NOTE

Non-invasive determination of the absorption coefficient of the brain from time-resolved reflectance using a neural network

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Abstract. We investigated the performance of a neural network for derivation of the absorption coefficient of brain from simulated non-invasive time-resolved reflectance measurements on the head. A five-layered geometry was considered assuming that the optical properties (except the absorption coefficient of brain) and the thickness of all layers were known with an uncertainty. A solution of the layered diffusion equation was used to train the neural network. We determined the absorption coefficient of brain with an RMS error of $< 6\,\%$ from reflectance data at a single distance calculated by diffusion theory. By applying the neural network to reflectance curves obtained from Monte Carlo simulations similar errors were found.

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Non-invasive optical measurement of the hemodynamics of the brain has become an important research area in recent years. A plethora of algorithms and models has been applied to investigate the possibility to retrieve the absorption coefficient of the brain from steady-state and time-resolved measurements (Arridge 1999, Barnett *et al* 2003, Comelli *et al* 2007, Fukui *et al* 2003, Okada *et al* 2003, Strangman *et al* 2003). Nevertheless, there is still an urgent necessity for the development of robust and fast methods for precise determination of the brain absorption which are not influenced by the hemodynamics of the upper layers.

In this study we report for the first time to our knowledge the application of a neural network for the determination of the absorption of brain. The neural network was trained with time-resolved reflectance data at a single distance from the source using a recently derived solution of the N-layered diffusion equation (Liemert *et al* 2010). It was assumed that the optical properties (except the absorption coefficient of brain) and the thickness of the layers are only known within a certain accuracy. The structure of the head was simplified to a five-layered model allowing the use of the solution of the

Table 1. Reduced scattering coefficient μ_s', absorption coefficient μ_a, thickness d, and refractive index n used as standard optical properties in the calculations for the different layers in the human head.

layer	μ_s' [mm^{-1}]	μ_a [mm^{-1}]	d [mm]	n
skin	1.30	0.018	1	1.40
fat	1.00	0.005	2	1.40
skull	1.20	0.016	7	1.40
CSF	1.00*	0.004	2	1.33
brain	1.25	0.01 - 0.02**	∞	1.40

* increased, see text

** see text

diffusion equation. However, we note that the neural network can also be trained using solutions of the more precise transport equation (Ishimaru 1978), e.g. with Monte Carlo simulations. By means of the Monte Carlo simulation the light propagation for little scattering media can be calculated. In addition, a more complex model of the head can be used since the Monte Carlo simulation is not restricted to a layered model that is needed for the analytical solution of the diffusion theory. However, for a basic test of the performance of the neural network it is sufficient to apply the diffusion equation for training the neural network. The use of the diffusion equation strongly decreases the calculation time for the creation of training data sets.

For the layered model of the head we assumed that the reduced scattering coefficient μ_s' as well as the absorption coefficient μ_a of the skin, fat, skull, cerebrospinal fluid (CSF) and the reduced scattering coefficient of the brain are known to a certain extent whereas the absorption coefficient of the brain $\mu_{a,b}$ is determined by the neural network. The optical coefficients are obtained from literature (Barnett *et al* 2003, Bevilacqua *et al* 1999, Comelli *et al* 2007, Fukui *et al* 2003, Okada *et al* 2003, Strangman *et al* 2003) and are given in table 1. Since the diffusion theory requires $\mu_s' \gg \mu_a$ we increased the reduced scattering coefficient of the CSF to $\mu_s' = 1.00\,\mathrm{mm}^{-1}$ which is higher than the values reported in literature. We stress that this assumption is not a general weakness of our method because for using the neural network in real measurements Monte Carlo simulations, that are more time-consuming, can be used.

In order to solve the forward model the time-resolved reflectance $R(t)$ at 30.5 mm from the incident point was calculated by the analytical solution of the diffusion equation (Liemert *et al* 2010). This distance is suitable since modifications of the optical properties of the brain can be seen at larger distances whereas modifications of the optical properties of the upper layers can be seen at smaller distances. Using the values given in table 1 we computed a set of 100 time-resolved reflectance curves which form one data set. For each curve $\mu_{a,b}$ was randomly chosen out of the range $0.005\,\mathrm{mm}^{-1} \leq \mu_{a,b} < 0.025\,\mathrm{mm}^{-1}$ to create the data set for the training of the neural network. This procedure was repeated twice by randomly modifying $\mu_{a,b}$ in a smaller range $0.01\,\mathrm{mm}^{-1} \leq \mu_{a,b} < 0.02\,\mathrm{mm}^{-1}$ in order to create two data sets for testing the neural network.

The principle of the applied neural network is explained in literature (Boone *et al* 1990, Farrell *et al* 1992). We used a neural network consisting of an input layer with eight neurons, one hidden layer with eight further neurons and an output layer with one neuron. For the eight neurons of the input layer we calculated the times at the maximum of the time-resolved reflectance curve $R(t)_{max}$ as well as at $0.9R(t)_{max}$ before the maximum and the times at $0.3R(t)_{max}$, $0.1R(t)_{max}$, $0.03R(t)_{max}$, $0.01R(t)_{max}$, $0.003R(t)_{max}$ and $0.001R(t)_{max}$ after the maximum. The neuron of the output layer represents the estimated absorption coefficient calculated by the neural network which is compared to the true absorption coefficient that belongs to the corresponding time-resolved reflectance curve. The neurons of the input layer are connected with those of the hidden layer and those again with the neuron of the output layer. Weights define the strength between those layers and are randomly chosen at the beginning of the learning process. During the learning process the weights are modified in order to minimize the RMS error

$$\sigma_{rel} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\mu^c_{a,b,i} - \mu_{a,b,i}}{\mu_{a,b,i}}\right)^2} \qquad (1)$$

between the true absorption coefficient of the brain $\mu_{a,b}$ and the absorption coefficient of the brain $\mu^c_{a,b}$ calculated by the neural network. In Eq. 1 N represents the number of $R(t)$ curves in one data set. In order to validate the neural network the determined weights were used to calculate $\mu^c_{a,b}$ and, thus, σ_{rel} for the two test data sets.

First of all a neural network was trained and tested with exactly known optical properties (see table 1). Therefore, only $\mu_{a,b}$ was randomly modified during the training procedure and afterwards calculated in the testing procedure. The neural network returned values for $\mu_{a,b}$ with $\sigma_{rel} \approx 0.2\,\%$ for the two test data sets.

However, the optical properties of the head are only known within a certain accuracy. We assumed that the optical properties of all layers above the brain $\mu'_{s,up}$ and $\mu_{a,up}$ as well as the reduced scattering coefficient of the brain $\mu'_{s,b}$ are known with an accuracy as listed in table 2. The values of these optical properties were randomly chosen with equal probability out of the given range, e.g. $((1-a_i)\mu'_{s,b} \leq \mu'_{s,b,a_i} < (1+a_i)\mu'_{s,b})$, in order to train and test the neural network. Also in these cases the neural network is capable of determining accurately $\mu_{a,b}$ and returned RMS errors for the two test data sets as shown in table 2.

Applying more realistic conditions with respect to measurement data, we assumed a Gaussian noise distribution of the time-resolved reflectance curves. To this end we took the training and test data sets from above and added a Gaussian noise with a standard deviation $\sigma = R(t)/[R(t)\cdot x]^{1/2}$ using $x = 50000/R(t)_{max}$ to the $R(t)$ curves within the accuracy a_4 (see figure 1). Here 50000 stands for the maximum number of counts

Table 2. Assumed accuracy a_i of the optical properties together with the corresponding RMS error σ_{rel} obtained from the application of the neural network.

a_i	$\mu'_{s,up/b}$ [mm^{-1}]	$\mu_{a,up}$ [mm^{-1}]	σ_{rel}
a_1	$\pm 1\,\%$	$\pm 2\,\%$	$\approx 0.3\,\%$
a_2	$\pm 5\,\%$	$\pm 10\,\%$	$\approx 1.0\,\%$
a_3	$\pm 10\,\%$	$\pm 20\,\%$	$\approx 1.3\,\%$
a_4	$\pm 20\,\%$	$\pm 40\,\%$	$\approx 4.0\,\%$

and the chosen noise is comparable to real measurements. For the input values of the

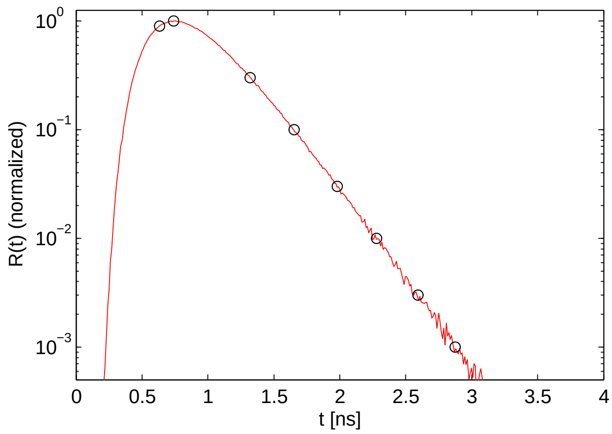

Figure 1. Time-resolved reflectance curve with a Gaussian noise distribution and the chosen time values (symbols) for the input layer of the neural network.

neural network the time values at $0.9R(t)_{max}$ before the maximum and at $R(t)_{max}$ were calculated. For the other input values the times at $0.3R(t)_{max}$, $0.1R(t)_{max}$, $0.03R(t)_{max}$, $0.01R(t)_{max}$, $0.003R(t)_{max}$ and $0.001R(t)_{max}$ after the maximum were calculated by using a polynomial of sixth order that was fitted to the noisy data in the range between $0.5R(t)_{max}$ and $0.0005R(t)_{max}$ after the maximum. The neural network was trained with 100, 300, 500 and 1000 $R(t)$ curves. By increasing the number of $R(t)$ curves for the training data set, the RMS error for the two test data sets decreased and was $\sigma_{rel} \approx 4.6\,\%$, when the neural network was trained with 1000 $R(t)$ curves.

Next, for a simulation of hemodynamic measurements on the head where $\mu_{a,b}$ changes and the other optical properties remain more or less the same, the optical properties (except $\mu_{a,b}$) were five times randomly chosen out of the range with the accuracy a_4 given in table 2. We obtained the data A, B, C, D, E that determine the optical properties $\mu'_{s,up}$, $\mu'_{s,b}$ and $\mu_{a,up}$, representing five patients. Then the absorption coefficient of the brain was systematically increased ($\mu_{a,b} = 0.01$, 0.012, 0.014, 0.016, 0.018 and $0.02\,\mathrm{mm}^{-1}$) and 30 time-resolved reflectance curves were calculated by the analytical solution of the diffusion theory (A1, A2 ... E6). The same amount of noise was added as above. The true absorption coefficient $\mu_{a,b}$ and the absorption coefficient calculated by the neural network $\mu^c_{a,b,A-E}$ for the cases A-E are depicted in figure 2. The RMS error for all curves was $\sigma_{rel} \approx 4.8\,\%$.

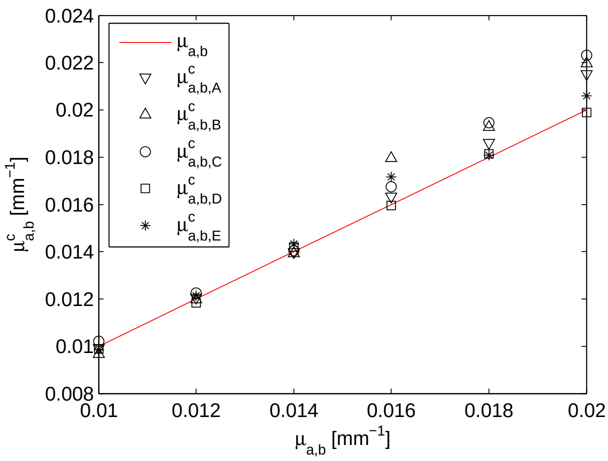

Figure 2. The absorption coefficients calculated by the neural network $\mu^c_{a,b,A-E}$ (symbols) are shown versus the true absorption coefficients $\mu_{a,b}$ (solid curve). The indices A-E stand for the five created data sets of optical properties, representing five different patients.

In the calculations described above we supposed that the layer thickness is exactly known, however, the thickness of the layers of the human head is varying between different patients. In the following we assumed that the thickness of the different layers is known within an accuracy of $\pm 20\,\%$. The accuracy a_4 was chosen for the optical properties and Gaussian noise was added as before to the $R(t)$ curves. A neural network was trained with 300 $R(t)$ curves and we obtained an RMS error of $\sigma_{rel} \approx 5.5\,\%$ for the two test data sets.

Finally, we applied Monte Carlo simulations to validate our results. We used the optical properties given in table 1 with six different values for the absorption coefficient of the brain ($\mu_{a,b} = 0.01$, 0.012, 0.014, 0.016, 0.018 and 0.02 mm^{-1}). Using the weights that were determined applying the solution of the diffusion equation for the training, the RMS error was $\sigma_{rel} \approx 5.5\,\%$. In comparison the RMS error was $\sigma_{rel} \approx 3.4\,\%$ if we utilize the solution of the diffusion equation and the same six combinations of optical properties for the validation of the neural network (see figure 3).

In summary, we showed that the neural network is a particularly suitable method for the determination of the absorption coefficient in the human brain. Even on the supposition that the optical properties of all layers (except $\mu_{a,b}$) are only known with an uncertainty of up to 20 % or 40 % the neural network is capable of determining $\mu_{a,b}$ with small errors. We added a Gaussian noise to the $R(t)$ curves in order to create typical measurement conditions. Also, the different thicknesses of the considered head layers for different patients were investigated. Nevertheless the neural network had the ability to accurately retrieve $\mu_{a,b}$. Moreover, the neural network that was trained with

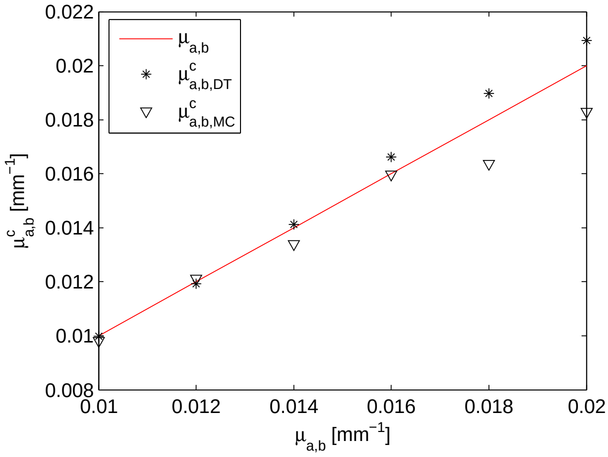

Figure 3. The absorption coefficients calculated by the neural network $\mu^c_{a,b,DT}$ and $\mu^c_{a,b,MC}$ (symbols) from $R(t)$ curves obtained with the solution of the diffusion theory and Monte Carlo simulation, respectively, are shown versus the true absorption coefficients $\mu_{a,b}$ (solid curve).

solutions of the diffusion theory was capable of determining accurately $\mu_{a,b}$ from $R(t)$ curves which were generated by Monte Carlo simulations.

In comparison with other methods, e.g. conventional fitting methods tested in our institute, the neural network obtained better results. It proved to be more robust to noisy $R(t)$ curves and to optical properties that are known within a limited accuracy. A further advantage of the neural network is that it can calculate the absorption coefficient of the brain from an unknown $R(t)$ curve much faster ($<1\,$ms using one processor of a state-of-the-art PC) than it is possible with conventional fitting routines.

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