Towards Automated OCT-Based Identification of White Brain Matter

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Abstract. A novel model-based identification of white brain matter in OCT A-scans is proposed. Based on nonlinear energy operators used in the classification of neural activity, candidates for white matter structures are extracted from a baseline-corrected signal. Validation of candidates is done by evaluating the correspondence to a simplified intensity model which is parametrized beforehand. Results for identification of white matter in rat brain *in vitro* show the capability of the proposed algorithm.

1 Introduction

Optical coherence tomography (OCT) is a powerful, real-time technique for investigating depth structure of biological tissue. Since entering the field of medical imaging it has been well established for imaging purposes in certain medical disciplines e.g. ophthalmology and dermatology [1]. Major advantages are the high resolution, the video-rate scanning capability, and the non-invasive nature of OCT-imaging. Recent research results show that OCT is also applicable to image brain morphology ex vivo and in vitro [2]. This motivates the usage of OCT for identification of brain structure which is of interest in other neurosurgery applications. As white matter provides a high-contrast structure in brain tissue, it is one of the best candidates for OCT-based identification. This contribution concentrates on an automated identification of white matter based on OCT-signals. Based on a simplified signal model of OCT and spike detection algorithms from neural acitivity analysis, a two-stage identification process is proposed. Capability of the algorithm is shown by identifying white matter in a coronal section of a rat brain.

2 State of the art and new contribution

Although OCT has been widely used to image tissue structures, little work has been done on brain imaging. Possible identification of white matter in OCT images has been shown for rat brains *in vitro* [3]. The authors analyzed the light intensity and attenuation coefficient of the backscattered signal based on Beer's law

$$I(z) = I_0 e^{-2\mu_t z} \tag{1}$$

where I_0 is the initial intensity, μ_t denotes the attenuation coefficient and z corresponds to the penetration depth. Results showed that I_0 and μ_t for a wavelength of 1300nm differ for various tissue structures (e.g cortex, external capsule) allowing a clear distinction of white and grey matter. In [4], the authors used a catheter-based OCT probe to examine the possibility of optical guidance in placing a deep brain stimulation electrode. OCT images were acquired by advancing the probe on characteristic tracks in human brains *in vitro*. Their results show that myelinated fibres are strong backscatterers of light and that penetration of light is shallow. Evaluation of OCT scans in both cases has been done manually and only for exclusive areas of white or grey brain matter. In areas where structures with different optical properties are scanned, Beer's law in equation (1) does not hold for the entire scan range. If multiple fibres of white matter are embedded into gray matter the signal features multiple peaks which are superimposed to the exponential decay. This establishes a backscattered signal featuring spiking intensity characteristics. Unfortunately, OCT images are subject to speckle noise which considerably distorts the acquired signal. Speckle noise is usually modeled as multiplicative Rayleigh distributed noise causing a signal-to-noise ratio (SNR) with a value of up to 1. This motivates the use of spike sorting and classification algorithms developed for analysis of neural activity where the signal-to-noise ratio is very low. Based on the model given in equation (1), a method of automated identification of white matter brain structures is proposed. It significantly improves the processing of OCT images of brain structures. This can be used to support an online validation of a desired path, to detect important areas or to improve consecutive steps like segmentation and registration to e.g. histology informations. Automated identification therefore leads to a better integration of OCT into neuronavigation settings.

3 Methods

Brain from a freshly decapitated rat was dissected in an ice-cold Krebs-bicarbonate buffer. A coronal section crossing the cortex, the external capsule and the striatum was scanned by a Swept Source OCT Microscope System (Thorlabs, Inc., Newton, USA) with a center wavelength of 1325nm and an axial scan rate of 16kHz. The field of view was was 2.14mm in depth (y), 3mm in transverse direction (x) and 5mm in dorsal direction (z). Figure 1 shows the coronal section and the intensities of a lateral OCT B-scan crossing the cortex, the external capsule and the striatum. Figure 2 shows an OCT scan at a lateral position of $x = 615\mu$m and the corresponding filtered and baseline-corrected signal. It can be seen that white matter corresponds to peaks in the local intensity neighborhood. As trauma reduction in neurosurgery applications is crucial, OCT probes are required to be as small as possible leading to a relatively small field of view.

Fig. 1. Coronal section and B-Scan of rat brain. Arrows mark corresponding structures

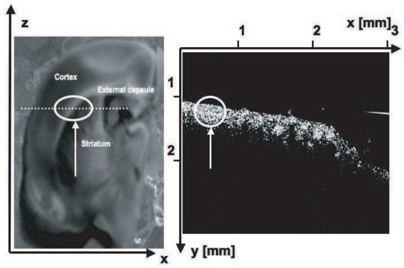
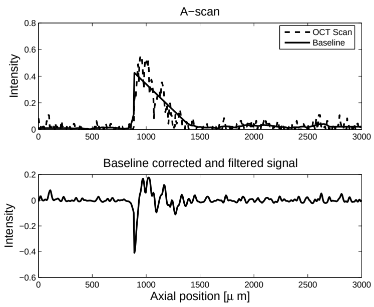


Fig. 2. (top) Log intensity versus penetration depth of a single A-scan and the corresponding baseline (bottom) baseline corrected and filtered signal



Peak identification in A-scans therefore presents a promising approach to find candidates for automated identification of white matter structures. Detection and sorting of spikes in noisy signals under very low signal-to-noise ratios has been extensively researched in the analysis of neural activity. In [5], the authors use a nonlinear energy operator (NEO) in order to extract action potentials from a recorded signal. The NEO-operator is given as

$$\psi_{\mathrm{NEO}}(x(n)) = x^2(n) - x(n+1)x(n-1) \tag{2}$$

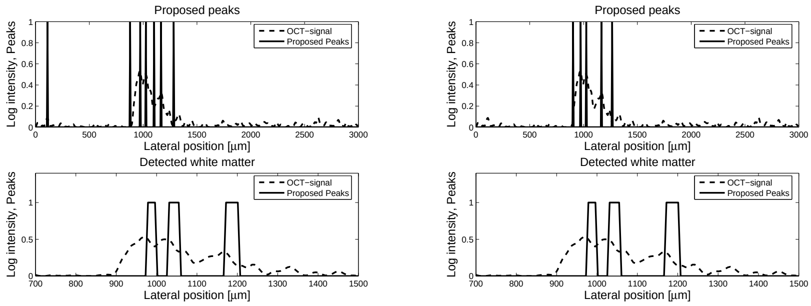
where $x(n)$ denotes the measured signal at time or location n. Another extraction operator is introduced in [6]. The shift and multiply operator (SAM) is given by

$$\psi_{\mathrm{SAM}}(x(n)) = x(n-3)x(n-2)x(n-1)x(n) \tag{3}$$

Both operators have been used for the analysis of spiky waveforms in neural recordings which motivates the use of NEO and SAM to identify candidates of white matter structures in OCT signals. The subsequent classification of a spike is done by thresholding.

The proposed algorithm consists of 3 steps where the first step preprocesses the data by baseline correction. The baseline was determined by fitting a linear regression curve into the linear descent of the intensity curve. The baseline before and after the descent was calculated by taking the mean within a window of 117.2μm. In a second step, the proposed operators are used to identify spikes

Fig. 3. Detection of white matter: (top) proposed peaks; (bottom) validated peaks



(a) NEO (b) SAM

in the baseline-corrected signal. This leads to a set of potential candidates for white matter structures. The third step is used to validate a potential spike and to determine the size of the structure by analyzing the slope in a local neighborhood of the spike candidate. Applying the log-operator on equation (1) yields a linear dependency of the log-intensity and the attenuation coefficient μ. For white matter, μ_t takes a characteristic value. The value $\mu_{t,ref}$ for white brain matter which can be identified by evaluating a set of test images where the white brain matter is classified manually. The parameters I_0 and μ_t at the position $z = z_1$ are subsequently identified by a fitting a linear regression curve into the intensity curve within a local neighborhood of z_1 e.g. in the interval $[z_1 - c_1 \dots z_1 + c_1]$ where c_1 denotes the size of the local neighborhood. Now, the regression result μ_t is compared to the manually classified $\mu_{t,ref}$. If μ_t lies in a user defined interval $[\mu - \sigma, \mu + \sigma]$, position z_1 is classified as white matter.

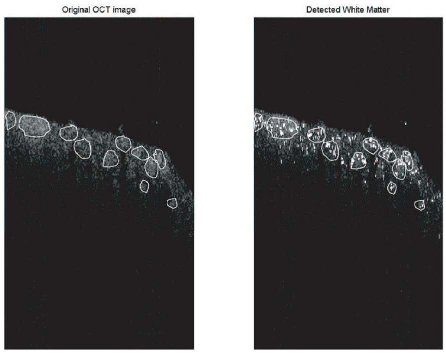
4 Results

The proposed algorithm was tested with the following parameter settings $\sigma_{NEO} = \sigma_{SAM} = 0.02$, $c_1 = 1$ and $\mu = 0.005$. Figure 3 shows the results of the detection by the NEO for one A-scan. It can be seen that both operators are able to identify peaks in noisy environment. The subsequent classification via slope identification excludes wrong propositions (e.g. the first proposition which corresponds to a negative spike in the baseline corrected signal). Figure 4 shows an automated identification for all A-scans of the acquired B-scan for the SAM operator. Identified white matter is shown as white dots in the total image. It can be seen that the detected white matter shows good correspondence to the manual classification.

5 Discussion

The proposed algorithm is able to detect white brain matter reliably in speckle noise corrupted OCT A-scans. Tuning of the parameters, essentially the respec-

Fig. 4. White matter detection for all A-scans: (left) original image with circles indicating white matter areas (right) automatically identified white matter with white dots indicate detection



tive thresholds, based on heuristic experiences might lead to better performance. It is important to note that the algorithm is signal-based. Peaks resulting from the stochastic speckle distribution in the A-scan image might therefore be proposed falsely in the first place. The second step, however, provides a validation of a proposition by analysing the correspondance of the local neighborhood to a simplified OCT-intensity model. This results in a robust classification of white structures.

References

1. Bouma BE, Tearney GJ. Handbook Of Optical Coherence Tomography. Marcel Dekker, Inc.; 2002.
2. Boehringer HJ, Boller D, Leppert J, et al. Time-domain and spectral-domain optical coherence tomography in the analysis of brain tumor tissue. Lasers in Surgery and Medicine 2006;38:588–597.
3. Jeon SW, Shure MA, Baker KB, etal. Optical coherence tomography and optical coherence domain reflectometry for deep brain stimulation probe guidance. Procs SPIE 2005;5686:487–494.
4. Safri MS, Farhang S, Tang RS, et al. Optical coherence tomography in the diagnosis and treatment of neurological disorders. J Biomed Opt 2005;10(5):1–11.
5. Kim KW, Kim SJ. Neural spike sorting under nearly 0-dB signal-to-noise ratio using nonlinear energy operator and artificial neural-network classifier. IEEE Trans Biomed Eng 2000;47:1406–1411.
6. Menne KL. Computerassistenz zur Implantation von Tiefenhirnstimulatoren. Ph.D. thesis. University of Luebeck; 2005.