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# EXTRACTING OPTICAL AND PHYSICAL PROPERTIES OF VARIOUS WATERS USING LIDAR WAVEFORMS AND DEEP NEURAL NETWORKS

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## ABSTRACT

In this paper, we propose a deep neural network architecture to estimate physical and optical properties of water bodies from bathymetric lidar waveforms. Although essential to the understanding of coastal and inland waters dynamics, this task remains challenging due to the complexity of waveform processing. Here, we use convolutional encoders to estimate seven parameters without the need for pre-processing, iterations, or existing measurements of the target properties. Using a data simulator based on radiative transfer models, the network is trained to be robust to a wide range of physical and acquisition settings. On simulated data, the results show the ability of the method to retrieve relevant  $K_d$ , depth, and bottom position estimates even for low signal-to-noise ratios in which the water bottom component is particularly weak and the water column difficult to identify.

**Index Terms**— bathymetric lidar, lidar waveforms, deep neural networks, water turbidity, bathymetry

## 1. INTRODUCTION

Estimating physical properties of water bodies such as turbidity or depth is essential to better comprehend the dynamics of coastal areas or inland waters. Turbidity affects the local biodiversity by limiting the solar irradiance underwater [1], and its spatial variability is a proxy for sediment transport [2], contaminants spreading or local water quality [3]. Similarly, an accurate modelling of shallow bathymetry is crucial for risks assessment, hydrological simulations, or watercourse management.

Bathymetric and topo-bathymetric lidar sensors are specifically designed for the survey of coastal and inland water extents and can thus be used to monitor such characteristics. Although they are often used to extract information about the relief through 3D point clouds or digital elevation models, they also record the complete series of received laser backscatters: the waveforms. Since waveforms are largely shaped by the way the emitted laser pulse interacts with the environment, processing them can serve two objectives: detecting intercepted targets – thus

increasing the number of returns extracted [4] – and extracting additional information on the studied area [5].

In particular, deriving inherent optical properties (IOP) of water bodies or water optical properties (WOP) from bathymetric lidar waveforms has been a research subject since the advent of airborne lidar bathymetry [6]. Several solutions have been proposed [5], [7], [8], [9], and all have shown that bathymetric waveforms could effectively be used to approach IOPs and WOPs. Up to this day, most of the existing methods rely on the decomposition of the bathymetric waveform into three main components – the air/water interface return, the water column return, and the water bottom return – and the analysis of the water column component’s characteristics [7], [8]. For example, fitting an exponential function to this part of the signal enables to approximate the diffuse attenuation coefficient  $K_d$ , which is linked to water turbidity. An other possibility consists of performing regression between waveform features and existing IOP or WOP measurements [10], [11], or inverting radiative transfer models [5].

However, existing methods suffer from two main limitations. Firstly, isolating the water column part in the waveform is impossible in cases where the signal is too noisy or too weakened by the strong attenuation of light in water to clearly delineate the three main parts of the bathymetric waveform. In such cases, it is also impossible to derive bathymetry and water depth. Secondly, regression approaches rely on the access to measurements of WOPs or IOPs. However, measuring WOPs and IOPs is strenuous as it requires performing in-situ measurements and lidar acquisitions simultaneously, with a large enough number of records over the studied area. Some approaches thus propose to use satellite measurements of such properties and rely on them for model fitting [10], [11]. However, such products are not adequate to study narrow land-water interfaces and inland waters such as lakes and rivers due to their spatial resolution.

In this work, we propose to use a deep neural network to perform WOPs and IOPs estimation, as well as the identification of water surface and seabed positions from bathymetric waveforms. We wish to assess the possibility of estimating these parameters in one shot, and without relying on in-situ measurements or satellite observations. To tackle

the issue of model training with scarce labelled data, we propose a weakly supervised method relying on data simulation through radiative transfer models. In particular, we investigate the ability of the network to deal with challenging settings such as weak bottom returns for which traditional decomposition methods are inapplicable due to the impossibility of isolating the water column.

### 3. PROPOSED NEURAL NETWORK

We propose to rely on a convolutional neural network to perform waveform encoding – as successfully made in [12] – and estimate seven different IOPs and WOPs:

- The diffuse attenuation coefficient,  $K_d$ ;
- The backscattering coefficient at  $180^\circ$ ,  $\beta\pi$ ;
- The loss of energy at the air/water interface,  $L_s$ ;
- The water bottom reflectance,  $R_b$ ;
- The position of the air/water interface,  $S$ ;
- The position of the water bottom,  $B$ ;
- The depth,  $D$ .

Based on the physical principles of lidar waveforms [6], we consider these parameters to be linked to the incident laser pulse and its angle of incidence on the water surface, which may cause geometrical pulse stretching. Consequently, our network takes them as inputs, along with the considered bathymetric waveform and a second waveform acquired at a low off-nadir angle on a plane, tar-like topographic surface, used to approximate the sensor’s impulse function.

Our network contains two parallel convolutional encoders, which each encode one of the input waveforms, as shown in Figure 1. Each block includes 1D convolution, batch normalization, ReLu activation, max pooling, and residual connections. At each layer, the number of filters is doubled. The feature maps resulting from the separate encoders are then concatenated and passed to three other convolutional blocks. The resulting feature vector is concatenated with the acquisition parameters, before entering four separate decoders, built to favour the use of features relevant to each type of parameter. A first convolutional decoder with ReLu activation estimates  $K_d$ , while three convolutional decoders with sigmoid activation are used to predict  $\beta\pi$  first,  $L_s$  and  $R_b$  in a second step, and  $S$ ,  $B$ , and  $D$ . All decoders embed four convolutional blocks with one filter, max pooling, and a perceptron per parameter to predict. They are optimized with individual MAE losses. The resulting architecture is illustrated in Figure 1.

The network is optimized with an Adam optimizer, mini-batches of size 1000, and a learning rate of  $10^{-4}$  until it reaches its lowest validation loss.

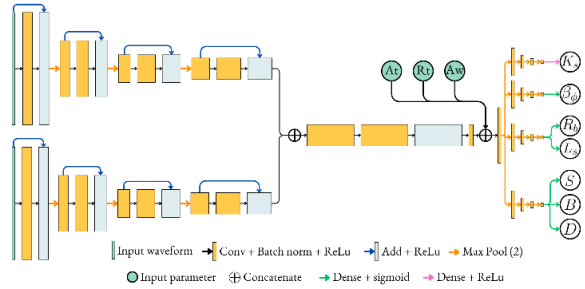


Figure 1. Proposed deep neural network architecture.

### 2. SIMULATION OF LABELLED DATASETS

Since WOP and IOP measurement campaigns are scarce, gathering enough pairs of waveforms and parameter values to train the network is challenging. To tackle this issue, we simulate training and test datasets of bathymetric lidar waveforms using a modified version of [13]. This allows us to fully control the acquisition parameters and to simulate a large range of different physical conditions to make the network robust to varying conditions. Table 1 summarizes the six different types of waveforms we generate.

Table 1. Characteristics of the simulated waveform types.

	$D$	$K_d$	$R_b$
Shallow turbid	1 to 3 m	0.7 to 1.5 $m^{-1}$	0.03 to 0.85
Deep turbid	3 to 5 m	0.7 to 1.5 $m^{-1}$	0.03 to 0.85
Shallow mod. turbid	1 to 4 m	0.1 to 0.7 $m^{-1}$	0.03 to 0.85
Deep mod. turbid	4 to 10 m	0.1 to 0.7 $m^{-1}$	0.03 to 0.85
Deep clear	6 to 20 m	0.1 to 0.4 $m^{-1}$	0.5 to 0.85
Shallow dark seabed	1 to 2.5 m	0.1 to 1 $m^{-1}$	0.03 to 0.2

For each simulated bathymetric waveform, a topographic waveform is simulated on a plane ground with a reflectance of 0.05 and an off-nadir angle of  $10^\circ$ .

We used different types of impulse functions, noise functions, and noise levels to account for different sensors. With this process, we wish to assess the feasibility of the method before applying it to large, real datasets.

### 5. RESULTS OBTAINED ON SIMULATED DATA

In this section, we present the results obtained on simulated data, with a focus on bathymetry and  $K_d$  extraction.

#### 5.1. Global results

Globally, the network manages to retrieve the seven parameters with low mean error, as Tables 2 and 3 illustrate. By analyzing the estimation errors depending on the waveform simulation parameters, we observe that the

network is robust to variations of bottom geometry, emitted power, emitted pulse duration and  $\beta\pi$  values. We also observe that the type of pulse used for simulation does not impact significantly the estimation performance. Similarly, the network seems to be robust to different noise types and levels.

Table 2. Estimation errors for the water parameters.

Target	$K_d$	$\beta\pi$	$R_b$	$L_s$
Mean	-0.01	0.0005	0.04	0.002
error	$\pm 0.026 \text{ m}^{-1}$	$\pm 0.002$	$\pm 0.02$	$\pm 0.095$

Table 3. Bathymetry and depth estimation errors.

Target	$S$	$B$	$D$
Mean	0.001	0.007	-0.02
error	$\pm 0.19 \text{ m}$	$\pm 1.31 \text{ m}$	$\pm 1.3 \text{ m}$

However, the poorer results for  $\beta\pi$  and  $R_b$  suggest that the network complexity does not enable it to capture all physical interactions between the parameters shaping the waveforms.

In the following sections, we provide a deeper description of the network's performance for bathymetry extraction and  $K_d$  estimation, which are two challenging tasks when processing bathymetric lidar waveforms in turbid environments.

### 5.1. Detection of faint returns and depth estimation

We simulated weak water bottom returns voluntarily to challenge the performances of our approach in cases where the detection of the bottom is difficult. Table 4 summarizes the results obtained for different water types and shows the robustness of the network to varying conditions of signal-to-noise ratio. In practice, qualitative results show that our model manages to detect bottom backscatters lost in noise. However, as expected, B and D errors are highest for deep moderately turbid water and for very deep waters, where depths reach 20 m. Additionally, further analyses show that when  $K_d$  increases, D tends to be overestimated in very deep clear and very turbid waters, and under-estimated in moderately turbid waters. However, the distribution of errors for B and D (Figure 2) follow Normal laws centred close to 0, suggesting they can be reduced with spatial averaging.

Table 4. Bathymetry and depth estimation errors depending on the waveform type.

Water type	B	D
Shallow turbid	$0.03 \pm 0.38 \text{ m}$	$-0.01 \pm 0.38 \text{ m}$
Deep turbid	$0.17 \pm 0.66 \text{ m}$	$0.14 \pm 0.65 \text{ m}$
Shallow mod. turbid	$0.01 \pm 0.45 \text{ m}$	$-0.07 \pm 0.47 \text{ m}$
Deep mod. turbid	$0.16 \pm 1.67 \text{ m}$	$0.01 \pm 1.53 \text{ m}$
Deep clear	$-0.13 \pm 3.04 \text{ m}$	$-0.28 \pm 3.11 \text{ m}$
Shallow dark seabeds	$-0.02 \pm 0.31 \text{ m}$	$-0.09 \pm 0.28 \text{ m}$

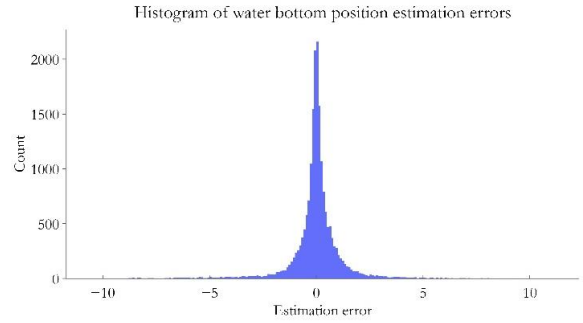


Figure 2. Distribution of the water bottom position estimation errors.

### 5.1. Diffuse attenuation coefficient estimation

The global estimation results for  $K_d$ , in Table 5, illustrate the ability of the network to retrieve relevant values even in challenging settings for which the water column component is impossible to isolate due to noise or signal extinction.

However, the network is challenged by extreme values of  $K_d$ , which tend to be less well estimated. Namely, in shallow waters with dark seabeds,  $K_d$  is systematically overestimated, while it is underestimated in turbid waters. In these cases, lower reflectance values are also associated with a higher overestimation of  $K_d$ . However,  $K_d$  estimation errors follow a Normal law centred on 0 too (see Figure 3), which makes it possible to reduce them with spatial averaging.

Table 5.  $K_d$  estimation error depending per waveform type.

Water type	$K_d$
Shallow turbid	$0.17 \pm 0.23 \text{ m}^{-1}$
Deep turbid	$-0.05 \pm 0.23 \text{ m}^{-1}$
Shallow mod. turbid	$-0.04 \pm 0.20 \text{ m}^{-1}$
Deep mod. turbid	$-0.002 \pm 0.19 \text{ m}^{-1}$
Deep clear	$-0.02 \pm 0.09 \text{ m}^{-1}$
Shallow dark seabeds	$-0.22 \pm 0.19 \text{ m}^{-1}$

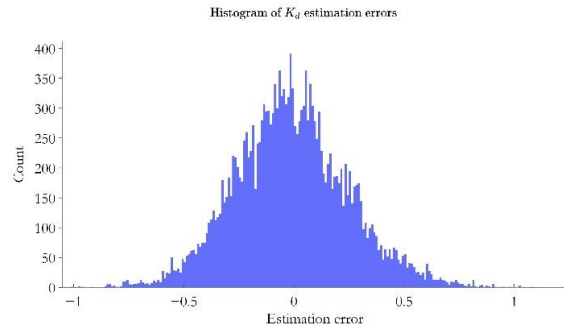


Figure 3. Distribution of the  $K_d$  estimation errors.

## 6. DISCUSSION AND CONCLUSION

In this paper, we have proposed a convolutional neural network dedicated to the estimation of water optical properties, and of water surface and bottom positions. The results appear promising, namely for water bottom positioning, depth estimation, and Kd evaluations. Indeed, our network predicts them precisely even in challenging cases such as deep or turbid environments, which are sometimes impossible to handle with existing methods based on the possibility to locate the water column, and thus the seabed [5], [7], [8]. These results are particularly interesting relative to the literature on this subject, which often implies iterative procedures dedicated to the estimation of a smaller range of parameters [7], [8], [9]. On the contrary, we propose a method to estimate several parameters in one shot, without the need for pre-processing. This method also does not rely on existing synchronous measurements of the properties estimated, thanks to the use of a data simulator. This particular feature also enables us to propose a network that is robust to noise and changes in seabed geometry, which tend to be a limiting factor for traditional processing approaches [14]. To improve these preliminary results, several strategies are possible. The first is related to the network architecture, which could be complexified to better capture the interconnections between some parameters. Lastly, evaluating the application of the network to real datasets is necessary to further confirm the deployability of our method.

## 8. ACKNOWLEDGEMENTS

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