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 (Hydrafurn 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 geometrical properties. For N acquired sets of waveforms at A wavelengths, N × A 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, Sphericity, Linearity, Normal reflectance and their geometric properties. For each 3D point. The final representation with \( \beta_{\text{max}} = \max(\beta) \) looks like

\[
F_v = \left[ \beta_{\text{max}} \left( \frac{A}{A_i} \right) \right] \left( \frac{P}{P_i}, \frac{S}{S_i}, L \right)
\]

Table 1 illustrates how these properties are computed, provided the Eigenvalues \( \mathbf{E}_i \) 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 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).

2 References