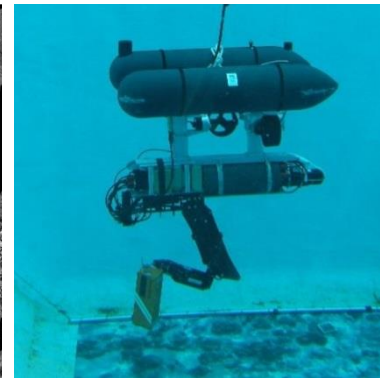
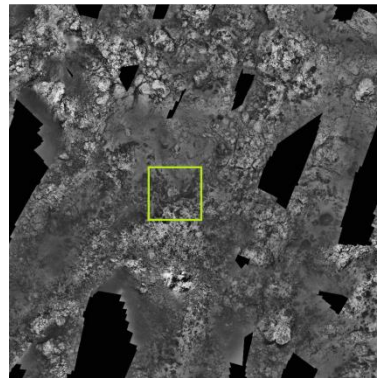
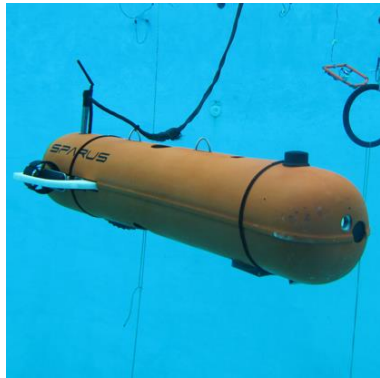
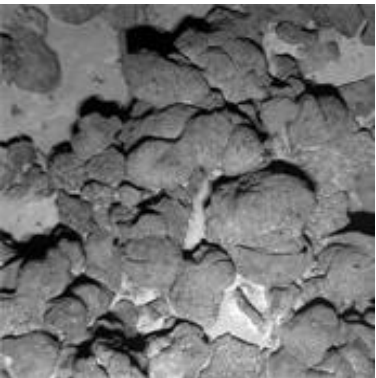


Topology Estimation and Global Alignment

Ricard Campos

Nuno Gracias

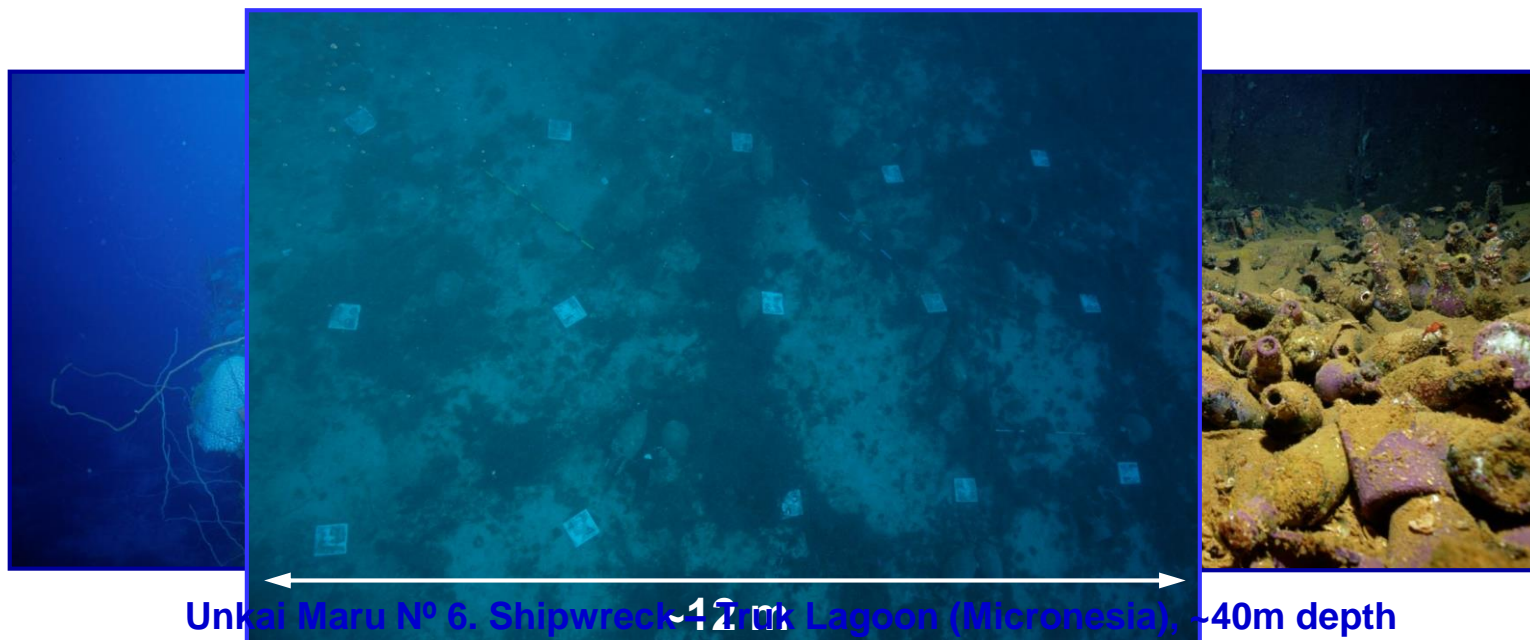
Rafael Garcia



Introduction

Photomosaic

- A single shot cannot provide a global perspective of the area:



Unkai Maru N° 6. Shipwreck - 17m Lagoon (Micronesia), ~40m depth

(Courtesy of <http://www.cloverfish.com>)
Pianosa Amphora, ~32m depth (from 10m camera to scene)

(Courtesy of Venus Project)

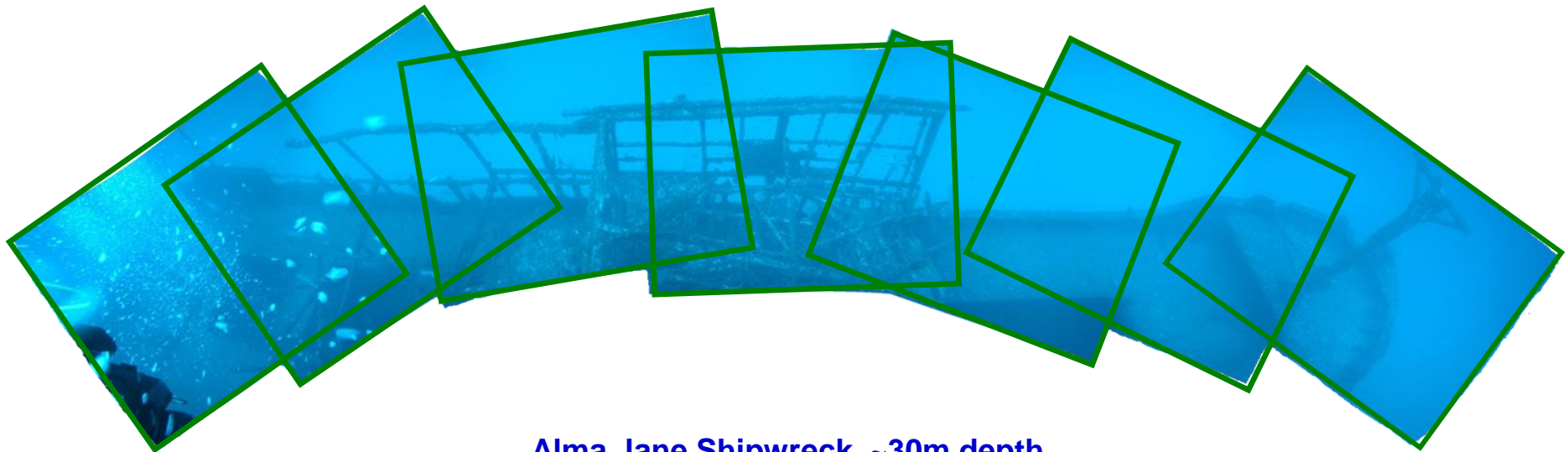
Solution: Build a photomosaic!

Introduction

Photomosaic

Photomosaic

Compose a single image from a set of overlapping images:

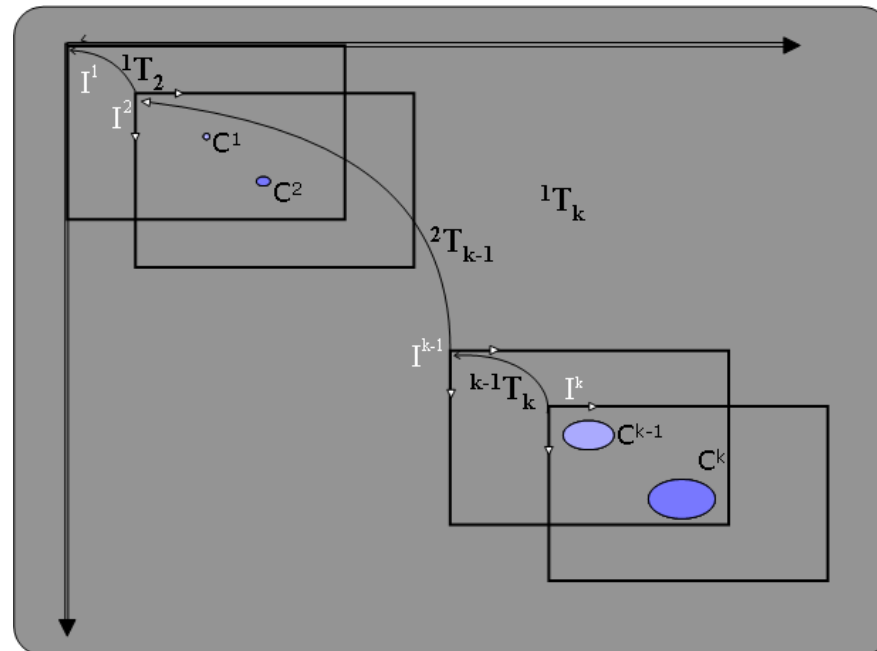


**Alma Jane Shipwreck, ~30m depth
(Courtesy of David Habi)**

Topology

Photomosaic: Initial estimation – Cascade of homographies

- So far, we have seen how to find the motion between pairs.
- How does this relate to global motion?
- Cascade the relative homographies:

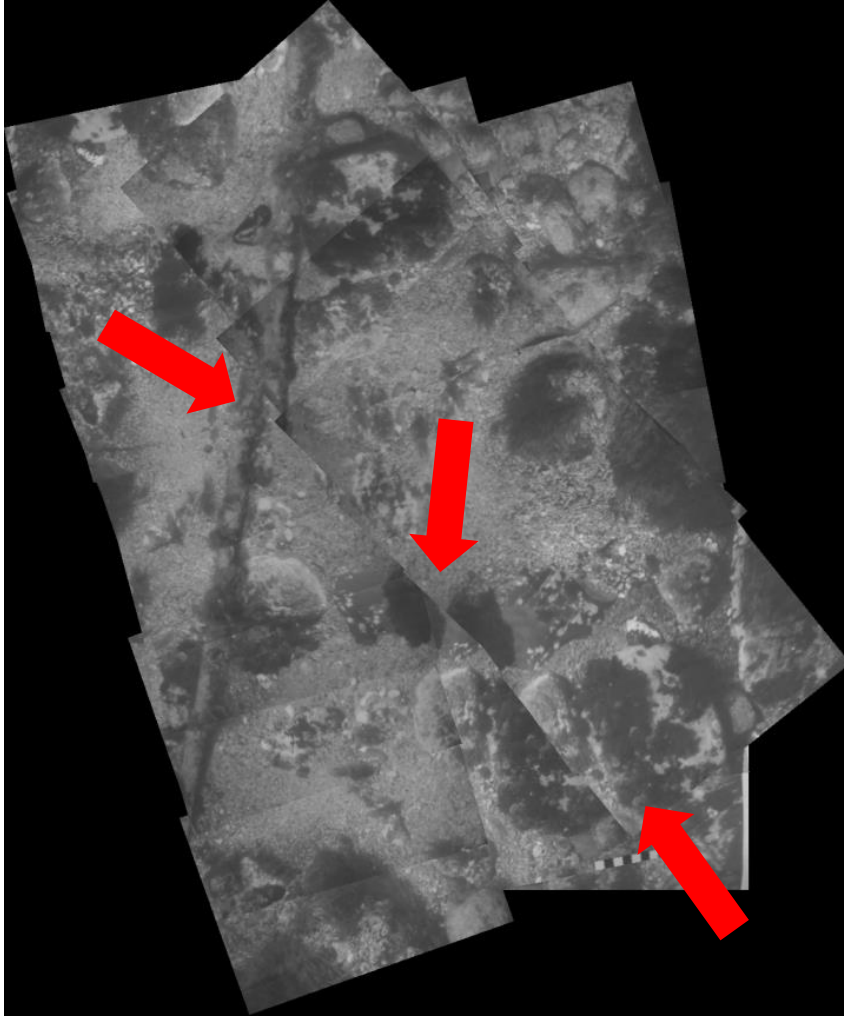


$${}^1T_k = {}^1T_2 \cdot {}^2T_3 \cdot \dots \cdot {}^{k-2}T_{k-1} \cdot {}^{k-1}T_k$$

Problem: Drifts quickly.

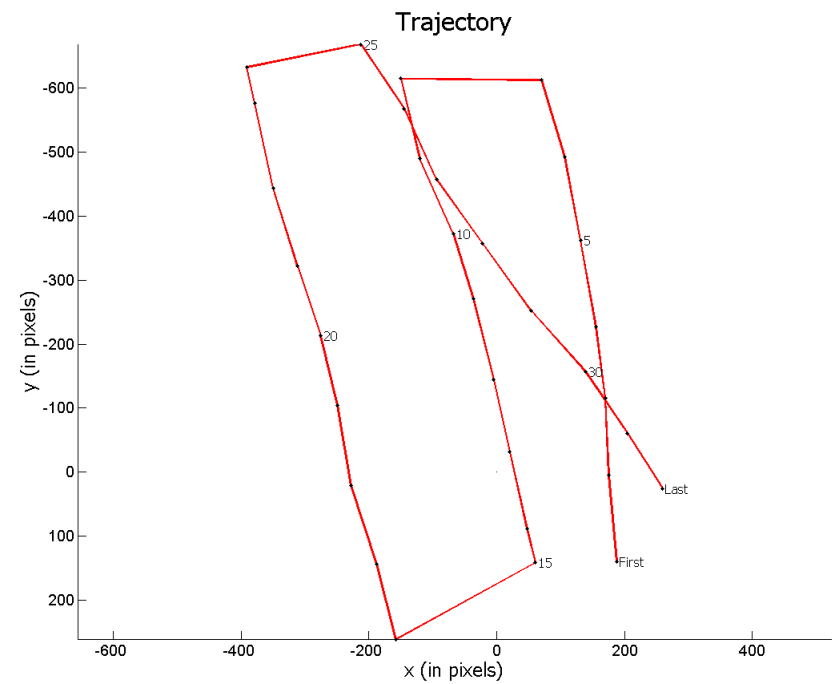
Topology

Definition



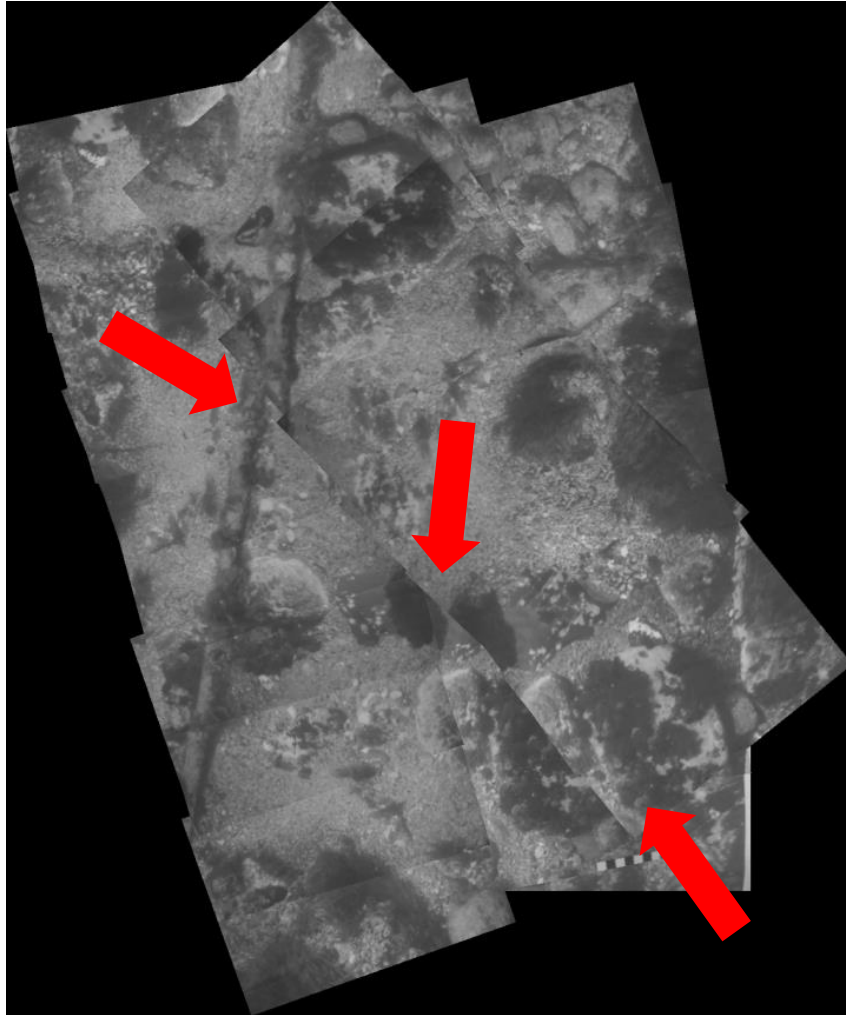
Topology refers to:

- Trajectory and
- Links among images



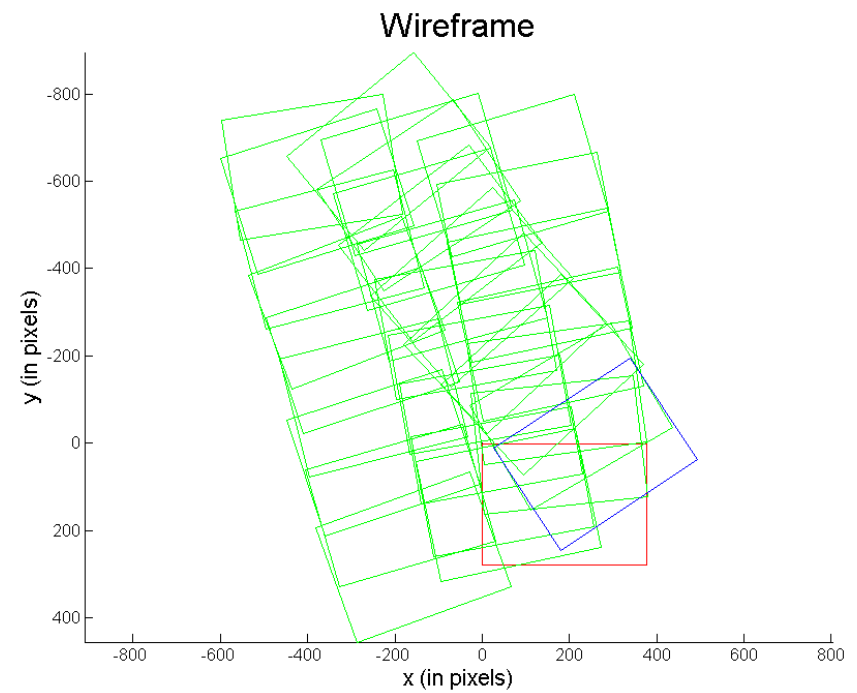
Topology

Definition



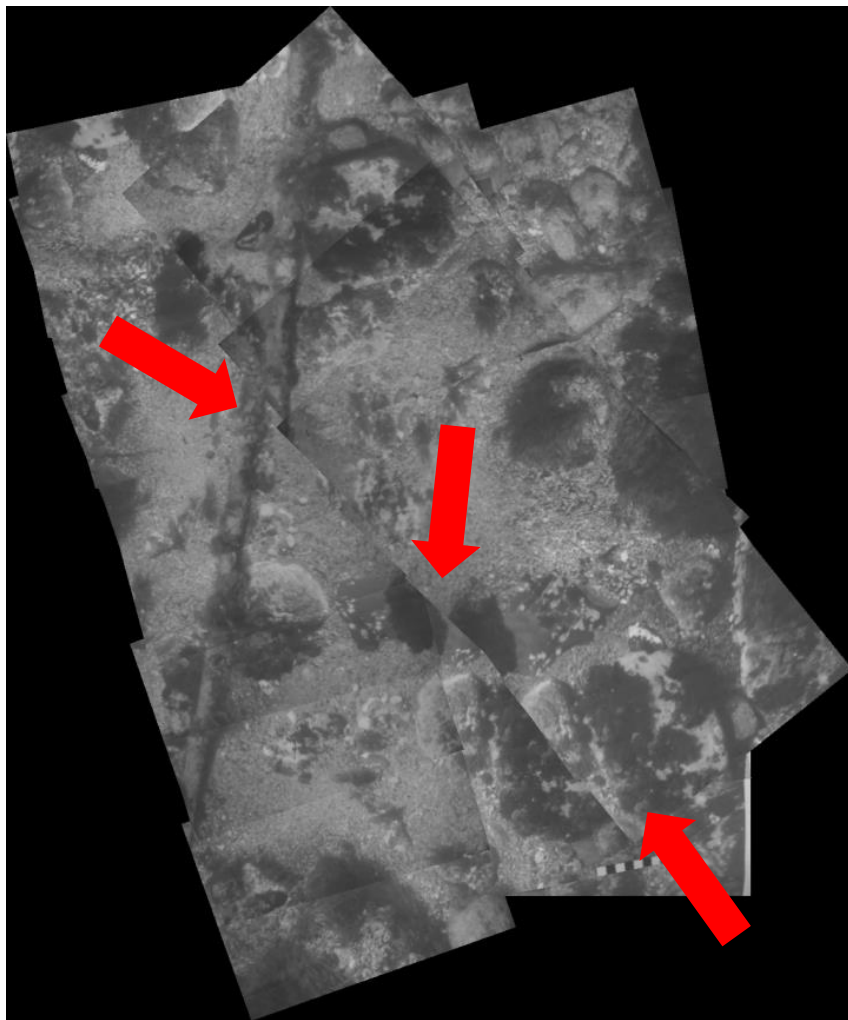
Topology refers to:

- Trajectory and
- Links among images



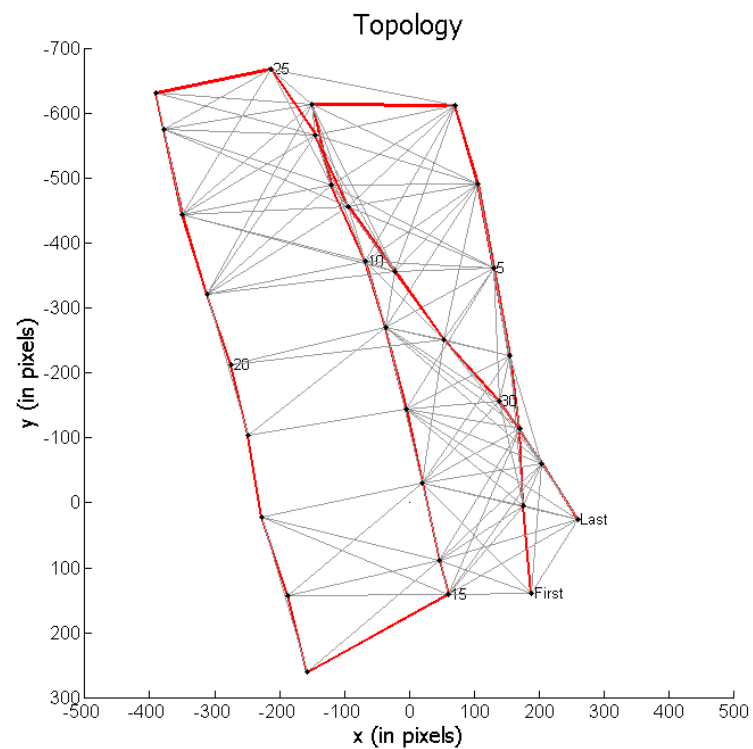
Topology

Definition



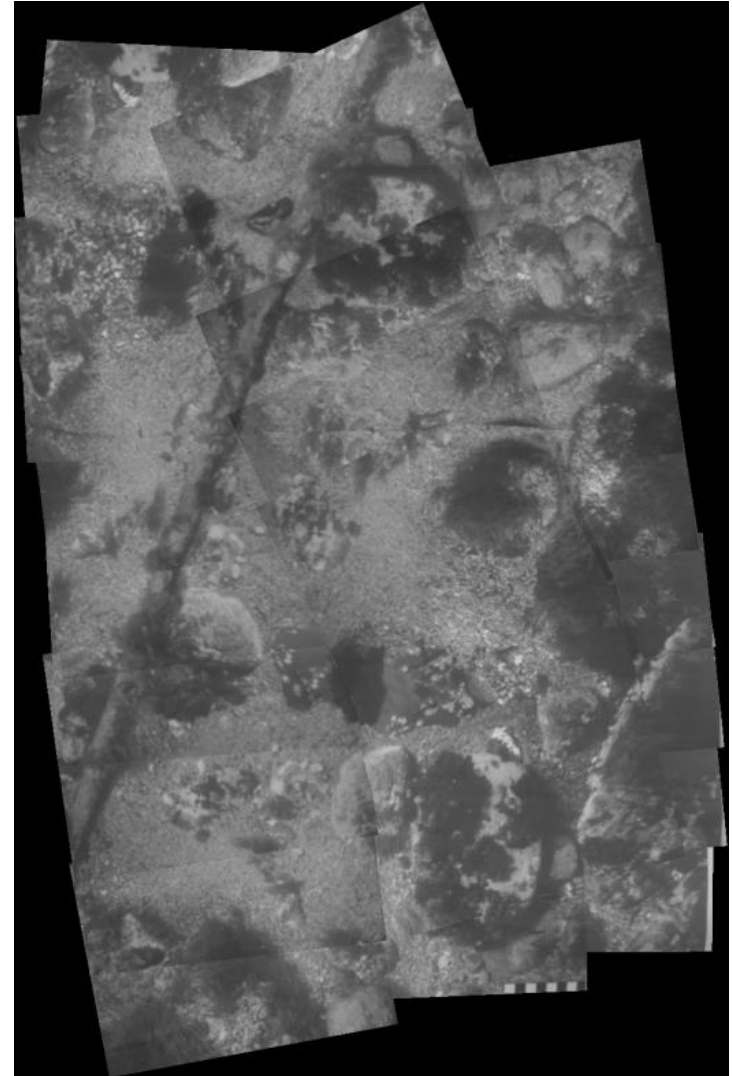
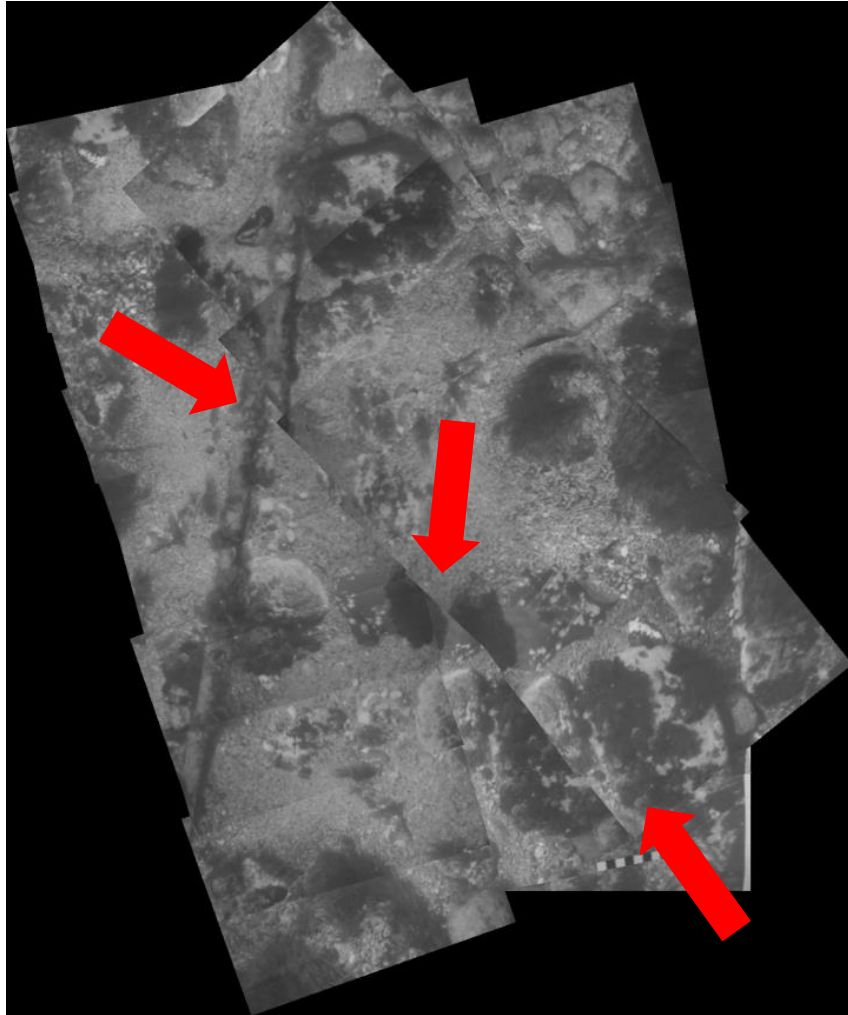
Topology refers to:

- Trajectory and
- Links among images

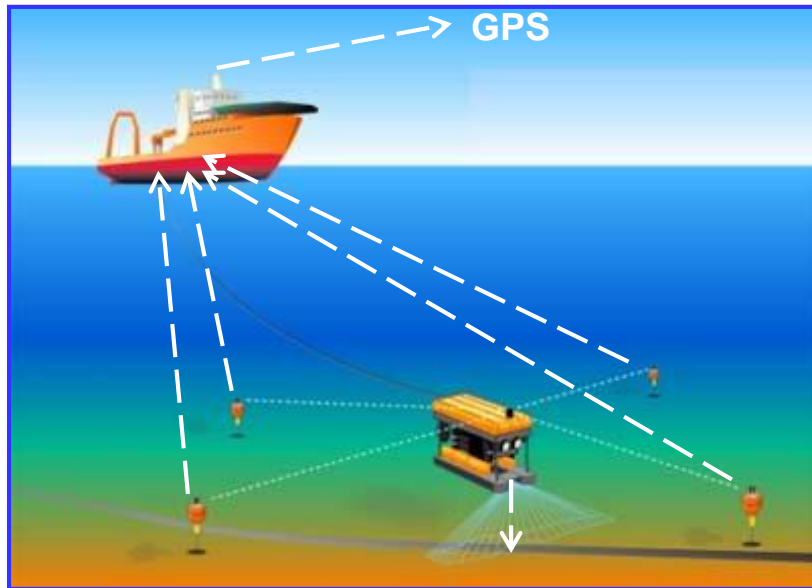


Topology

Definition



Vehicle Navigation Pose



- **Global Position:**
 - X, Y from LBL Transponder Network or USBL
 - Z (Seafloor depth) from acoustic Altimeter
- **Orientation:**
 - Vehicle Roll & Pitch from Inclinometer
 - Heading from Compass

Topology

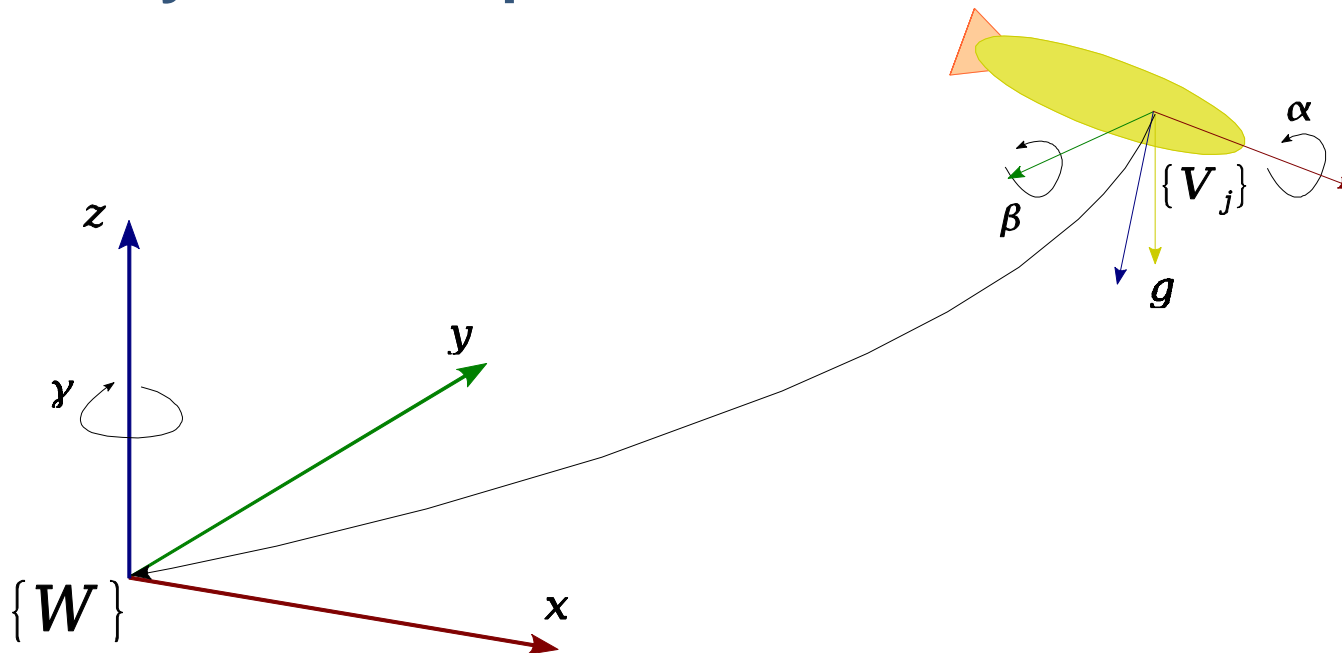
Photomosaic: Initial estimation – Navigation information

- **Knowing:**

- Camera Intrinsic Parameters
 - K
- Vehicle Poses
 - $(x, y, z, \text{Roll}, \text{Pitch}, \text{Heading})$

- **System Setup:**

$\{W\}$ 3D World Frame
 $\{V_j\}$ Vehicle Poses



g Gravity vector
 α Roll
 β Pitch
 γ Yaw

Topology

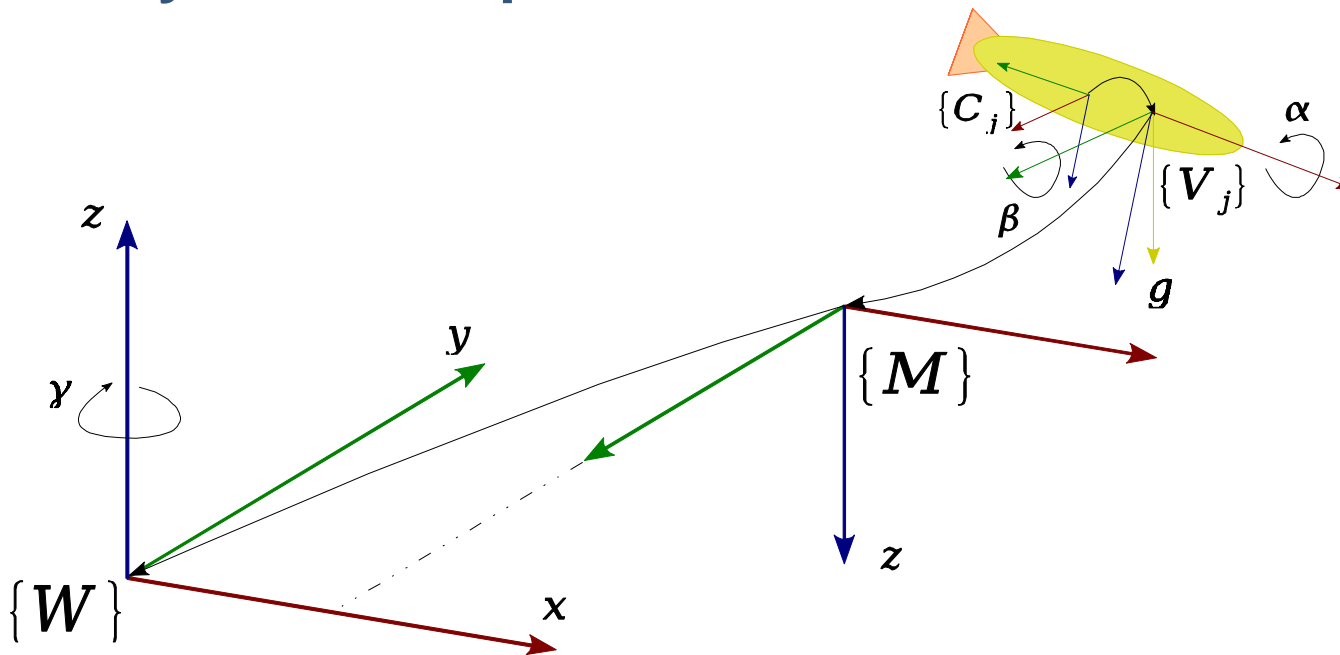
Photomosaic: Initial estimation – Navigation information

- **Knowing:**

- Camera Intrinsic Parameters
 - K
- Vehicle Poses
 - $(x, y, z, \text{Roll}, \text{Pitch}, \text{Heading})$

$\{W\}$ 3D World Frame
 $\{V_j\}$ Vehicle Poses
 $\{M\}$ 3D Mosaic Frame
 $\{C_j\}$ Camera Frame

- **System Setup:**



g Gravity vector
 α Roll
 β Pitch
 γ Yaw

Topology

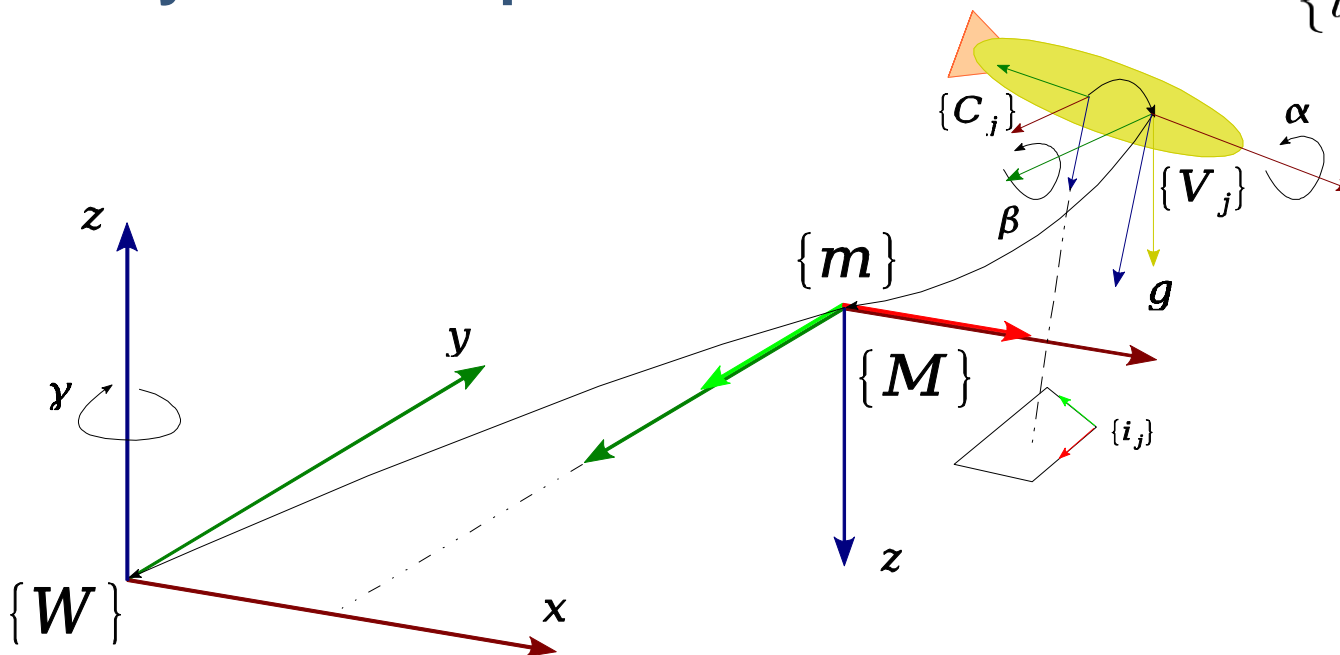
Photomosaic: Initial estimation – Navigation information

- **Knowing:**

- Camera Intrinsic Parameters
 - K
- Vehicle Poses
 - $(x, y, z, \text{Roll}, \text{Pitch}, \text{Heading})$

- **System Setup:**

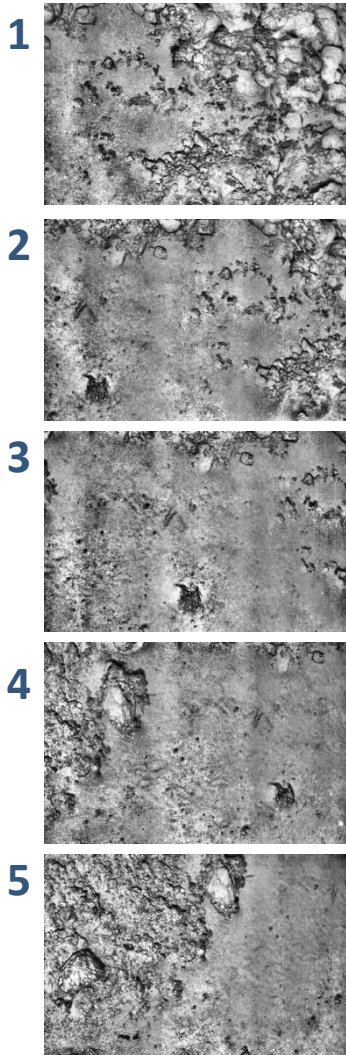
- $\{W\}$ 3D World Frame
- $\{V_j\}$ Vehicle Poses
- $\{M\}$ 3D Mosaic Frame
- $\{C_j\}$ Camera Frame
- $\{m\}$ 2D Mosaic Frame
- $\{i_j\}$ Image Frame



- g Gravity vector
- α Roll
- β Pitch
- γ Yaw

Topology

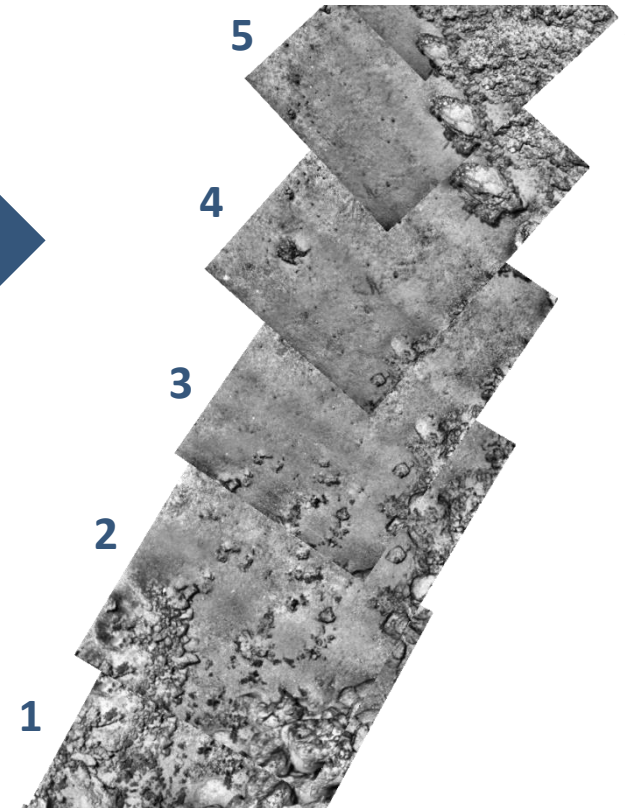
Photomosaic: Initial estimation – Navigation information



Project images to the zero-altitude plane



- Mosaic from Navigation:
 - Very inaccurate





Global Alignment

- Different sources of measurements:
 - Seen so far:
 - Navigation.
 - Optical.
 - Other possibilities:
 - Relative navigation.
 - Fiducial points.
- They all provide valuable information that needs to be taken into account to build the mosaic.
- We need a generic framework able to merge them.
- Non-linear minimization!



Global Alignment

Factor Graphs

- **Factor graphs:** General tool to model factorizations of large functions with many variables into smaller local subsets.
- Problem as a bipartite graph with two types of vertices:
 - **Nodes:** corresponding to the variables to optimize (poses).
 - **Factors:** joining one, two, or more nodes representing a constraint on them, given a measure (encapsulates the error to minimize).
- **Problem:** find the node configuration minimizing the error introduced by the constraints.

Global Alignment

Factor Graphs – Front End

- **Pose Graph:**



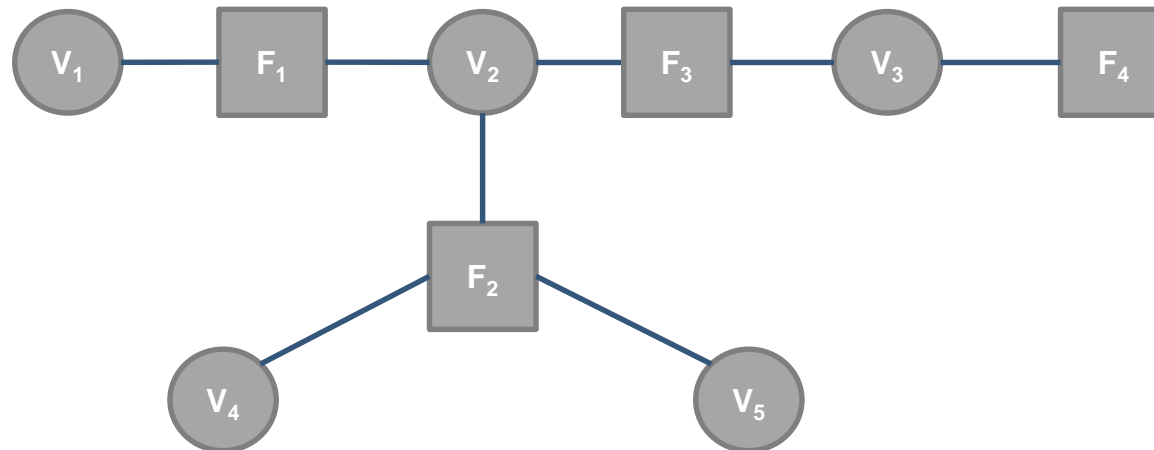
- **Nodes represent Poses:**

- E.g. Vehicle/camera pose at each time (6 DOF).



- **Factors:**

- Constraints for the poses w.r.t. some measures.

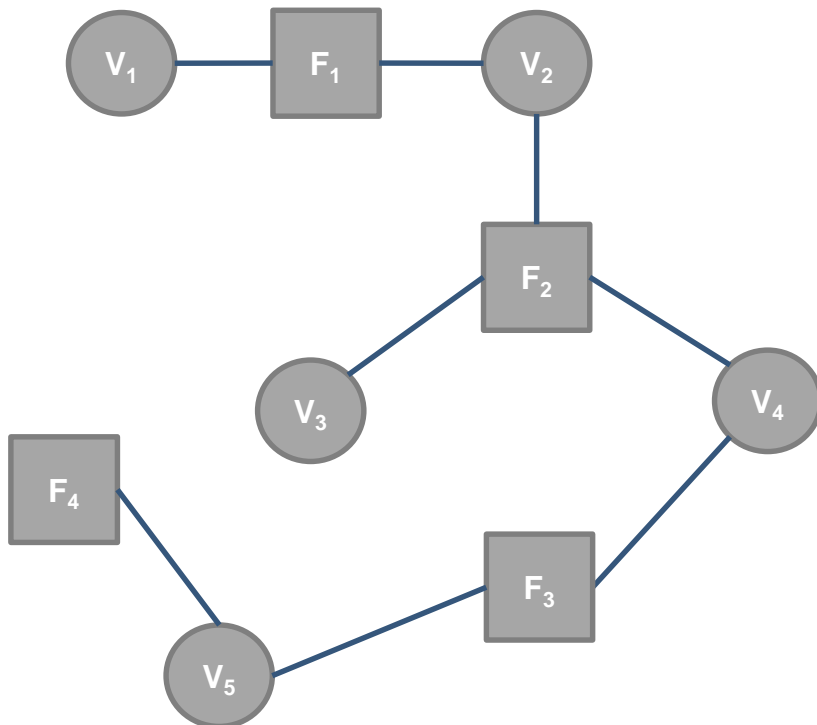


Global Alignment

Factor Graphs

Front-End

- Sensor data.
- Builds the factor graph:



Back-End

- Optimizes the non-linear problem described by the graph.
- Many available tools:
 - g2o (<https://openslam.org/g2o.html>)
 - Gtsam (<https://collab.cc.gatech.edu/borg/gtsam>)
 - iSAM (<https://openslam.org/iSAM.html>)
 - Toro (<https://openslam.org/toro.html>)
 - (...)
- Optimizers:
 - Gauss-Newton.
 - Levenberg-Marquardt.

Global Alignment

Factor Graphs – Back End

- The non-linear problem described by the graph:

$$\mathbf{x}^* = \underset{\mathbf{x}}{\operatorname{argmin}} F(\mathbf{x})$$

$$F(\mathbf{x}) = \sum_{\{i,j\} \in \text{Factors}} \mathbf{e}(x_i, x_j, z_{ij})^T \boldsymbol{\Omega}_{ij} \mathbf{e}(x_i, x_j, z_{ij})$$

- $\mathbf{e}(x_i, x_j, z_{ij})^T$ is a vector error function measuring how well the variables' blocks x_i, x_j satisfy the measure z_{ij} .
- $\boldsymbol{\Omega}_{ij}$ is the covariance associated to the measure.
- **Note:** a factor only involves some poses (variables).
 - Sparsity allows for faster solvers.

Global Alignment

Factor Graphs

- How to solve the problem (non-linear):
 - Good initial guess.
 - Error functions are supposed to be «smooth» in the neighborhood of the minima (may not be global!).
 - Thus, we can solve the problem by **iterative linearizations**.

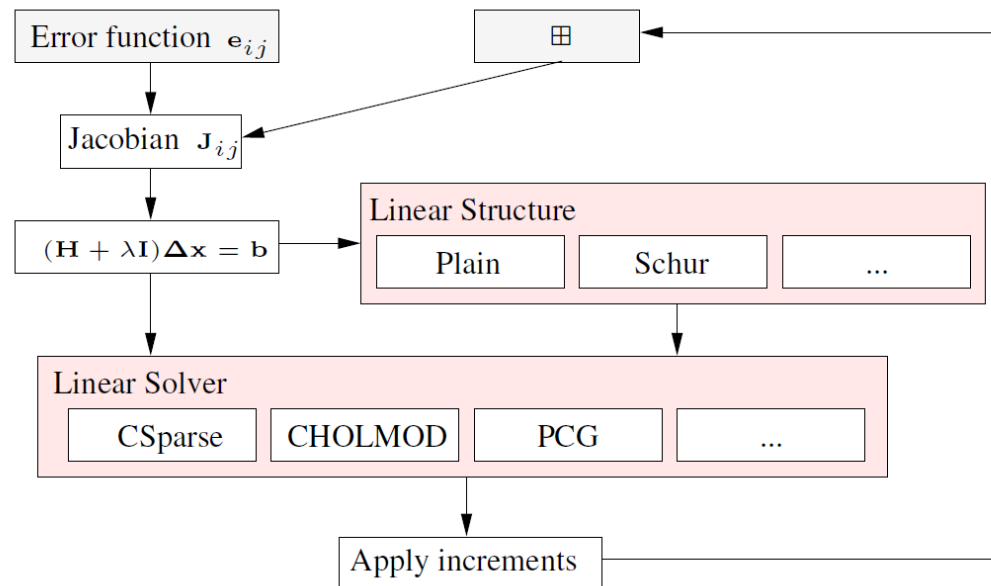
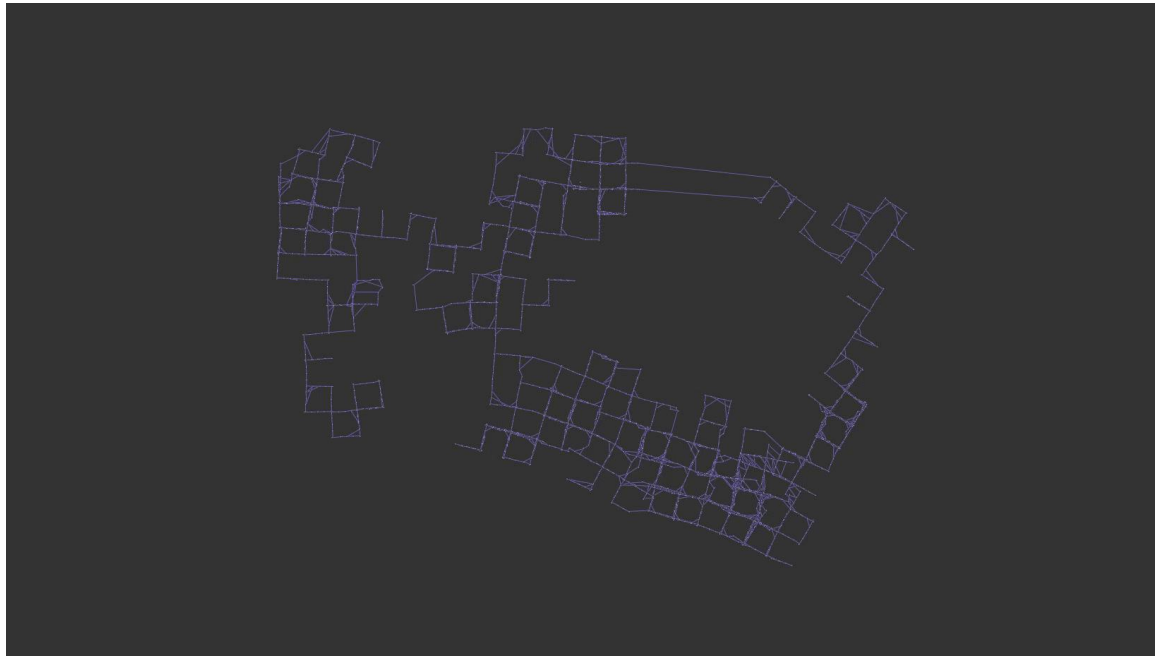


Figure extracted from Kuemmerle et al. "A General Framework for Graph Optimization". IEEE International Conference on Robotics and Automation (ICRA) 2011.

Global Alignment

Factor Graphs – Back End

- **Optimizer:**
 1. Linearize the error term around the current solution/initial guess.
 2. Compute first derivative of the squared error function, set it to zero and solve it.
 3. Obtain a new state, and iterate from 2.





Global Alignment

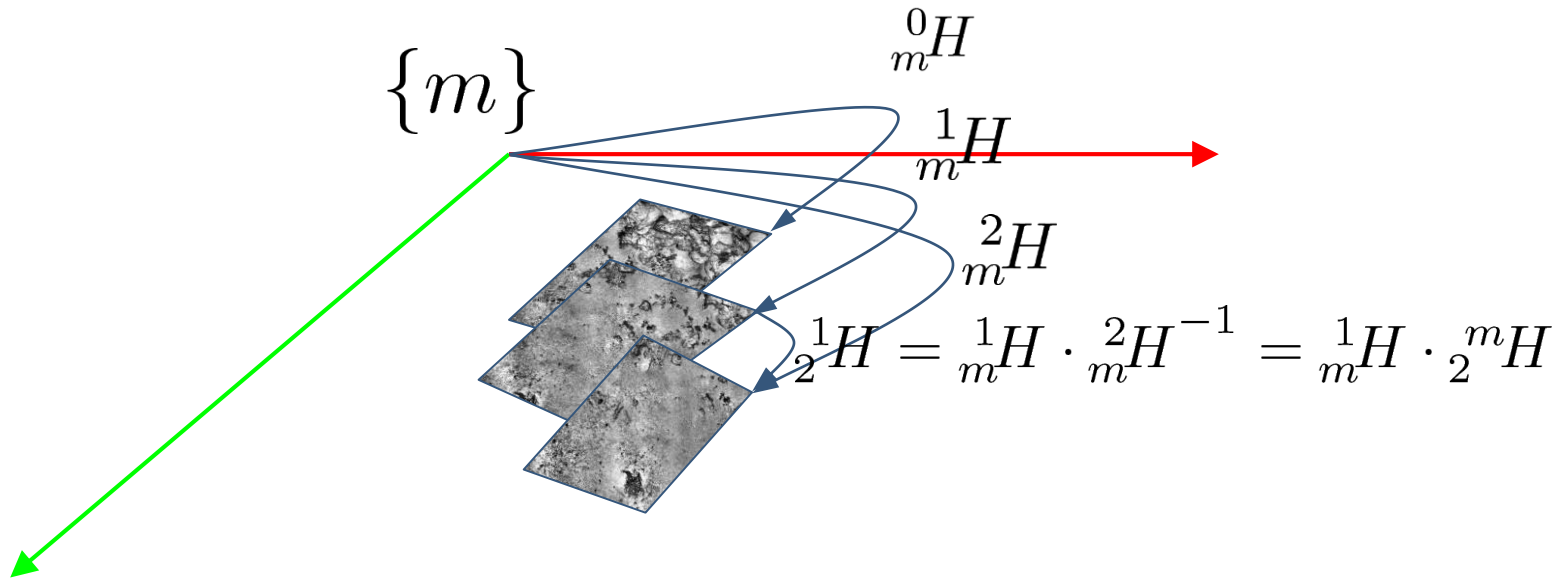
Factor Graphs - Photomosaics

- Global Alignment of a Photomosaic.
- Which are our *measurements*?
 - Pairwise 2D Motion (Homographies).
 - Navigation priors (Nav. Poses).
- Nodes: Pose of the camera/vehicle (6 DOF).
- Factors/Constraints?

Global Alignment

Optical constraint: matching error

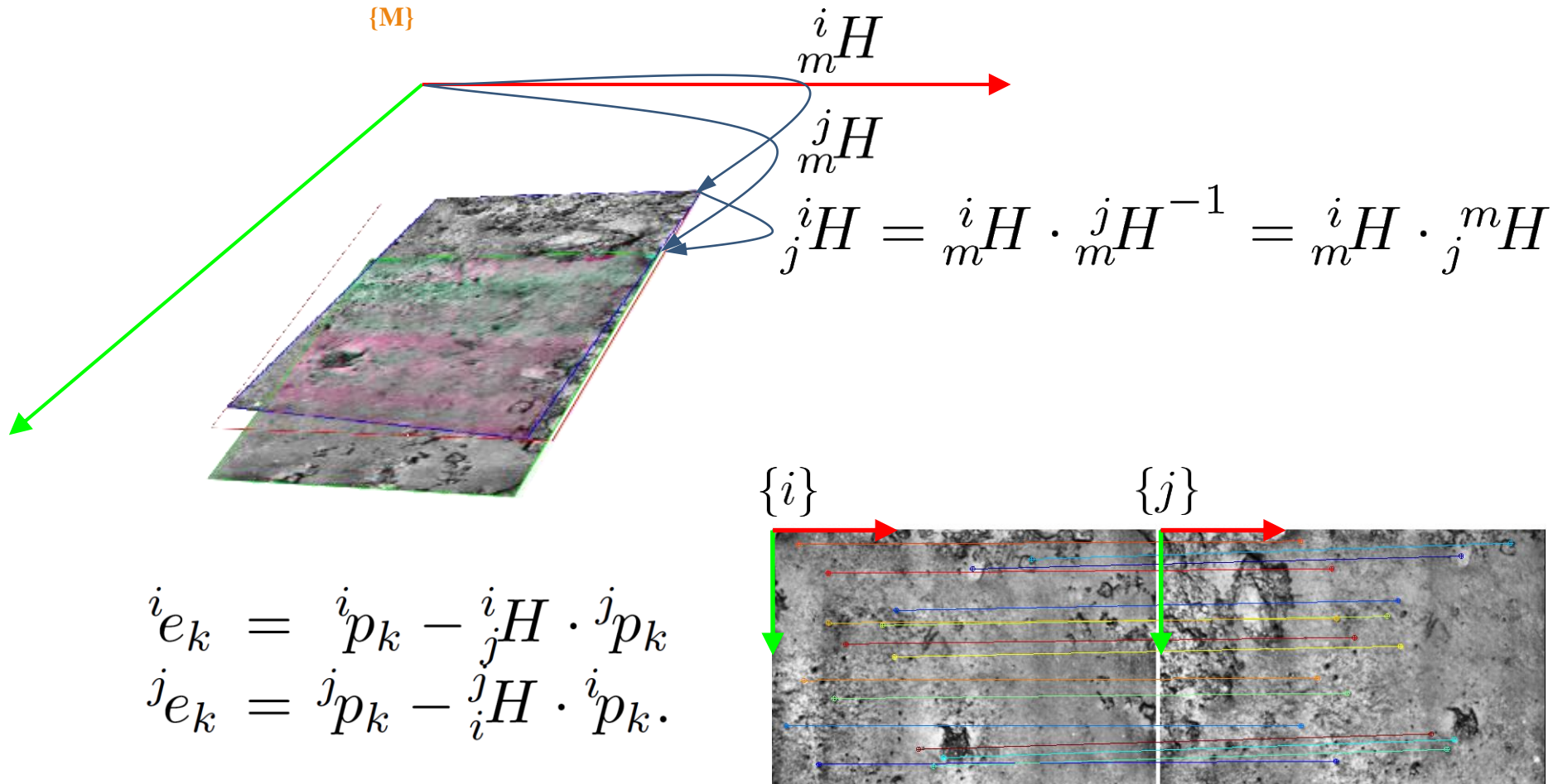
- We optimize poses, from which we can derive absolute homographies.
- From the absolute ones, we compute the relatives:



- And use them to compute the error with respect to the matches.

Global Alignment

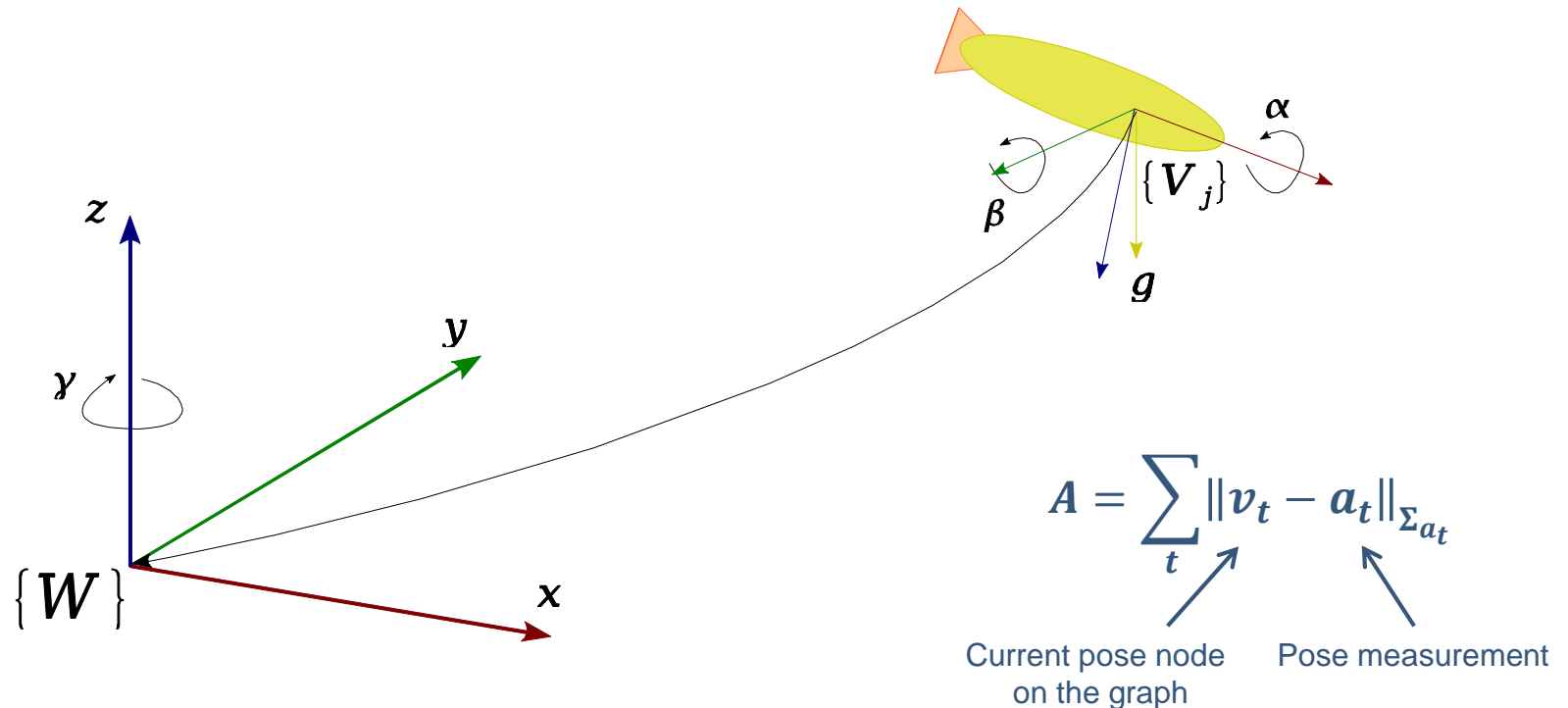
Optical constraint: matching error



How far a 2D point in an image falls from its match through the homography computed from the poses.

Global Alignment

Navigation Constraint: Absolute Pose Priors



- Absolute Pose Priors: Impose the navigation of the robot.
- Provides georeferencing of the mosaic!

Global Alignment

Pose Graph Example

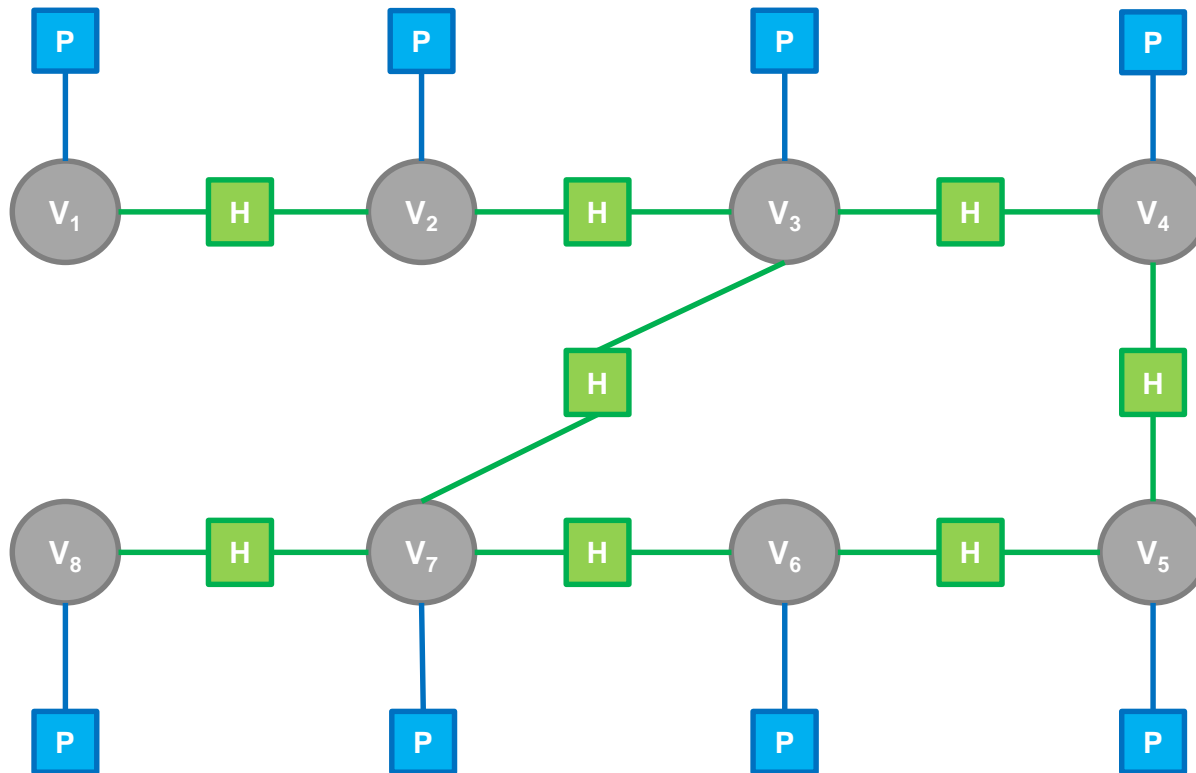
Absolute constraints



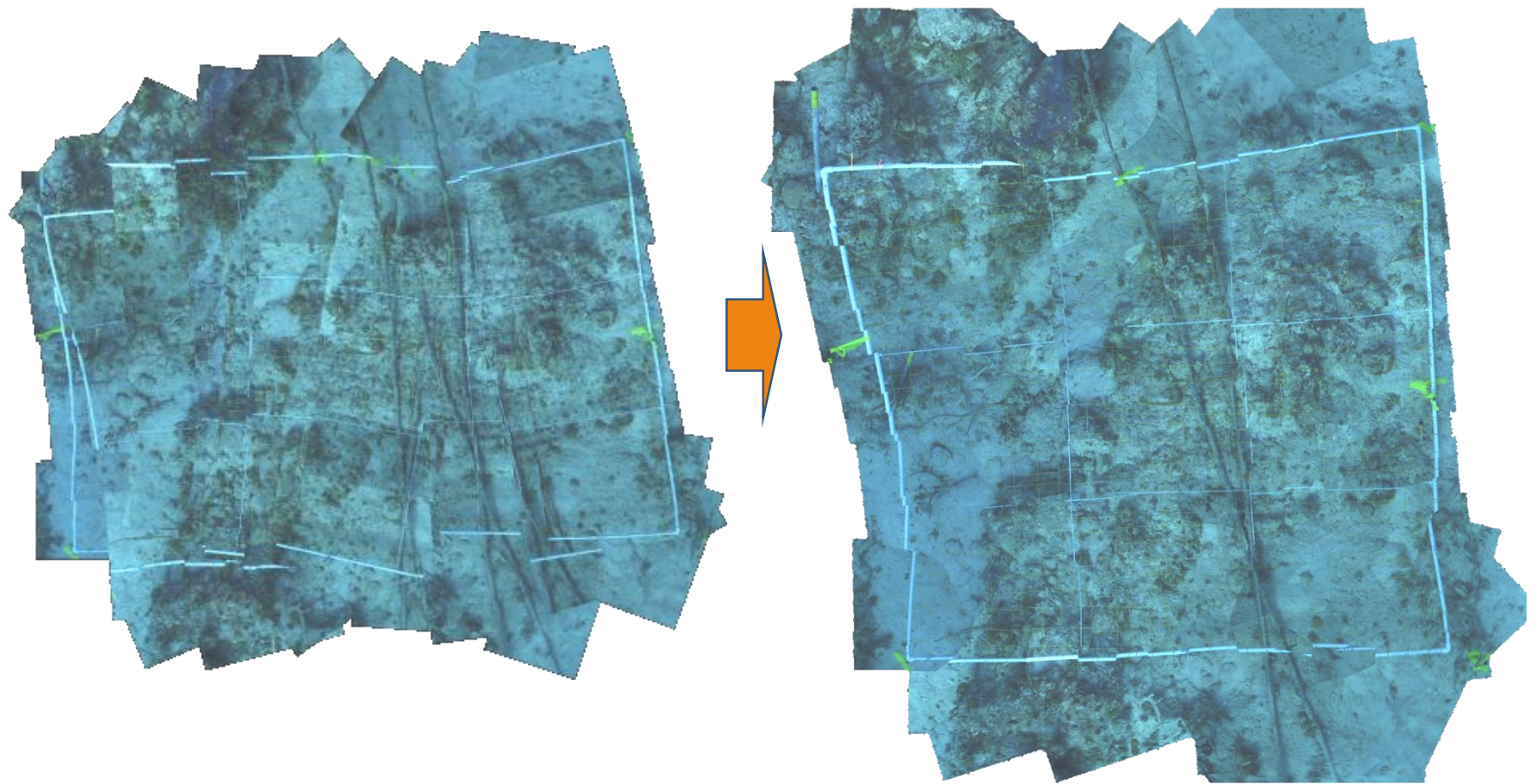
Homography constraints



Camera poses



Examples



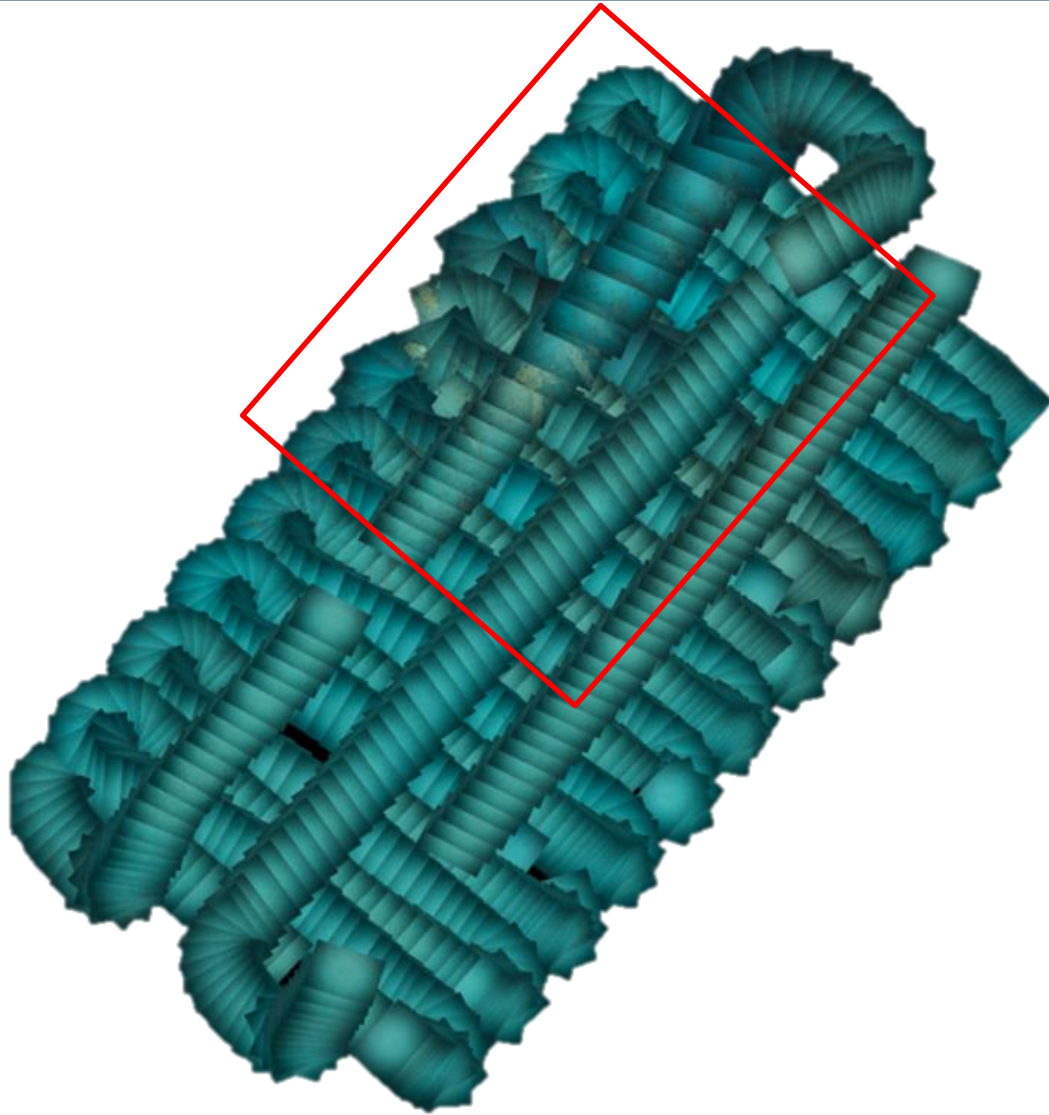
Examples

Large-scale Mosaicing



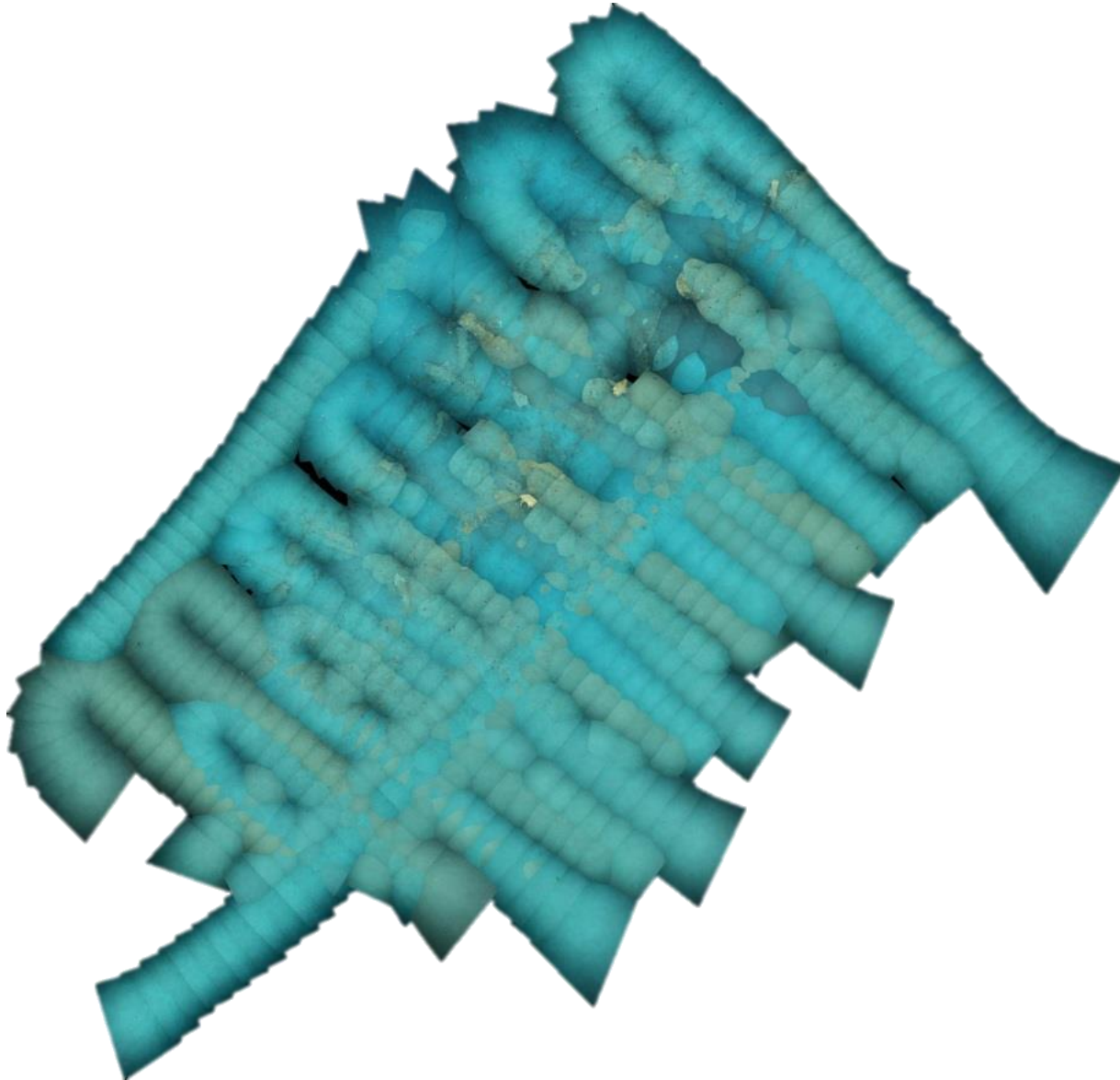
Examples

La Lune: Mosaic From Navigation (Initialization)



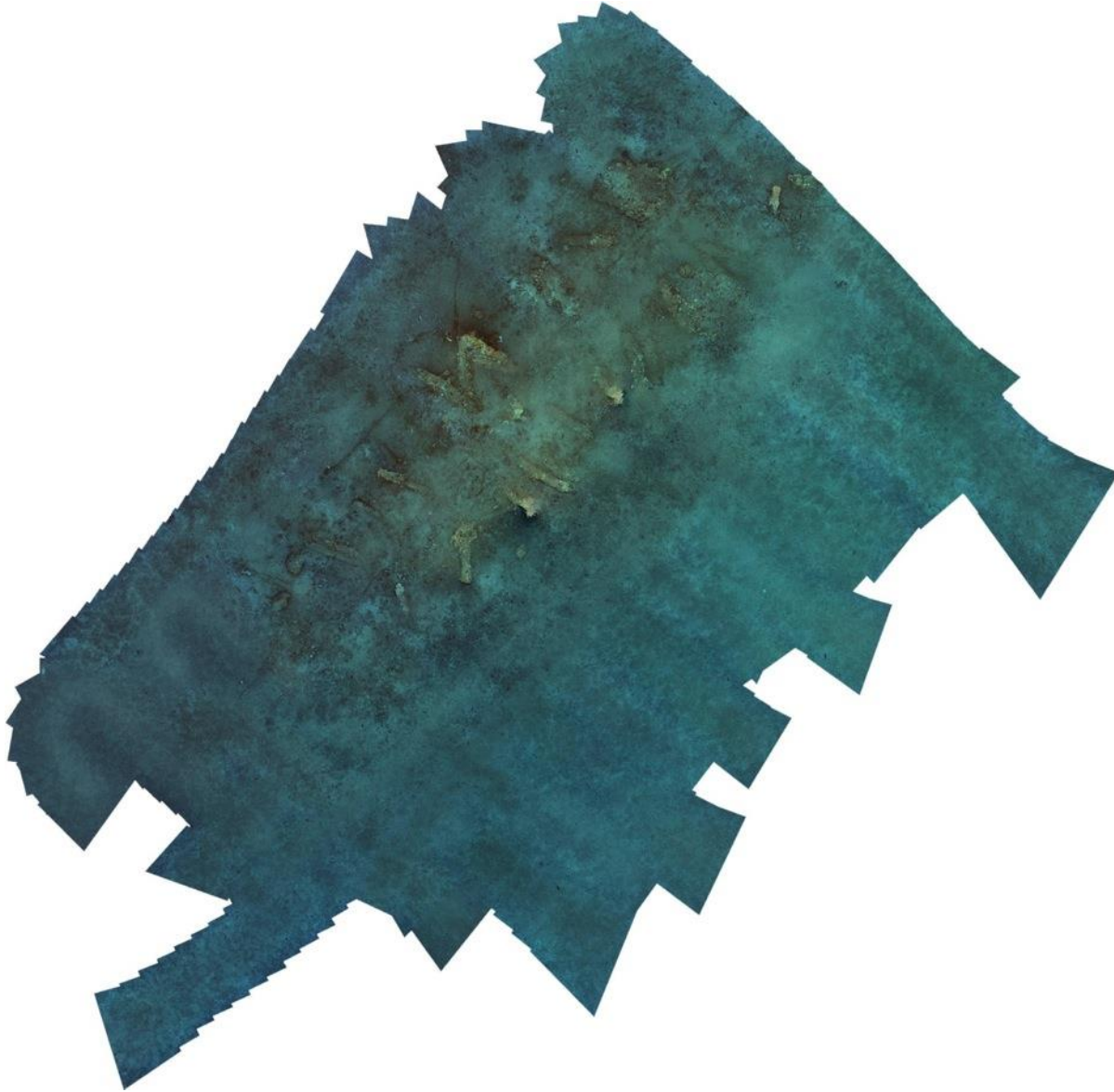
Examples

La Lune: Mosaic From Correspondences



Examples

La Lune: Mosaic From Correspondences (Blended)



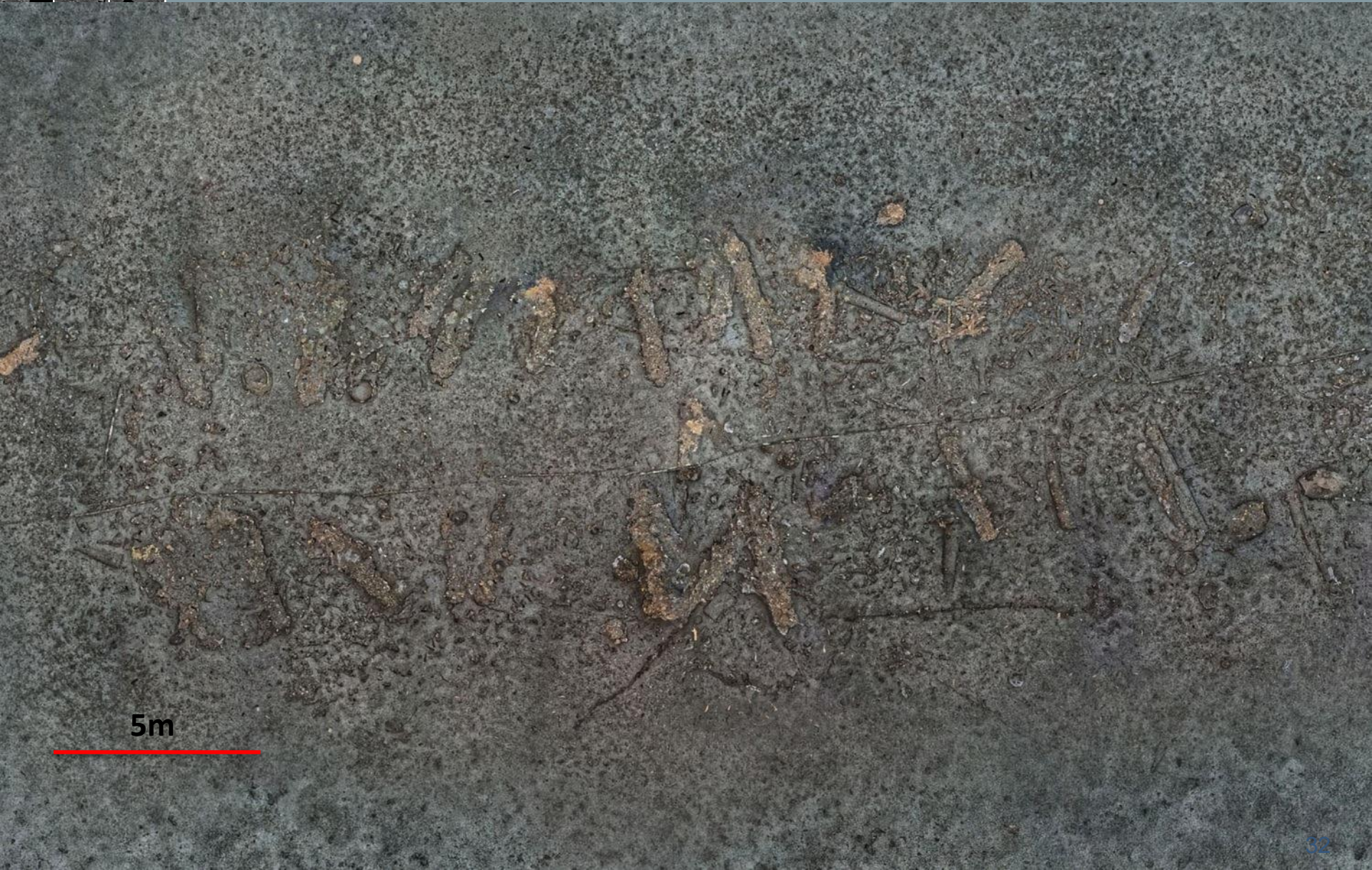
Examples

La Lune: Mosaic From Correspondences (Dehazed)



Examples

La Lune: Mosaic From Correspondences (Dehazed)



5m





Conclusions

- Photomosaics:
 - Larger perspective of an area by composing individual images.
- We need to infer the topology of the mosaic:
 - Trajectory (navigation).
 - Links among images (sequential/non-sequential matches).
- The different measures taken are merged through global alignment (pose graphs):
 - Homographies.
 - Navigation priors.
 - Landmarks.
 - Etc.



Hands-on Mosaicing Tutorial

- Tutorial doc:
 - http://coronis.udg.edu/winter_school/hands-on_learning_building_a_photomosaic.pdf
- Code:
 - http://coronis.udg.edu/winter_school/strongmar_winter_school_mosaicing_code.zip
- Datasets:
 - http://coronis.udg.edu/winter_school/strongmar_winter_school_mosaicing_examples.zip