# Underwater imaging using single-photon multispectral Lidar

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*Heriot-Watt University*

*UDRC Themed Meeting, Newcastle University,*
*May, 16th 2017*

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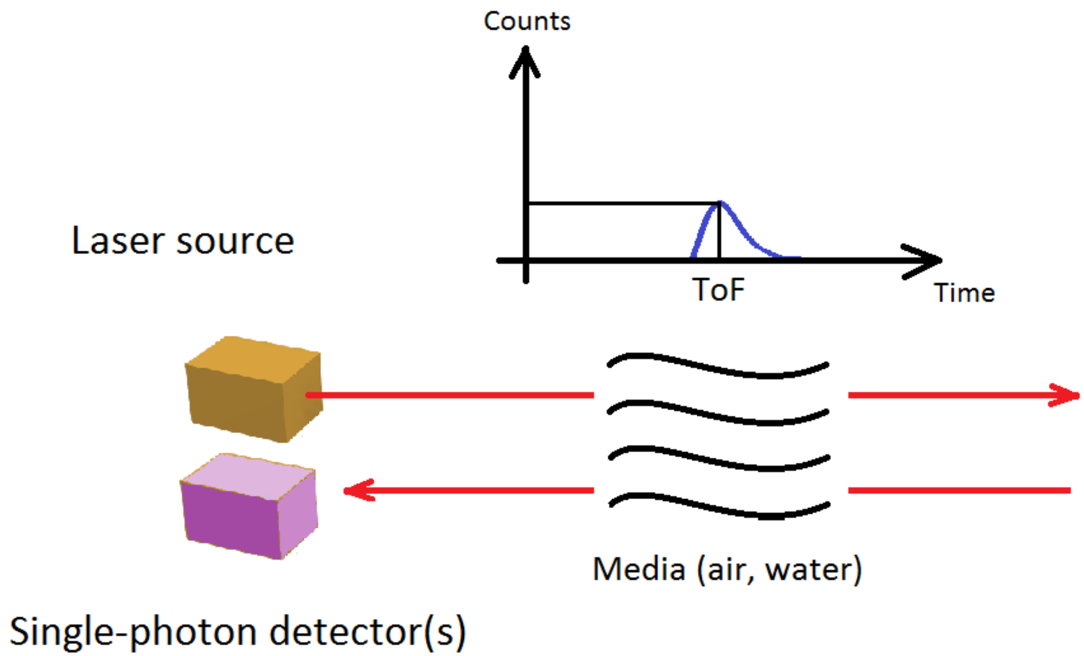
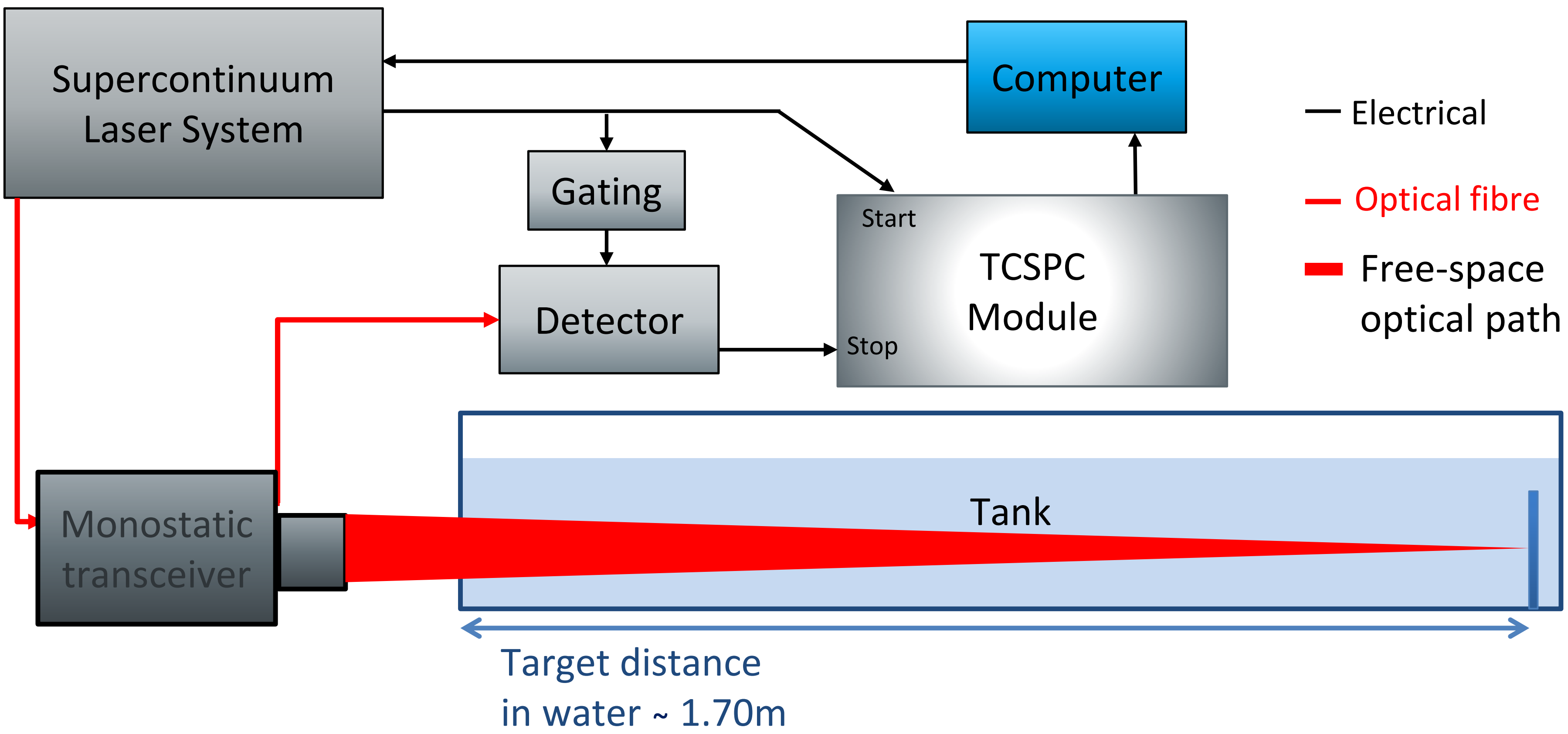
# Single-photon Lidar




- Pulsed laser (20 MHz), low power (≈ $\mu$W)
- Detector: single-photon avalanche diode (SPAD)
- Time of flight: for each detected photon (precision ≈$10^{-12}$ s)
  - Path length precision ≈ 600$\mu$m

# Underwater imaging



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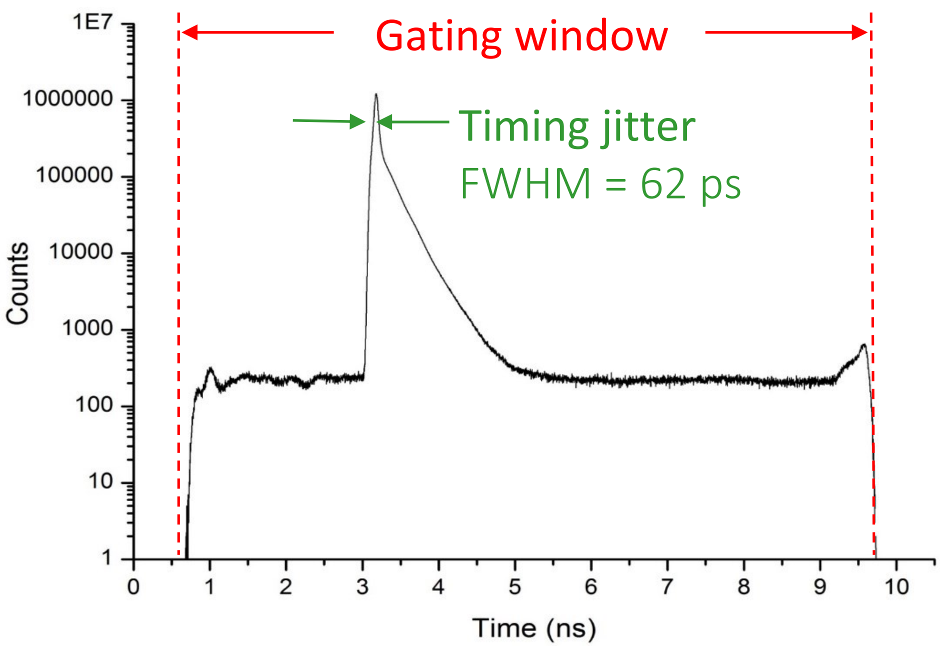
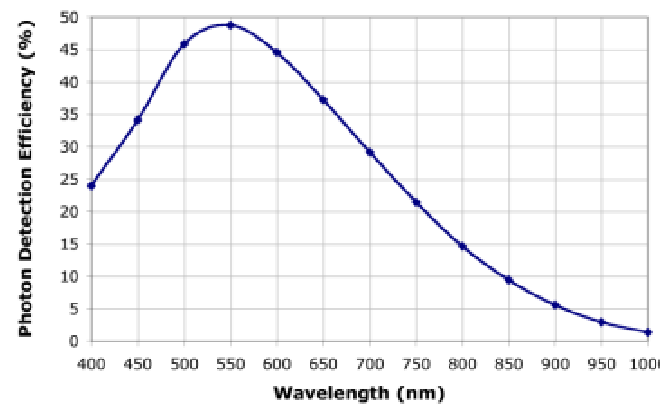
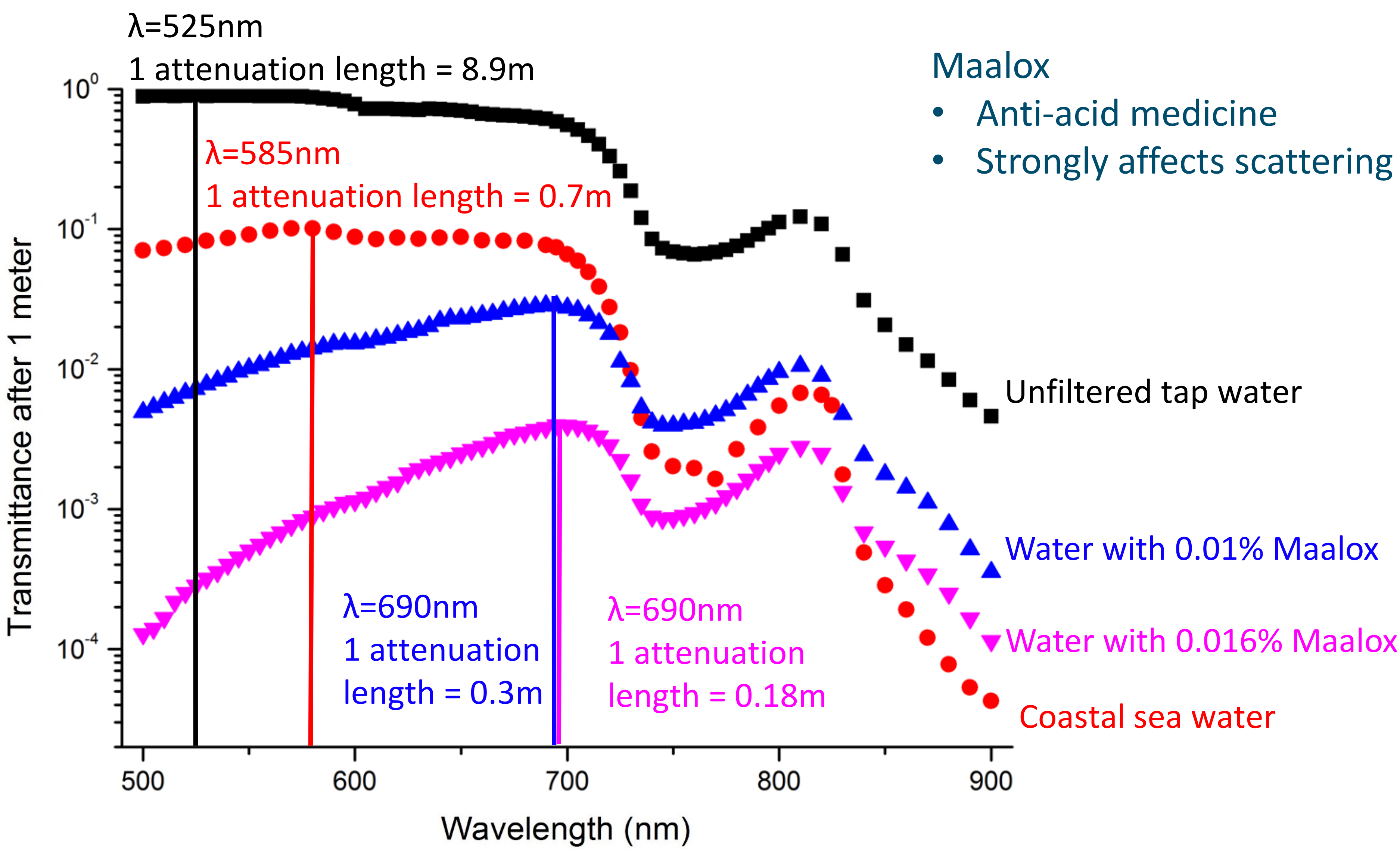



- Dark counts < 50 cps
- Timing jitter ~ 60 ps
- Detection efficiency of 49% at λ=550 nm

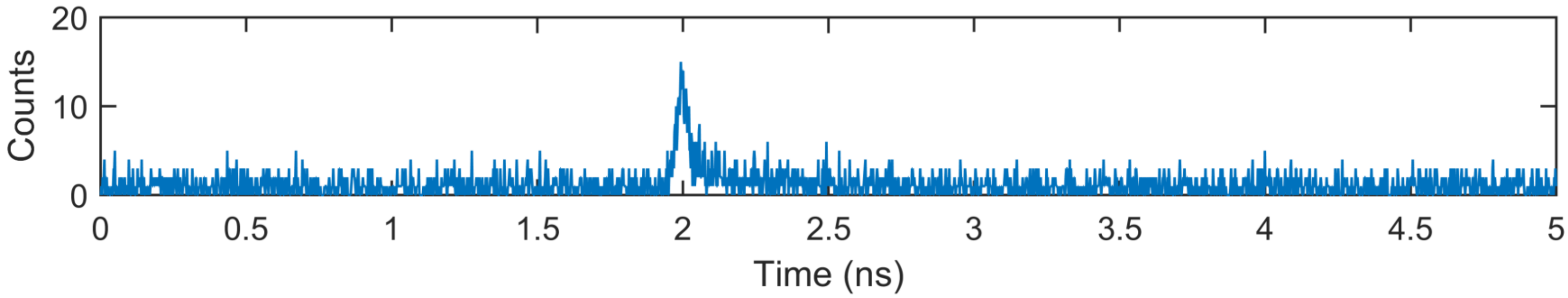
# Underwater imaging

Maalox
- Anti-acid medicine
- Strongly affects scattering



# Observation model

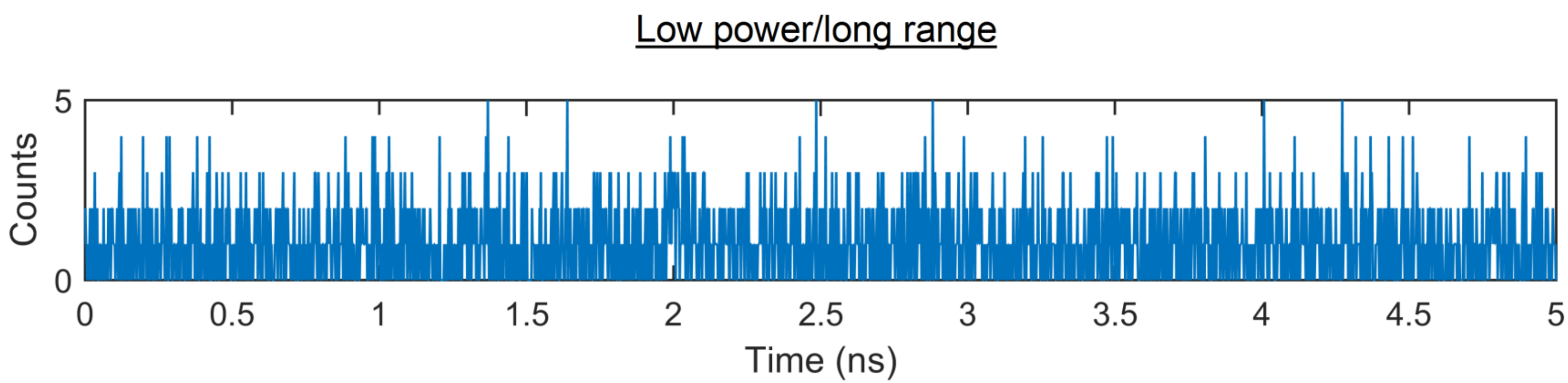
Ideal scenario




$$y_{n,t} = \mathcal{P}\left(\alpha_{n,t_n} r_n g_0(t - t_n) + b_n\right), \qquad t \in \{1, \dots, T\}$$

- $y_{n,t}$: photon count in tth bin
- $g_0(\cdot)$: instrumental response
- $\alpha_{n,t_n}$: attenuation factor
- $b_n$: background level
- $r_n$: target reflectivity
- $t_n$: Time-of-flight (ToF)

# Observation model

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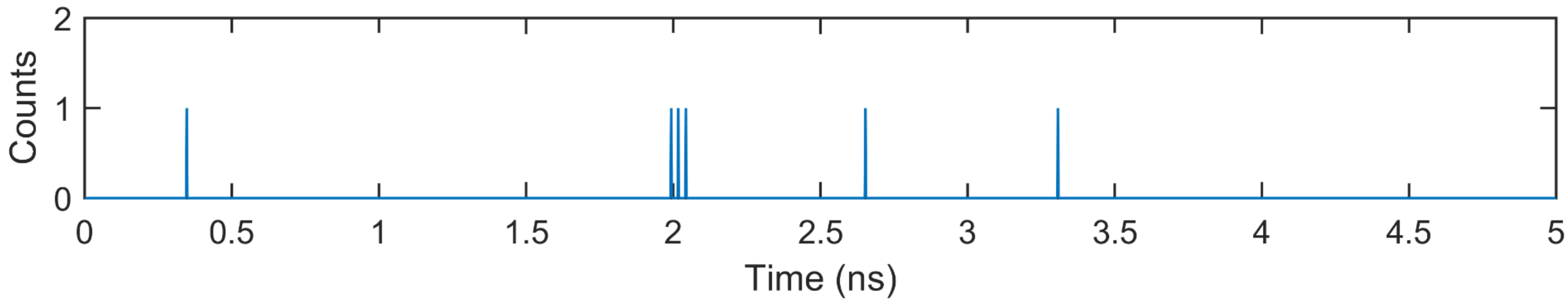
# Observation model

Short acquisition

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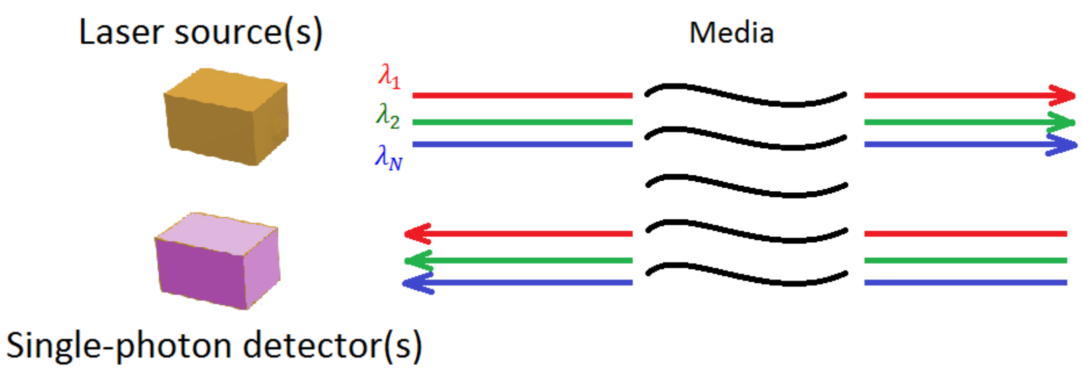
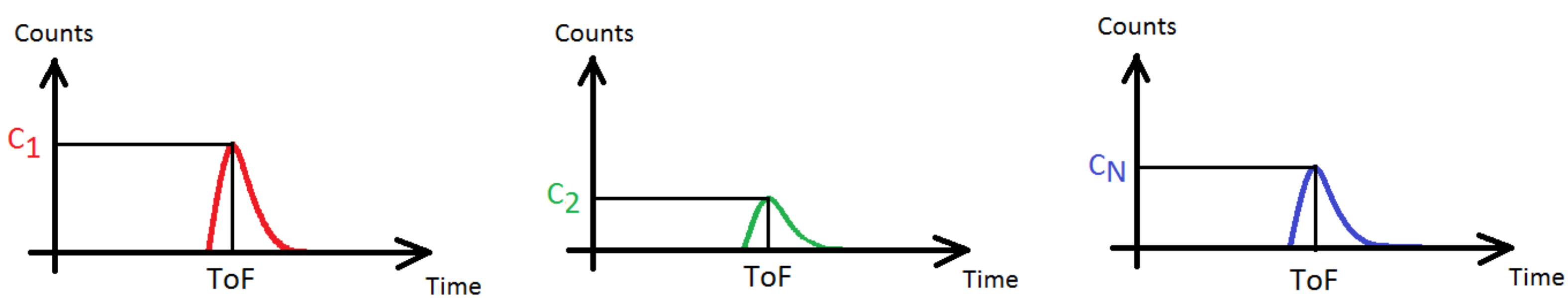
**Target detection/identification from extremely sparse histograms**

# Multispectral Lidar



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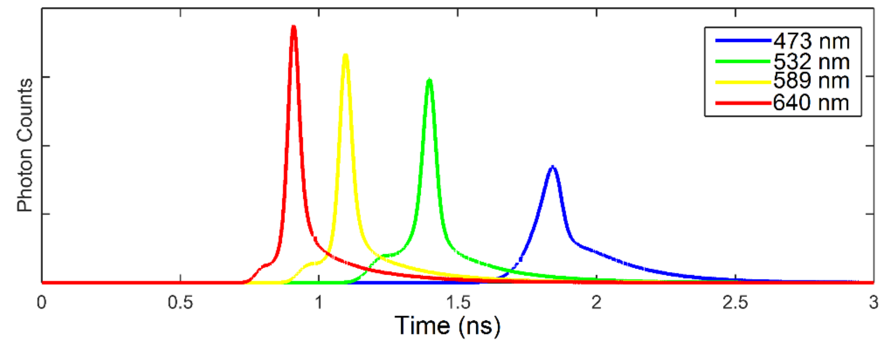
# Motivations

- Joint extraction of geometric and spectral information
  - Limited data registration issues
  - High depth resolution (<1cm)
- Robustness
  - Energy spread across wavelengths (range estimation)
- Fast/long range imaging
  - < 10 of useful photons
- But… ill-posed problems
  - High uncertainty, sparse data
  - Regularization required

**Bayesian methods** preferred

# Observation model

$$y_{n,\ell,t} = \mathcal{P}\left(\alpha_{n,\ell,t_n} r_{n,\ell} g_{0,\ell}(t - t_n) + b_{n,\ell}\right)$$
$$t \in \{1, \dots, T\}, \ell \in \{1, \dots, L\}$$



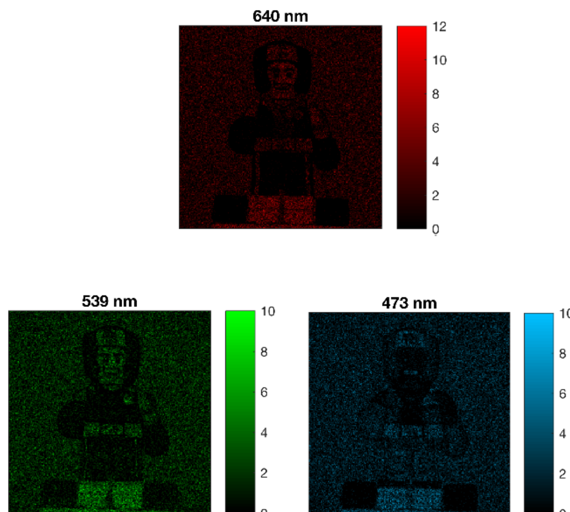

Examples of instrumental responses

- $y_{n,\ell,t}$: photon count in *t*th bin ($\ell$th band)
- $g_{0,\ell}(\cdot)$: instrumental response
- $\alpha_{n,\ell,t_n}$: attenuation factors
- $b_{n,\ell}$: background level
- $r_{n,\ell}$: target reflectivity
- $t_n$: ToF

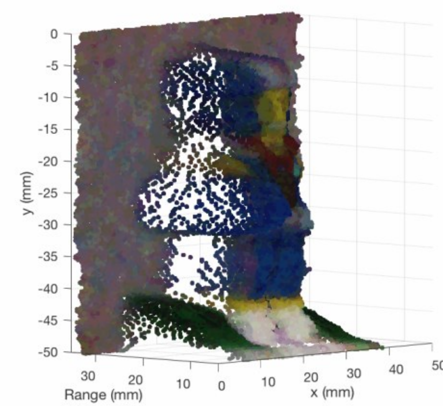
Estimation of $t_n$, $\{b_{n,\ell}\}$ and $\{r_{n,\ell}\}$ for each pixel

# 3D scene reconstruction


*Scene of interest*



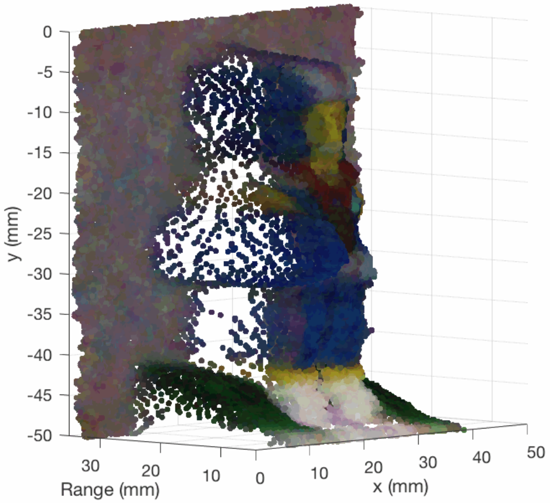

*Observations (≈1 photon/pixel)*



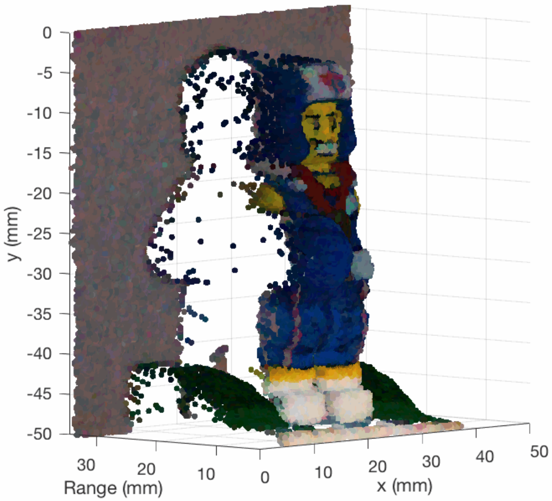

*Estimated 3D profile*

- Recovery of range and colour profiles (3 wavelengths) from extremely low photon counts (denoising)

# 3D scene reconstruction



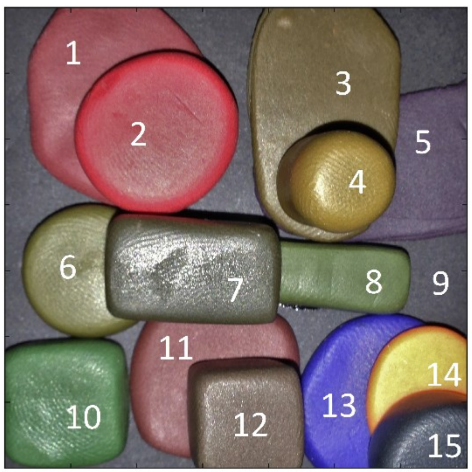

≈1 photon/pixel



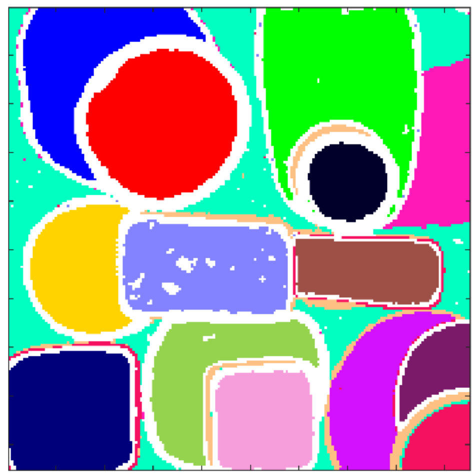

≈10 photon/pixel

- Efficient extraction of information from multispectral Lidar data

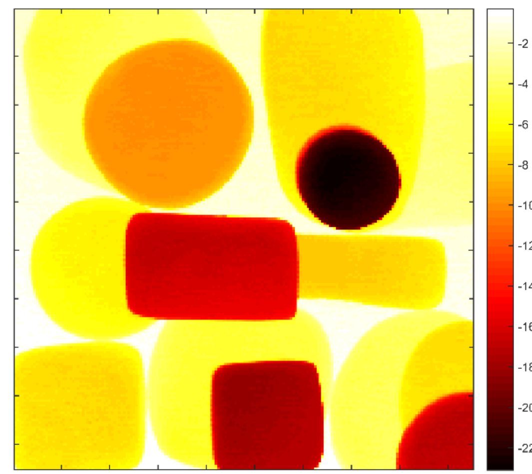
# Spectral classification




RGB image (5 x 5 cm)



Unsupervised spectral classification



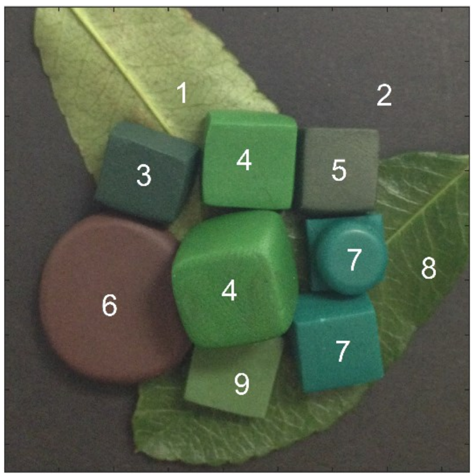

Estimated range profile (in mm)

- 33 spectral bands, 500– 820 nm, 200x200 pixels

**First computational methods for spectral analysis from extremely photon-limited (terrestrial) multispectral Lidar data[1]**

[1]Altmann et al., EUSIPCO 2016, IEEE SSP 2016, WHISPERS 2016

# Spectral clustering

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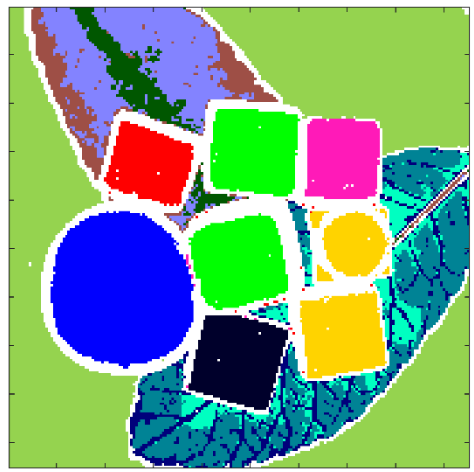
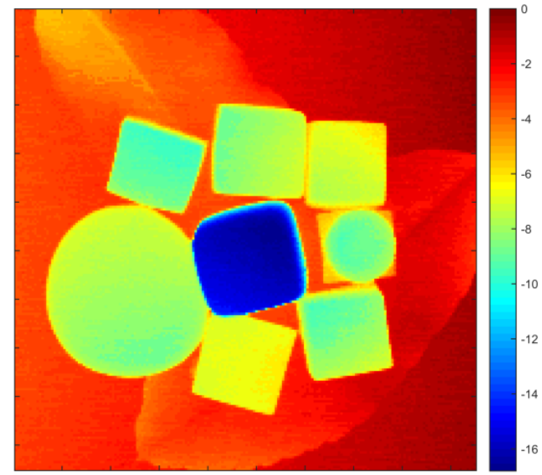


Unsupervised spectral clustering

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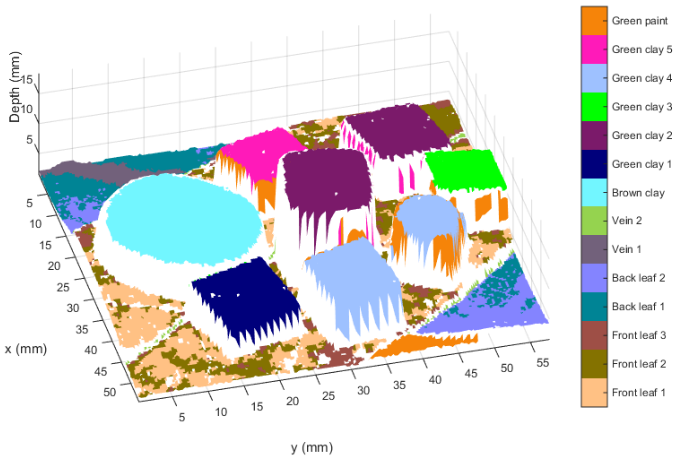
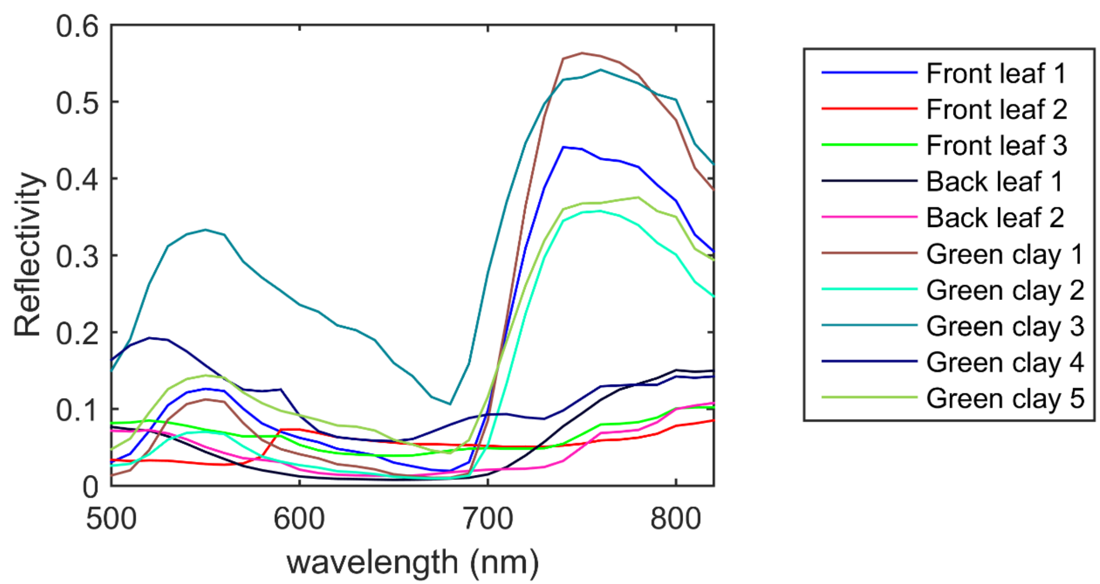
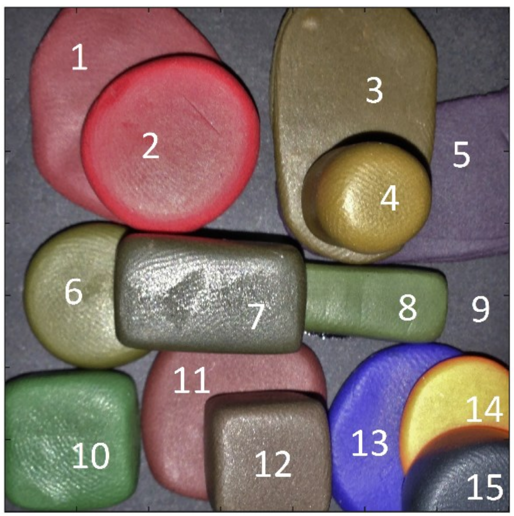



Depth/classification profile




Main spectral signatures

# Spectral unmixing

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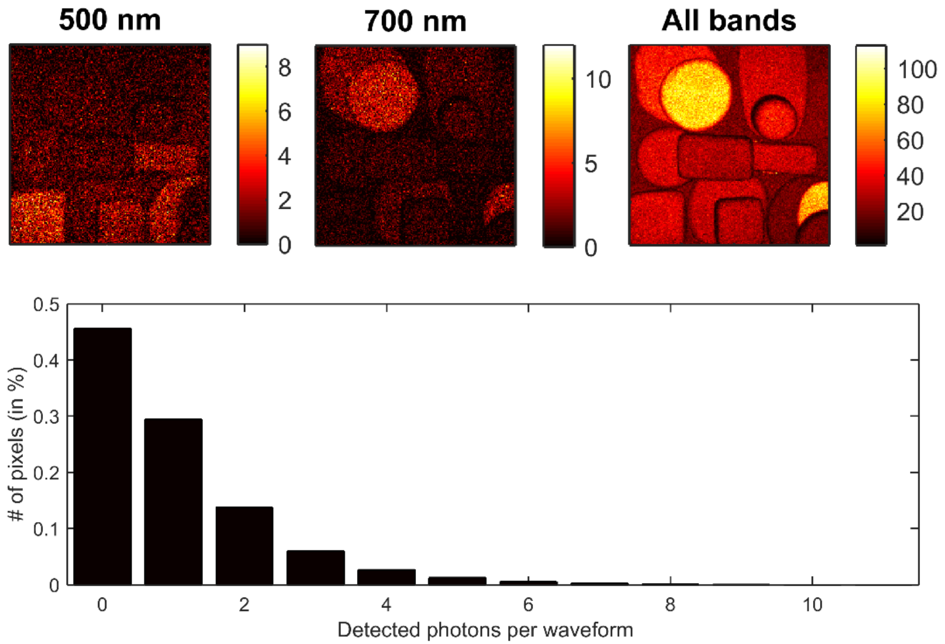
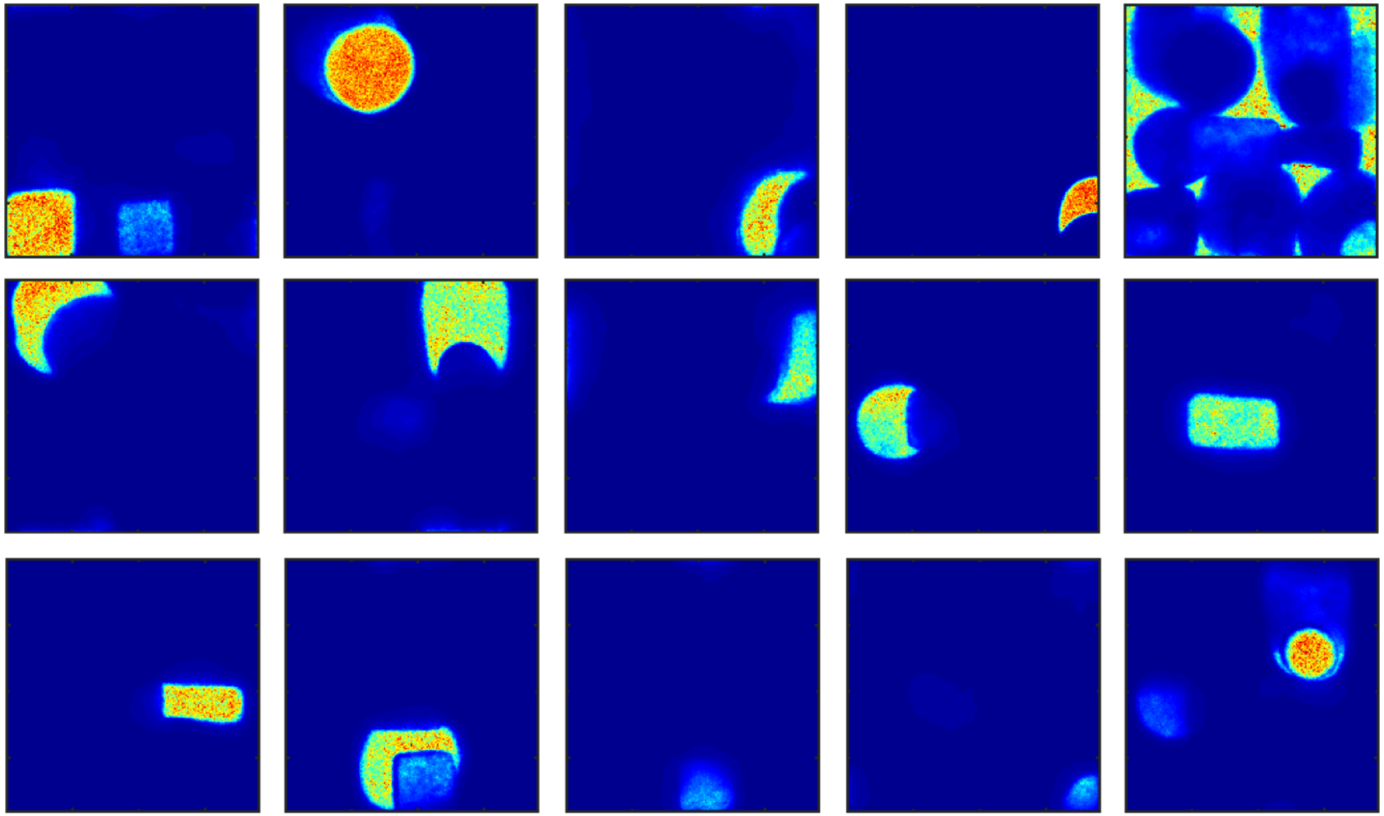



Data sparsity (1 photon/pixel) for each band

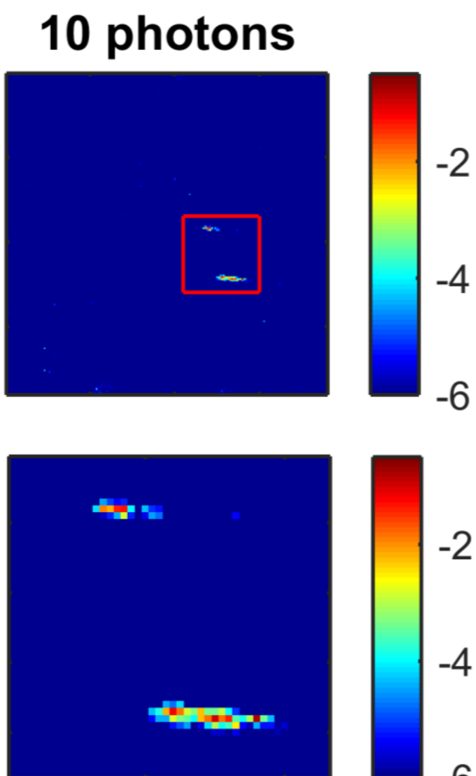
- Material quantification, anomaly detection (range ≈ 1,80 m)
- Known spectral library

# Abundance estimation

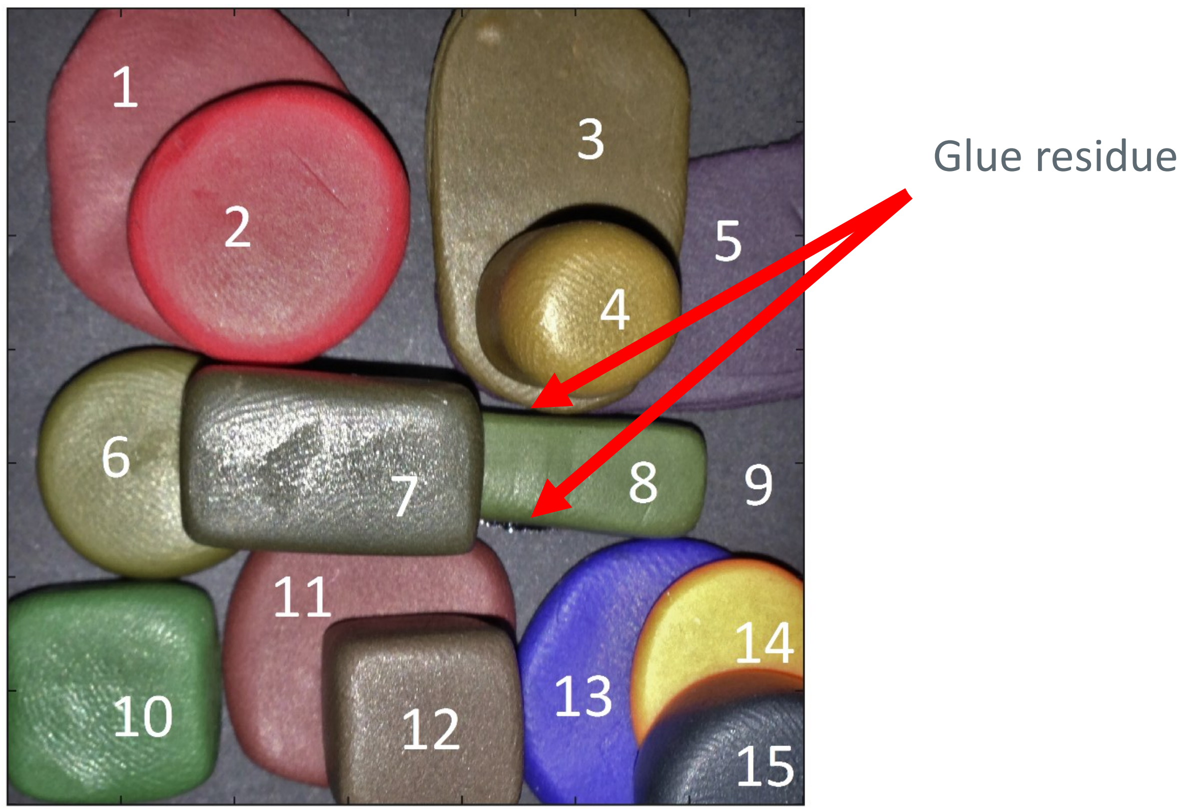


Estimated abundances: 1 photon per pixel (per band)

# Anomaly detection




Anomaly maps

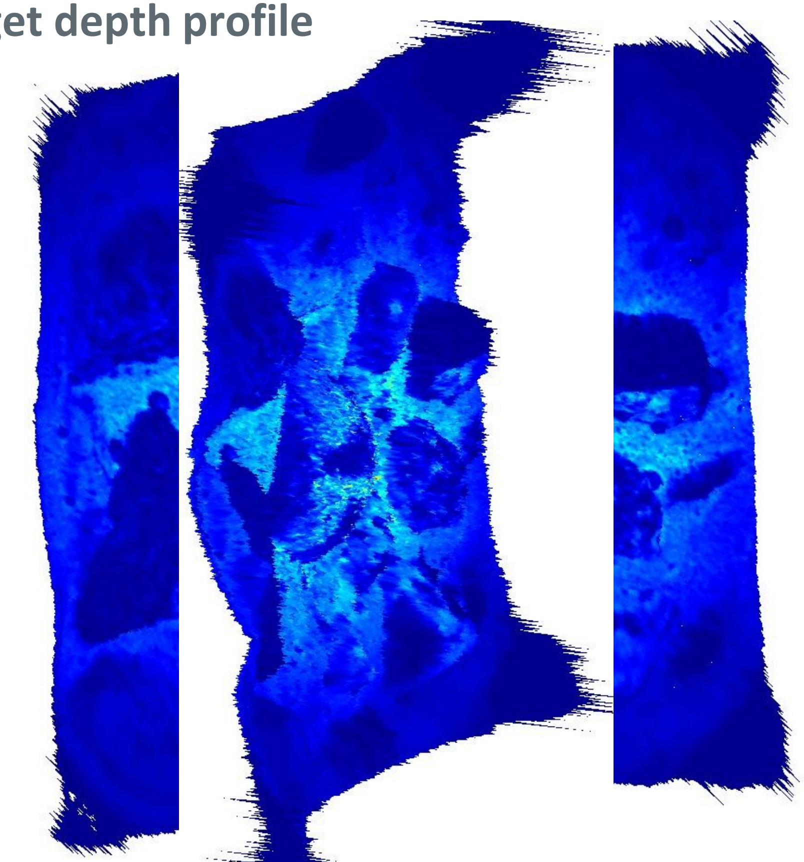


# Underwater imaging

- **Unfiltered tap water**
- Average power ~ 330 nW
- Pixel format = 300 x 300
- Target distance in water ~ 1.33 m
- Acquisition time per pixel = 10 ms
- Wavelength range: 500 nm – 725 nm

**Target photograph**

**Target depth profile**



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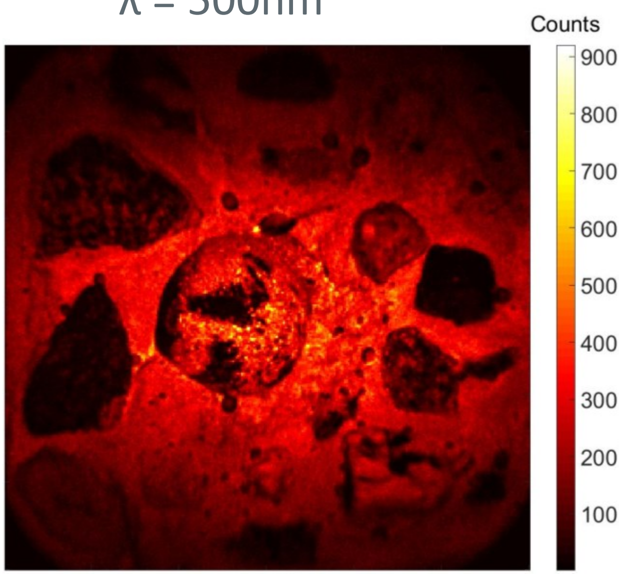
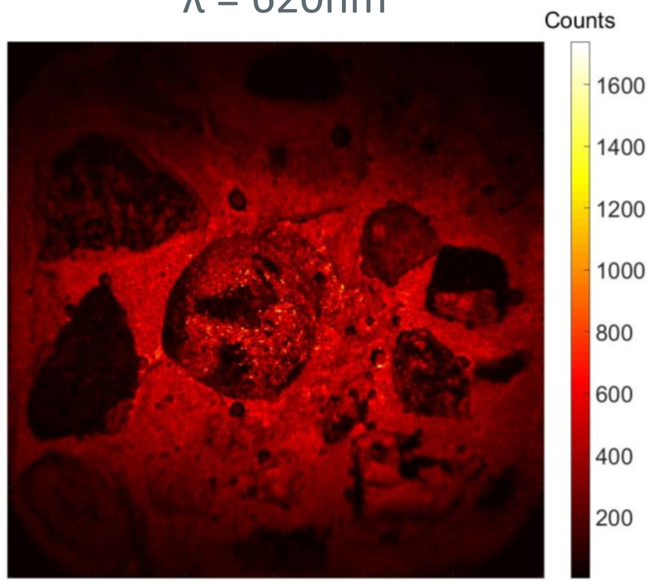
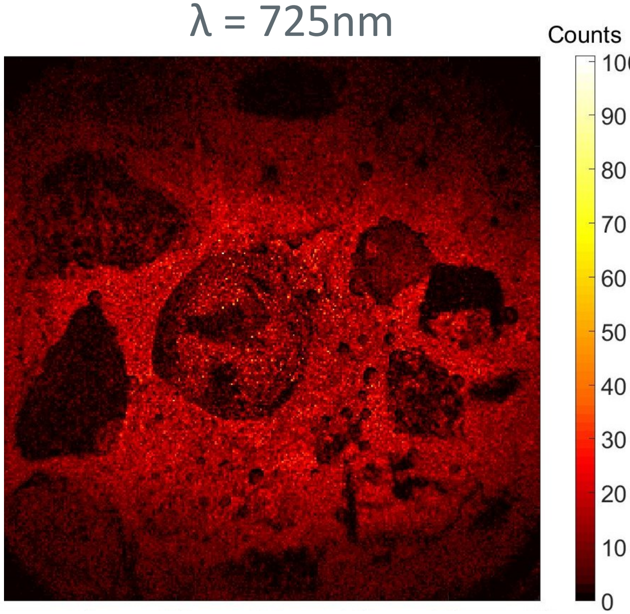
$\lambda$ = 500nm




$\lambda$ = 620nm




$\lambda$ = 725nm



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# Underwater object detection

# Multispectral measurements

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- Pixel format = 300 x 300
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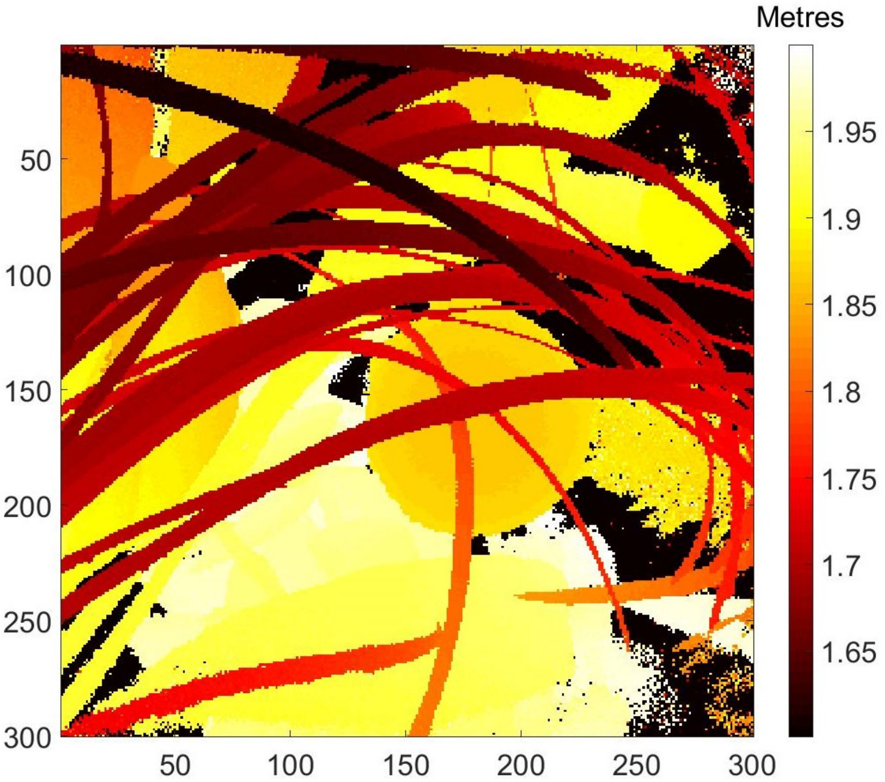
- Acquisition time per pixel = 10 ms



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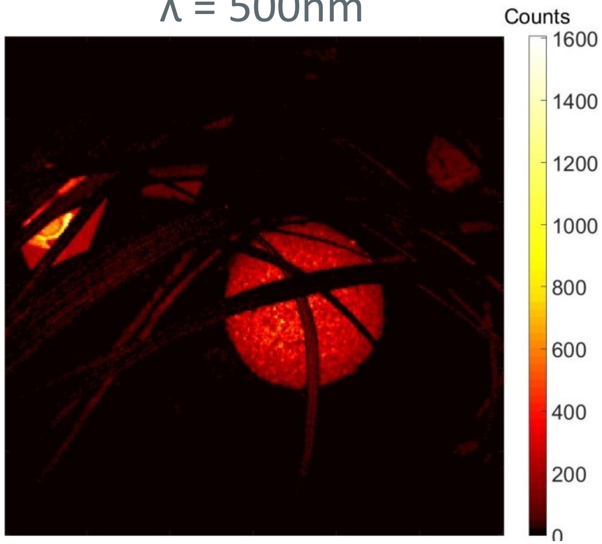
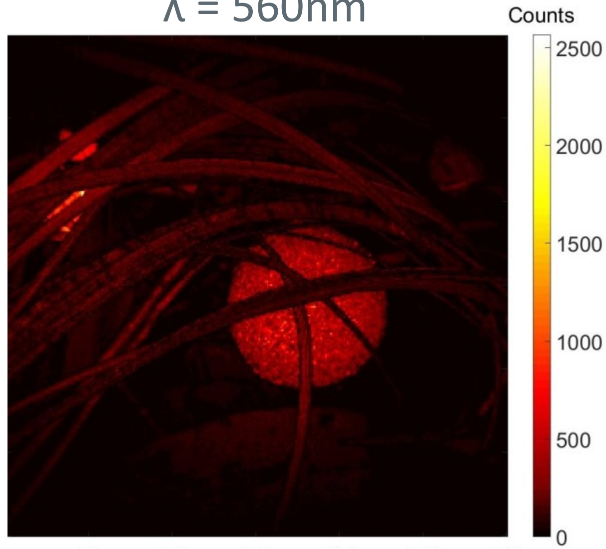
# Multispectral measurements

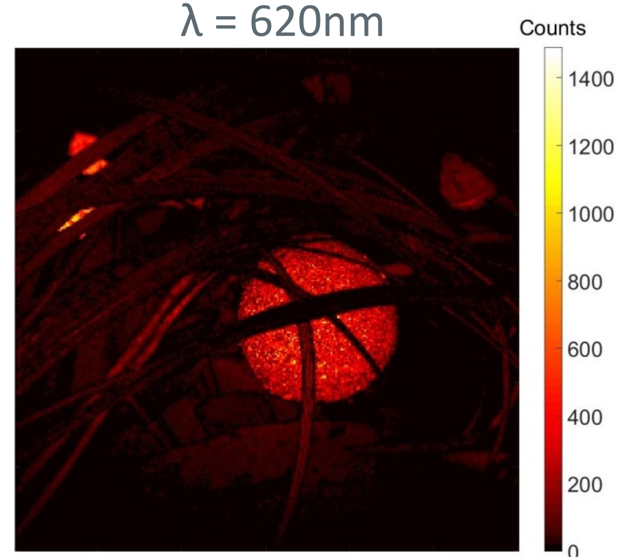
λ = 500nm



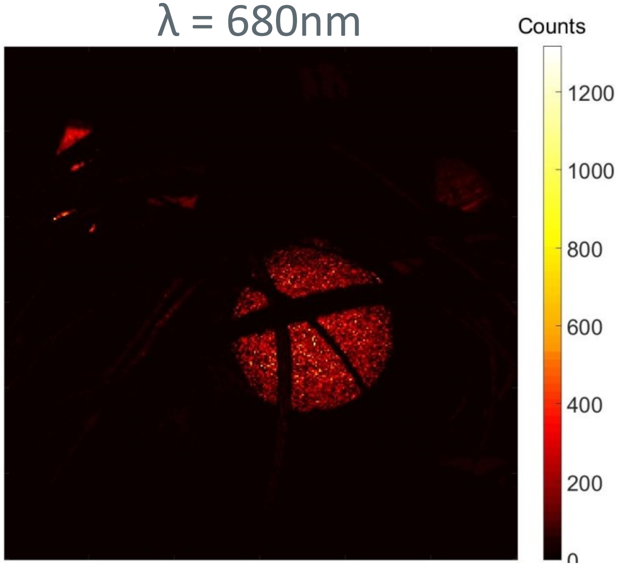

λ = 560nm



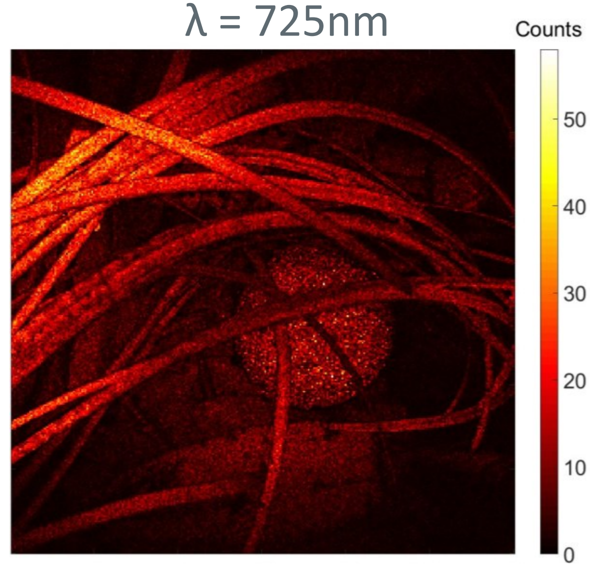

λ = 620nm




λ = 680nm




λ = 725nm



# Conclusion

- **Conclusions**
  - Joint extraction of spectral and geometric information
    - Detection – classification – quantification
  - Multispectral Lidar / combined modalities
  - MCMC methods: system assessment
    - Faster analysis → Optimization-based methods

- **Ongoing/future work**
  - Color/geometry-based analysis (Chhabra et al., SSPD 2016)
  - Actual 3D scene analysis
    - need for fast and reliable methods
  - Sampling strategies
    - Sparse sampling (compressive sampling, mosaic filters)
    - Adaptive sampling (multimodality)
    - Data storage/representation

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# Thanks for you attention !

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