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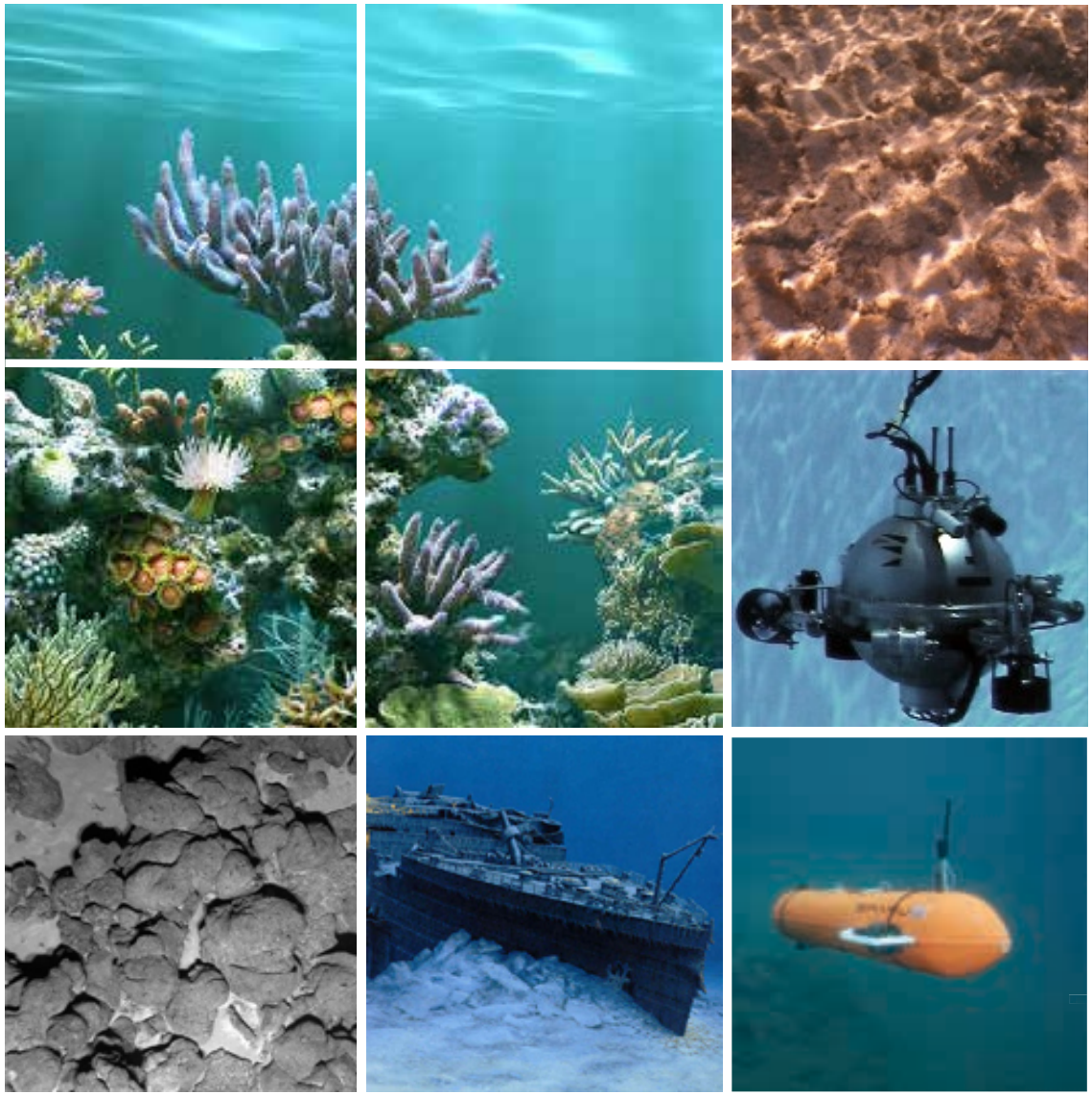


Introduction to Underwater Imaging and its challenges

Computer Vision and Robotics Institute

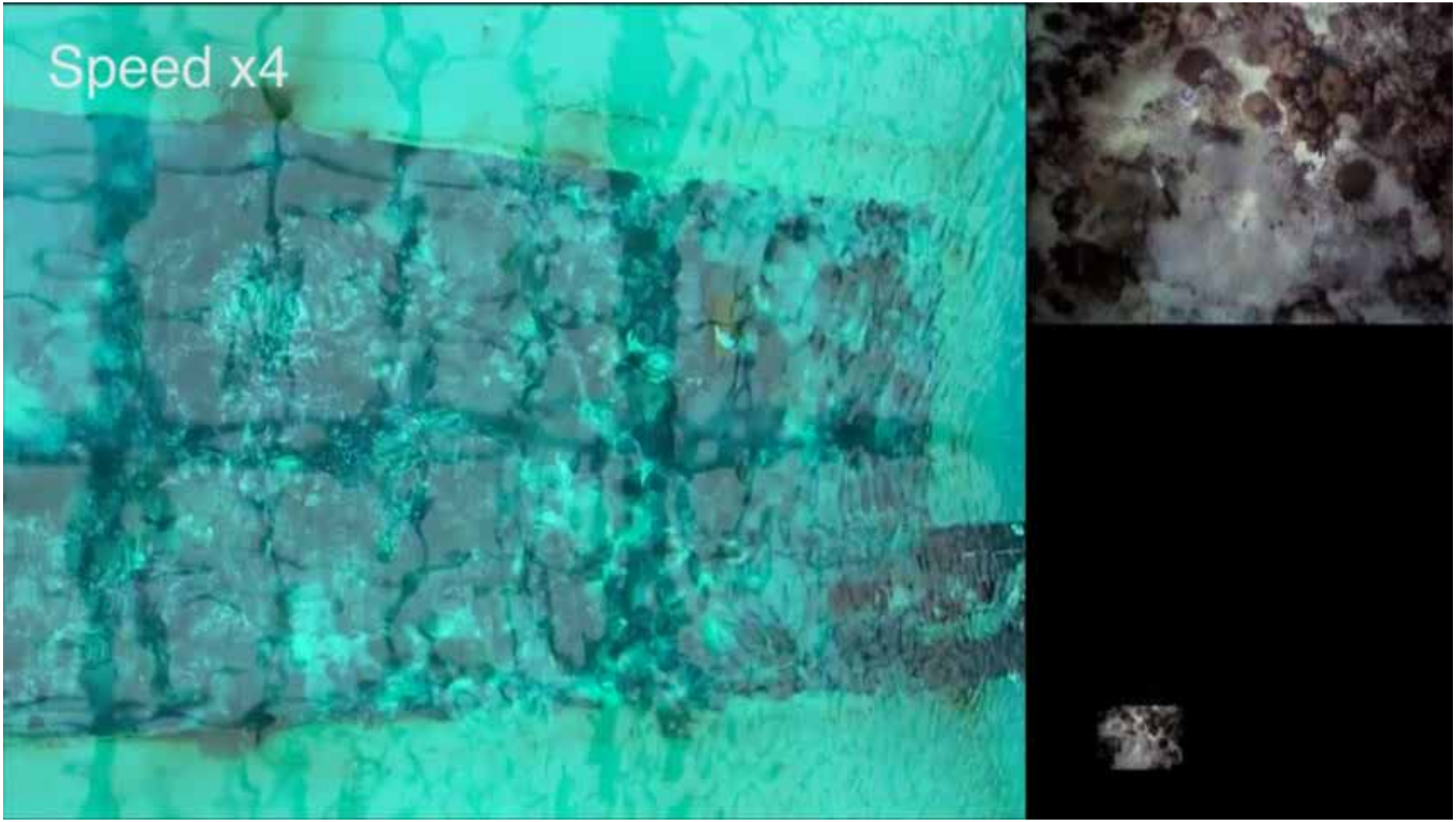
Rafael Garcia

Joint work with: L. Neumann, N. Gracias, R. Campos, T. Nicosevici, A. Elibol, R. Prados, J. Escartin

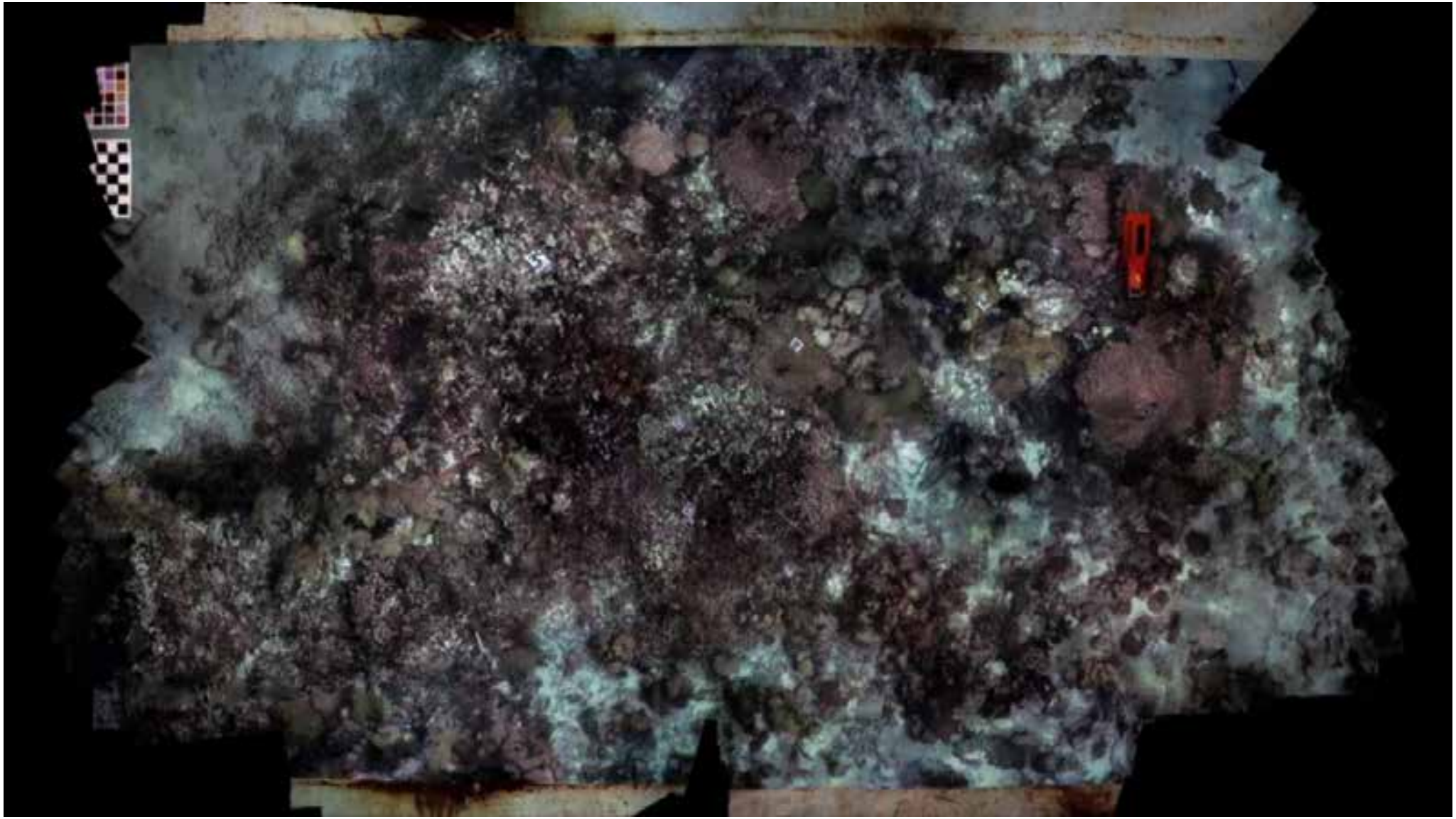
Main Objective:

Optical mapping of the seabed

We need robots that hover…



Optical mapping



Schedule for the seminar

PART 1

- Introduction to underwater Vision
- Pre-processing

PART 2

- Feature detection and description
- Feature matching

PART 3

- Motion estimation and outlier rejection

PART 4

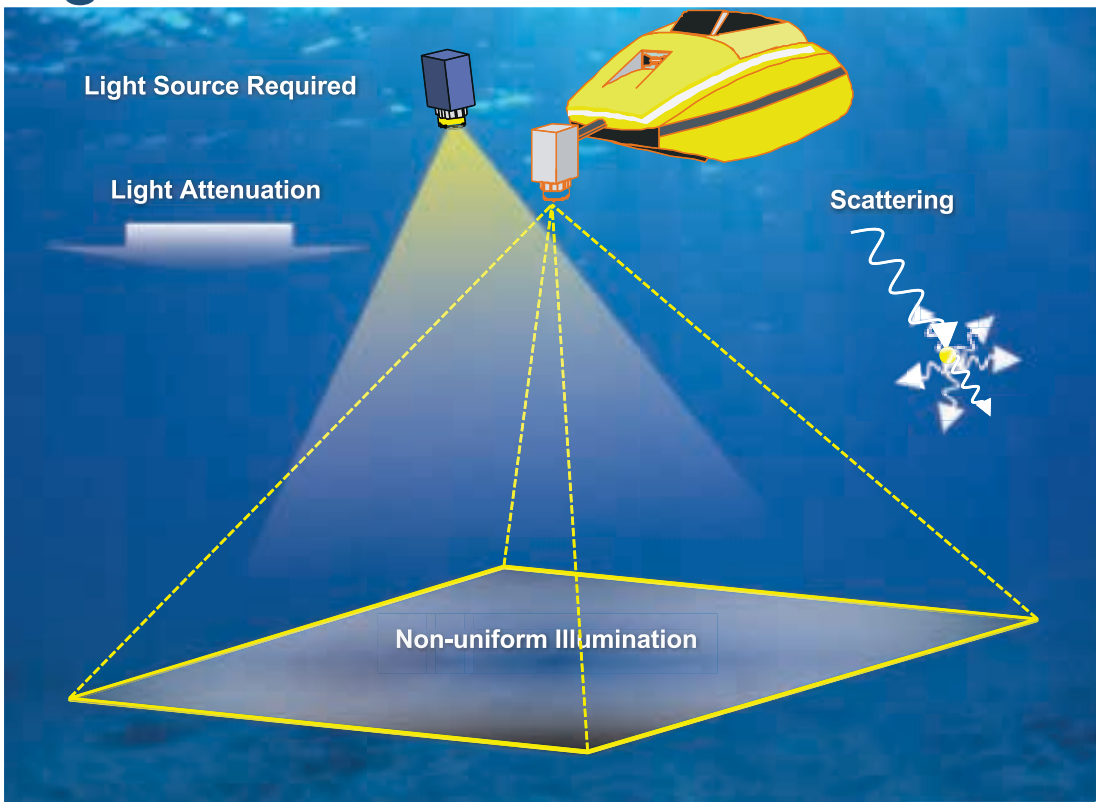
- Topology Estimation and Global Alignment

PART 1

- Introduction to underwater Vision
- Pre-processing

Using vision underwater, uhm…

- Light and water are not good friends:
  - Absorption
  - Scattering
  - Blurring
  - Non-uniform lighting



- We need to get close to the seafloor to collect data → data gathering is expensive

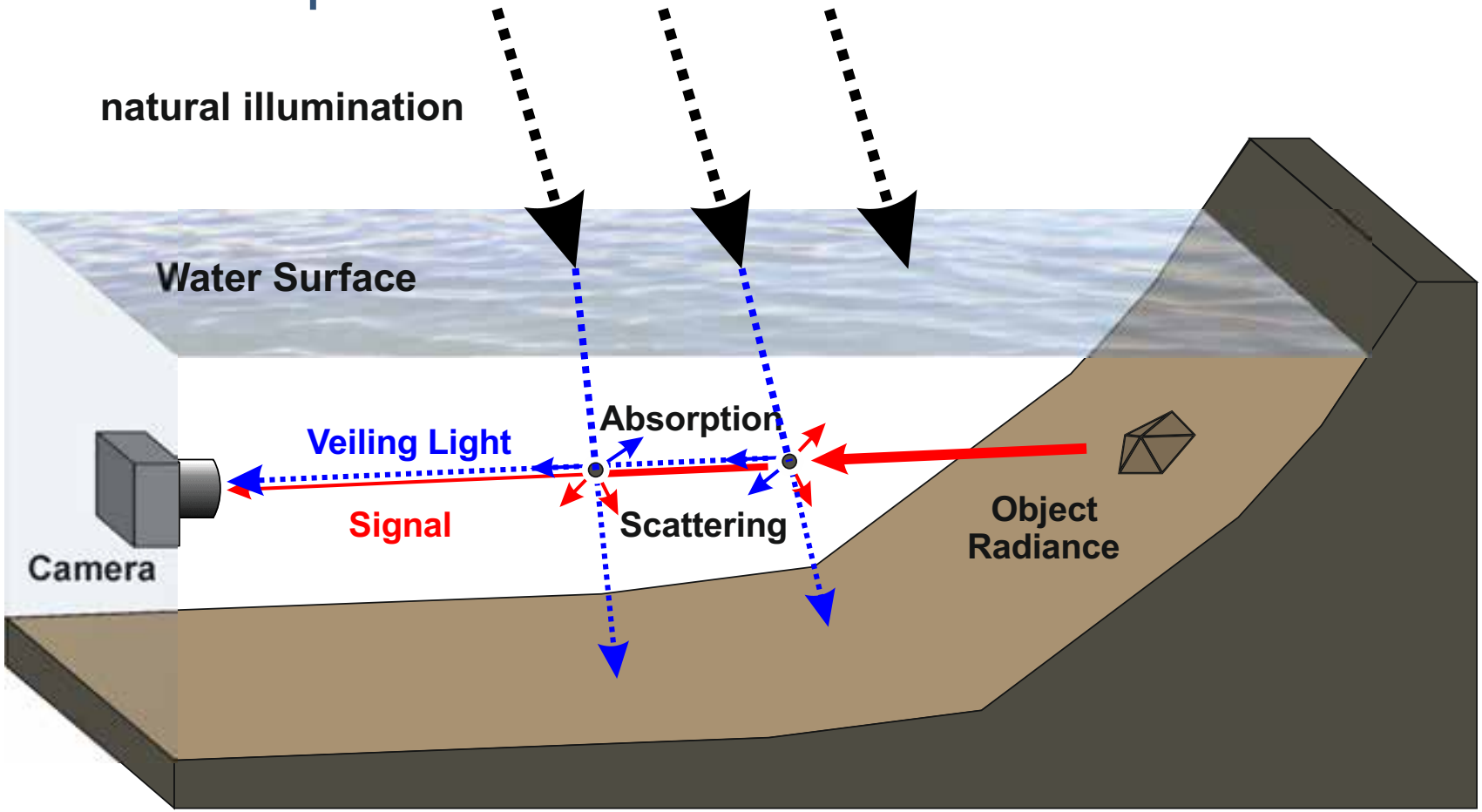
Underwater imaging

- Poor visibility
- Distance dependent

Underwater imaging

Veiling light = Spacelight = Path radiance = Backscatter

- Poor visibility
- Dist. dependent

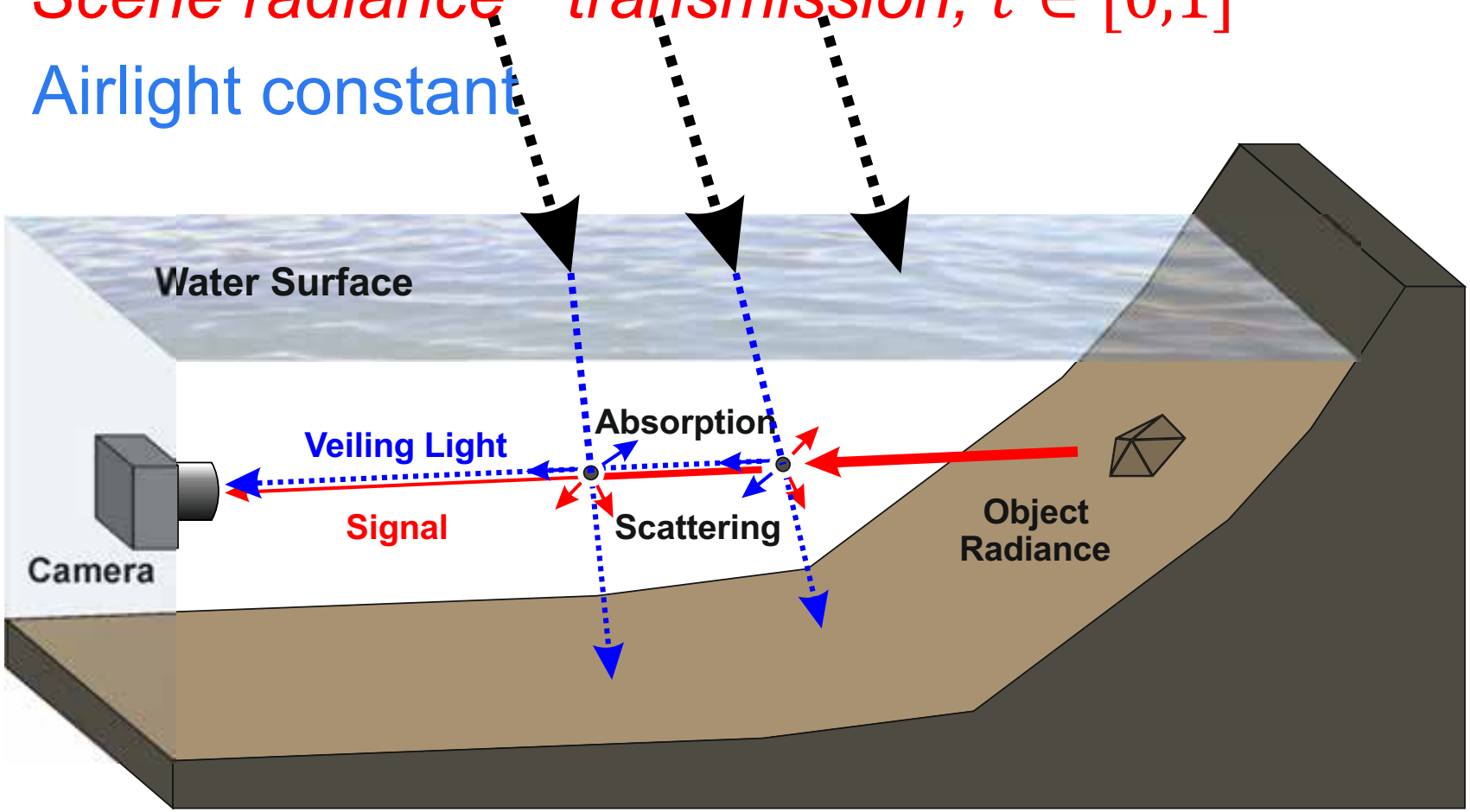


Underwater imaging

$I(x) = J(x) \cdot t(x) + A \cdot (1 - t(x))$

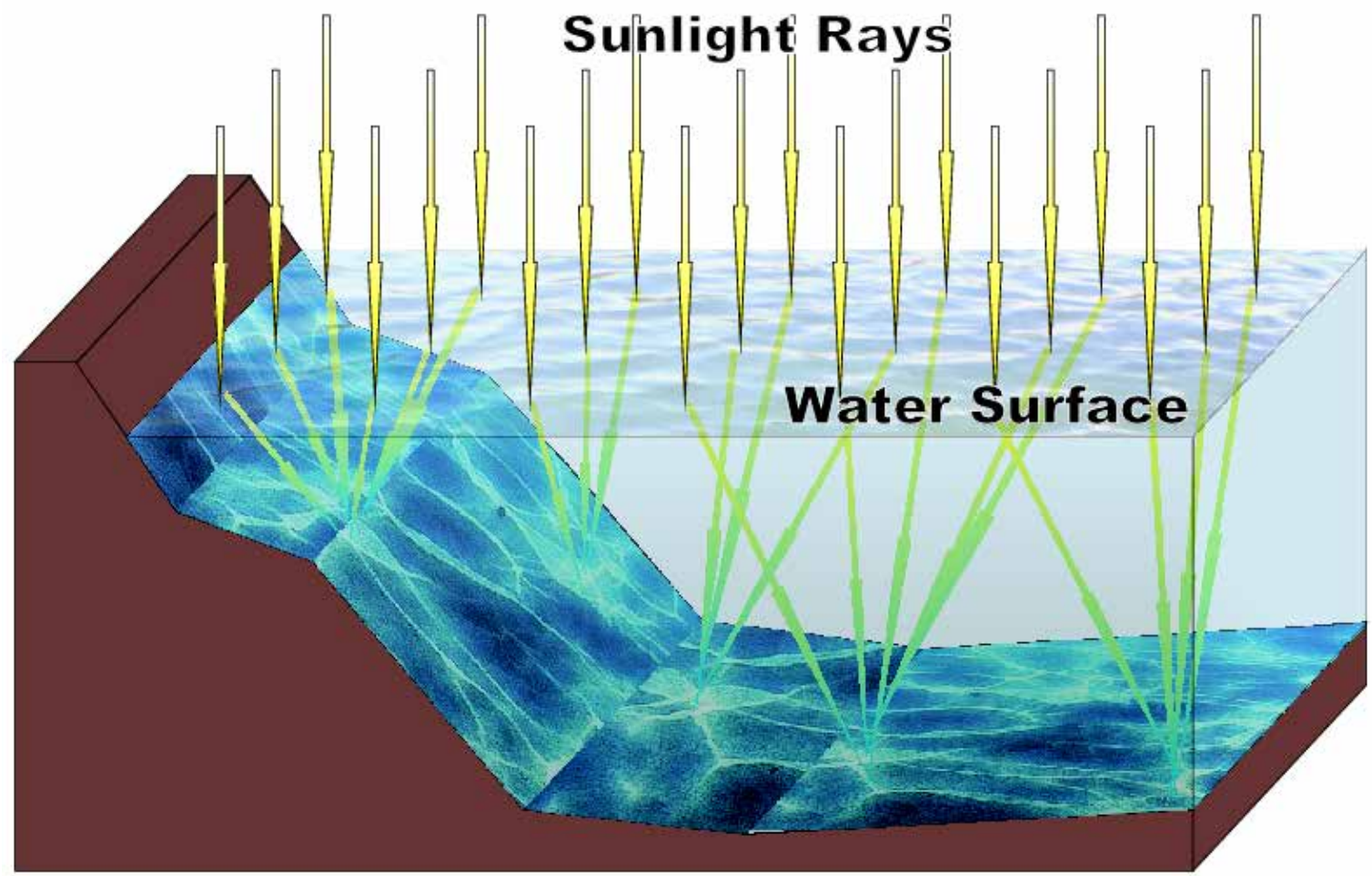
Scene radiance · transmission; $t \in [0,1]$

Airlight constant



Underwater imaging

- Flickering caustic pattern



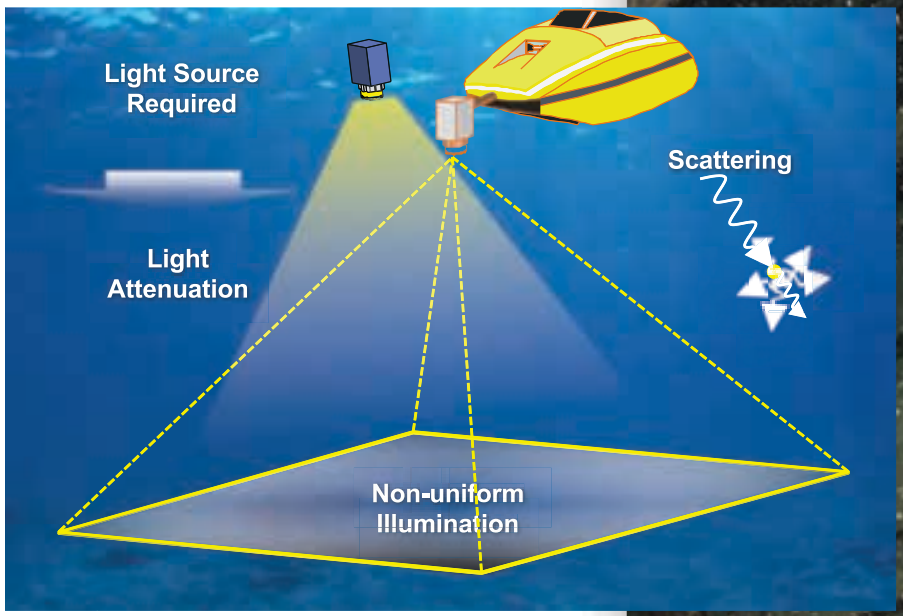
Underwater imaging

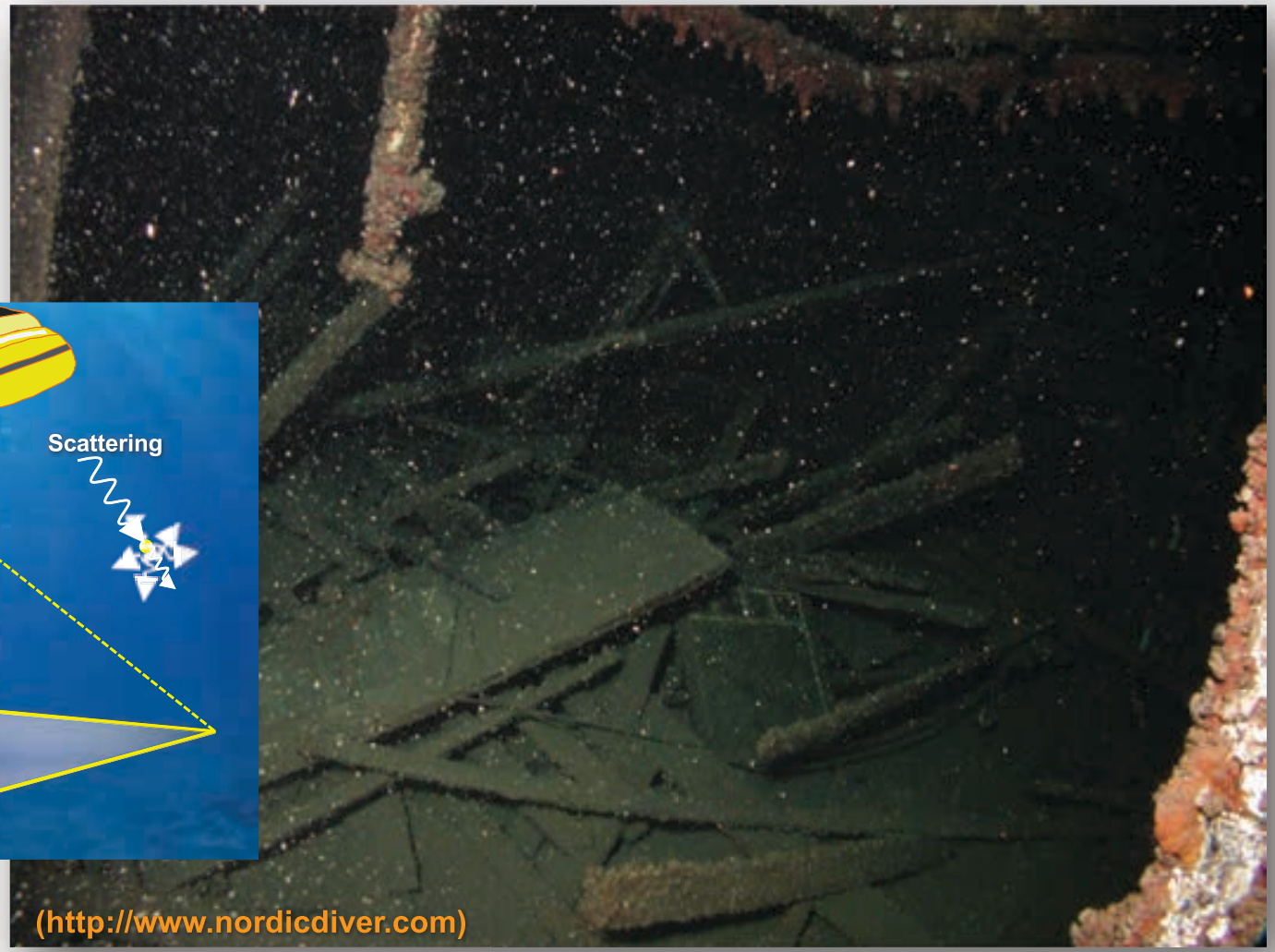
- Flickering caustic patterns

Underwater imaging

❖ Scattering

Lakeland Shipwreck – Lake Michigan, ~67m depth





(http://www.nordicdiver.com)

Underwater imaging

- Colors change with distance

Underwater imaging

Bathyluck cruise (2009). PI: Javier Escartin

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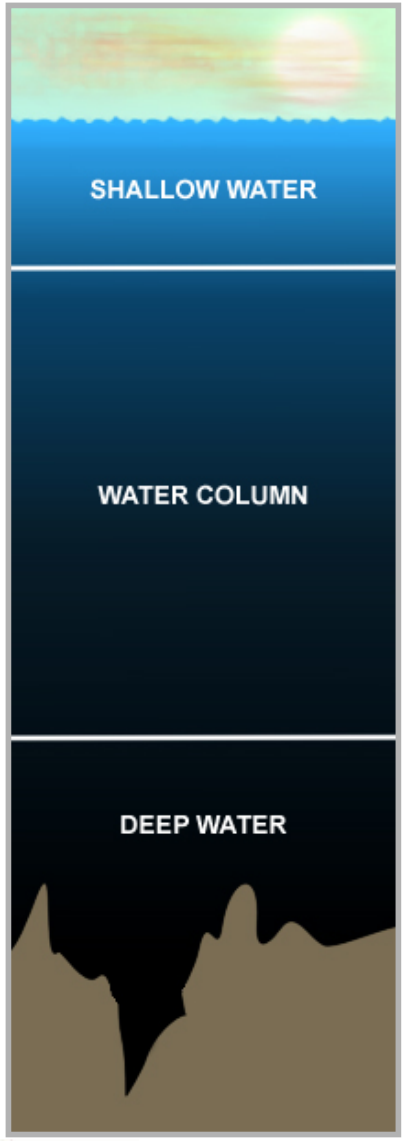
Photometric Artifacts: summary

Underwater Imaging Environment



SHALLOW WATER

Sun Flicker (caustics)

Cast Shadows

Suspended Particles

Turbulence

High Turbidity

Visual Cues from Natural Features and Manmade Structures

WATER COLUMN

Artificial Lighting

Back-Scatter

Visual Cues from floating Life Forms (marine larval ecology, e.g., plankton)

DEEP WATER

Artificial Lighting

Shading

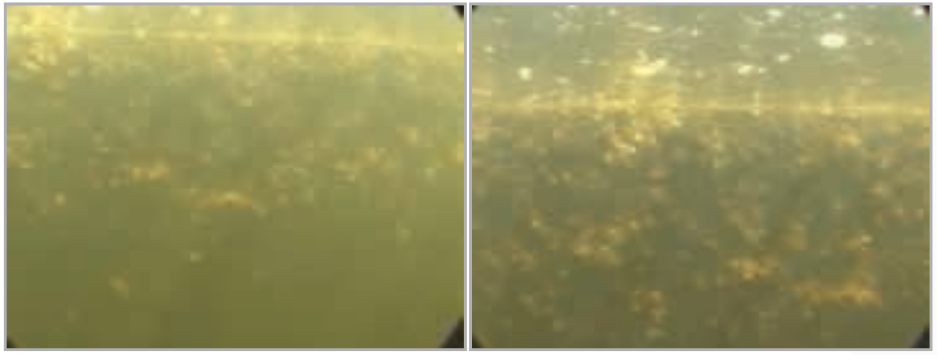
Cast Shadows

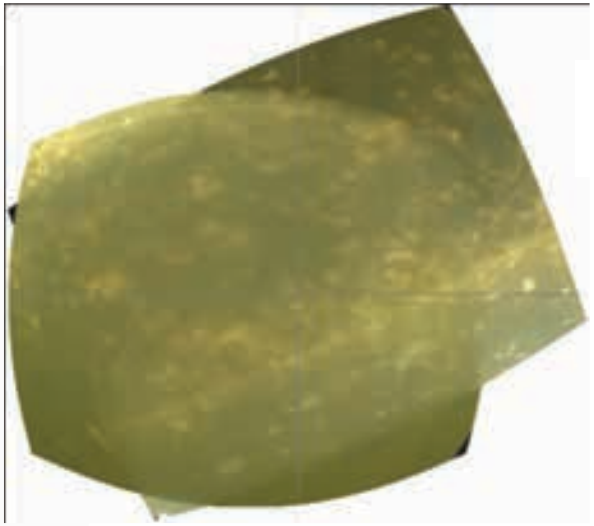
Loss of Color

Strong Visual Cues from Benthic Features

Image Registration Underwater

Extreme Cases





FAILS!

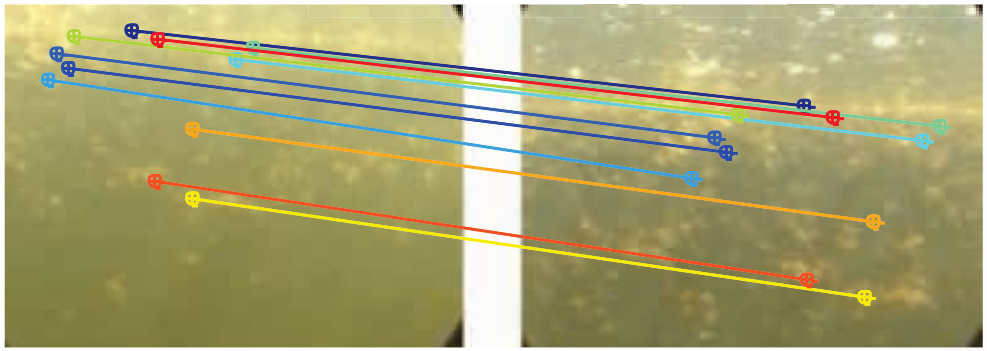
SIFT

Fails!

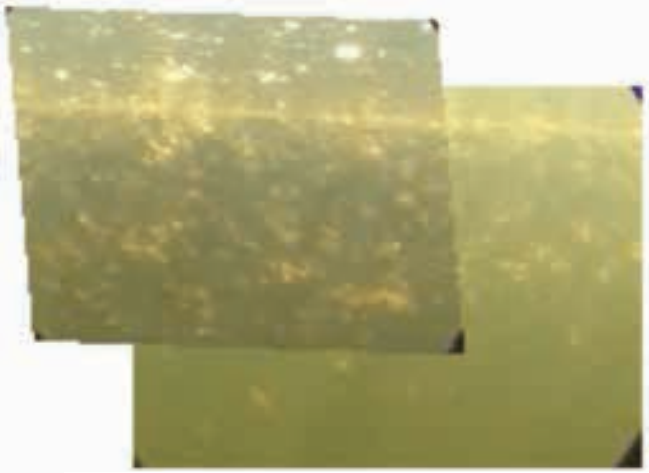
Image Registration Underwater

PRE-PROCESSING Adapted to Underwater Imaging

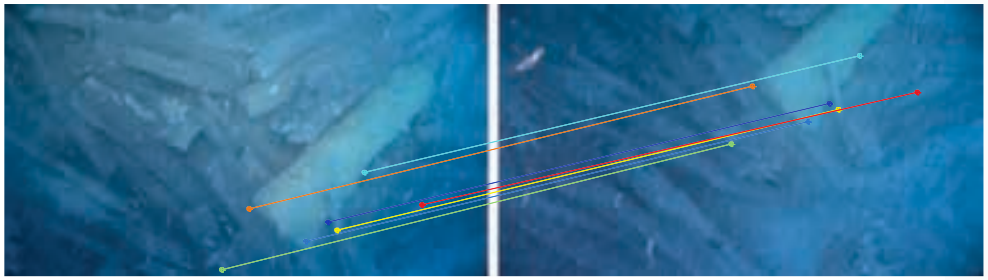
Equalization + Sunflicker Removal



SIFT



Both Image Pairs are Successfully Matched!



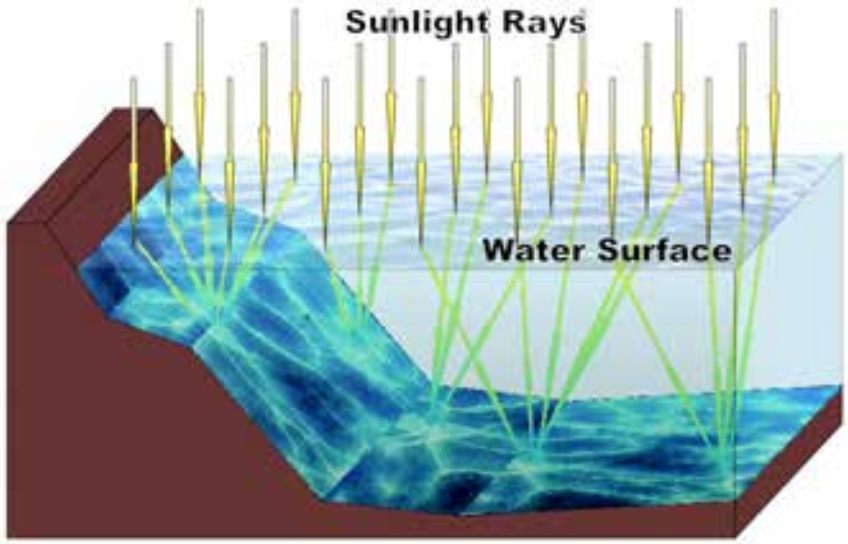
SIFT

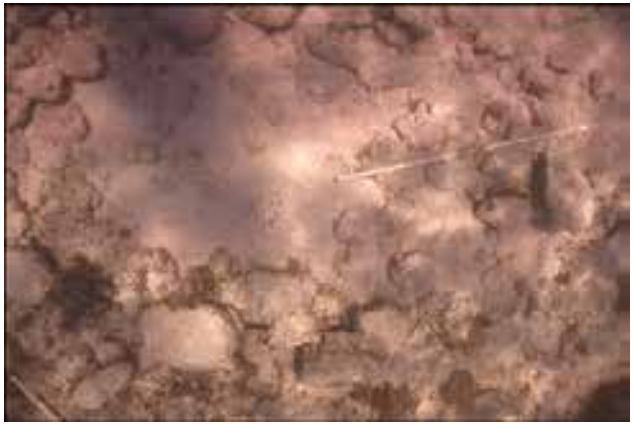
CLAHE

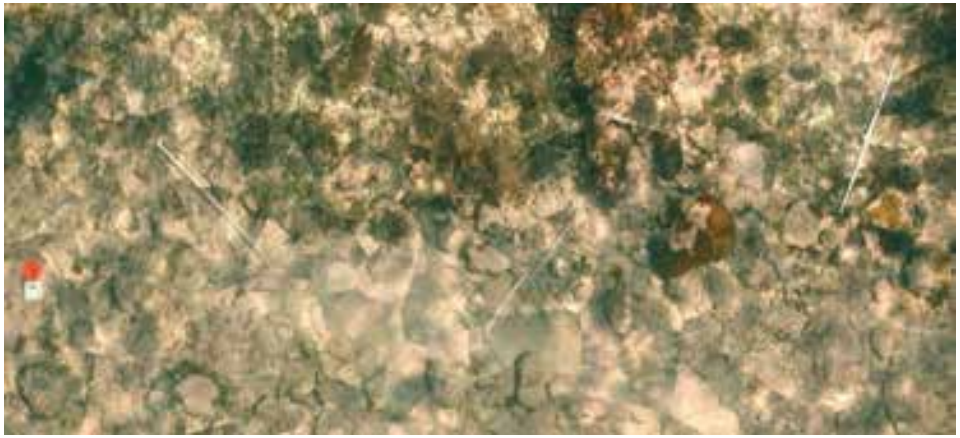
Most of the features that you detect (that show up) in the underwater environment are kind of non-discriminant.

Removing sunlight flicker

Refracted sunlight creates irradiance (light) fluctuations







Refracted Sunlight

- Can disrupt image processing algorithms (matching and segmentation)
- Makes it harder to interpret benthic structures

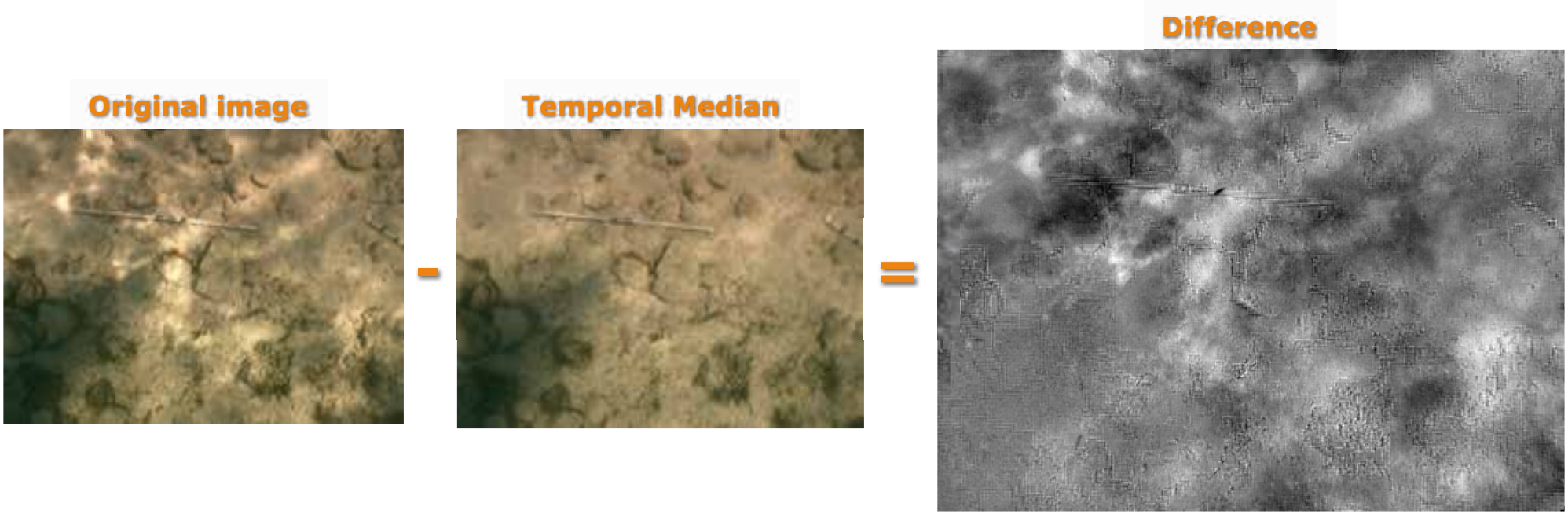
Our Approach – 2 key observations

❖ *Observation 1*

- The difference between an image and the temporal median *has two components*

  Component 1 – Instant illumination field from sun light

  Component 2 – Artifacts from registration errors



Our Approach – 2 key observations

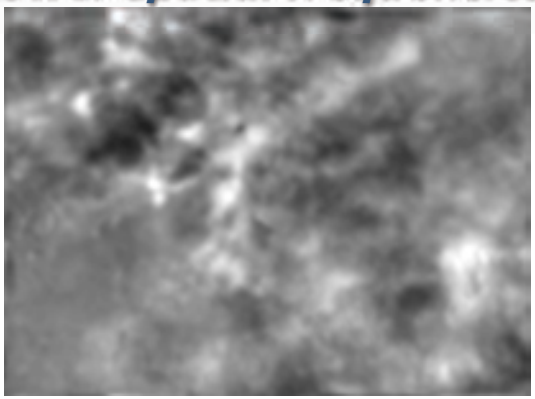
❖ *Observation 2*

- The two components are (usually) *easily separable in the frequency domain*

Difference

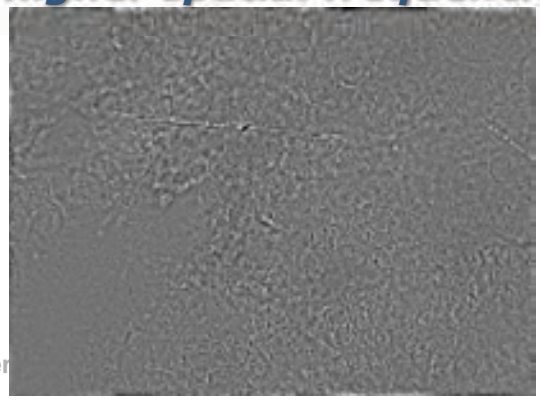
Low Pass Filter

Illumination field has lower spatial frequencies

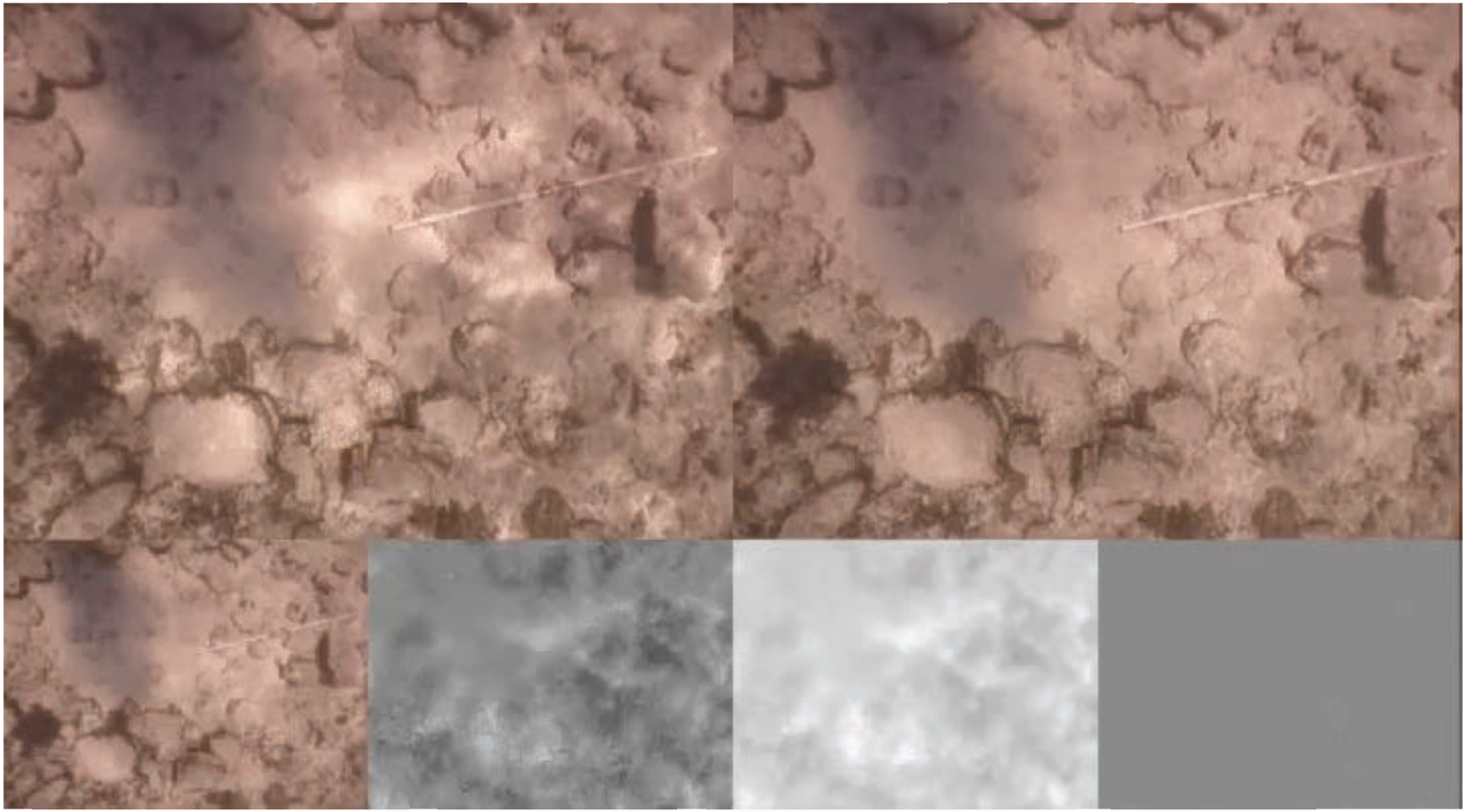


High Pass Filter

Registration artifacts have higher spatial frequencies

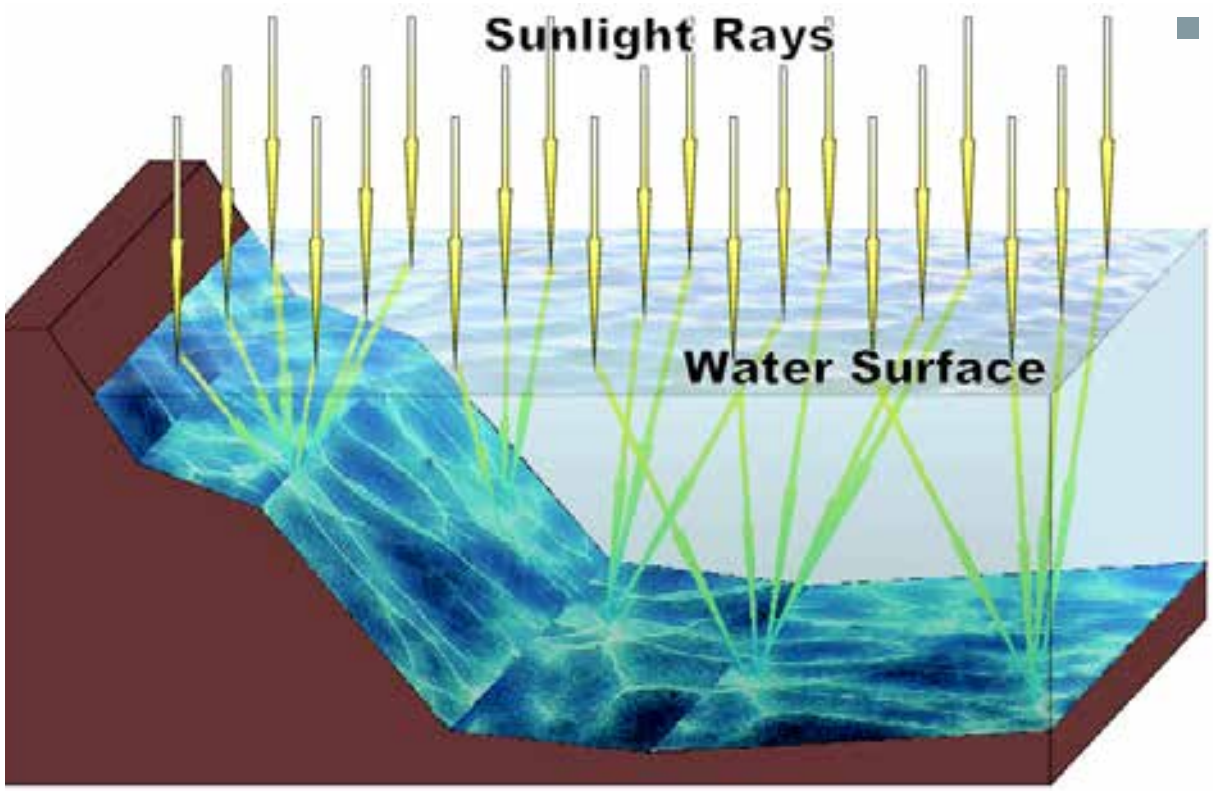


Removing sunlight flicker



sunlight flicker revisited

- Created by refracted sunlight
- Degrades image quality and the information content
- Inversely proportional to depth

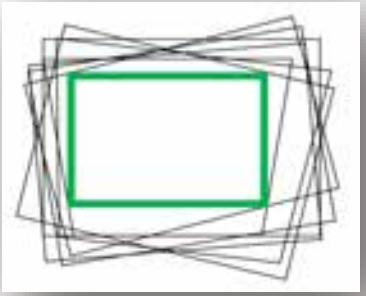


- **Generates dynamic patterns**

Wu Y. N. Doretto G., Chiuso and S. Soatto. Dynamic textures. Journal of Computer Vision, 2003, Kluwer Academic Publishers, pages 51(2):91-109, 2003.

Pipeline

Warp previous illumination field to the current frame



Predict the current illumination field

Coarsely recover the image

Finding homography between the previously recovered image and current coarsely recovered image

Remove sunflicker pattern from the images

Assumptions:

1. Illumination field is a dynamic texture
2. Smooth camera movement
3. Flat (approximately) bottom of the sea

Dynamic texture modeling

1 2 3

4 5 6

1. Input image
2. Coarsely recovered image
3. Finally recovered image
4. Original illumination field
5. Predicted illumination field
6. Median image

A. Shihavuddin, N. Gracias, R. Garcia. "Online Sunflicker Removal using Dynamic Texture Prediction". International Conference on Computer Vision Theory and Applications, pp. 161-167, Rome (Italy).

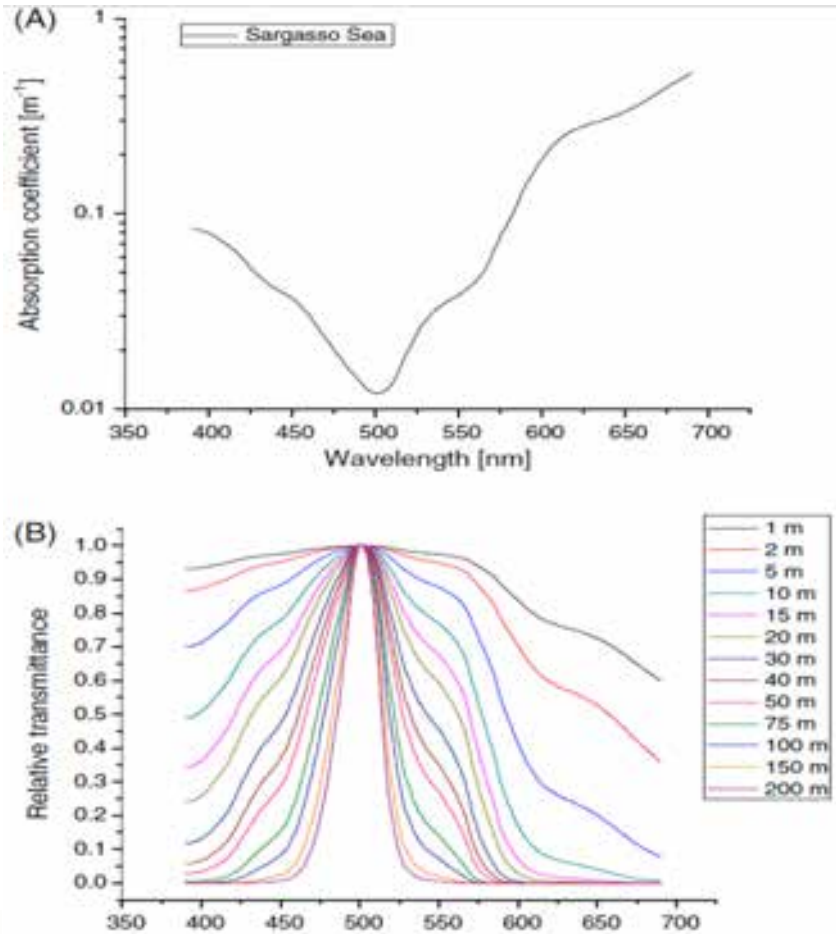
Light effects in Underwater Imaging

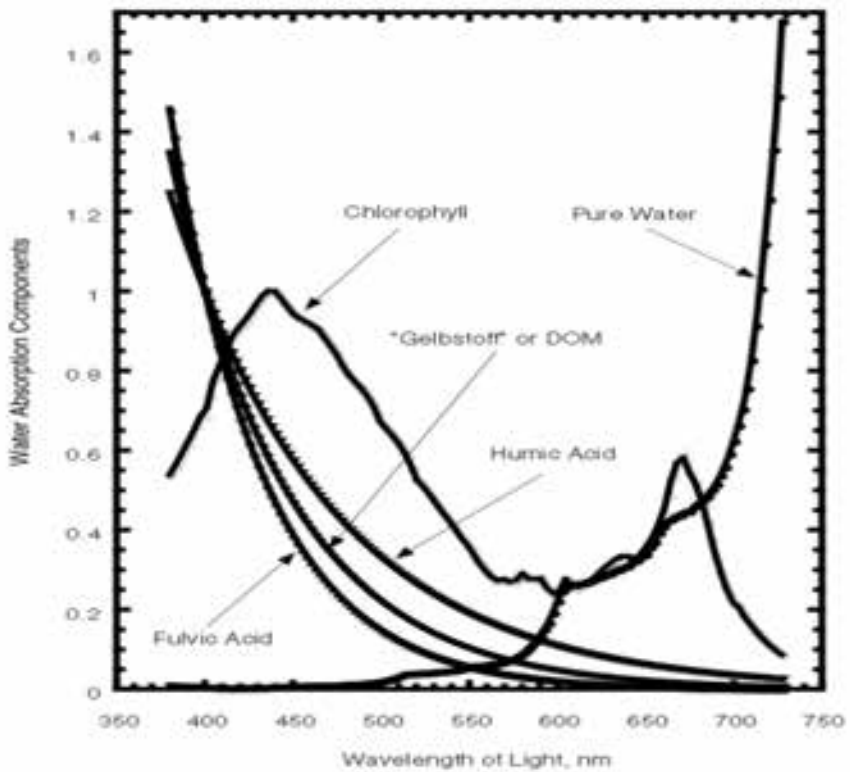
- **Poor visibility: light interactions with water molecules and impurities dissolved and suspended in water**
  - **Absorption effects**
  - **Scattering effects**
    - Forward scattering
    - Backward scattering
  - Fluorescences of biological objects
  - Swimming macroscopical particles
  - Lighting inhomogeneities
    - Shallow water: sun flickering
    - Deep water: artificial lighting, vignetting, limited lightpower

Light effects in Underwater Imaging

The absorption of light power is exponential - Lambert Law of Absorption. Attenuation Factor dependence on distance:

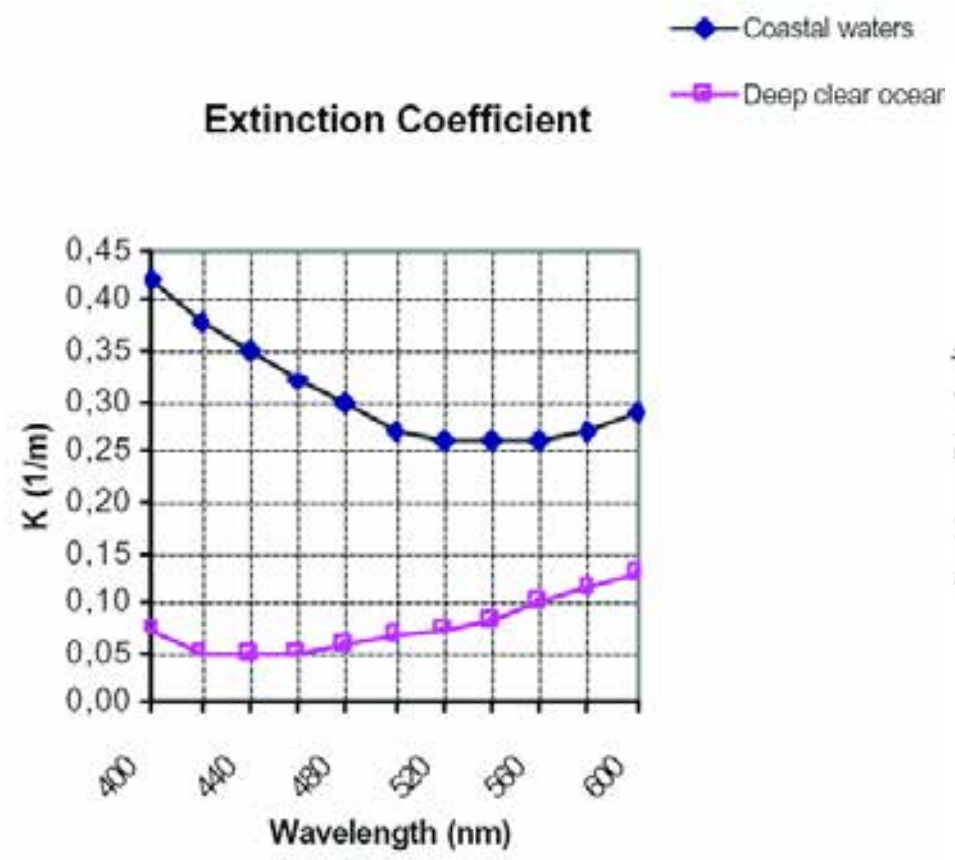
F = exp(— a(λ) * d), where a(λ) is the spectral absorbance.

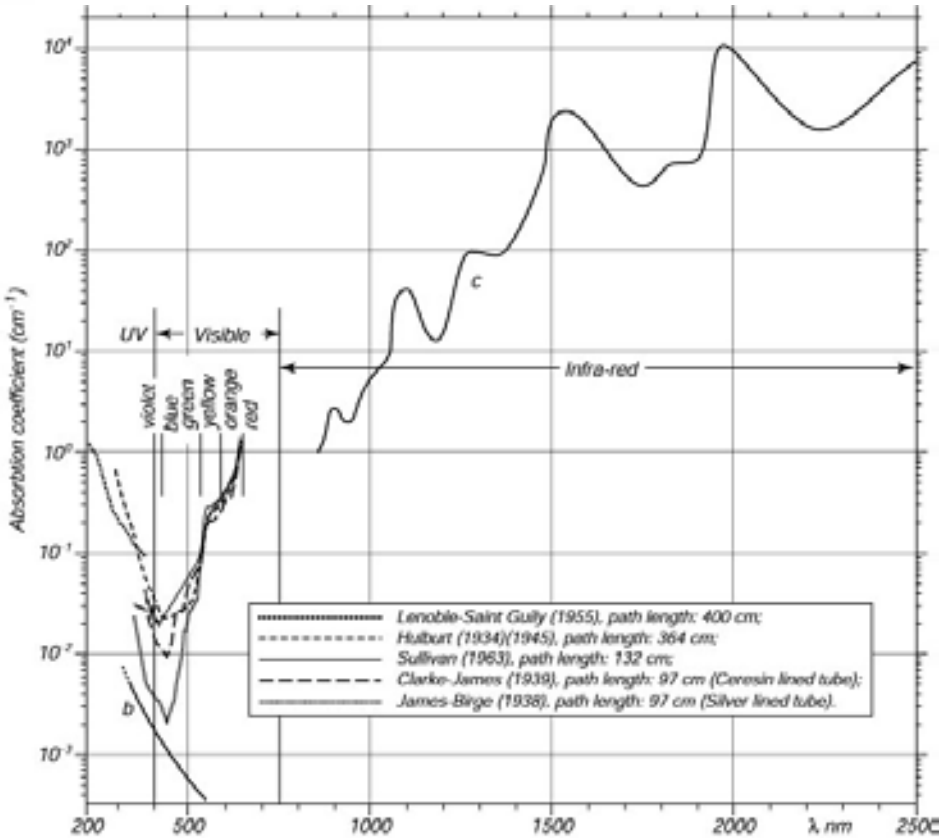




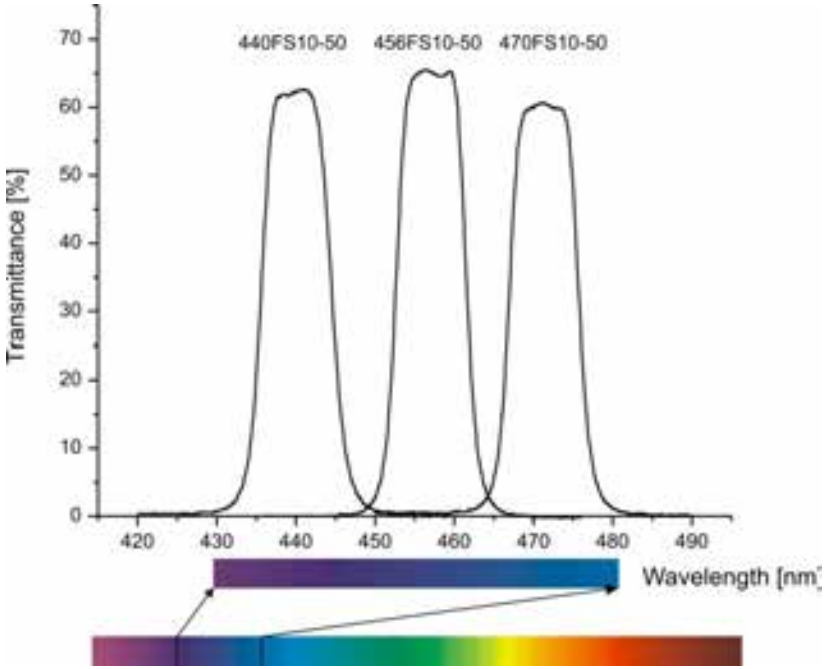
Light effects in Underwater Imaging

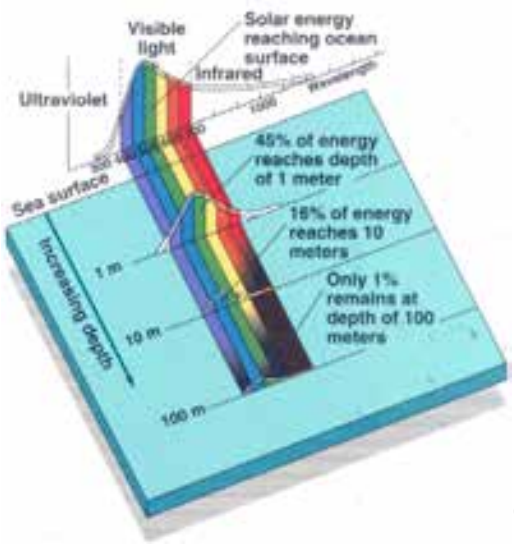
Basically, the water only for the bluish visible range of electromegnetic waves is transparent for relative longer distance, but this range has often strong scattering effects, thereby it is loss in sharpness and contrast



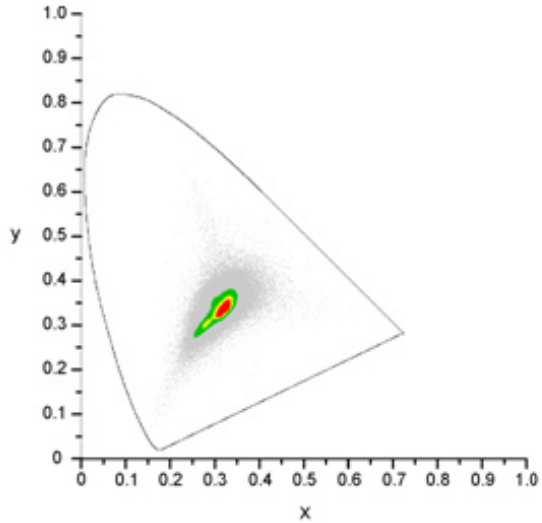


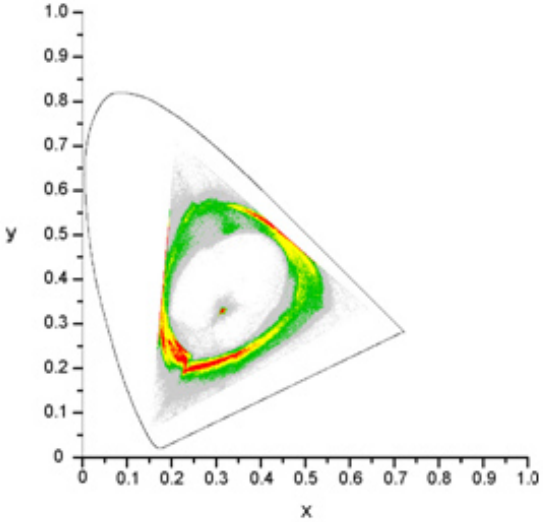
A non-dehazing approach for visualization in tight blue spectral range





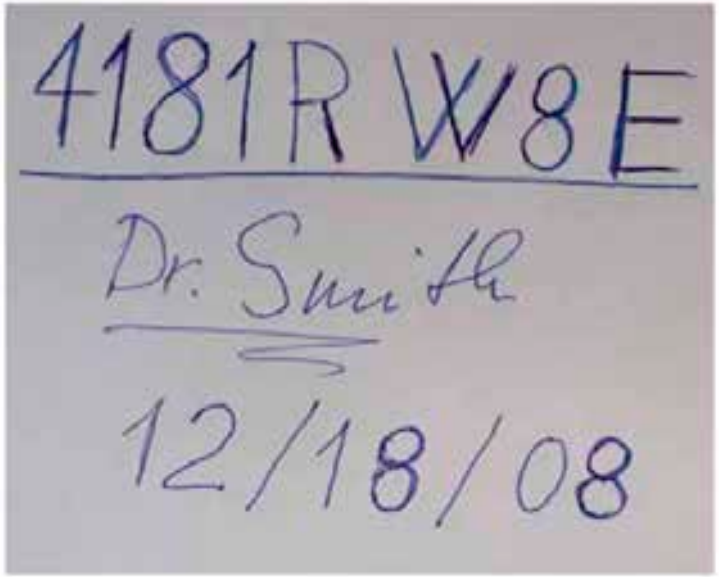
Narrow Spectral Imaging

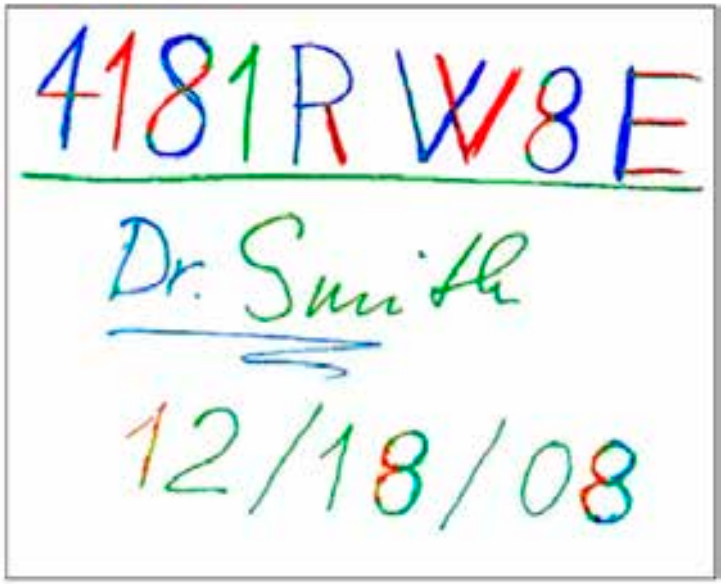


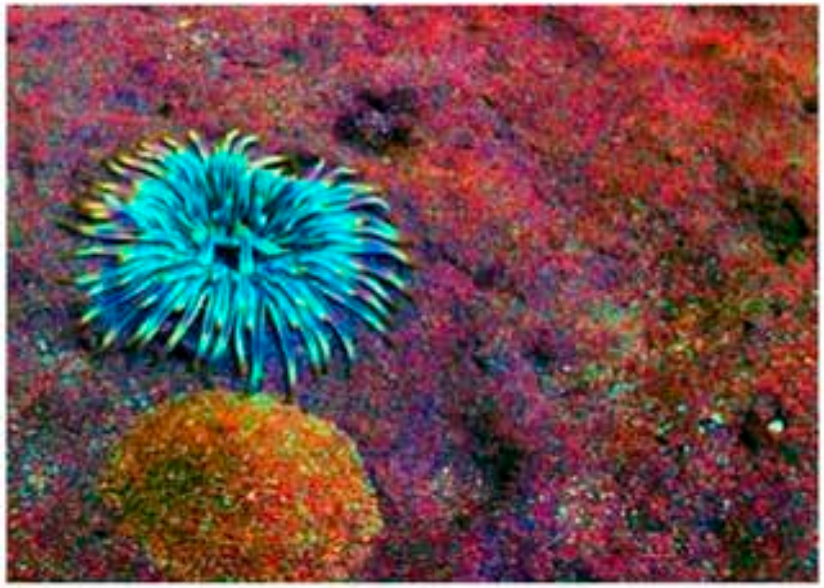


L. Neumann, R. Garcia, J. Basa, R. Hegedus. "Acquisition and Visualization Techniques for Narrow Spectral Color Imaging", Journal of the Optical Society of America A. Vol. 30, no. 6, pp. 1039–1052, 2013.

Narrow Spectral Imaging



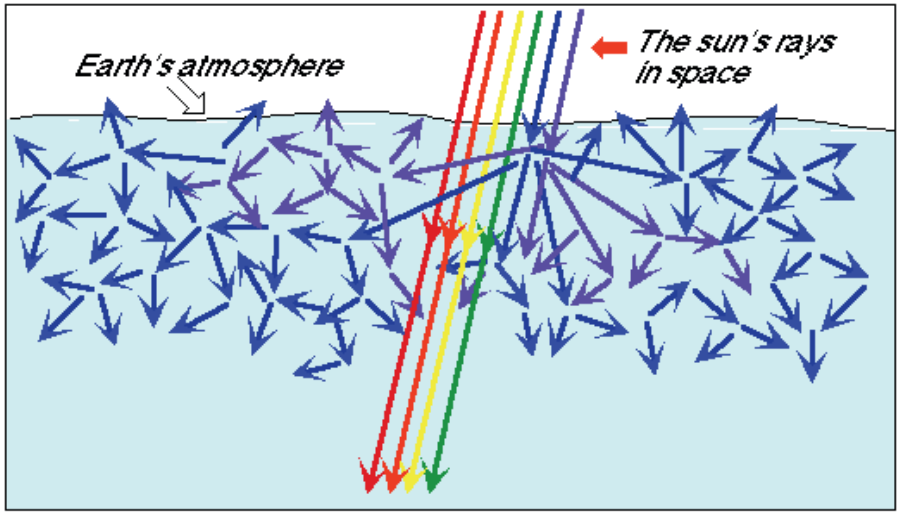




Light effects in Underwater Imaging

Rayleigh scattering results in hazy images and Mie scattering in blurry, murky, faded appearance

Density fluctuation of water molecules vs. any kind of physical inhomogeneity that is larger than water molecule (R vs. M)



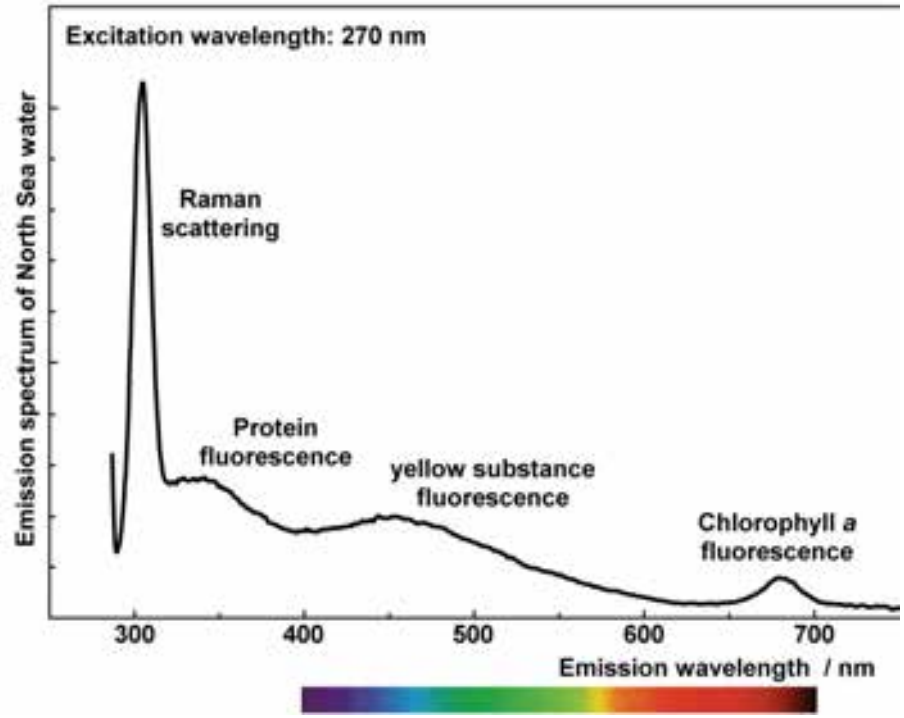
- Rayleigh angular scattering in pure water
- Appr. Wavelength´s power = 4

$$\beta_W(\lambda, \vartheta) = b_W(\lambda) p_W(\cos\vartheta),$$

$$b_W(\lambda) = (0.001\,458\,4\,\mathrm{m}^{-1}) \left(\frac{550}{\lambda}\right)^{4.34}$$

Light effects in Underwater Imaging

There are also natural (self illuminating) and excited fluorescence effects, characterizing some biological activities



- Fluorescence is not disturbing, low-light
- Nice and useful future work, but we do not deal with this phenomena in the **image enhancement algorithms**

Polarization

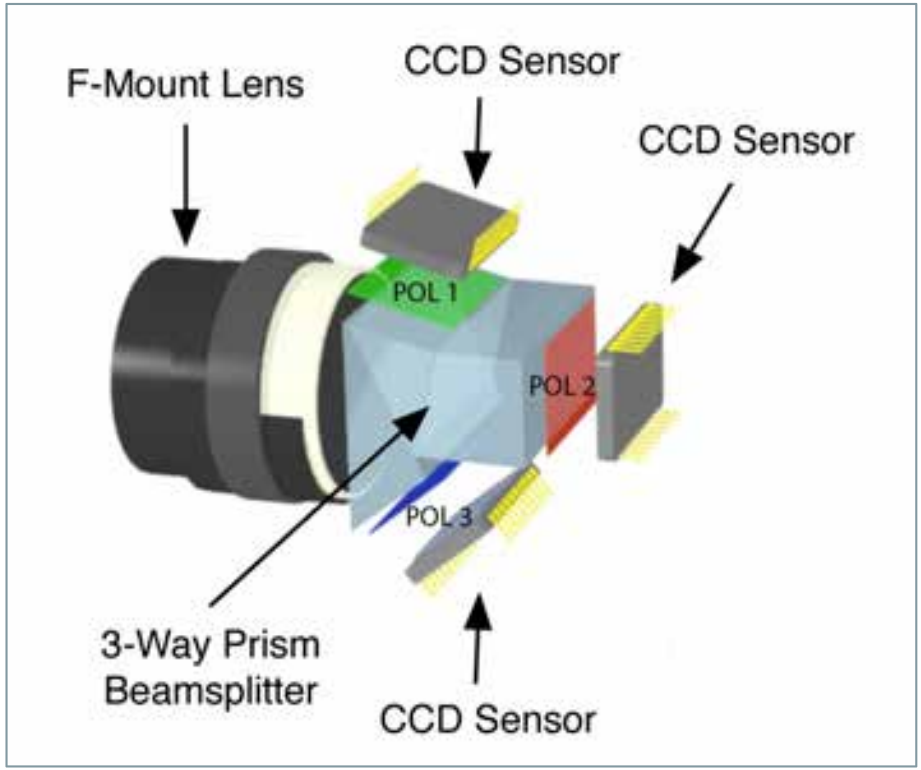
1. **Simple Cross-polarization (orthogonal light + lens-filter)**
2. **Imaging Polarimetry – pixelwise 3 (or 4) data for R, G and B**

- Cross-polarization has a limited application area (Yoav Y. Schechner and Nir Karpel, 2005) and not really efficient
- It works with only with homogeneos illumination in shallow water in horizontal direction

- More general approach is possible with **imaging polarimetry** and with polarized light. A given part of the scattered light is linearly polarized. It can this part or somewhat more removed ensuring sharper images with color correction (L.Neumann-R.Hegedus-R.Garcia-2009).

Polarization camera

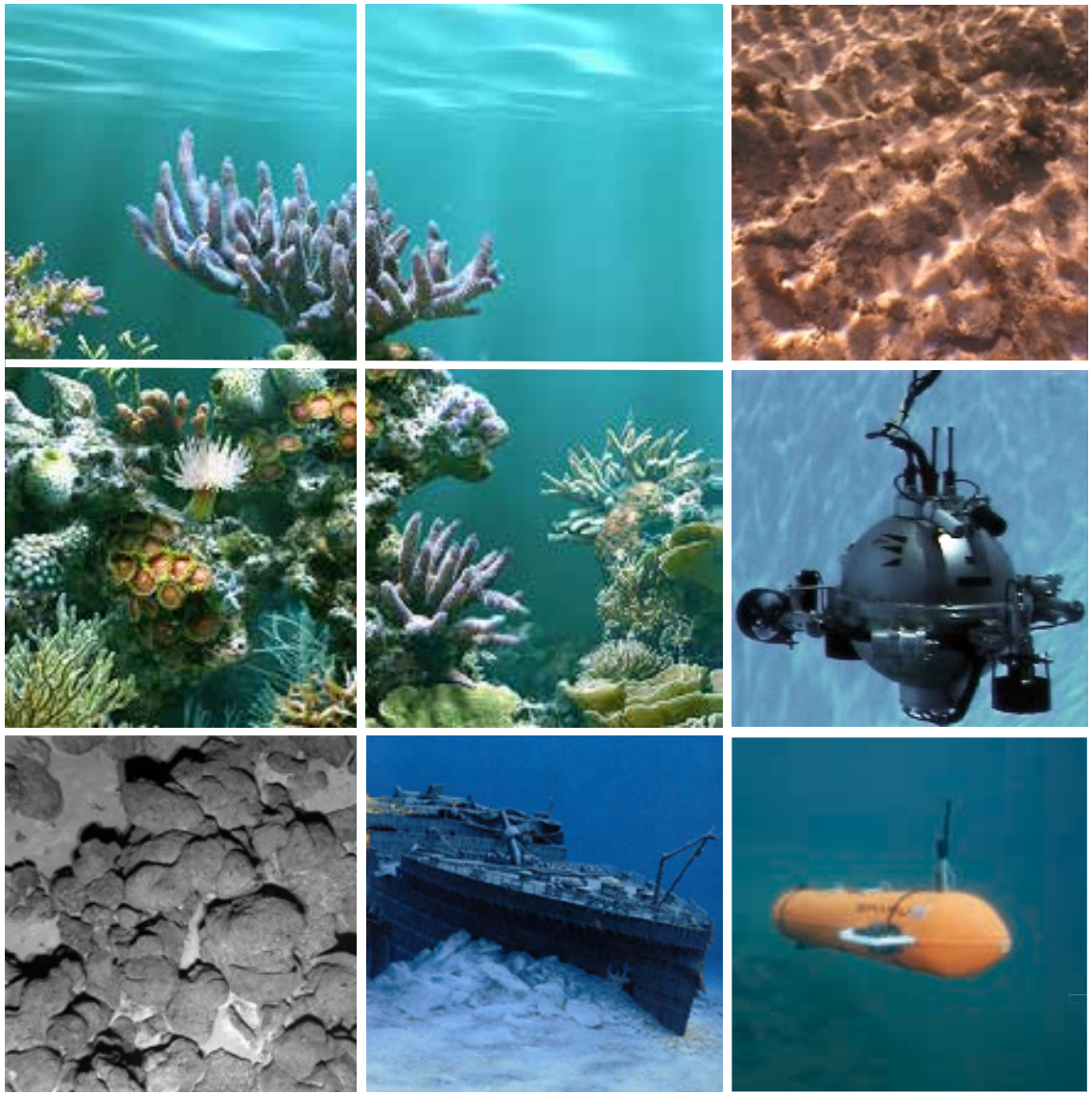
- Primary objective: acquiring the full polarization information pro pixel in underwater photography



Fluxdata Polarization camera: 3 CCD sensors with differently oriented linear polarizers

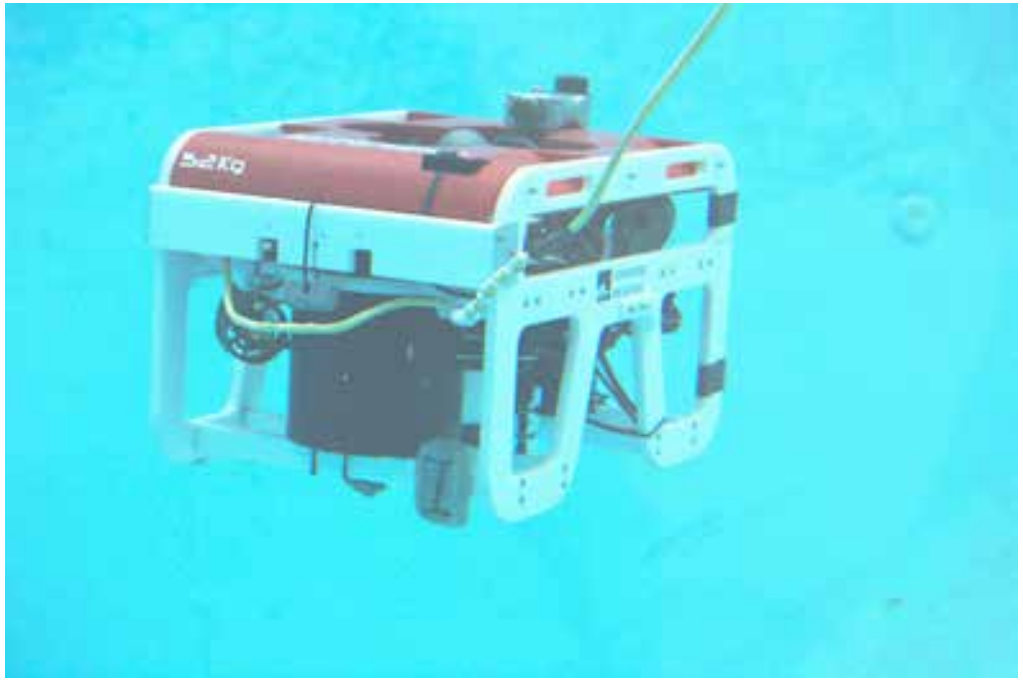
A non-underwater example with over-depolarization

A non-underwater example with over-depolarization



Underwater dehazing examples

Underwater dehazing



Underwater dehazing

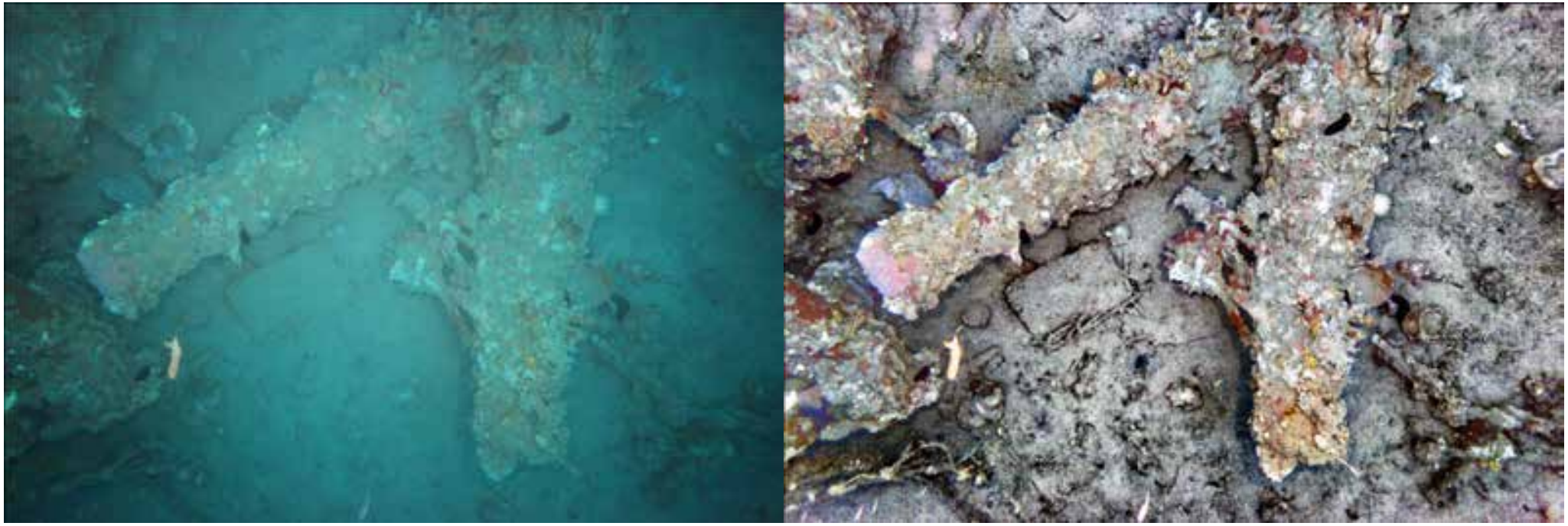
Some RED deficite, yet – in 2010 test

Underwater dehazing

Original image

Enhanced image

Underwater dehazing



Original image **Enhanced image**

Image Dehazing

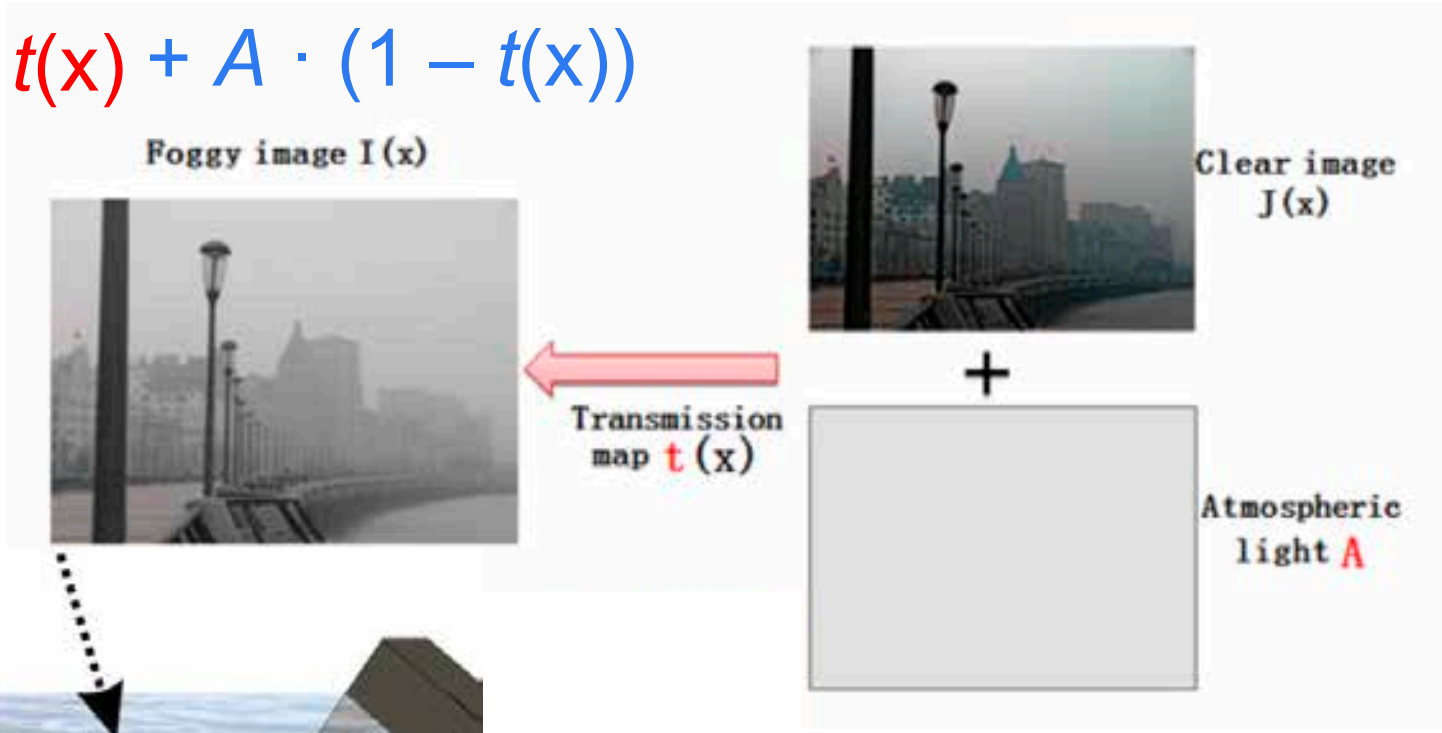
First depth-map based approaches:

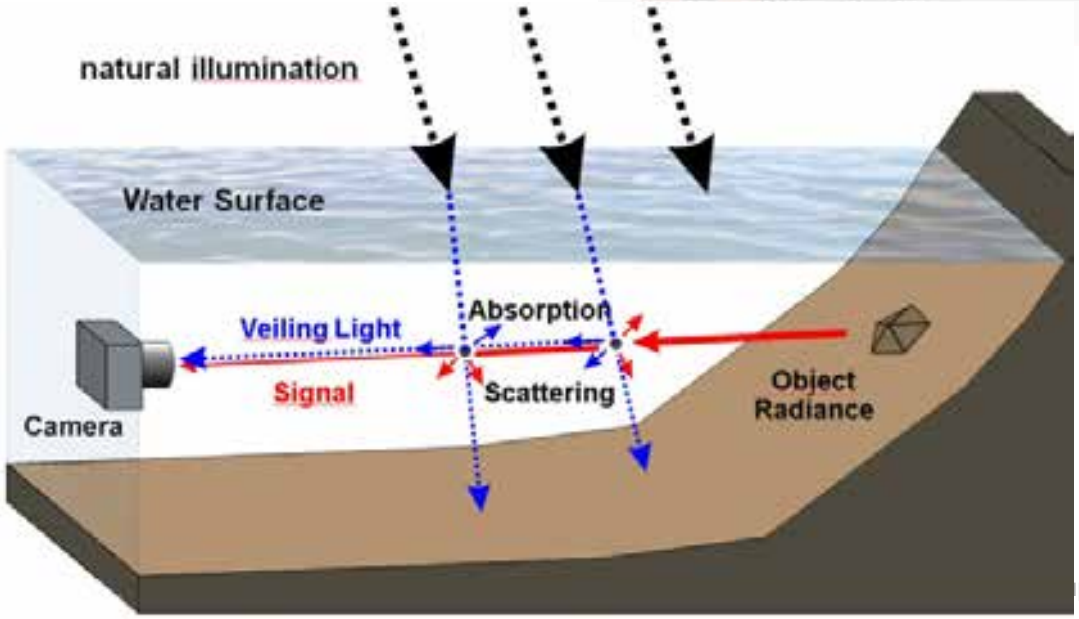
- Dark-channel based approach
  - Based on the observation that most local patches in haze-free outdoor images contain some parts which have very low intensities in some **dark pixels (ρ=5…10%?)** in at least one color channel, so that these will contain **only scattered** component in a hazy image (“near blue and far orange” – undefined problem)
- Estimation using a stereo-camera setup
  - Missing depths on feature-point less areas,
  - and on parts visible only with one camera
  - Edge preserving inter- and extrapolation

Image Dehazing

Basic idea

$$I(x) = J(x) \cdot t(x) + A \cdot (1 - t(x))$$





- $I(x)$ has 3 equations (R, G and B)
  - defined in 2D (x and y)
  - 3 equations per pixel
- $t(x)$ is a scalar (pixel dependent)

Dark Channel Prior

$$I(x) = J(x) \cdot t(x) + A \cdot (1 - t(x))$$

Unknowns:

- $J(x)$ has 3 unknowns (for R, G and B)
  - defined in 2D (x and y)
- $t(x)$ is a scalar (pixel dependent)
- Plus another 3 unknowns for A
  - image dependent

Koschmieder equation in the air and in water

$$I(\mathbf{x}) = J(\mathbf{x}) \cdot t(\mathbf{x}) + A \cdot (1 - t(\mathbf{x}))$$

$$I(\mathbf{x}) = J(\mathbf{x}) \cdot e^{-\beta z} + A \cdot (1 - e^{-\beta z})$$

In the underwater case absorption (alpha) cannot be neglected,

So it becomes slightly different:

$$I(\mathbf{x}) = J(\mathbf{x}) \cdot e^{-(\alpha+\beta)z} \quad + \quad A \cdot \frac{\beta}{\alpha + \beta}\left(1 - e^{-(\alpha+\beta)z}\right)$$

Absorption coefficient *alpha* and scattering coefficient *beta*

Are also wavelength dependent!

Dark Channel Prior

$$I(x) = J(x) \cdot t(x) + A \cdot (1 - t(x))$$

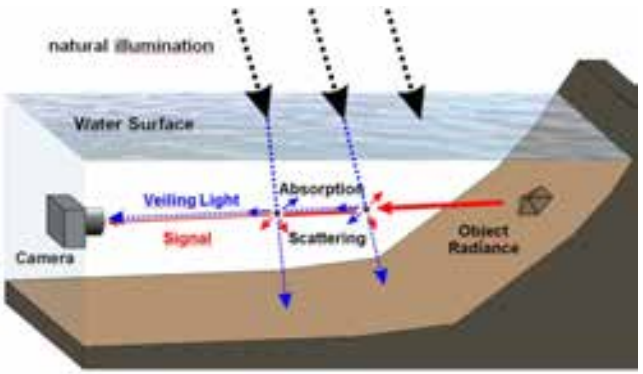
Observation:

- *on haze-free outdoor images, most of the non-sky patches have at least one color channel which has very low intensity at some pixels.*
- *If I find some pixels that are black*
- *Visually, the intensity of the dark channel is a rough approximation of the thickness of the haze*

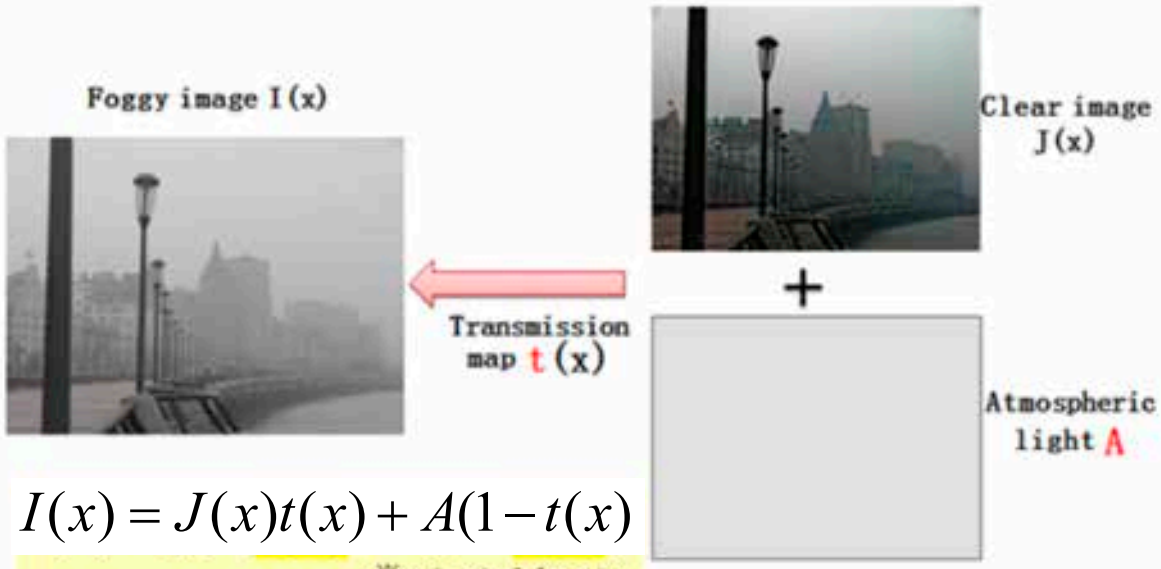
Dark Channel Prior

Image Dehazing method

Basic idea



The basic idea of defogging is, foggy image = clear image + fog density. That means foggy images are clear images polluted by fog. If we estimate the fog density and remove it, then the clear image can be got. The foggy image model is shown as follows.



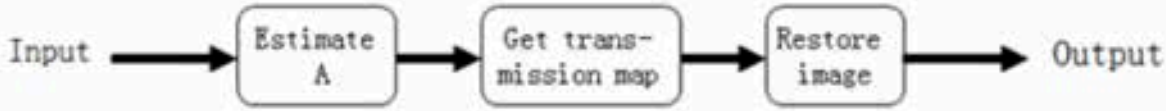
$$I(x) = J(x)t(x) + A(1 - t(x))$$

※ x is pixel location

Estimate A and t(x) from I(x), then calculate J(x)

Estimate the fog density for each pixel, and then remove it. (light in near, and heavy in far)

The procedure of defogging is as follows.



Dark channel prior (He et al.):

Most local patches in haze-free outdoor images contain some pixels which have very low intensities in at least one color channel, so that for these pixels:

$$I(\mathbf{x}) = \cancel{J(\mathbf{x}) \cdot t(\mathbf{x})} + A \cdot (1 - t(\mathbf{x})) \quad \textit{where} \quad t = e^{-\beta z}$$

Dark channel can be defined as:

$$I^{dark}(x) = \min_{c \in \{R,G,B\}} \left(\min_{y \in \omega(x)} I^{(c)}(x) \right)$$

From here we can get transmission map t, given that we know A

Given the distance map (z) of the scene, let's use the 'dark channel' trick, but now for `z`-distance classes:

$$I_{\min}^{(c)}(z) = \min_{z1 \le z \le z2} I^{(c)} = A_c\left(1 - e^{-\beta_c z}\right)$$

From here:

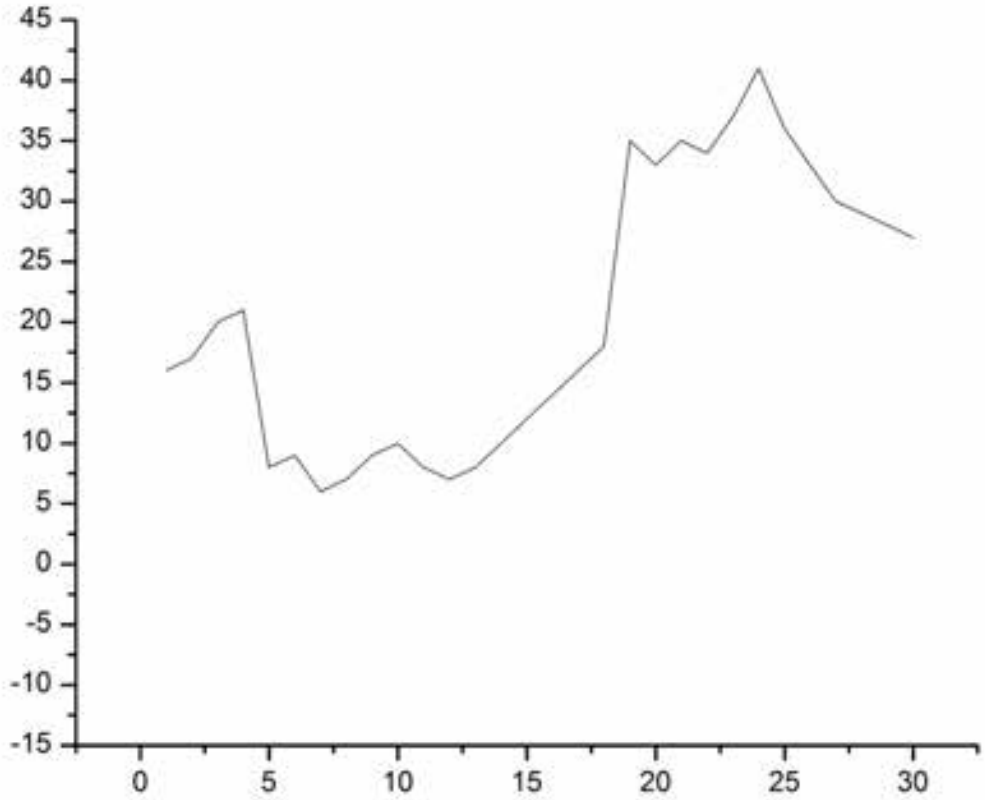
$$\log\left(1 - \frac{I_{\min}^{(c)}(z)}{A_c}\right) = \beta_c z$$

Which means that assuming the correct A parameter, the log(.) values vs. z distance should fit onto a line, the slope of which is b

Scan A values and accept that one, when best fitting occurs – RANSAC like approach.

Instead of depth-based fitting, first let's have the estimation of 'Veiling light' in the blue channel by Tarel-Hautière method.

Then seek darkest points in red and green, and fit the blue veiling light map (⇔ optical depth map) to this points with keeping its gradient structure. In this way we can expectedly strip the haze completely.



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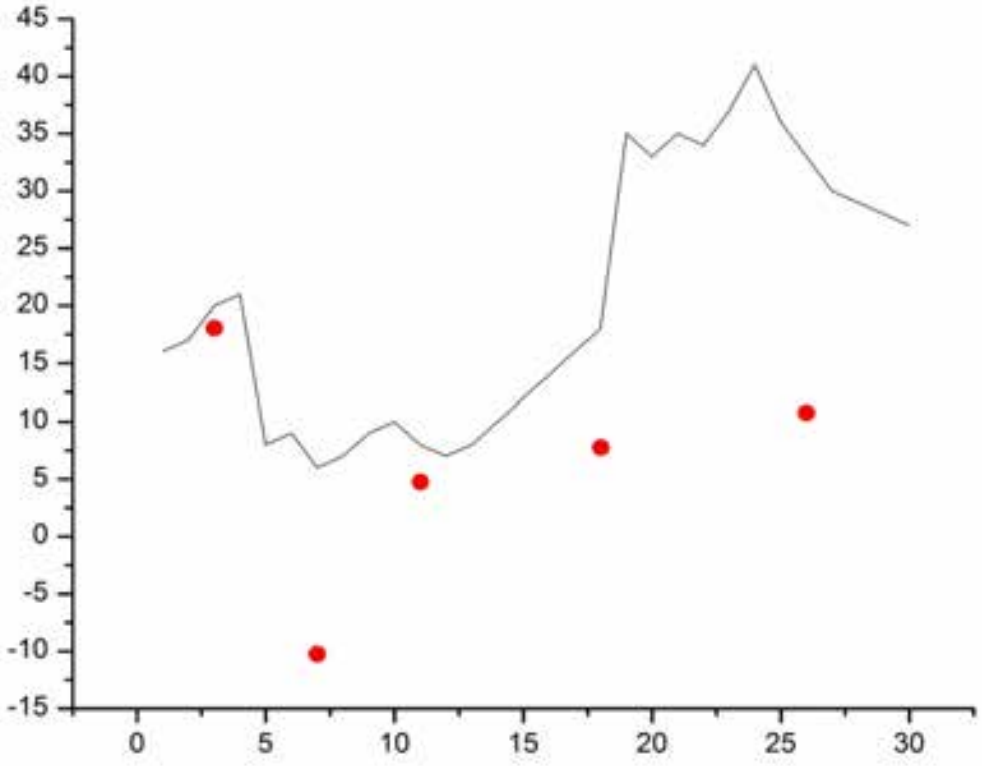
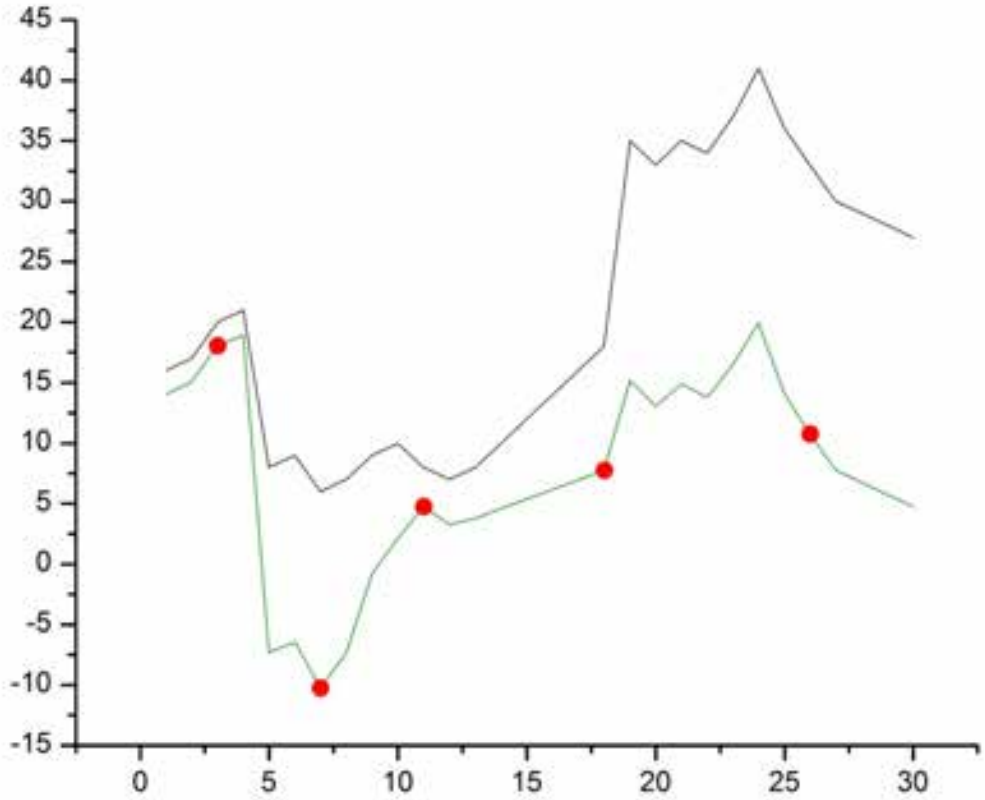
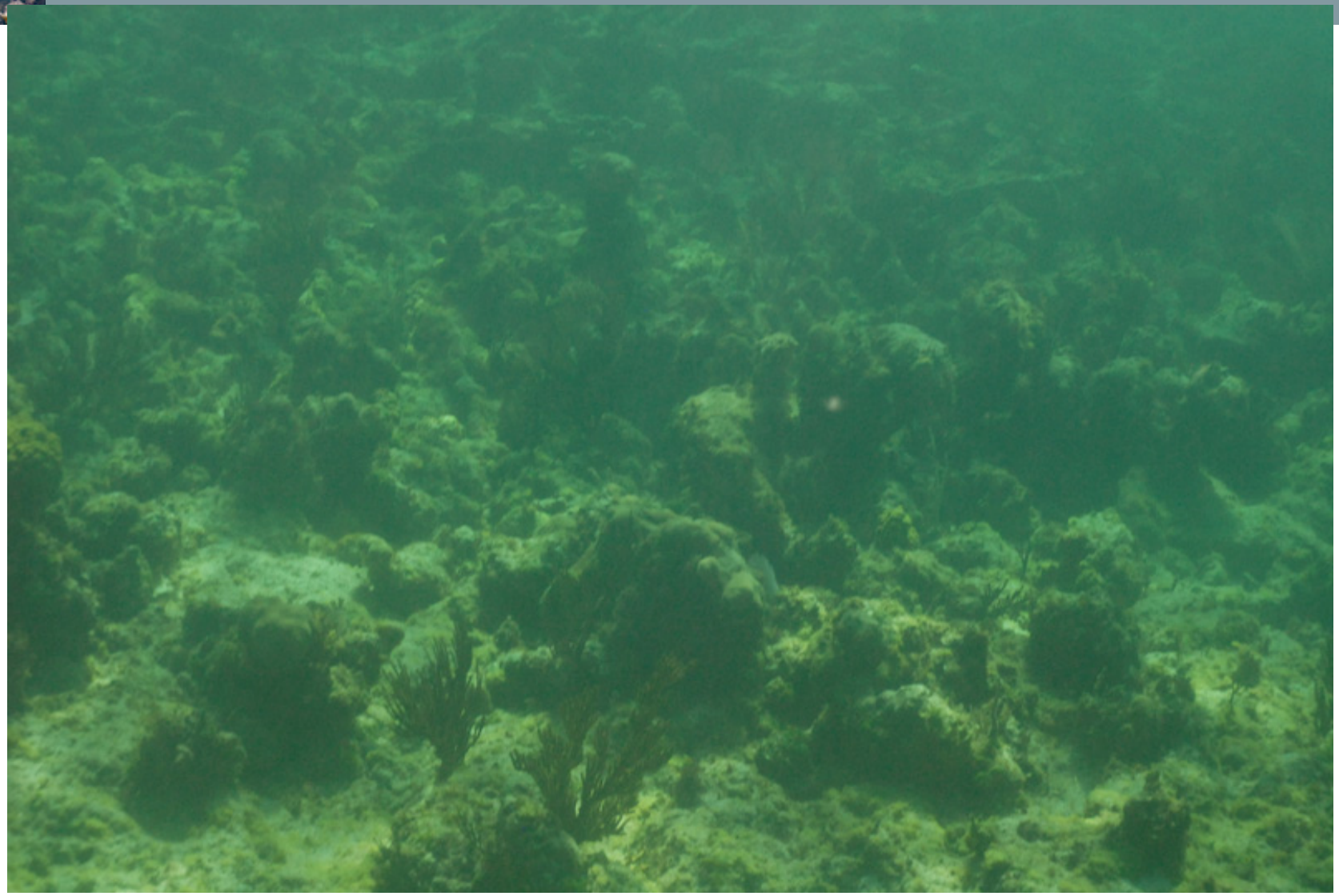


Instead of depth-based fitting, first let's have the estimation of 'Veiling light' in the blue channel by Tarel-Hautière method.

Then seek darkest points in red and green, and fit the blue veiling light map (⇔ optical depth map) to this points with keeping its gradient structure. In this way we can expectedly strip the haze completely. BLUE CHANNEL CORRECTED SHAPE!

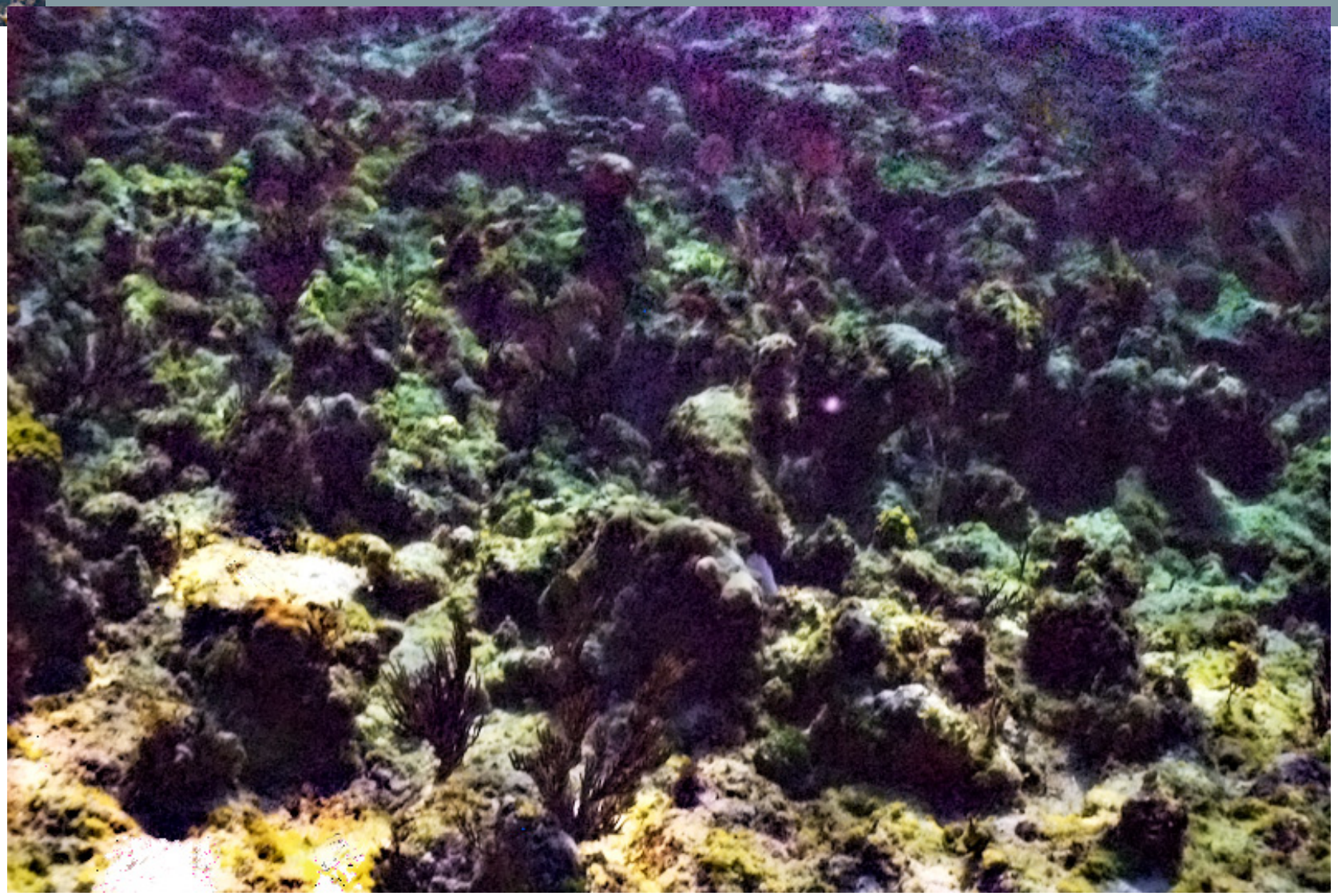


Single image dehazing



Original image

Single image dehazing



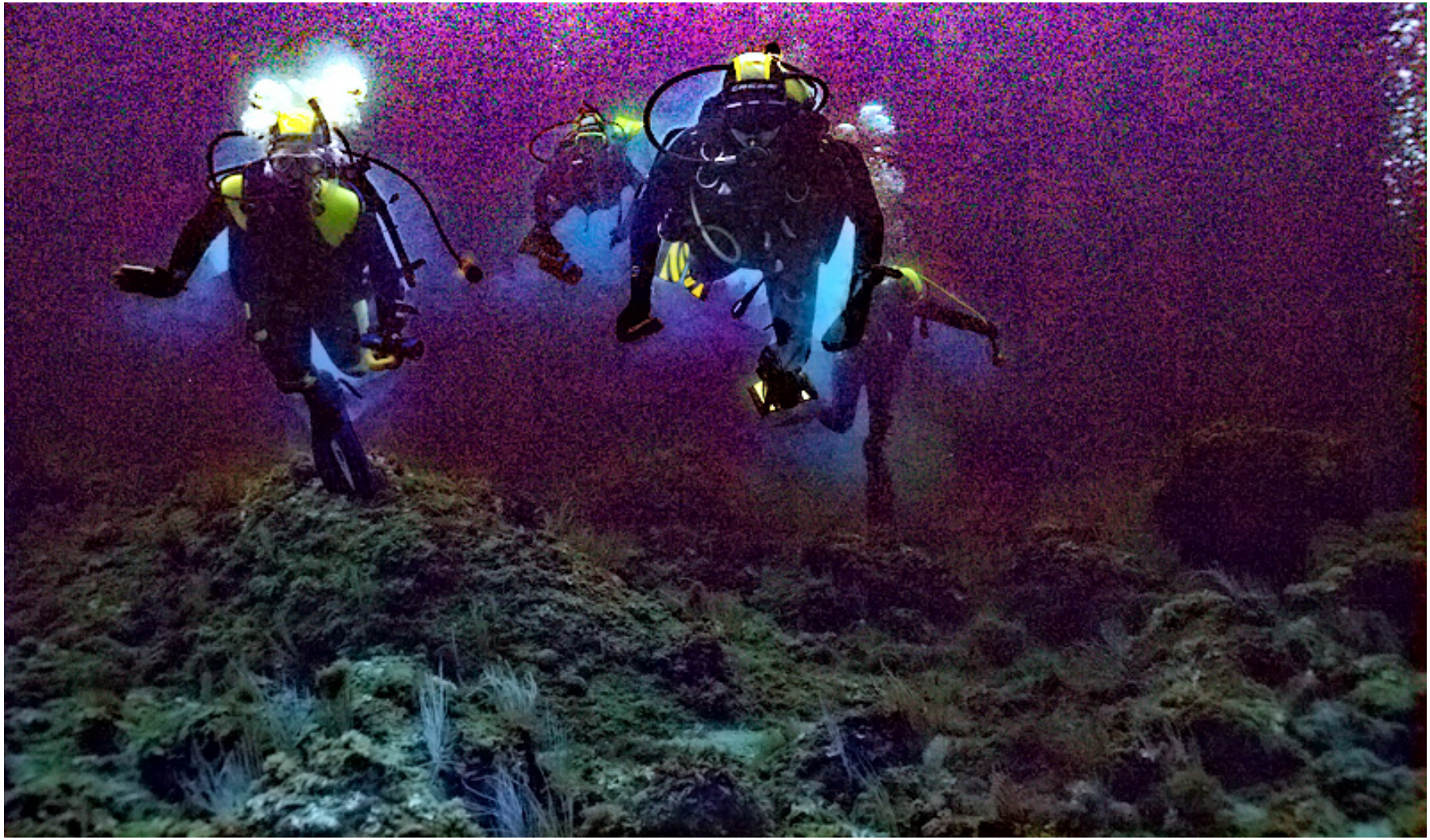
Corrected image

Single image dehazing

Original image

Single image dehazing – possible artifacts (color, halo, etc.)

All dark channel method has some problem (artifacts, speed)



Artifacts, based on widely used dark channel method, and starting from noisy, high ISO image

Non depth-map based techniques

- The simplest method (L.Neumann – G.Blanco – R.Garcia, 2015) applies a medium-gray based color transer in Ruderman color space, and a luminance stretching. Pleasant results, a non-linear optimized “orange-glass” approach.
- There are some approaches using multiscale features to estimate the local luminance-gradient changes. Fast, robust (has some color estimation problems) the weighted image pyramid based method of Codtruta Ancuti et al.,2013).

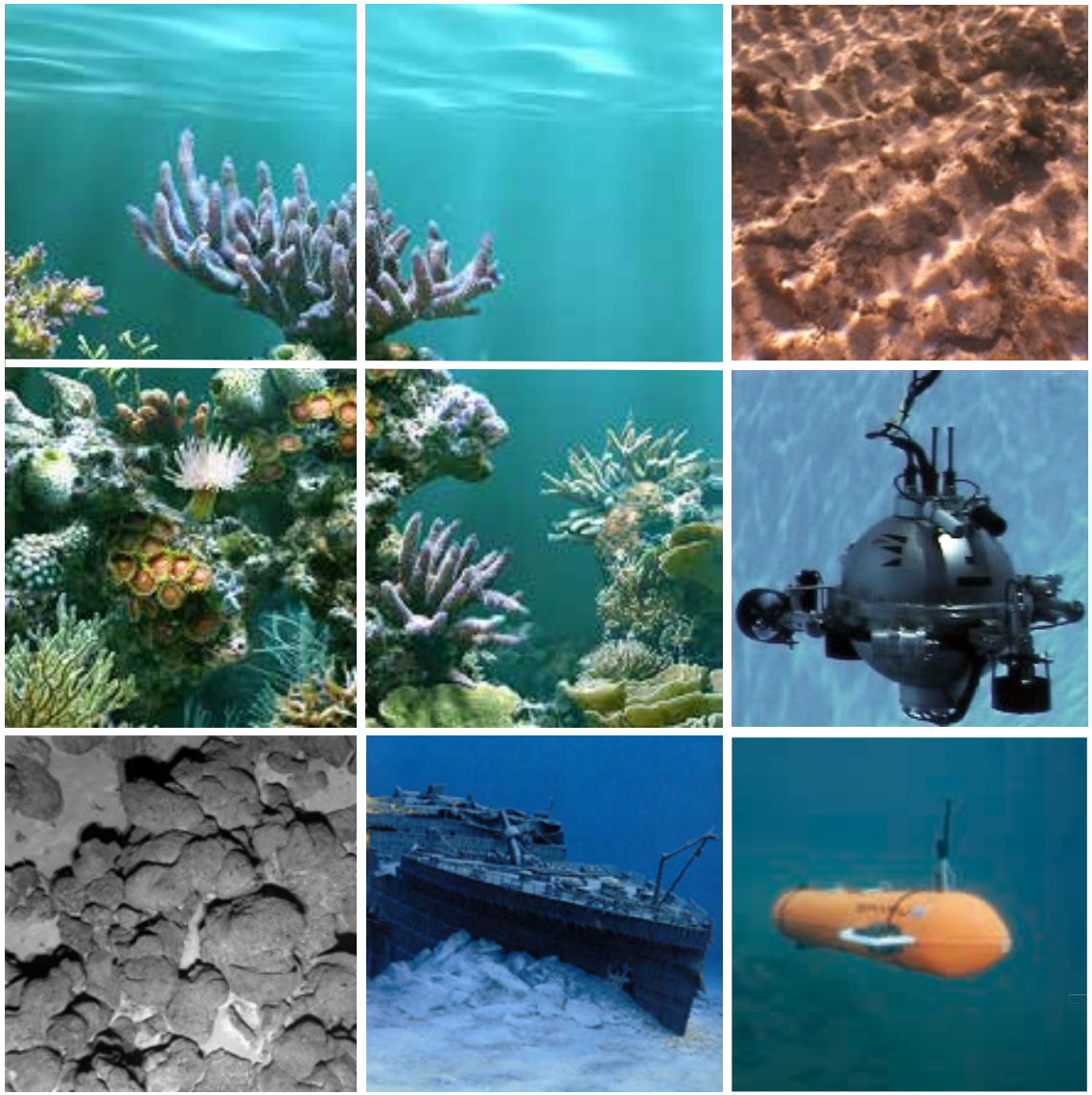
Some of our running research images


POLICE

Jpg artifacts > some luminance gradiens

We need uncompressed images

Universitat de Girona



Thank You !

http://vicorob.udg.edu/