained by the procedure described in Sec. 2.1]. M_1 represents a measure of the width of the distribution and N_2 is characteristic of the shape of the distribution; it is more heavily influenced by photons emerging further from the source. In practice, the maximum detector position is at $r=1000$ mfp. Moments are advantageous because they are

Table 1 Polarization-discriminating detection schemes. Forward scattered light is defined as light that has emerged from the scattering medium via a series of forward scattering events. Weakly scattered (opposite helicity) describes light that has emerged via backscattering.

Channel	Illumination	Detection	Categories of Light
1	Linear (horizontal)	Linear (horizontal)	Polarization maintaining and multiply scattered light
2	Linear (horizontal)	Linear (vertical)	Multiply scattered light
3	Circular (right)	Circular (right)	Forward scattered and multiply scattered light
4	Circular (right)	Circular (left)	Weakly scattered (opposite helicity) and multiply scattered light

dependent on the shape of the distribution, not on the absolute intensity. Absolute intensity measurements are highly dependent on surface reflections and accurate calibration of both the light source and detector, and are therefore not considered in this study. The moments of the different polarization channels are used to train the neural networks. The moments of intensity measurements alone, i.e., unpolarized light, are also used for comparison to determine whether polarized light measurements are necessary.

2.5 *Neural Network*

The neural network is implemented using a backpropagation architecture with three layers of nodes: an input layer, a hidden layer, and an output layer.[21,22] To ensure that the network training is generalized, rather than a lookup table that recognizes features in the noise, independent Monte Carlo simulations are used for training and testing. In the work reported in Secs. 3.1 to 3.3, four training and four testing sets of data are used, each consisting of 562,500 photons. In Secs. 3.4 to 3.6, two training and two testing sets, each containing 25e6 photons, are used as the data have also been used for polarization subtraction studies.[3] As in other neural network applications, all input data (i.e., moments) are scaled to an appropriate range (between 0 and 1) before being fed into the network. Conversely, all output data predicted in testing by the network are subsequently rescaled to obtain meaningful values. Percentage errors are calculated for all predicted values to evaluate the sensitivity of the measurements.

3 Results

We investigated the ability of a neural network to determine μ_{a1}, μ_{a2}, and d of a two-layer scattering medium from polarized light measurements. In all cases we assumed that the values of g and the scattering coefficients of both layers are known from *in vitro* studies. We used an approach similar to that of Pham et al.[14] and initially varied one parameter at a time and then extended the number of variables. This allows better characterization of the performance of the neural networks at different stages in the complexity of the inversion. Sections 3.1 and 3.2 describe measurements varying μ_{a2} only and μ_{a1} only, respectively, keeping one layer at a constant absorption. In Sec. 3.3, both μ_{a1} and μ_{a2} are varied. In Sec. 3.4, the measurement of the layer is thickness alone is considered. Recovery of both μ_{a1} and d is discussed in Sec. 3.5. Finally, the effects of restricting the range of variables are considered in Sec. 3.6. For all the tables, data are presented to two significant digits.

3.1 *Varying Absorption* (μ_{a2}) *of the Lower Layer*

This section describes the ability of a neural network to recover μ_{a2} over the range 7.55e-3 to 0.04005 mfp^{-1} in steps of 2.5e-4 mfp^{-1}. The remaining optical coefficients are fixed at $\mu_{a1}=0.001\,\mathrm{mfp}^{-1}$, $\mu_{s1}=1\,\mathrm{mfp}^{-1}$, and $\mu_{s2}=0.5\,\mathrm{mfp}^{-1}$. Three thicknesses are considered; $d=5$, 10, and 30 mfp. A typical plot ($d=5$ mfp, network trained on the first-order moments of channels 1 and 2) of actual versus recovered μ_{a2} is shown in Fig. 2 to demonstrate the effectiveness of the method. A straight line representing the ideal case is also shown to aid visualization. As observed by Pham,[14] at low absorption values the percentage of errors is high even though the absolute errors are small.

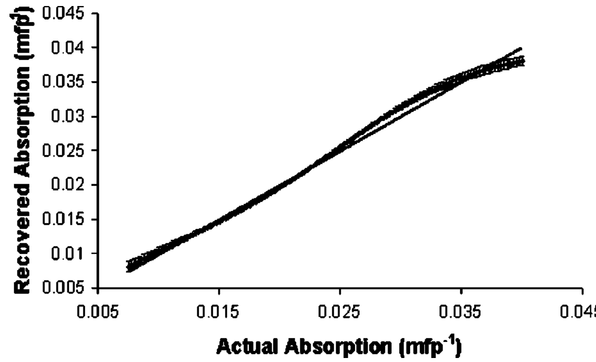

Fig. 2 The μ_{a2} values obtained with a neural network trained on first-order moments of channels 1 and 2 ($d=5$ mfp). A straight line is shown to aid visualization.

The percentage error for networks trained with different combinations of the first- and second-order normalized moments for different thicknesses of a layer is shown in Table 2. In principle, the network should be able to take all input parameters and weight each input accordingly to provide the optimum performance. However, to gain a better physical insight into the problem, the network is also trained using either the first- or second- or both first- and second-order moments of the linear channels (1 and 2) or the circular channels (3 and 4). This will reveal whether all the required information is contained in a particular combination of measurements. To determine whether polarization measurements are essential, the moments of the total intensity (unpolarized) measurements are also included. The mean values of rows and columns are shown to emphasize trends in the results.

For the $d=5$ mfp and $d=10$ mfp layers, the majority of the results are within the acceptable margins of error (<20%).

Table 2 Percentage error in μ_{a2} when it is varied over the range 7.55e-3 to 0.04005 mfp^{-1} and μ_{a1} is constant (0.001 mfp^{-1}).

d (mfp) Training data	5 (%)	10 (%)	30 (%)	Mean (%)
Channels 1 and 2, first-order moment	7.1	17	35	20
Channels 3 and 4, first-order moment	4.8	5.1	34	15
Total intensity, first-order moment	20	2.4	27	17
Channels 1 and 2, second-order moment	18	49	59	42
Channels 3 and 4, second-order moment	14	14	49	26
Total intensity, second-order moment	12	9.7	17	13
Channels 1, 2, 3, and 4, first- and second-order moments	7.7	23	54	28
Total intensity, first- and second-order moments	12	9.8	39	20
Mean (%)	12	16	39	22

Table 3 Percentage error in μ_{a1} when it is varied over the range 7.55e-3 to 0.04005 mfp^{-1} and μ_{a2} is constant (0.001 mfp^{-1}).

d (mfp) Training data	5 (%)	10 (%)	30 (%)	Mean (%)
Channels 1 and 2, first-order moment	7.9	18	5.6	11
Channels 3 and 4, first-order moment	13	2.2	1.3	5.6
Total intensity, first-order moment	2.4	2.1	41	15
Channels 1 and 2, second-order moment	19	29	19	22
Channels 3 and 4, second-order moment	16	2.9	49	22
Total intensity, second-order moment	6.8	6.0	14	8.8
Channels 1, 2, 3, and 4, first- and second-order moments	1.8	13	25	13
Total intensity, first- and second-order moments	9.0	8.6	15	11
Mean (%)	9.5	10	21	14

In general, the polarized light measurements offer no significant improvement over total intensity measurements. For the thinnest layer ($d=5$ mfp), the error in μ_{a2} is lowest because the upper layer has relatively little effect on the measurements.

3.2 *Varying Absorption (μ_{a1}) of the Upper-Layer*

In this case μ_{a1} is varied over the range 7.55e-3 to 0.04005 mfp^{-1} in steps of 2.5e-4 mfp^{-1} while keeping μ_{a2} at a constant value of 0.001 mfp^{-1}. Again, three thicknesses are considered: $d=5$, 10, and 30 mfp. Table 3 contains the percentage of errors for neural networks trained using the same parameters as in Sec. 3.1. Again for the polarized light measurements, the values obtained using networks trained on the first-order moments are more accurate than those obtained with networks trained on the second-order moments. In the majority of cases considered, the results are within acceptable error limits.

3.3 *Varying Absorption of Both Layers (μ_{a1} and μ_{a2})*

We now consider the more difficult case of recovering the absorption coefficient of both the upper and lower layers. The range of μ_{a1} and μ_{a2} is an order of magnitude less than in Secs. 3.1 and 3.2 (6.9e-4 to 0.00405 mfp^{-1} in steps of 1.6e-4 mfp^{-1}), owing to the reduction in signal-to-noise ratio that occurs when both media are heavily absorbing. Table 4 shows the percentage errors over the 2-D grid of μ_{a1} and μ_{a2} values. In the majority of cases the error in μ_{a1} is unacceptable (>20%), owing to the small thickness. As anticipated, when the thickness of the upper layer increases, the error in μ_{a1} decreases because the emerging light is spending a higher proportion of the time in the upper layer. The training set using all the available data (both spatial and polarization) provides the optimum performance for obtaining μ_{a1}, although only acceptable performance is achieved for $d=30$ mfp.

The performance in determining μ_{a2} is far better than that of obtaining μ_{a1} because of the greater propagation time of the light in the lower medium. As the thickness of the upper layer increases, the error in μ_{a2} increases. The best performance in obtaining μ_{a2} is provided by the total intensity measurements, indicating that polarized light provides little information about the properties of the lower layer.

3.4 *Varying Layer Thickness (d)*

Previously[3] we demonstrated the sensitivity of the different polarization channels to thickness where thickness was modeled using a single-layer medium. This is equivalent to an upper layer with a varying *d* above a second layer that is totally absorbing. The advantage of this approach is that a single Monte Carlo simulation can be used to model different *d* is by recording the maximum visitation depth of a photon and discarding those absorbed in the second medium. This

Table 4 Percentage error in μ_{a1} and μ_{a2} when both are varied simultaneously over the range 0.00069 to 0.00405 mfp^{-1}.

	5		10		30		
d (mfp) Training Data	μ_{a1} (%)	μ_{a2} (%)	μ_{a1} (%)	μ_{a2} (%)	μ_{a1} (%)	μ_{a2} (%)	Mean (%)
Channels 1 and 2, first-order moment	92	14	88	48	88	86	69
Channels 3 and 4, first-order moment	99	10	79	23	60	68	57
Channels 1 and 2, second-order moment	109	44	66	38	62	21	57
Channels 3 and 4, second-order moment	88	15	24	7.2	23	17	29
All channels, first- and second-order moments	41	24	32	12	17	19	24
Total intensity, first- and second-order moments	97	5.0	100	7.9	97	7.3	52
Mean (%)	88	19	65	23	58	36	48

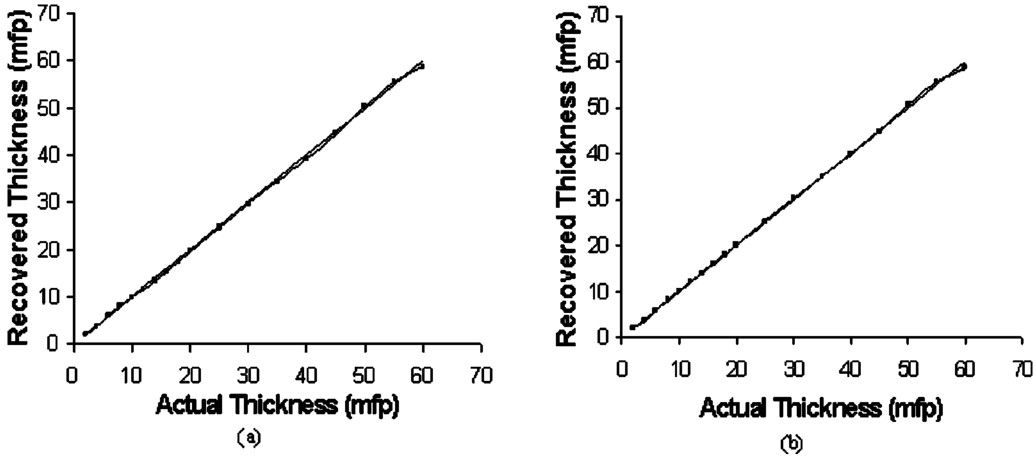

Fig. 3 Values of *d* obtained from networks trained on (a) first-order moments of channels 1, 2, 3, and 4; (b) second-order moments of channels 1, 2, 3, and 4. A straight line is shown to aid visualization.

improves the efficiency of the simulations and allows the moments of the distributions over a range of layer thicknesses to be calculated ($d=2$ to 20 mfp in steps of 2 mfp and $d=20$ to 60 mfp in steps of 5 mfp). However, it should be noted that this represents the extreme contrast for a two-layer medium. For typical tissue-scattering mean-free paths (0.1 mm), this corresponds to a thickness of 0.2 to 6 mm, which covers the range of burn thicknesses and the thickness of many skin lesions. For studies of superficial skin lesions, more investigation is required although we anticipate the trends observed in this case to be valid. Figure 3 contains the values of *d* for networks trained on the first- and second-order moments of the polarization channels 1, 2, 3, and 4 [Figs. 3(a) and 3(b)]. A straight line representing the ideal case is also shown to aid visualization. When both scattering and absorption are fixed, all measurements accurately extract the layer's thickness (first-order moment error=2.5%, second-order moment error =1.2%).

3.5 *Varying d and μ_{a1}*

The case considered in Sec. 3.4 is relatively straightforward because the optical coefficients are constant. Here, *d* is varied over the same range of thicknesses as in Sec. 3.4, and μ_{a1} is varied over 7.55e-3 to 0.04005 mfp^{-1} (in steps of 2.5e-4 mfp^{-1}). Four networks are trained on the data from (1) first-order moment, channels 1, 2, 3, and 4; (2) second-order moment, channels 1, 2, 3, 4; (3) combined first- and second-order moments, channels 1, 2, 3, and 4; and (4) combined first- and second-order moments, total intensity. Table 5 shows that over the range of values considered, the only training set capable of obtaining a thickness value of acceptable accuracy consists of the combined first- and second-order moments of the four channels. The error in retrieving *d* using the total-intensity value is particularly poor. Similarly, the error in absorption coefficient is lowest for the first- and second-order moments of the four channels and highest for the total-intensity first- and second-order moments. The networks trained on first-order moments outperform those trained using second-order moments.

3.6 *Restricting the Range of d and μ_{a1}*

In the work reported in Sec. 3.5, *d* and μ_{a1} were varied over a relatively wide range. This section describes the performance of networks trained on data where the range of *d* or μ_{a1} was restricted Table 6 shows the error in μ_{a1} and *d* when the absorption range is restricted to (1) 7.55e-3 to 0.04005 mfp^{-1}, (2) 7.55e-3 to 0.03005 mfp^{-1}, (3) 7.55e-3 to 0.02005 mfp^{-1}, and (4) 7.55e-3 to 0.01005 mfp^{-1}. In practice this will occur when there is prior knowledge of the tissue's optical properties. It can be seen that for networks trained on the polarized light data, restricting the range of μ_{a1} offers no significant improvement in the accuracy of the values of μ_{a1} or *d* obtained, and the performance is acceptable for most ranges. For the total-intensity measurements, restricting the range has a significant effect on the performance of the networks in obtaining both μ_{a1} and *d*, improving from 67 to 8.7% for μ_{a1} and from 197 to 33% for *d*.

When the range of *d* is restricted (Table 7), improvements are obtained for polarized and unpolarized light measurements in both μ_{a1} and *d*. For all ranges considered, the per-

Table 5 Percentage error in μ_{a1} and *d* when μ_{a1} and *d* are varied simultaneously over the range 7.55e-3 to 0.04005 mfp^{-1} and 2 to 60 mfp, respectively.

Training Data	*d* (%)	μ_{a1} (%)
Channel 1, 2, 3, and 4, first-order moment	41	10
Channels 1, 2, 3, and 4, second-order moment	78	20
Channels 1, 2, 3, and 4, first- and second-order moments	18	4.0
Total intensity, first- and second-order-moments	197	67

Table 6 Percentage error in μ_{a1} and d when μ_{a1} and d are varied simultaneously. The thickness is varied over the range of 2 to 60 mfp, but the absorption is varied for different ranges, i.e., (1) 7.55e-3 to 0.04005 mfp^{-1}, (2) 7.55e-3 to 0.03005 mfp^{-1}, (3) 7.55e-3 to 0.02005 mfp^{-1}, and (4) 7.55e-3 to 0.01005 mfp^{-1}.

Error in μ_{a1}	(1) (%)	(2) (%)	(3) (%)	(4) (%)
Channels 1, 2, 3, and 4, first- and second-order moments	5.8	9.3	10	11
Total intensity, first- and second-order moments	67	57	21	8.7
Error in d	**(1) (%)**	**(2) (%)**	**(3) (%)**	**(4) (%)**
Channels 1, 2, 3, and 4, first- and second-order moments	18	30	17	12
Total intensity, first- and second-order moments	197	164	59	33

formance of polarized light measurements is better than that of unpolarized measurements.

4 Discussion

We have investigated whether polarized light measurements can be used to determine the absorption coefficient and thickness of a two-layer scattering medium. Inversion of the measured data cannot be achieved by analytical solutions such as diffusion theory, owing to the presence of weakly scattered polarization-maintaining light. A neural network therefore provides a useful tool for analyzing such data and determining the measurable parameters that are most sensitive to absorption or thickness of the layer.

Our results show that polarized light measurements are more sensitive to the properties of superficial tissue than unpolarized measurements. This is demonstrated by the lower errors obtained with polarized light measurements when the upper layer's absorption is extracted as described in Secs. 3.3, 3.5, and 3.6, and d is obtained as described in Sec. 3.5 and 3.6. This is because the destruction of polarization information by scattering causes sensitivity to superficial tissue.[2,3,9,10] However, for the same reason, polarized light measurements offer no significant improvement over unpolarized measurements when they are used to obtain μ_{a2}.

In the majority of cases, training the network on all the available polarized data provides the best performance. The advantage of using combined first- and second-order moments rather than only the first- or second-order moments was discussed in a previous paper[3] using a method in which contours were plotted for measured values of first- and second-order moments for different values of μ_{a1} and μ_{a2}. The steep gradients and orthogonal contours that were observed indicated that the data are robust and suitable for inversion. Therefore although networks trained using data from only the first-order moments generally outperform those trained using only normalized second-order moment data, there is still more information to be obtained by combining the two sets. This indicates that this application benefits from the ability of neural networks to extract subtleties from the data.

To completely characterize a two-layer scattering medium, seven parameters need to be determined: d, μ_{a1}, μ_{a2}, μ_{s1}, μ_{s2}, and the values of g in both layers. This is an ill-conditioned problem and so it is necessary to assume prior knowledge of some of the parameters. In this paper we considered the recovery of absorption and thickness while leaving g and the scattering coefficients constant. In the majority of cases considered, polarized light measurements are capable of determining the absorption coefficient relatively well. Clearly, when only the absorption of a single layer is varied (Tables 2 and 3), it is a comparatively simple problem to determine the absorption coefficient, and the only significant increase in error occurs when the top layer is thin (5 mfp) and light does not adequately sample this region. In the more difficult cases of varying the absorption and thickness of the layer, it is still possible to determine the absorption coefficient to an acceptable accuracy if the most appropriate measurables are selected. Tables 4 and 5 show that if neural networks are trained using both the first- and second-order moments of the polarized light measurements, then acceptable accuracy can be achieved. The only exception is obtaining μ_{a1} when both μ_{a1} and μ_{a2} are varied (Table 3) and in this case neural networks trained using both the first- and second-order moments of the polarized light measurements still provide the lowest errors.

Determination of the thickness of a layer is more difficult than determining absorption because when both absorption and thickness are varied, d can only be determined when all the available polarized light data are used (Table 5). When the range of absorption is restricted (Table 6), the accuracy of unpolarized light measurements is improved significantly, but the improvement in polarized light measurements is insignificant. When the range of thickness is restricted, significant improvements in the performance of both polarized and unpolarized measurements are observed. It is not unreasonable to make assumptions about the optical properties of the tissue under investigation since these are well documented.[1] For certain applications, it is useful to restrict the range of absorption

Table 7 Percentage error in μ_{a1} and d when μ_{a1} and d are varied simultaneously. The absorption is varied over the range of 0.015 to 0.025 mfp^{-1}, but the thickness is varied for different ranges, i.e., (1) 2 to 60 mfp, (2) 10 to 60 mfp, (3) 10 to 30 mfp, (4) 20 to 30 mfp, and (5) fixed 30 mfp.

μ_{a1} (mfp^{-1})	(1)	(2)	(3)	(4)	(5)
Channels 1, 2, 3, and 4, first- and second-order moments	7.6	4.7	2.9	2.2	0.18
Total intensity, first- and second-order moments	12	9.7	13	5.2	0.86
d (mfp)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Channels 1, 2, 3, and 4, first- and second-order moments	22	28	12	6.5	0.0
Total intensity, first- and second-order moments	70	87	26	17	0.0

values to known *in vitro* measurements to provide accurate inversion, e.g., necrotic tissue overlying healthy tissue in characterization of burns or a lesion containing melanin overlying melanin-free tissue. Further improvements could possibly be achieved by using a larger training set since at present relatively few independent Monte Carlo simulations are used in the training process.

We have presented preliminary results that demonstrate the potential of using polarized light and neural networks for characterizing layered media. However, several factors need to be considered for practical implementation. As previously discussed, some assumption of the optical properties or the range of optical properties from known *in vitro* values is necessary. In addition, we have assumed an ideal geometry with layers that are uniform in thickness and infinite in the lateral dimension. In this case photons that are multiply scattered and sample a large volume provide better data for training the neural networks. In practice, the layer's thickness will vary and the spatial localization obtained by the subtraction of different polarization channels may be beneficial. As an indication of the potential of this approach, we have obtained preliminary results for networks trained on data from subtracted polarization channels for the case considered in Table 5. The error in μ_{a1} was 5%, but the error in d was relatively high (35%). Future research will investigate this approach further.

One potential approach is to obtain the properties of the upper layer using polarized light measurements and then use this knowledge to obtain the properties of the lower layer from unpolarized light measurements. To ensure accurate determination of the moments, a high dynamic range detector is required, owing to the range of intensities observed in backscattered distributions. First-order moments are more easily measured because the normalized second-order moments are more heavily weighted by photons emerging further from the source and are susceptible to noise. An alternative method we are currently investigating is whether the neural network approach can be applied to single-point polarized light measurements at a range of wavelengths. This would be advantageous because it would allow a full-field measurement to be obtained using a simple CCD camera configuration.[10] In the specific case of diagnosis of melanoma, other parameters,[6,23] such as melanoma shape or size, could also be useful additions to the neural network training data. Other issues that need to be resolved before implementation of such techniques becomes practical include the effects of the birefringence of collagen,[24] layer nonuniformity, and a mismatch of the refractive index between the tissue layers.

5 Conclusions

The potential use of neural networks for determining the properties of a two-layer scattering medium has been demonstrated. Polarized light measurements provide better performance than unpolarized measurements in obtaining the absorption coefficient of the upper layer and the layer's thickness because of the sensitivity of polarized light to superficial tissue. However, polarized light measurements offer no significant benefit in obtaining the absorption of the lower layer. Improvements in performance can be achieved by restricting the range of optical coefficients to those corresponding to the documented range of tissue values.

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