Discriminating Underwater LiDAR Target Signatures using Sparse Multi-spectral Depth Codes

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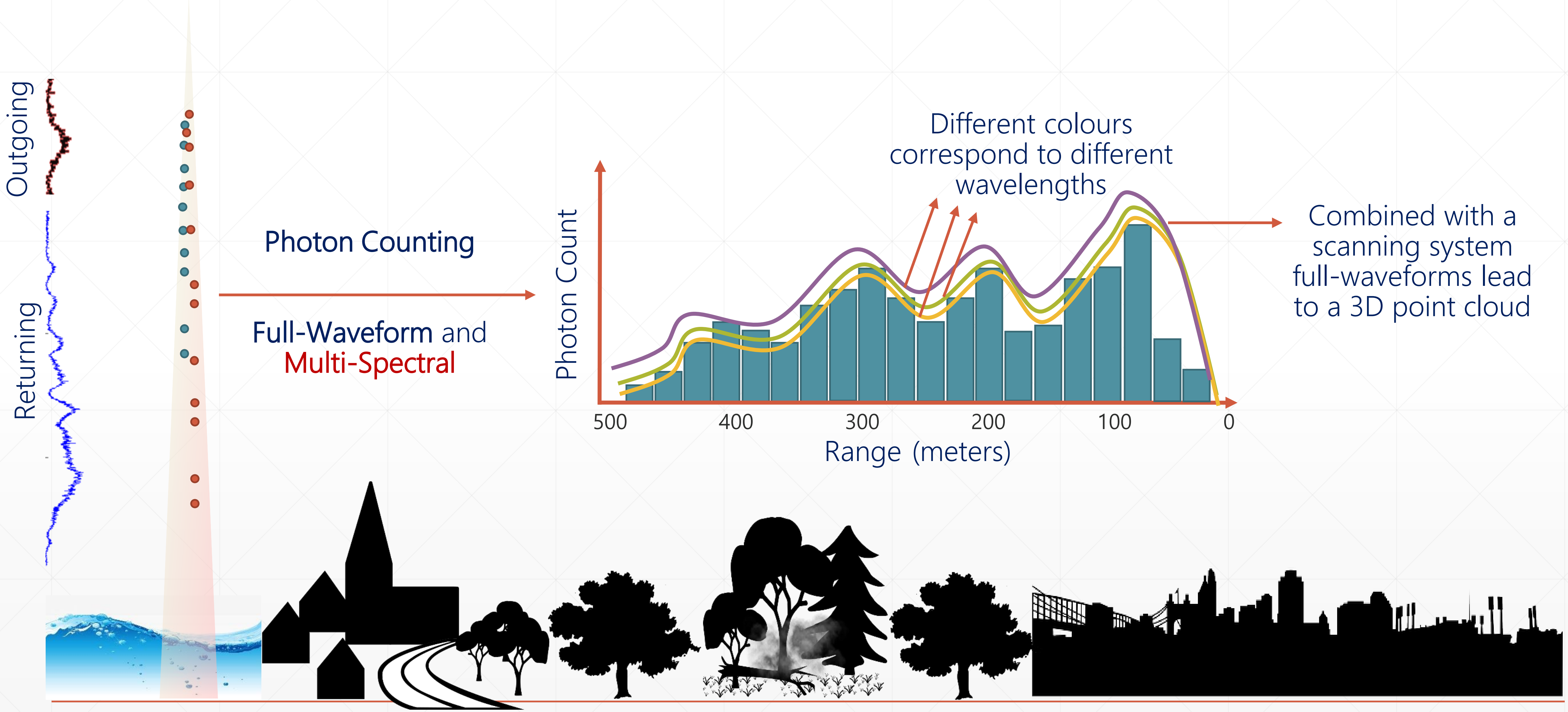
"Aim: Analyse Full-Waveform Multi-Spectral Single Photon Counting (SPC) LiDAR data in order to improve aerial and bathymetric situational awareness".

"First piece of work to show that underwater LiDAR can be an alternative to sonar based mine-countermeasures…"

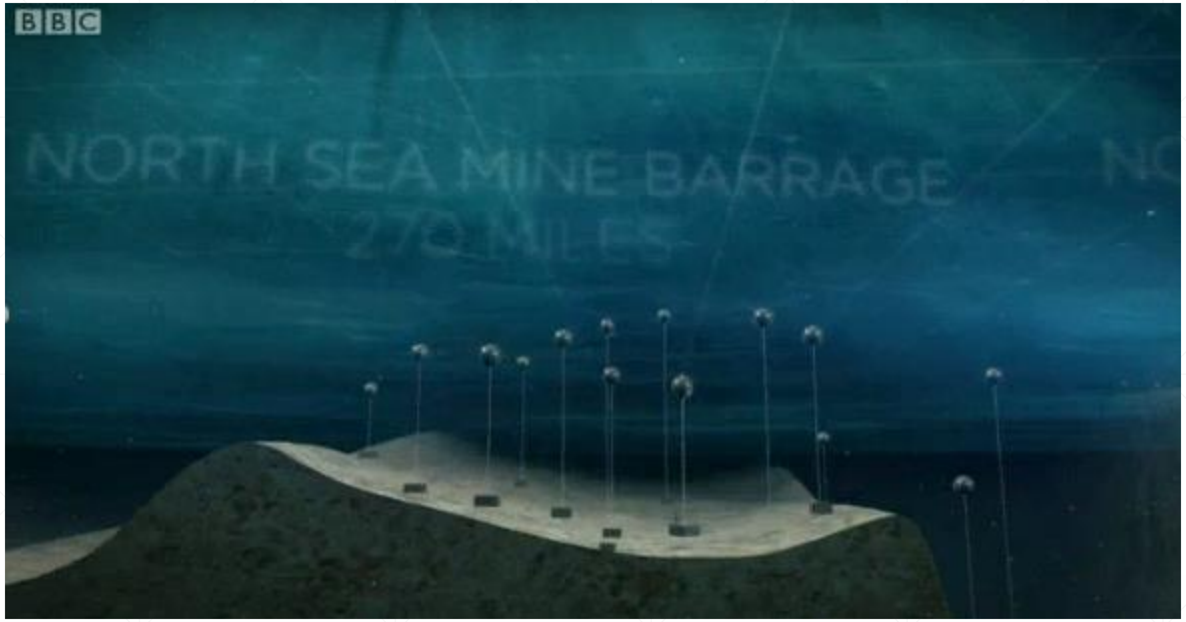
*"Aim: Analyse **Full-Waveform** Multi-Spectral **Single Photon Counting (SPC) LiDAR** data in order to improve aerial and bathymetric situational awareness".*



Underwater Mine Countermeasures

Aims

- Classify target (mine) signatures…
  using FW multi-spectral LiDAR
- Combining material classification
  plastics, concrete, metal
- Potentially hidden behind foliage
  plants or other materials



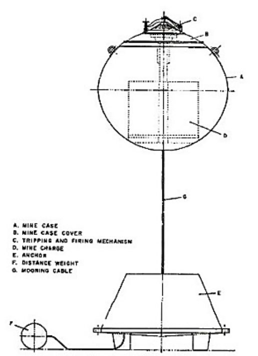


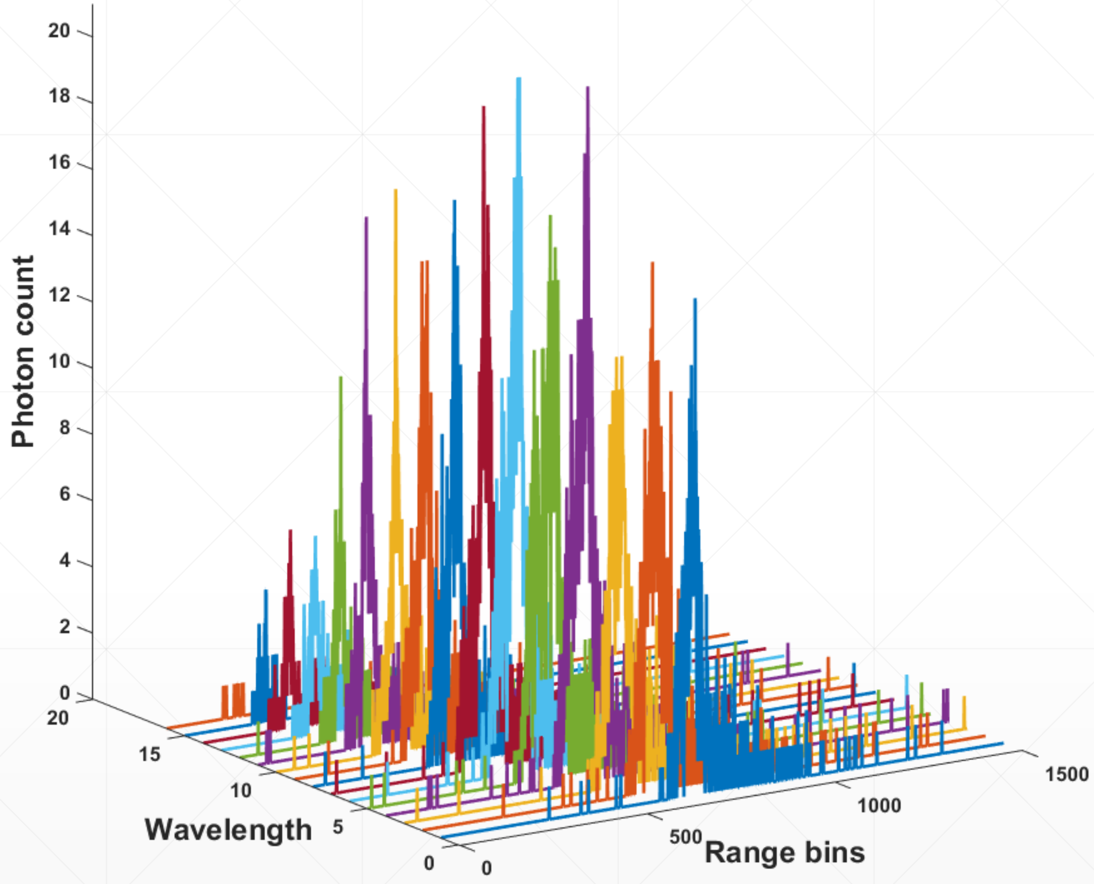
Figure 14.—Naval defense mine Mk 2.

1917- 1919 Mine Dump at Inverness*, Scotland

* http://www.worldwar1.com/dbc/nsminebr.htm

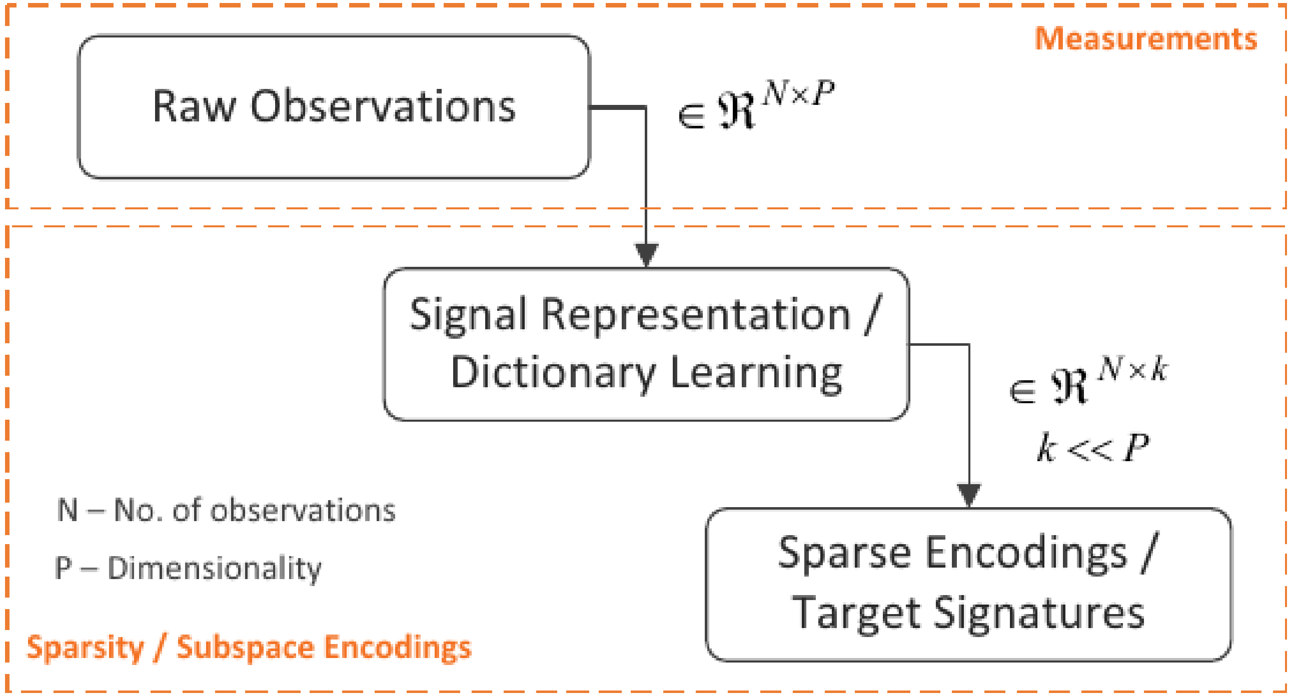
Outline

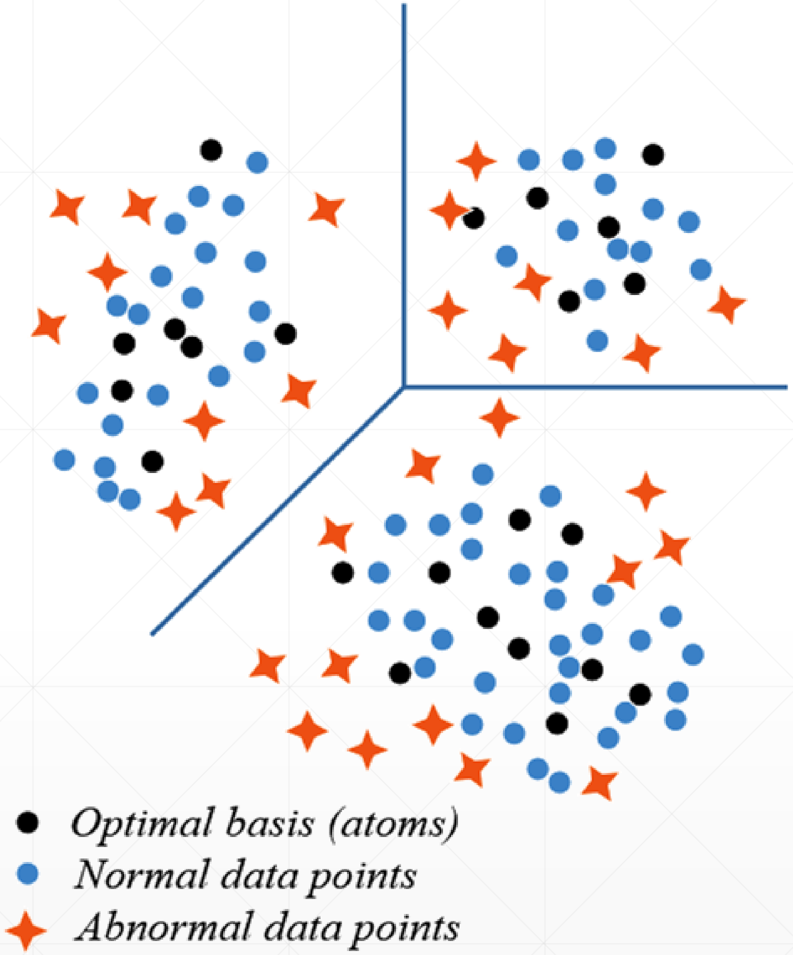
- **Problem Overview**
- **SPC Experimental Setup**
- **Methodology**
- **Results**
- **Future work & Improvements**



Multi-Spectral Single Photon Counting Waveforms

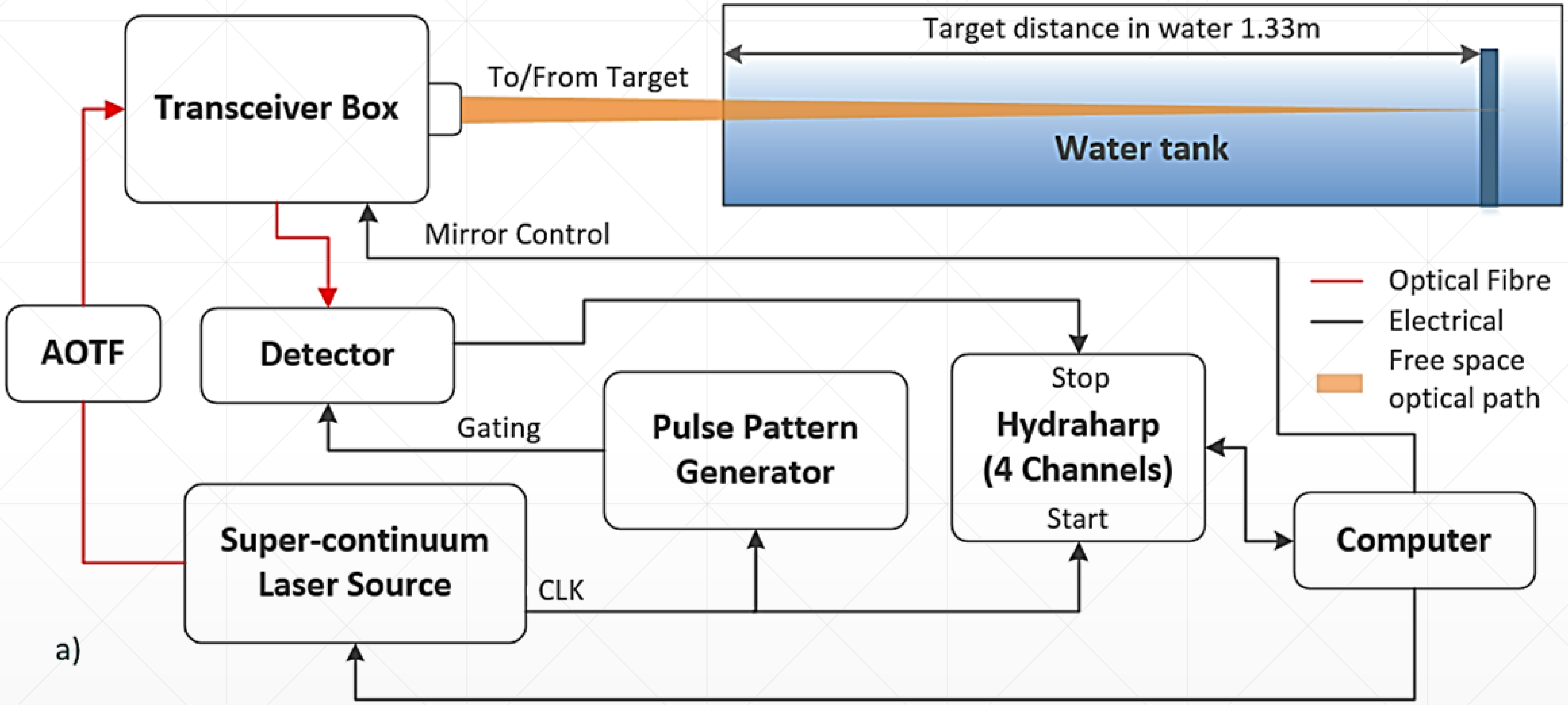
Problem Overview





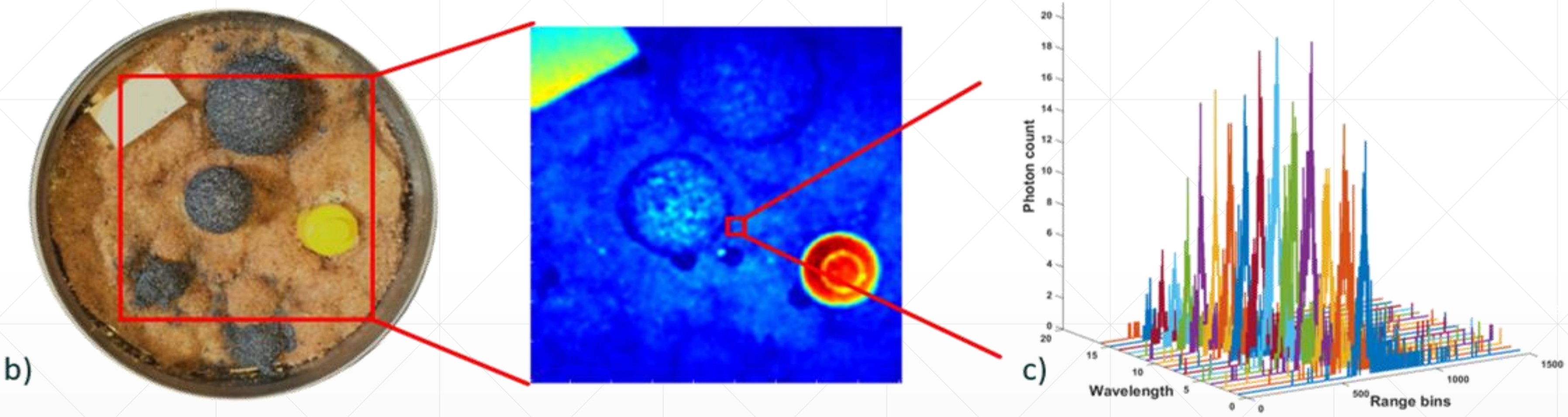
Discriminatory Dictionary

SPC Experimental Setup



A. Maccarone, A. McCarthy, X. Ren, R. E. Warburton, A. M. Wallace, J. Moffat, Y. Petillot, and G. S. Buller, “Underwater depth imaging using time-correlated single photon counting,” Optics Express, vol. 23, no. 26, pp. 33911–33926, 2015.

SPC Experimental Setup



Target Under Investigation

Materials used

Sand

Waterproof glue

Texture Paint

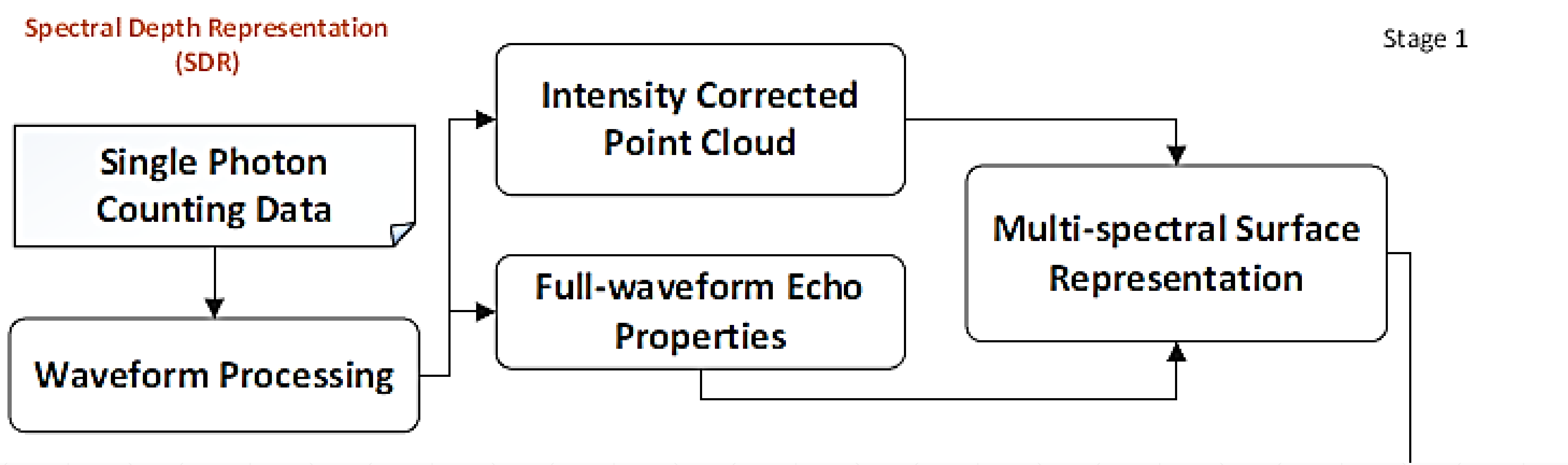
Metal ball bearings

Lego blocks

Methodology

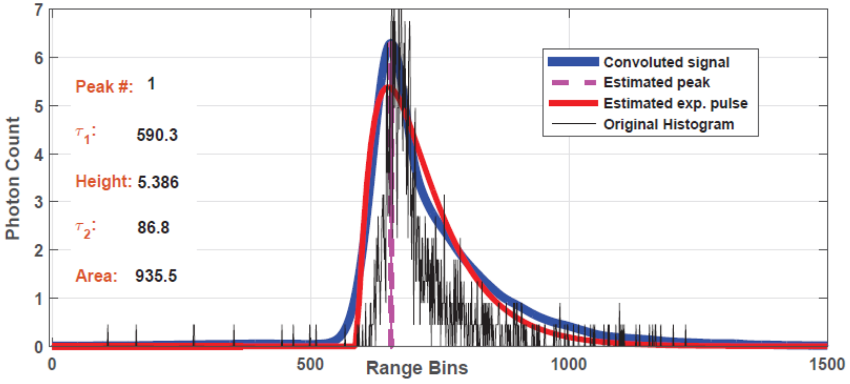
- A novel **reflectance aware surface representation**, a **"Spectral Depth Representation (SDR)"** is proposed for underwater SPC and aerial LiDAR data.

Methodology



Stage 1: Spectral Depth Representation

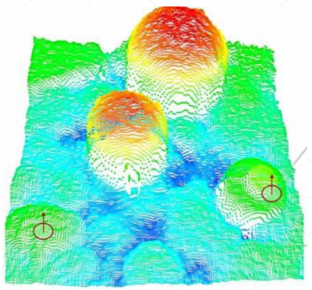
Full-waveform Spectral Properties

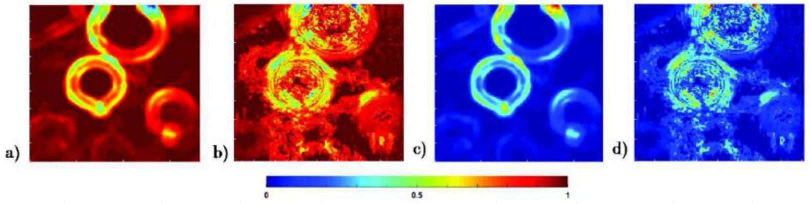


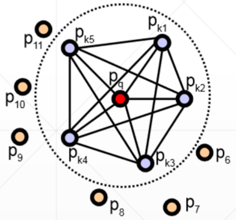
$$f(t) = k\left(e^{-t\mathcal{T}_1} - e^{-t\mathcal{T}_2}\right), \quad (t \geqslant 0),$$

$$\text{where, } k = \frac{\mathcal{T}_2 e^{(t_p - t_0)\mathcal{T}_1}}{(\mathcal{T}_2 - \mathcal{T}_1)}, \text{ and } \quad t_p = \frac{\ln(\mathcal{T}_2/\mathcal{T}_1)}{(\mathcal{T}_2 - \mathcal{T}_1)}$$

Depth Representation







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

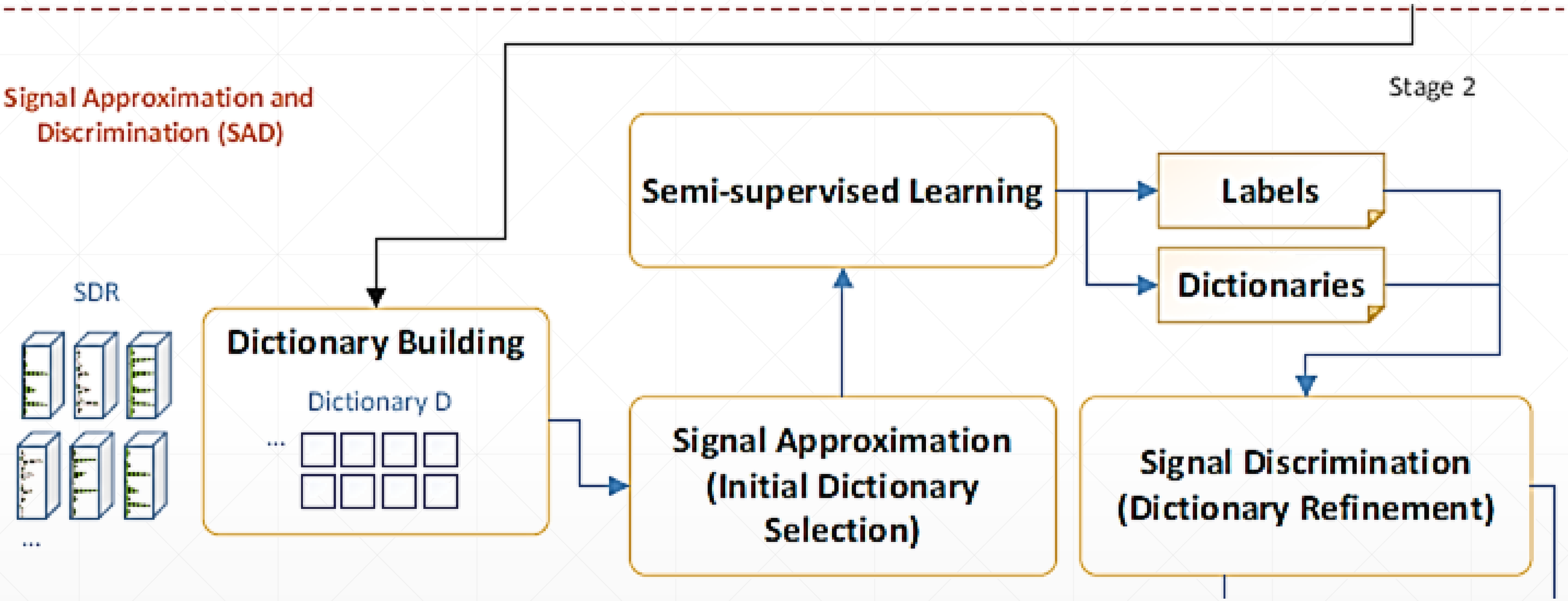
SPECTRAL DEPTH REPRESENTATION (SDR)

$$F = \Big[\{\mathcal{T}_{1,\lambda}\}_{\lambda=1}^{\Lambda}, \{\mathcal{T}_{2,\lambda}\}_{\lambda=1}^{\Lambda}, \{A_{\lambda}\}_{\lambda=1}^{\Lambda}, A_{\mathcal{E}}, P_{\mathcal{E}}, S_{\mathcal{E}}, L_{\mathcal{E}}, D_z \Big]$$

Stage 2.1: Signal Approximation & Discrimination

- **Discriminatory Sparse Codes are created** using a novel semi-supervised **“Signal Approximation and Discrimination (SAD)”** scheme.

Stage 2.1: Signal Approximation & Discrimination



$$\min_{\mathbf{Q},\mathbf{Z}} \left[\beta_2 \sum_{n=1}^{N} ||f_n - q_n \mathbf{Z}||^2 + \beta_1 \sum_{n=1}^{N} |q_n|_1 + G(\mathbf{Q}) \right],$$

$$\text{subject to } |q_n| \leqslant 1, \ \forall n = 1, 2, ..., N$$

Stage 2.1a: Discriminant term $G(\mathbf{Q})$

Given: Set of coefficients $\mathbf{Q} = [q_1, q_2, ..., q_{\mathrm{K}}]$ $\quad \Omega_c$, for $1 \leqslant c \leqslant \Omega$ $\quad \mu = \frac{1}{\mathrm{K}} \sum_{k=1}^{\mathrm{K}} q_k$

Class-wise mean

$$\mu_c = \frac{1}{\mathrm{K}_c} \sum_{q \in \Omega_c} q$$

Class-wise variance

$$v_c^2 = \frac{1}{\mathrm{K}_c} \sum_{z \in \Omega_c} ||z - \mu_c||_2^2$$

$$\mathrm{G}\left(\mathbf{Q}\right) = S_w^{-1} S_b$$

Inter-class scatter matrix

$$S_b = || \sum_{c=1}^{\Omega} \mathrm{K}_c \left(\mu_c - \mu\right) \left(\mu_c - \mu\right)^T ||_2^2$$

Intra-class scatter matrix

$$S_w = \sum_{c=1}^{\Omega} v_c^2$$

Stage 2.1b: Greedy Solution

Input: $\mathbf{F} = \{f_n\}_{n=1}^{N} \in \mathbb{R}^{\mathrm{N}\times\mathrm{P}}$, β_1, β_2
Output: Dictionary, atom indices and coefficients
$\mathbf{R}_0 \leftarrow \mathbf{F}$, $dictIdx \leftarrow \phi$
while $\mathbf{R}_0 \to 0$ **do**

$t \leftarrow 0$ Select $z_k \in \mathbf{Z}$, such that

$$\min_{\mathbf{Q},\mathbf{Z}} \left[\beta_2 \sum_{n=1}^{\mathrm{N}} ||f_n - q_n \mathbf{Z}||^2 + \beta_1 \sum_{n=1}^{\mathrm{N}} |q_n|_1 + G(\mathbf{Q}) \right],$$
$$\text{subject to } |q_n| \leqslant 1, \forall n = 1, 2, ..., N$$

$dictIdx \leftarrow dictIdx \cup k$

```
// Projection and residual
```

$\mathbf{O}_t \leftarrow \mathbf{Q} * inv(\mathbf{Q}^T * \mathbf{Q}) * \mathbf{Q}^T$
$\mathbf{R}_t \leftarrow \mathbf{F} - \mathbf{O}_t\, \mathbf{F}$
$t \leftarrow t + 1$

end
return $\mathbf{Q}, \mathbf{Z}$, $dictIdx$

Recall…

Spectral Depth Representation (SDR)

$$\mathbf{F} = \left[\{\mathcal{T}_{1,\lambda}\}_{\lambda=1}^{\Lambda}, \{\mathcal{T}_{2,\lambda}\}_{\lambda=1}^{\Lambda}, \{A_\lambda\}_{\lambda=1}^{\Lambda}, A_{\mathcal{E}}, P_{\mathcal{E}}, S_{\mathcal{E}}, L_{\mathcal{E}}, D_z \right]$$

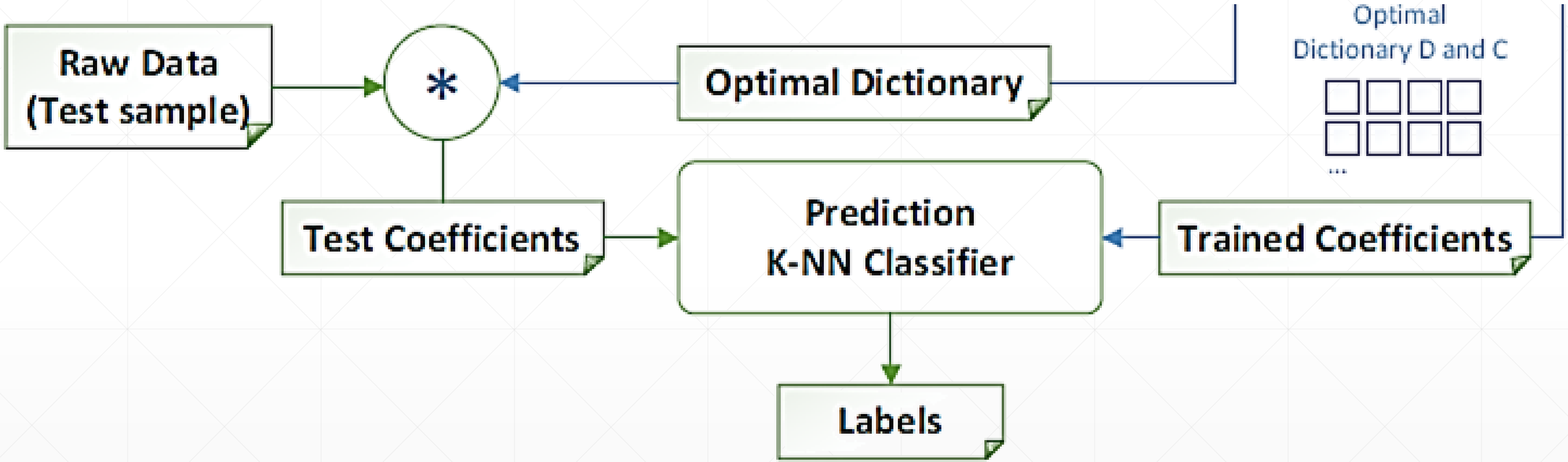
Trying to solve…

$$\min_{\mathbf{Q},\mathbf{Z}} \left[\beta_2 \sum_{n=1}^{\mathrm{N}} ||f_n - q_n \mathbf{Z}||^2 + \beta_1 \sum_{n=1}^{\mathrm{N}} |q_n|_1 + G(\mathbf{Q}) \right],$$
$$\text{subject to } |q_n| \leqslant 1, \forall n = 1, 2, ..., N$$

Stage 3: Prediction

- Signal **labels** are generated using a classification scheme

Stage 3: Prediction



Summary…

Full-waveform + Shape Properties

Stage I (Algorithm 1 in the paper)

↓

Sparse Spectral Depth Codes

Stage II (Algorithm 1 & 2 in the paper)

↓

Pixel-wise Prediction

Stage III (Algorithm 1 in the paper)

Experiments

- **No. of samples:** **40,000 – 90,000**
- **Signal dimension:** **53**
- **No. of wavelengths:** **16 (500 – 725nm)**
- **Laser repetition:** **19.5Mhz**
- **Laser beam-diameter:** **~ 300µm**
- **Environment:** **Clear tap water**
- **Target signature classification (pixel-wise)**
- **10 - fold cross-validation**
- **Compared against ground truth**

Experiment 1 – Material Discrimination

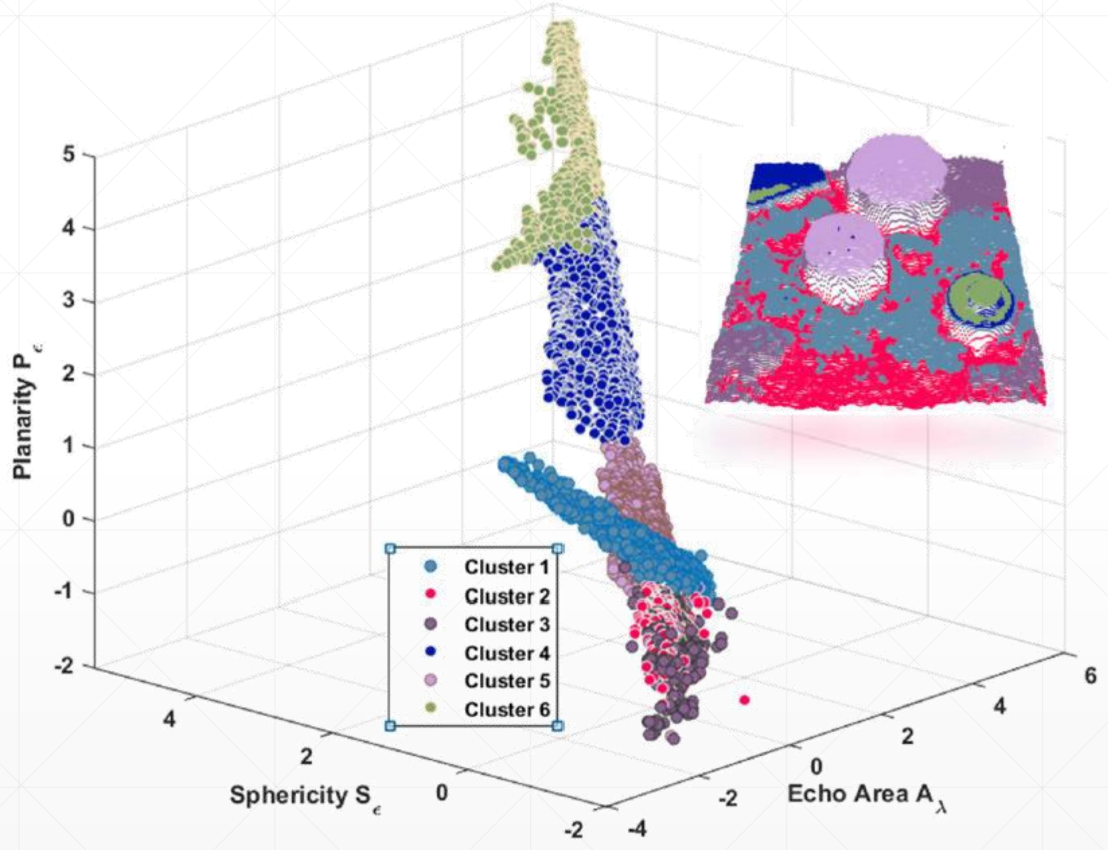
Sand Plastic Metal

Experiment 2 – Mine Discrimination

Sand Plastic 1 Plastic 2 Metal 1 Metal 2

Experiment 3 – Without depth/curvature features

Results



Material Discrimination

	Sand	Plastic	Metal
Sand	**0.9721**	0.0144	0.0133
Plastic	0.0151	**0.9823**	0.0024
Metal	0.0140	0.0035	**0.98239**

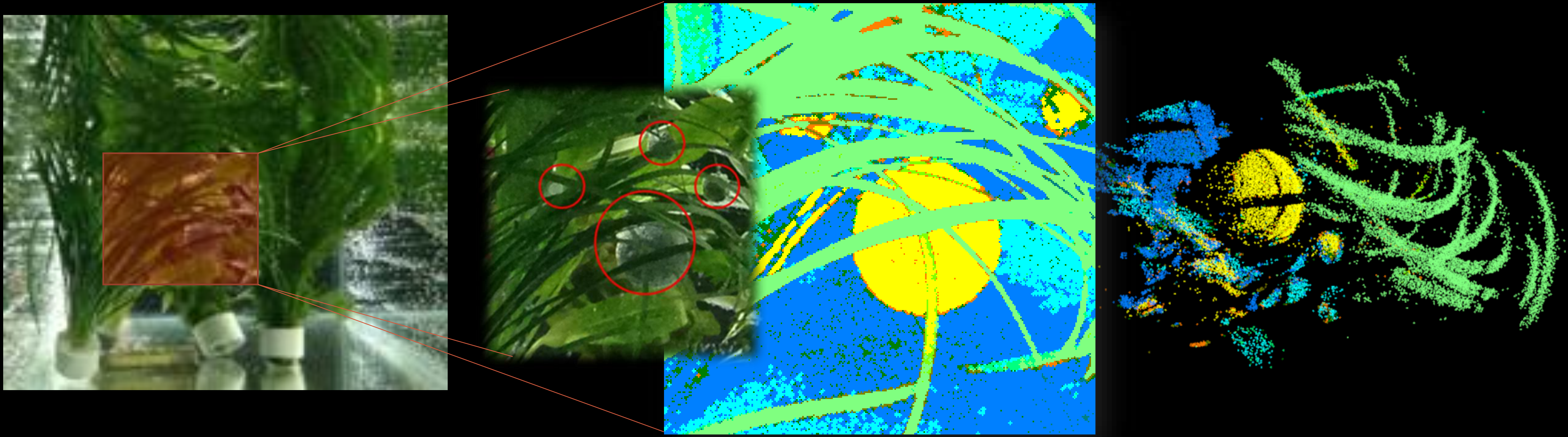
Mine Type Discrimination

	Plastic 1	Plastic 2	Metal 1	Metal 2	Sand
Plastic 1	**0.9755**	0	0.0020	0	0.0224
Plastic 2	0.0054	**0.9905**	0.0007	0.0020	0.0014
Metal 1	0.0014	0.0027	**0.9946**	0	0.0014
Metal 2	0.0014	0.0068	0	**0.9891**	0.0027
Sand	0.0102	0.0007	0	0.0007	**0.9884**

Effect of 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**

Underwater Foliage Penetration



- Preliminary results on floating mines
- Unsupervised clustering
- Performed only at **500nm**

Improvements

Future Work

- **Greedy methods can be slow and do not scale for large real-world datasets… not anymore!**
- **How to handle non-linearity in the data?**
- **Different marine environments**

More targets under investigation

- Different materials and background
- Floating targets behind foliage

A fast kernel discriminatory orthogonal dictionary learning method to classify large-scale, high-dimensional datasets and **handle non-linearity.**

Thank you!

University Defence Research Collaboration

For more information on the UDRC group please visit: http://www.mod-udrc.org