Analysis of Foliage Penetrating Photon Counting LiDAR Data for Underwater MCM

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In this work we present an alternative to sonar based underwater mine countermeasures (MCM) using an active optical system based on light detection and ranging (LiDAR) sensor. Multi-spectral (MS) full-waveform (FW) single photon (SPC) data is analysed for material and structural discrimination. Terrestrial and aerial LiDAR has enabled researchers to explore the third dimension, *depth*; this has advantages in bathymetric mapping [2] and defence and security [1]. Commercial and academic focus [2] on bathymetric LiDAR has only been on shallow waters and uses either monochromatic laser sources or a maximum of two wavelengths. This work is the first to report signal analysis for foliage penetration and discrimination of underwater LiDAR data. The multi-spectral depth imaging system [4] used in this study is based on the time-of-flight (ToF) approach using time-correlated single photon counting (TCSPC). The TCSPC module (Hydraharp in Figure 2) time-stamps each photon event reflecting from a target and records it using a single-photon detector. The photon counts can then be time gated to form a histogram, a *full-waveform*, whose inherent nature depends on several factors, e.g., the laser wavelength, surface geometry and transmission medium.

1 Multi-spectral Depth Feature Encoding and Learning

The proposed target signatures embed the full-waveform properties, *i.e.* spectral reflectance and their geometric properties. For N acquired sets of waveforms at Λ wavelengths, $N \times \Lambda$ waveforms are processed and the echo properties are extracted. The transmitted time signature of the super-continuum laser source is an exponential pulse and the degree of modulation on the backscattering beam depends on the surface geometry and its spectral reflectance. We use the RJMCMC approach [3], which uses several piece-wise exponential functions as an initial estimate and refines the peak position(β), background photon count and peak amplitude (A) parameters using a Bayesian approach. In this work we use the peak amplitudes and relative peak positions as spectral features. Four local 3D surface features, Anisotropy,

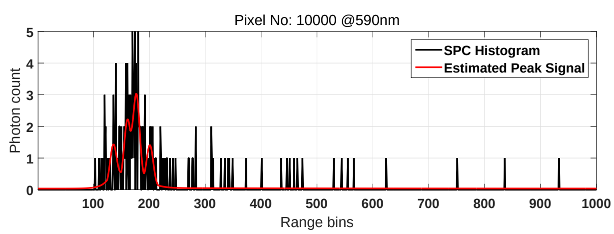

Figure 1: Extracted peak locations (red) over the original histogram (black) using the RJMCMC approach.

$A_{\mathcal{E}}$, Planarity, $P_{\mathcal{E}}$, Sphericity, $S_{\mathcal{E}}$ and Linearity, $L_{\mathcal{E}}$ are computed within a neighbourhood, governed by radius r, of each 3D point. The final representation with $\beta_{max} = max(\{\beta\}_{\lambda=1}^{\Lambda})$ looks like

$$F_v = \Bigg[\underbrace{\beta_{max}}_{spectral response} , \underbrace{\{A_\lambda\}_{\lambda=1}^{\Lambda}, A_{\mathcal{E}}, P_{\mathcal{E}}, S_{\mathcal{E}}, L_{\mathcal{E}}}_{depth features} \Bigg] \quad (1)$$

Table 1 illustrates how these properties are computed, provided the Eigenvalues $\mathcal{E}_1 > \mathcal{E}_2 > \mathcal{E}_3$. The Eigenvalues computed are invariant to 3D rotation and view-point since they are computed locally.

Given the feature vector F_v, we propose a learning algorithm that learns a basis, *dictionary*. Our learnt dictionary not only generates a sparse low-dimensional encoding of our feature vector F_v but also maximises discriminatory properties of its coefficients. A K-NN classifier model is learnt for

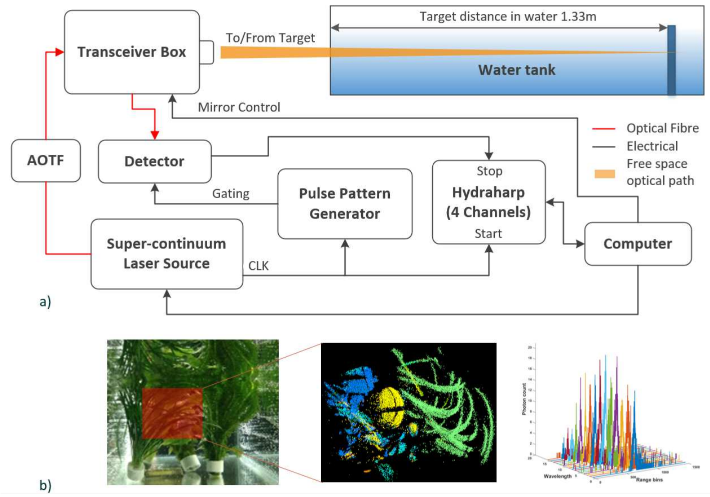

Figure 2: a) A schematic of the experimental set-up; b) (left) several targets were hidden behind marine plans; (middle) 3D point cloud extracted using the RJMCMC approach c) 16 full LiDAR waveforms at different wavelengths for a single pixel.

Table 1: Depth Representations using Eigenvalues

Linearity $L_{\mathcal{E}}$	$(\mathcal{E}_1 - \mathcal{E}_2)/\mathcal{E}_1$	Sphericity $S_{\mathcal{E}}$	$\mathcal{E}_3/\mathcal{E}_1$
Planarity $P_{\mathcal{E}}$	$(\mathcal{E}_2 - \mathcal{E}_3)/\mathcal{E}_1$	Anisotropy $A_{\mathcal{E}}$	$(\mathcal{E}_1 - \mathcal{E}_3)/\mathcal{E}_1$

the coefficients which is then used for classification. Table 2 illustrates the impact our depth representation has on material classification. Point cloud segmentation based on target signature encodings is shown in Figure 2b(center).

Table 2: Impact of *Depth Representation* (DR) on accuracy

	Plastic 1	**Plastic 2**	**Metal 1**	**Metal 2**
Without DR(%)	92.65	95.65	97.62	98.10
With DR(%)	**97.55**	**99.05**	**99.46**	**98.91**

2 References

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