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# Sea-waves reconstruction from moving platforms

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# Why are we interested in sea-waves 3D reconstruction?

Spectral properties of wind waves are usually inferred from buoys installed at fixed locations at sea

> Can acquire elevation time-serie at a single point

However...

the information of a single time-serie cannot describe the complete wave dynamics that develops over an area



# Why are we interested in sea-waves 3D reconstruction?

Vision-based 3D reconstruction of the sea surface have proved to be a game-changer in the study of small scale wind waves.

In practice, we are now able to acquire with unprecedented accuracy the evolution of the wave spectrum in an area over time (4D space+time data)



## Our contribution

In the past years, we proposed state-of-the-art methods in this field, contributing in the diffusion of the topic among the oceanographic community

In particular, we developed the fastest open-source sea-waves reconstruction pipeline:  
<http://www.dais.unive.it/wass/>



# Challenges

- Extrinsic calibration of the stereo rig
- Reliable dense stereo matching in presence of sun glares, specular reflections, droplets..
- **Alignment of all the reconstructed surface to the mean sea plane**

if the stereo rig is firmly placed to a non-moving support (ie. fixed-platform, lighthouse, etc) the alignment process is relatively easy...



# Challenges

For the Gaussian nature of the sea-surface elevations, we demonstrated that averaging the estimated sea plane over time is a good way to obtain an accurate estimation of the “true sea-plane” in the camera reference frame.

This implicitly assumes that the stereo rig is not moving wrt. the sea

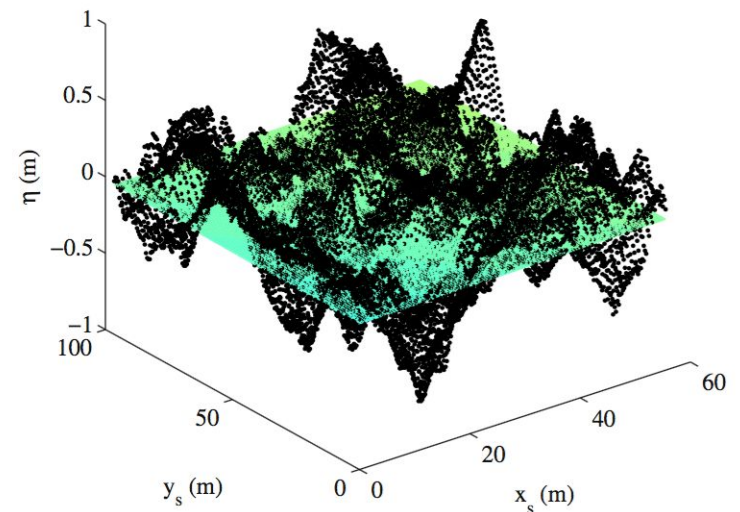
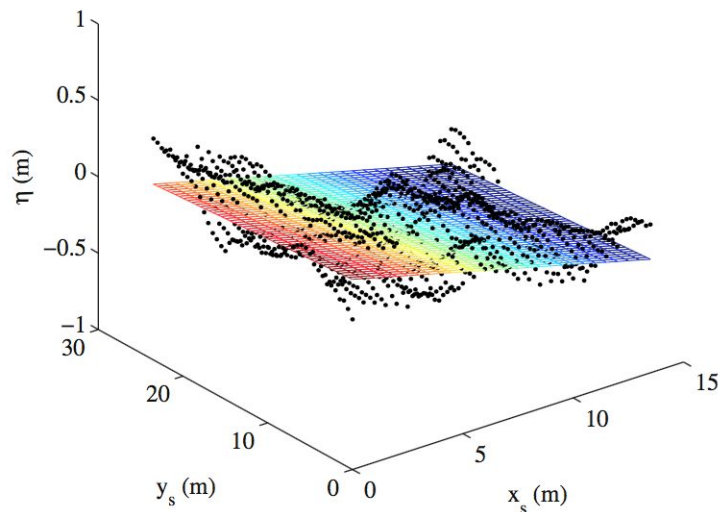
However, this heavily limit the applicability of the method as it require a fixed platform

# Sea-plane accuracy from a single frame

We experimentally assessed the reliability of the estimated sea-plane from a single 3D reconstruction wrt. the sea state condition

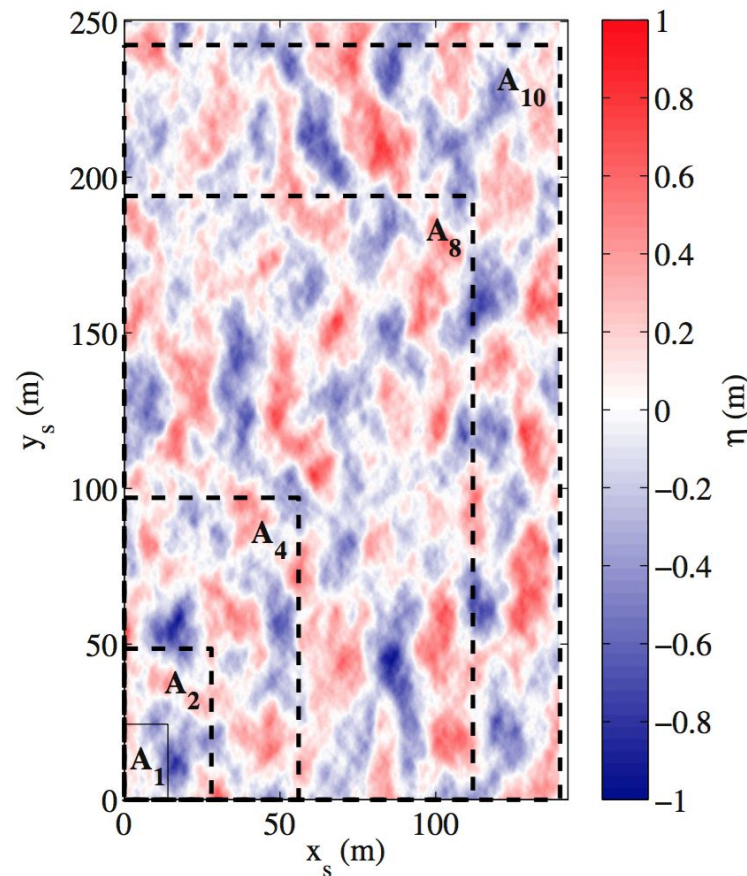
Benetazzo, A., Barbariol, F., Bergamasco, F., Torsello, A., Carniel, S., Sclavo, M. *Stereo wave imaging from moving vessels: Practical use and applications*, 2016, Coastal Engineering, 109, pp. 114-127.

**DOI: [10.1016/j.coastaleng.2015.12.008](https://doi.org/10.1016/j.coastaleng.2015.12.008)**



# Sea-plane accuracy from a single frame

Variable		$A_1 = L_x L_y$	$A_2 = 2^2 L_x L_y$	$A_4 = 4^2 L_x L_y$	$A_8 = 8^2 L_x L_y$	$A_{10} = 10^2 L_x L_y$
$a_x$ (°)	Max	95.9	91.9	90.3	90.1	90.0
	Min	83.4	88.1	89.7	89.9	90.0
	Avg	90.0	90.0	90.0	90.0	90.0
$a_y$ (°)	Max	92.3	90.5	90.1	90.0	90.0
	Min	87.6	89.5	89.9	90.0	90.0
	Avg	90.0	90.0	90.0	90.0	90.0
$D$ (m)	Max	1.15	0.52	0.20	0.06	0.04
	Min	-1.02	-0.50	-0.16	-0.06	-0.04
	Avg	0.00	0.00	0.00	0.00	0.00



In practice we require at least 16 spatial waves in the fov to derive a realistic estimation of the mean sea plane for subsequent statistical analysis





# Sea-plane accuracy from a single frame

To analyze interesting (not ridiculously small) sea waves from a moving stereo rig we cannot simply align each frame independently

Well-known **structure-from-motion techniques cannot be used** due to the intrinsic ambiguity between the camera motion and the surface evolution over time



# Moving WASS Approach

## **Our solution:**

Use an IMU to acquire the 6-dof parameters (rotation angles / position) of the vessel and apply that transformation to each reconstructed surface.

- > Either directly or after some statistical filtering

## **Problem:**

The rigid transformation between IMU and the stereo rig **must be calibrated** a-priori.

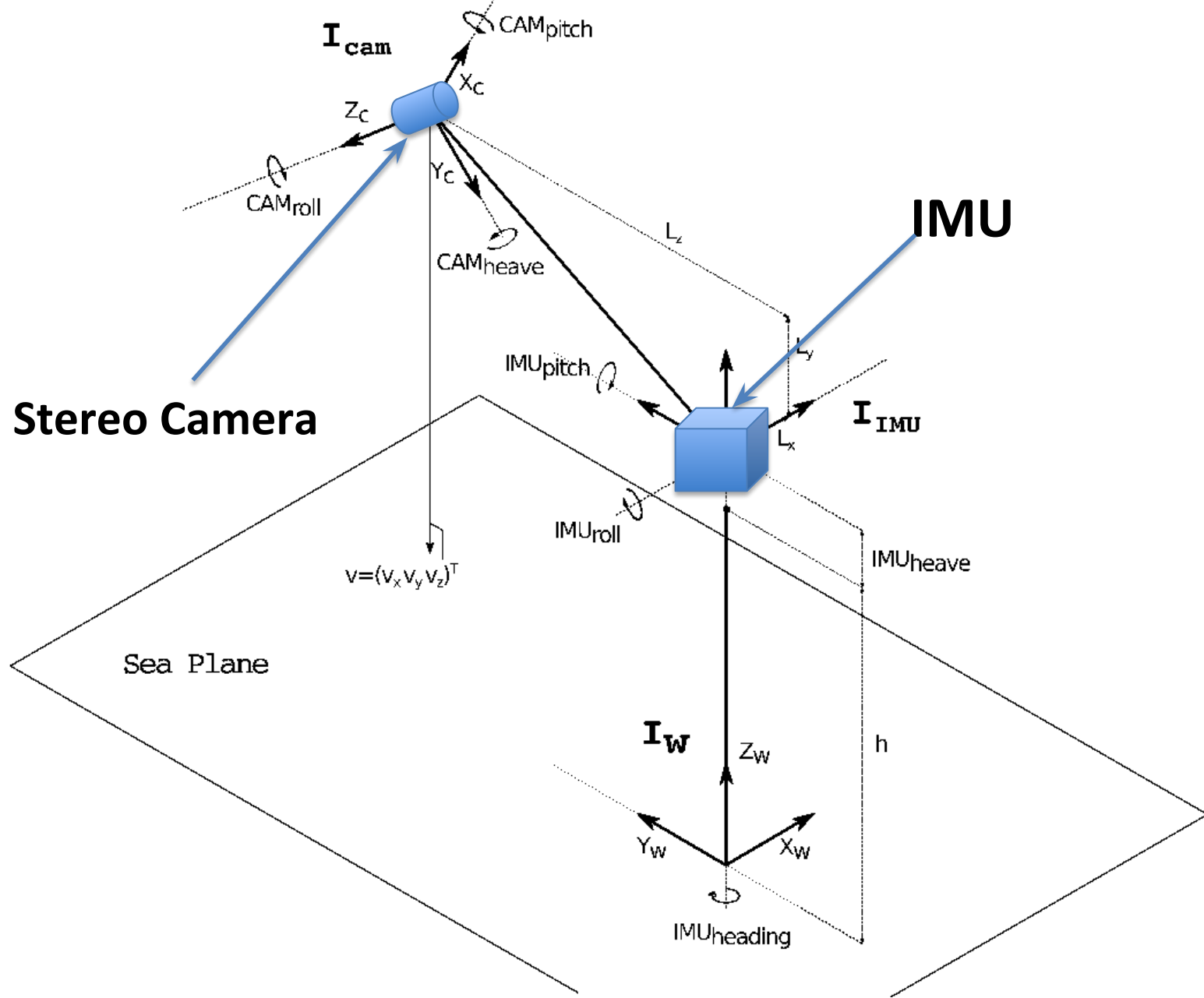


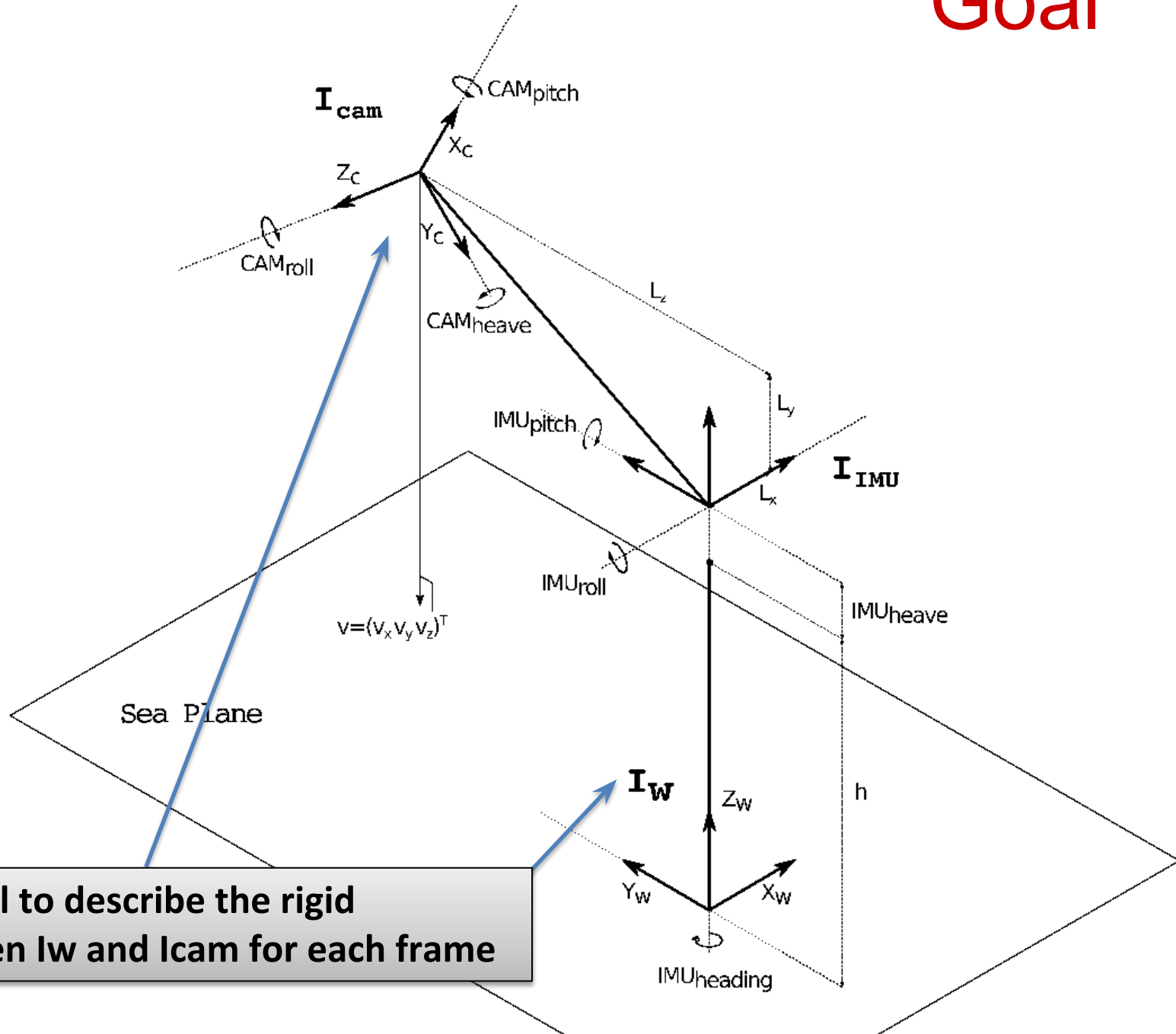
**IMU unit  
is placed  
at the  
center of  
gravity**

**Stereo Camera rig placed at  
highest possible position at port**



# System Geometry

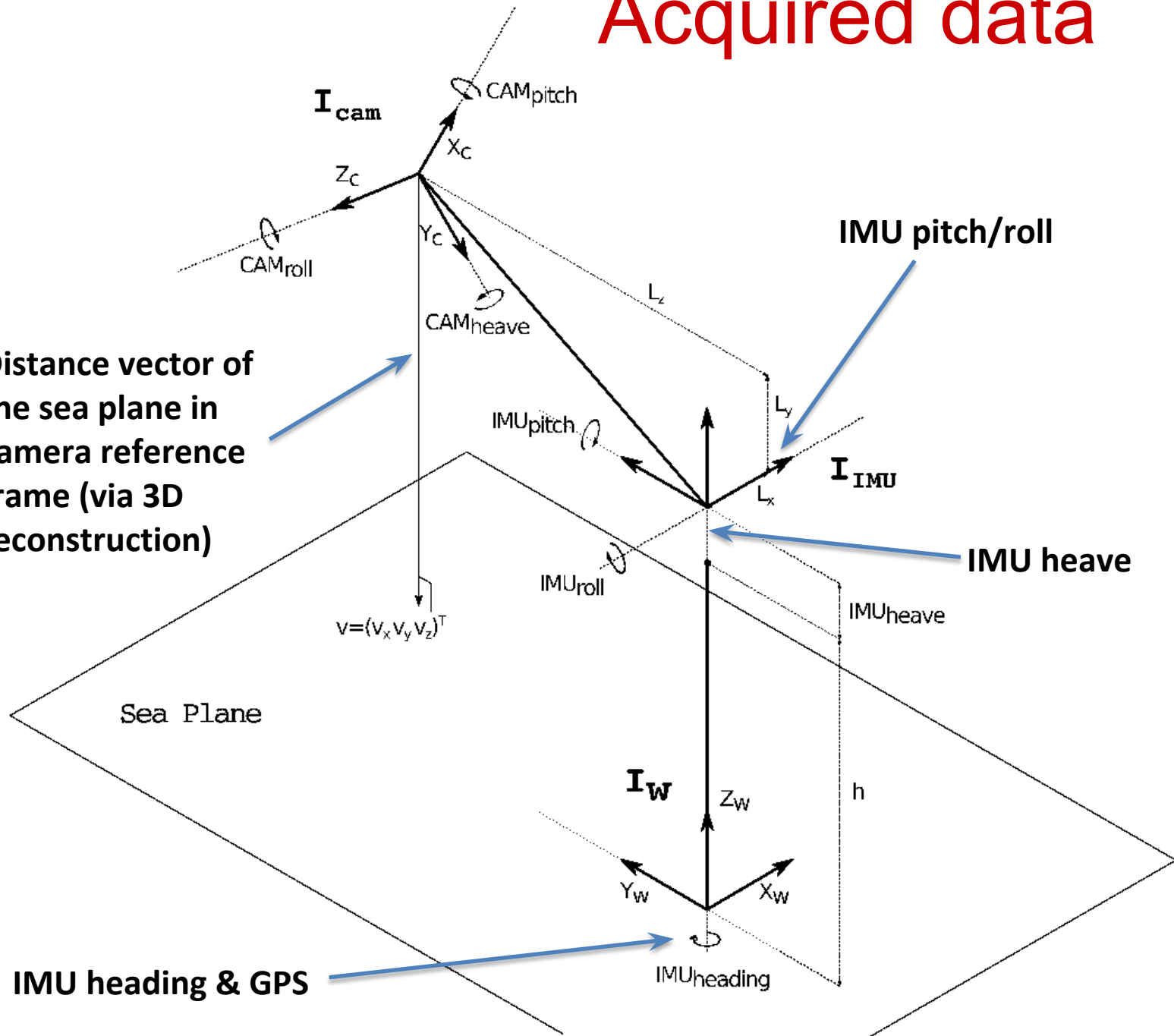




Derive a model to describe the rigid motion between  $I_w$  and  $I_{cam}$  for each frame

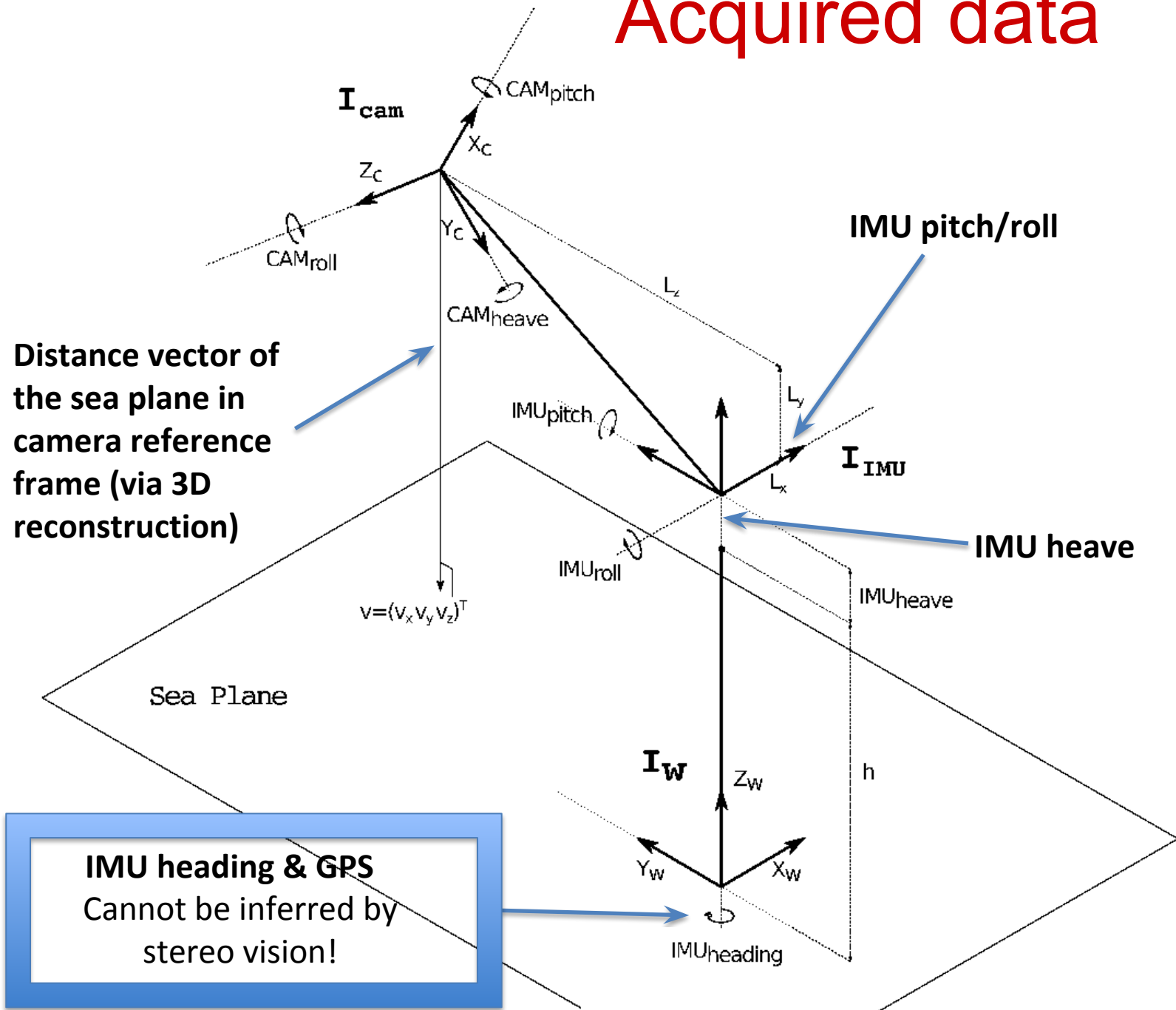
# Acquired data

Distance vector of the sea plane in camera reference frame (via 3D reconstruction)



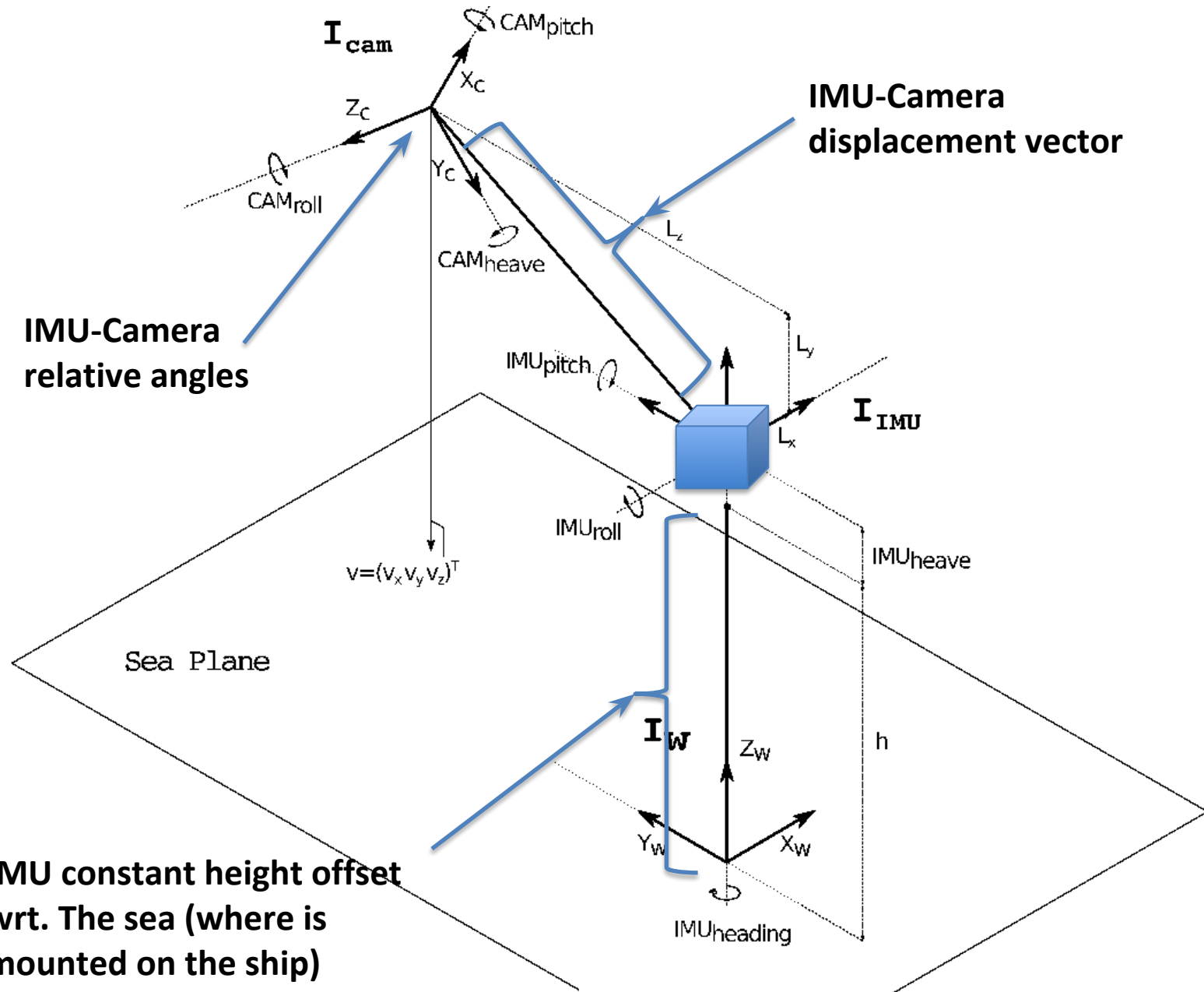
# Acquired data

Distance vector of the sea plane in camera reference frame (via 3D reconstruction)



**IMU heading & GPS**  
Cannot be inferred by  
stereo vision!

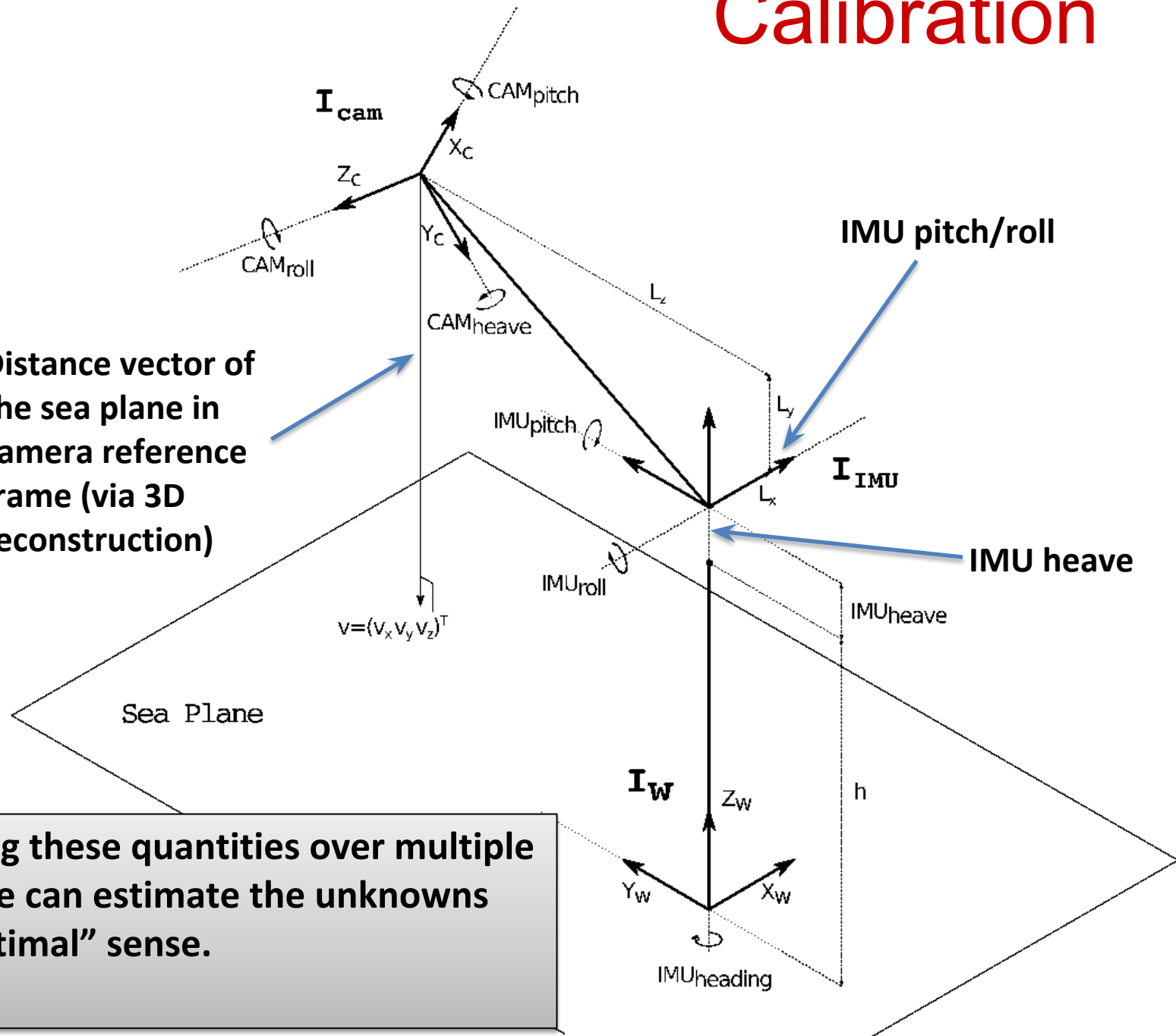
# Unknowns to be estimated





# Calibration

Distance vector of the sea plane in camera reference frame (via 3D reconstruction)



By relating these quantities over multiple frames we can estimate the unknowns In an “optimal” sense.



# Kinematic Chain Modelling

Rigid motion  $T$  between  $I_w$  and  $I_{cam}$  (passing through  $I_{IMU}$ ) is modelled as a CPC kinematic chain described by the composition of 8 motions:

$$T = G * B1 * B2 * B3 * B4 * B5 * B6 * B7$$

- $G$  is the 4x4 matrix that translates  $I_w$  according to the gps coordinates and aligns  $X_w$  with the geographic north (z-upward)



# Kinematic Chain Modelling

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$$T = G * B1 * B2 * B3 * B4 * B5 * B6 * B7$$

- $B_i, i=1\dots7$  are 4x4 matrix (chain joints) factorized as a product of  $V_i Q_i$  where:
  - $Q_i$  describes the joint motion and  $V_i$  is the rigid transformation connecting two joints.



# Kinematic Chain Modelling

A  $Q_i$  joint can be either:

- Prismatic: pure translation along z-axis with length  $p_i$
- Revolution: pure rotation around z-axis with an angle of  $p_i$  radians

Each  $V_i$  joint is a combination of:

$V_i = Tr_i Rz_i Rj_i$ , where:

- $Tr_i$  is a translation along  $[lx,ly,lz]^T$
- $Rz_i$  is a rotation around z of  $a_i$  radians
- $Rj_i$  is a rotation depending by  $[bx,by,bz]^T$



# Kinematic Chain Modelling

Joint	Type	$p_i$	$[l_x, l_y, l_z]^T$	$[b_x, b_y, b_z]^T$	$a_i$
B1	Prismatic	IMU <sub>heave</sub>	$[0 \ 0 \ h]$	$[0 \ 0 \ 1]$	0
B2	Revolution	IMU <sub>pitch</sub>	$[0 \ 0 \ 0]$	$[0 \ 1 \ 0]$	0
B3	Revolution	IMU <sub>roll</sub>	$[0 \ 0 \ 0]$	$[1 \ 0 \ 0]$	0
B4	Revolution	0	$[0 \ 0 \ 0]$	$[-1 \ 0 \ 0]$	$\pi/2$
B5	Revolution	Cam <sub>heading</sub>	$[L_x \ L_y \ L_z]$	$[0 \ 0 \ 1]$	0
B6	Revolution	Cam <sub>pitch</sub>	$[0 \ 0 \ 0]$	$[0 \ 1 \ 0]$	$\pi/2$
B7	Revolution	Cam <sub>roll</sub>	$[0 \ 0 \ 0]$	$[1 \ 0 \ 0]$	0

# Kinematic Chain Modelling

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B1	Prismatic	IMU <sub>heave</sub>	$[0 \ 0 \ h]$	$[0 \ 0 \ 1]$	0
B2	Revolution	IMU <sub>pitch</sub>	$[0 \ 0 \ 0]$	$[0 \ 1 \ 0]$	0
B3	Revolution	IMU <sub>roll</sub>	$[0 \ 0 \ 0]$	$[1 \ 0 \ 0]$	0
B4	Revolution	0	$[0 \ 0 \ 0]$	$[-1 \ 0 \ 0]$	$\pi/2$
B5	Revolution	Cam <sub>heading</sub>	$[L_x \ L_y \ L_z]$	$[0 \ 0 \ 1]$	0
B6	Revolution	Cam <sub>pitch</sub>	$[0 \ 0 \ 0]$	$[0 \ 1 \ 0]$	$\pi/2$
B7	Revolution	Cam <sub>roll</sub>	$[0 \ 0 \ 0]$	$[1 \ 0 \ 0]$	0

**Parameters to estimate (unknowns)**

$$p_c = (h, L_x, L_y, L_z, \text{Cam}_{\text{heading}}, \text{Cam}_{\text{pitch}}, \text{Cam}_{\text{roll}})$$

# Kinematic Chain Calibration

For each frame  $k=1\dots n$ , we have:

- $\mathbf{p}_m^k = (\text{IMU}_{\text{pitch}'}, \text{IMU}_{\text{roll}'}, \text{IMU}_{\text{heave}'})$
- $\mathbf{v}^k = (v_{x'}, v_{y'}, v_{z'})$

We pose the parameters estimation problem as a non-linear least squares optimization:

$$\mathit{argmin}_{pc} \sum_{i=1}^k \left( \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} T \begin{pmatrix} 0 \\ 0 \\ 0 \\ -1 \end{pmatrix} - \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} T \begin{pmatrix} v_x \\ v_y \\ v_z \\ 0 \end{pmatrix} \right)^2$$

# Kinematic Chain Calibration

$$\mathit{argmin}_{pc} \sum_{i=1}^k \left( \underbrace{\begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} T \begin{pmatrix} 0 \\ 0 \\ 0 \\ -1 \end{pmatrix}}_{\text{Expected distance vector}} - \underbrace{\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} T \begin{pmatrix} v_x \\ v_y \\ v_z \\ 0 \end{pmatrix}}_{\text{Measured distance vector transformed to the world reference frame } l_w} \right)^2$$

**Expected distance vector**

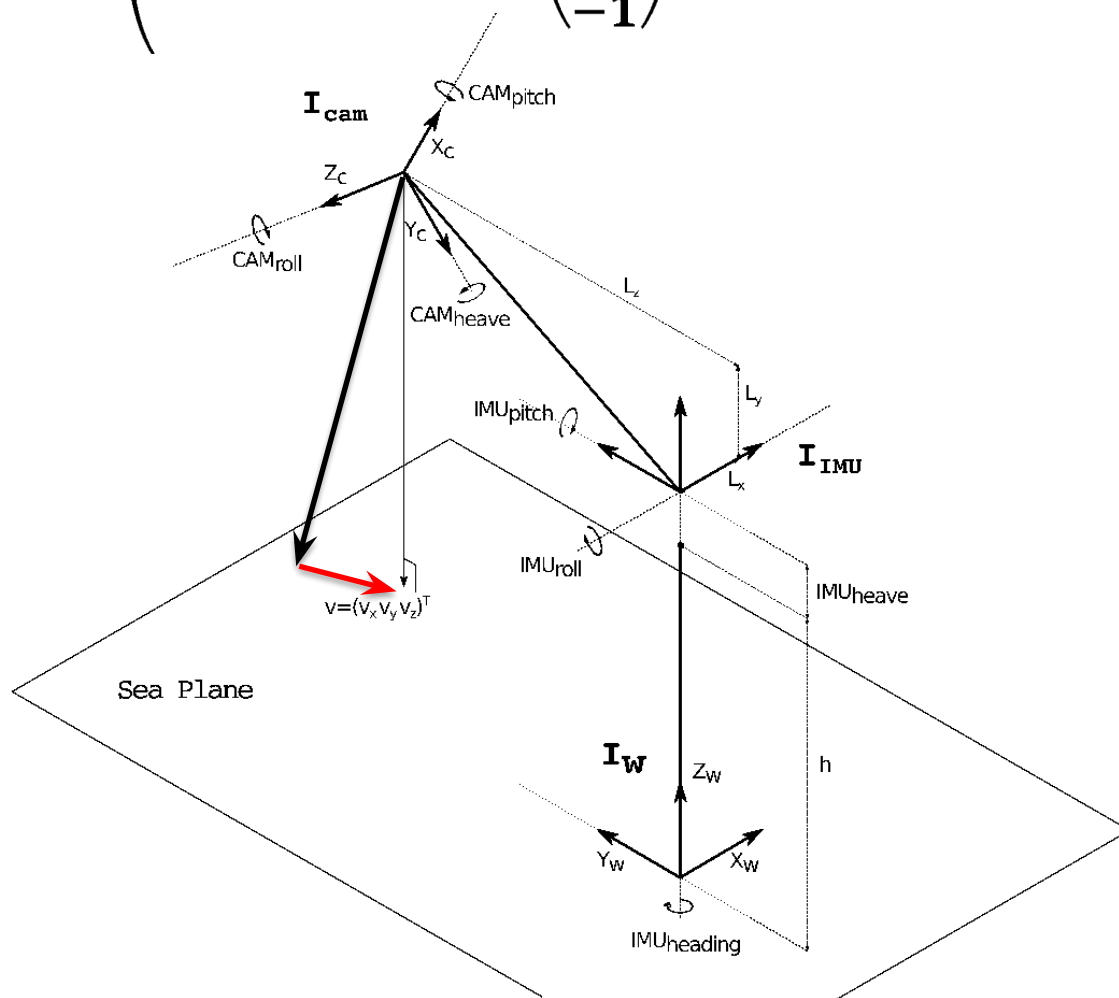
**Measured distance vector  
transformed to the  
world reference frame  $l_w$**

Optimization is solved via Levenberg-Marquardt



# Kinematic Chain Calibration

$$\operatorname{argmin}_{pc} \sum_{i=1}^k \left( \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} T \begin{pmatrix} 0 \\ 0 \\ 0 \\ -1 \end{pmatrix} - \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} T \begin{pmatrix} v_x \\ v_y \\ v_z \\ 0 \end{pmatrix} \right)^2$$





# KC Calibration with regularizer

If in the calibration sequence we observe no significant motion, parameter estimation may still be under-determined (many local minima).

## **Possible workaround:**

Force the solution to be close enough to an empirically estimated imu-camera displacement prior

# KC Calibration with regularizer

$$\operatorname{argmin}_{pc} \sum_{i=1}^n \left( \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} T \begin{pmatrix} 0 \\ 0 \\ 0 \\ -1 \end{pmatrix} - \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} T \begin{pmatrix} v_x \\ v_y \\ v_z \\ 0 \end{pmatrix} \right)^2$$

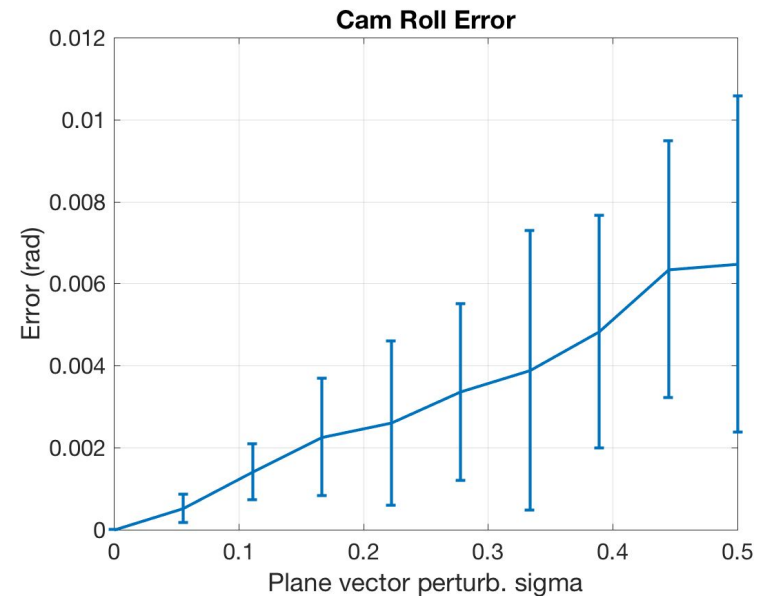
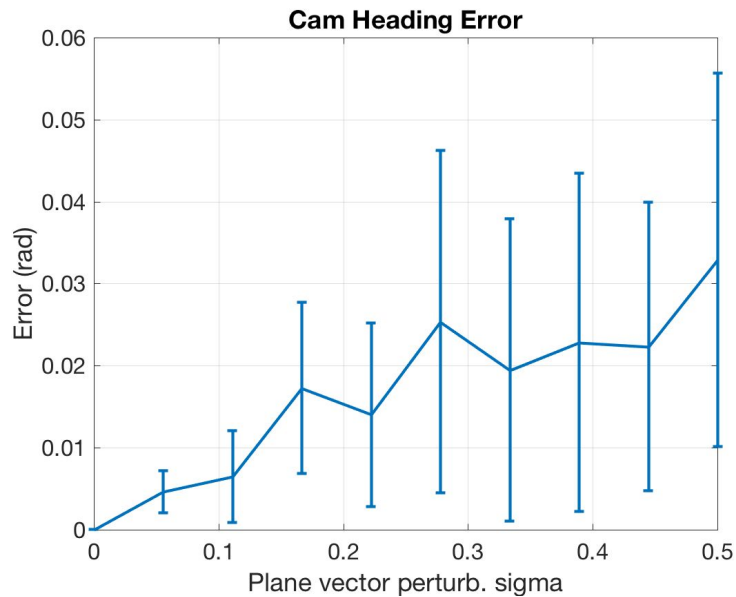
$$+ \frac{\alpha}{n} \left( \begin{pmatrix} L_x \\ L_y \\ L_z \end{pmatrix} - \begin{pmatrix} Lg_x \\ Lg_y \\ Lg_z \end{pmatrix} \right)^2$$

IMU-Camera  
displacement prior

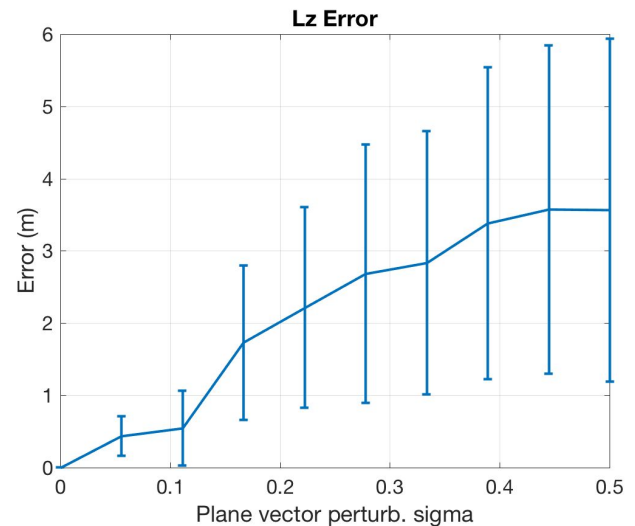
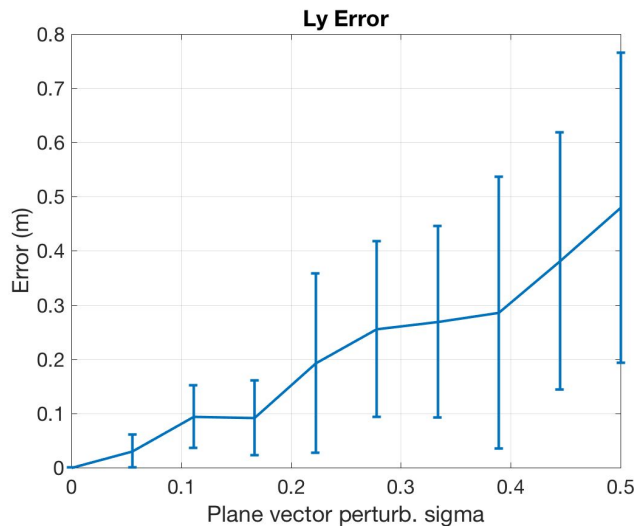
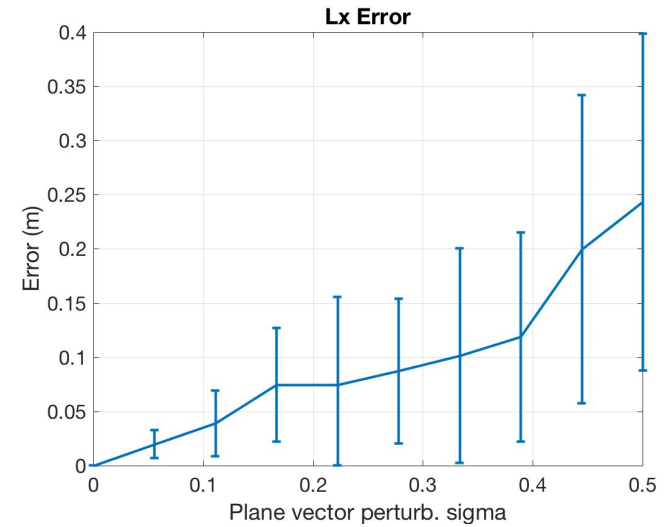
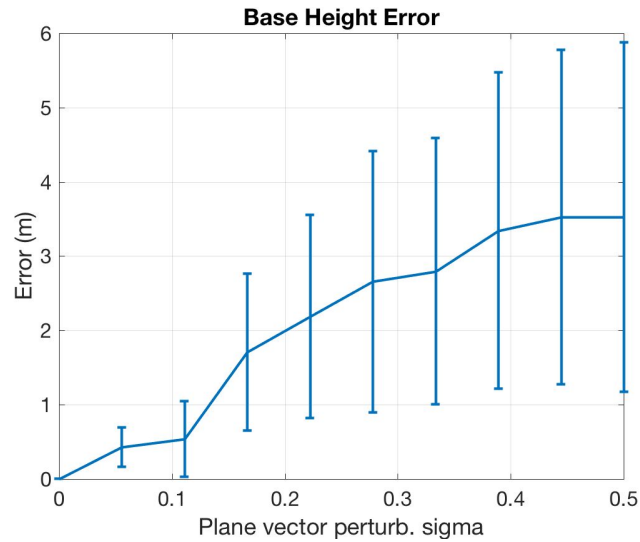
Regularization strength

# KC Calibration tests

KC calibration tests with synthetic data. Sea-plane vector  $v$  is perturbed with a zero-mean gaussian noise with standard deviation  $\sigma$  and the final KC shape variables are compared to the ground truth



# KC Calibration tests





# Using the kinematic chain

Once calibrated, the KC can be directly used to align each reconstructed surface to the mean sea plane

- Translation applied as-is from the GPS data
- Rotation around plane normal applied as-is from the IMU heading

IMU estimation uncertainty may heavily affect the alignment accuracy



# Using the kinematic chain

## **A better approach:**

We use a Kalman Smoother to average the the sea-plane estimated by the stereo cameras with the transformation given by the KC

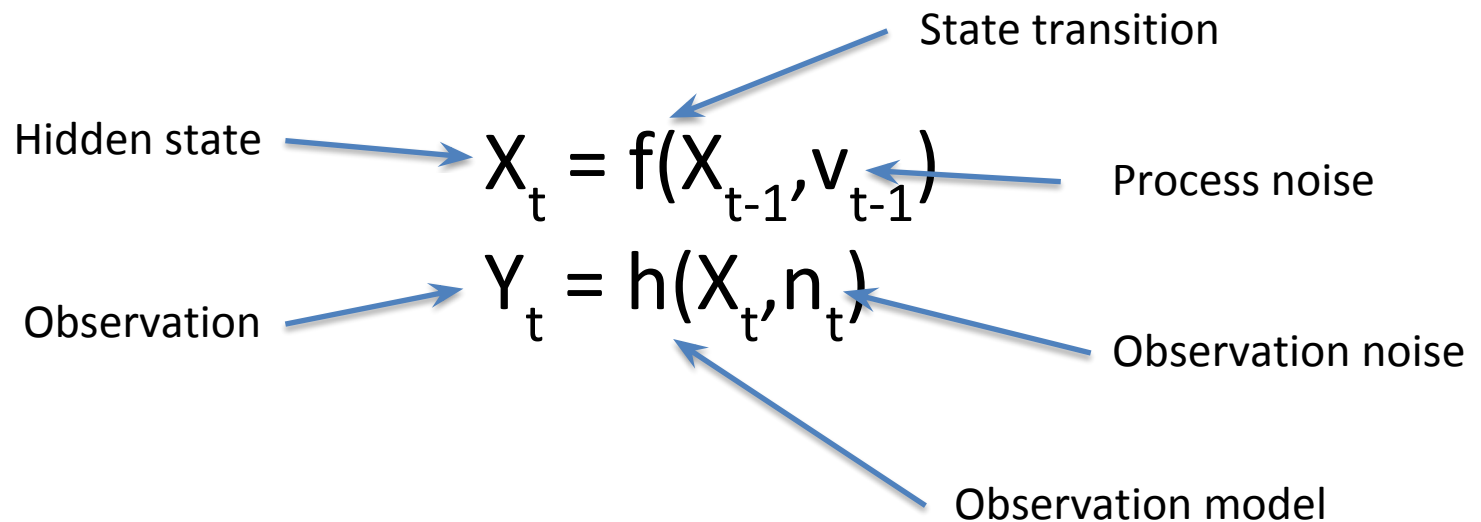
Optical plane estimation helps in the alignment of the rig exactly where the IMU is more prone to fail (heave and roll angle)



# Using the kinematic chain

## Ingredients of a Kalman smoother:

Kalman smoother is an efficient algorithm to estimate moments of hidden state variables of a dynamical system given a series of measurement observed over time







# Using the kinematic chain

In our case, we modelled our system considering:

Kalman state:

$$X=[\text{pos,heading,heave,pitch,roll}]$$

Measurement vector:

$$Y=[\text{pos,heading,heave,pitch,roll,v}]$$




# Using the kinematic chain

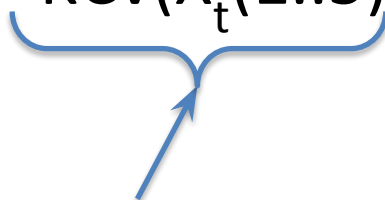
- Identity function is used as state transition function  $f()$
- Observation model function:

$$Y_t = h(X_t) = [X_t(1..5), T(X_t(1..5))^{-1} KCv(X_t(1..5))]$$

Pos, heading,  
heave, pitch, roll

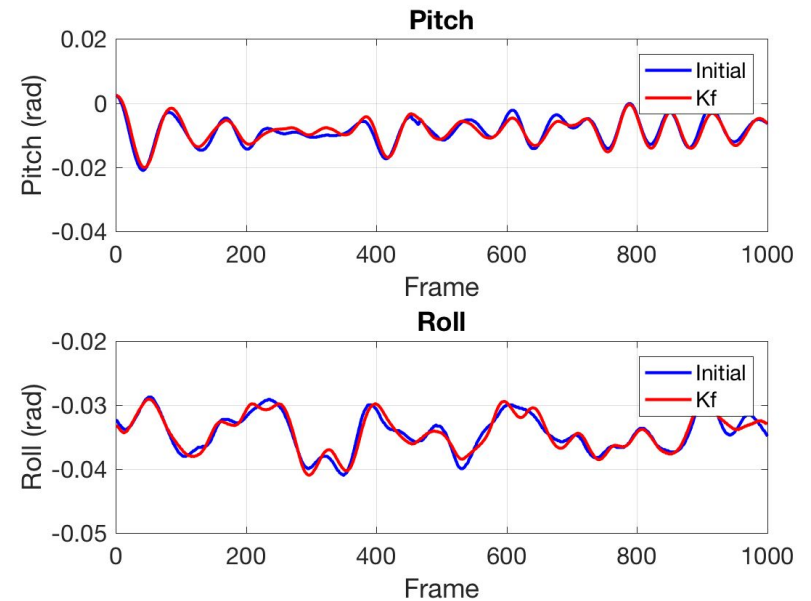
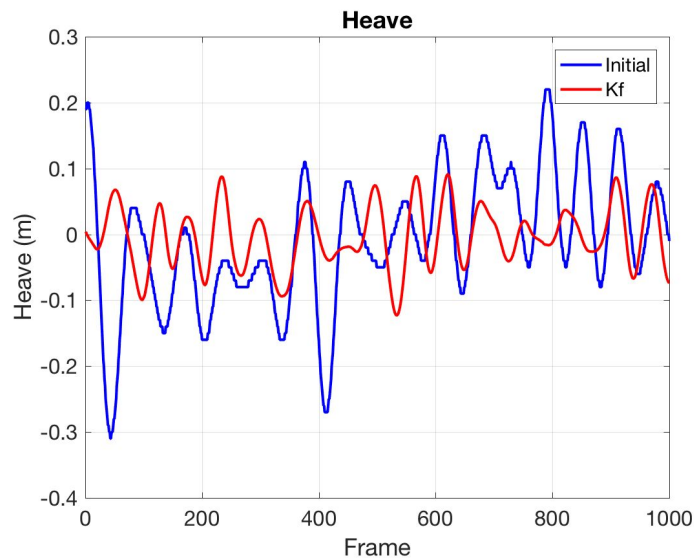


Plane distance vector (in world  
reference frame) as computed by  
the KC



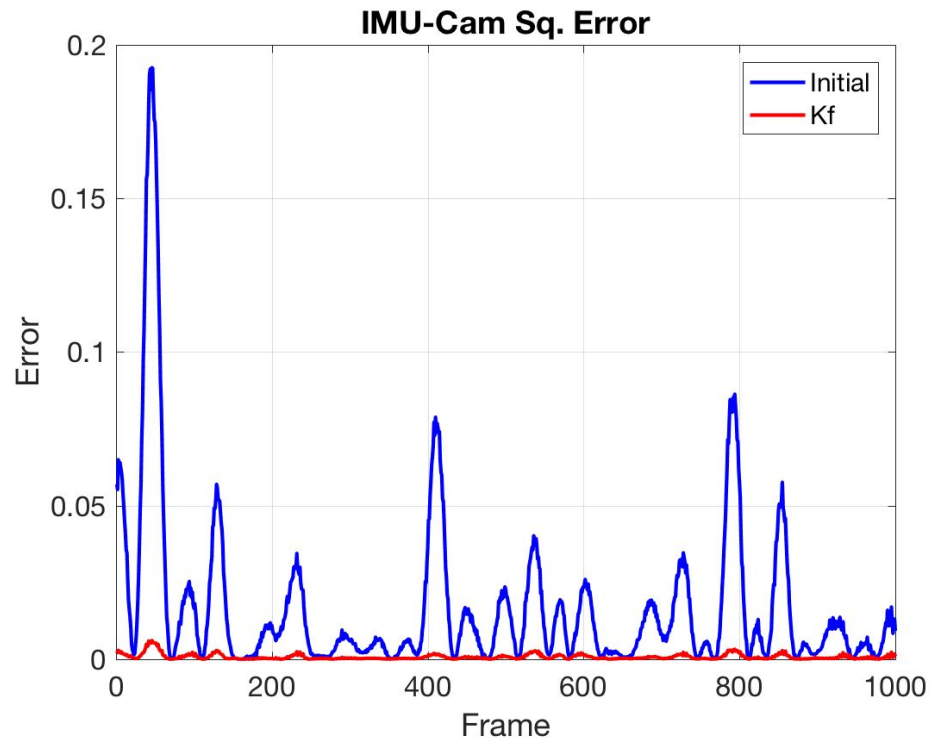
# Motion estimation performance

Effect of the kalman smoother on a real dataset. Plane distance vector covariance was set to 10 cm, IMU measurements was set to the standard error reported in the manual



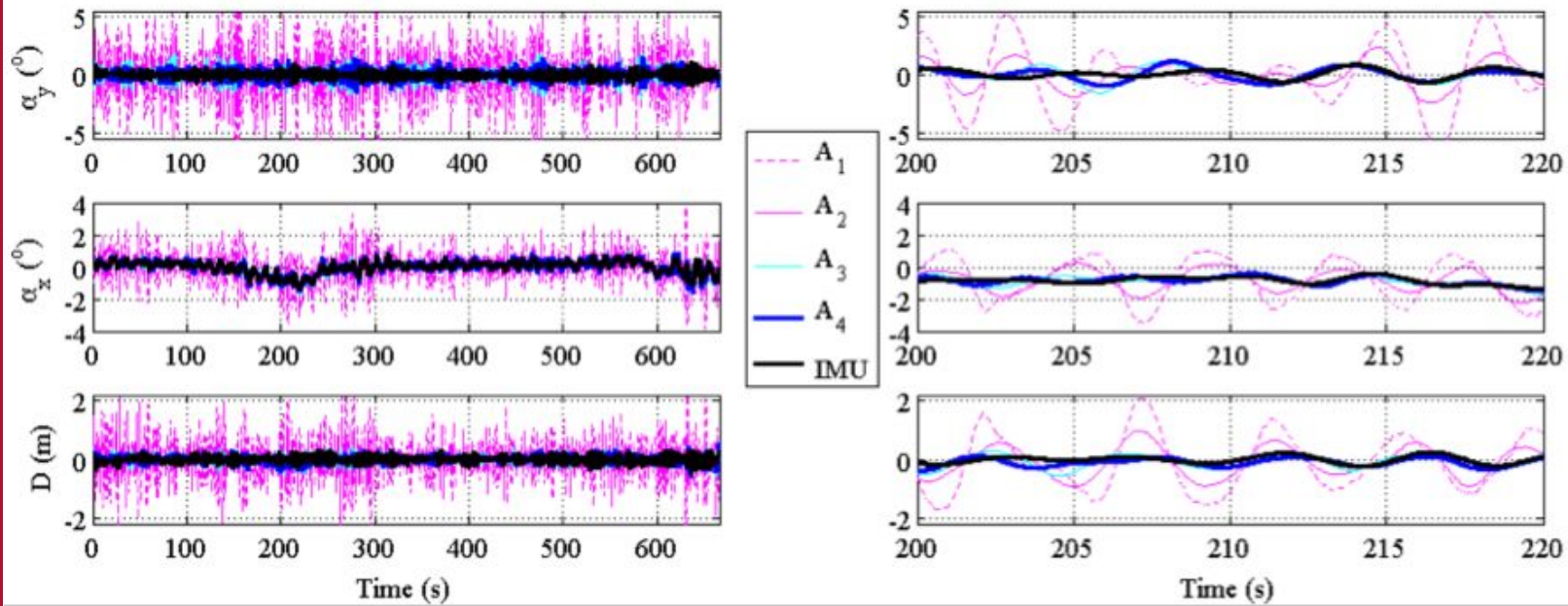
# Motion estimation performance

Effect of the kalman smoother on a real dataset. Plane distance vector covariance was set to 10 cm, IMU measurements was set to the standard error reported in the manual



# Motion estimation performance

Final sea surface alignment performance on a real dataset with different reconstructed area sizes (ie. different number of waves simultaneously observed in the scene)





# Conclusions

- Sea-waves 3D reconstruction from a moving platform must rely to external positioning sensors to provide a good surface alignment
- We proposed an effective method to:
  - Calibrate the relative position between the IMU and the stereo rig
  - Filter the inaccurate 3D-based plane fitting with the IMU data to improve the alignment



# Future research directions

- Coupling WASS with a RADAR based reconstruction system
- Real-time 3D reconstruction to collect extreme wave events statistics
- Multi-view reconstruction of a single wave crest over time



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**Thank you and Merry Christmas**

