

Geodetic Research and Technical Development Projects on BIM 4.0 and Agriculture 4.0 in the HKA Laboratory on GNSS and Navigation

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<http://goca.info/Labor.GNSS.und.Navigation/index.php>

RaD

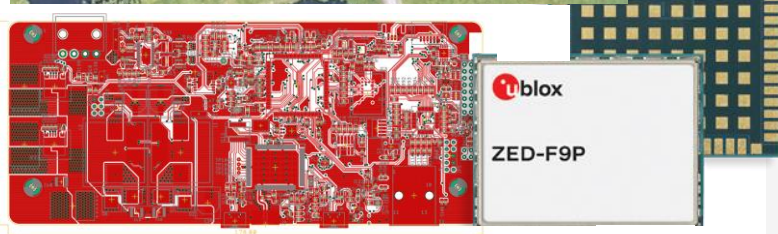
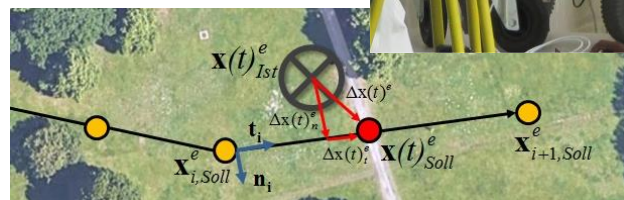
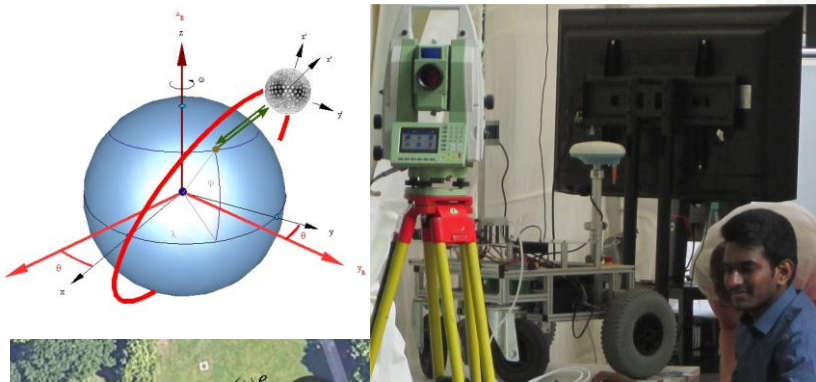
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University of
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HKA

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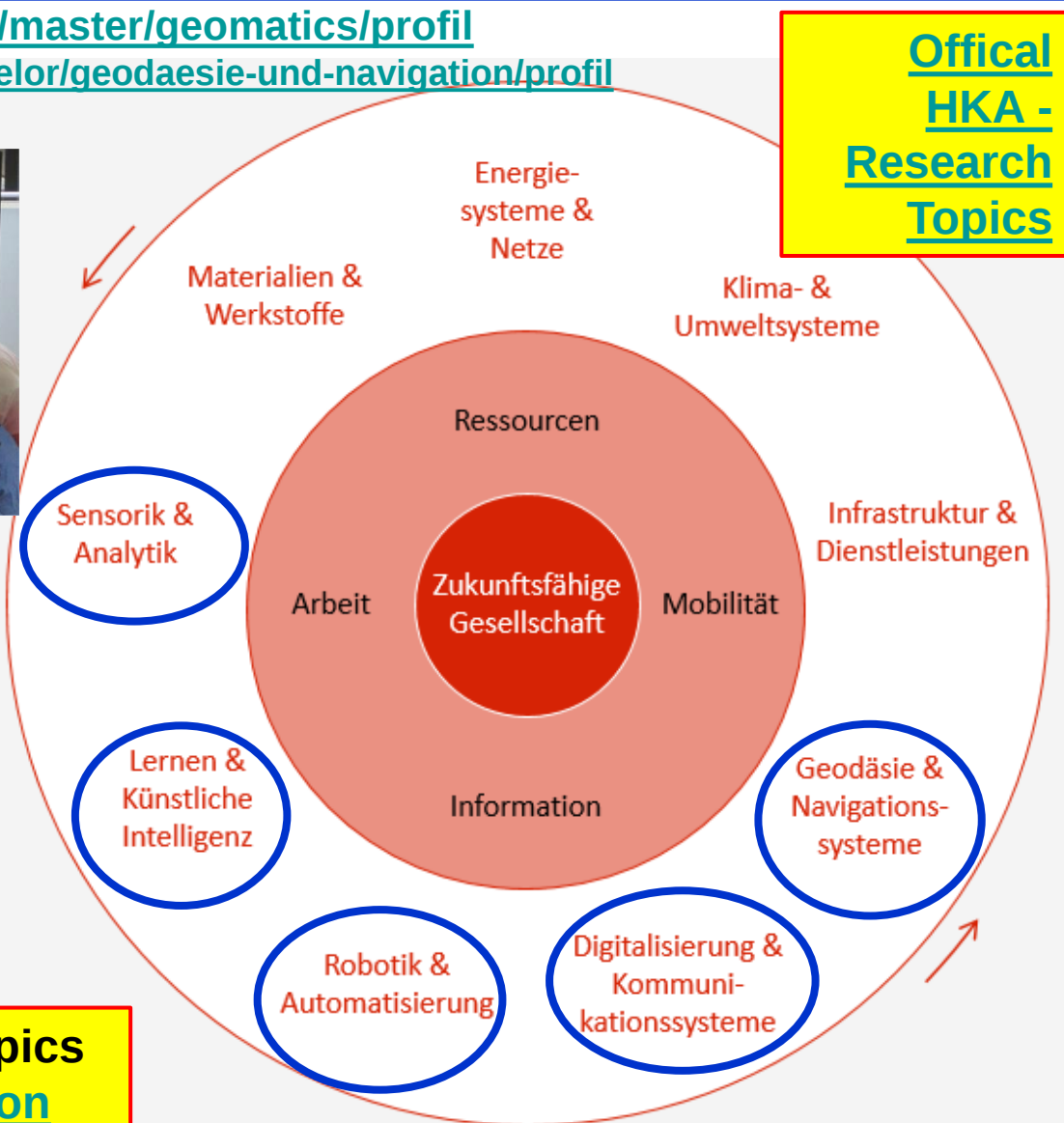


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Sensor Systems Technology

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Study Programs and Research Topics
Laboratory on GNSS and Navigation



GNSS PPP & DGNSS Positioning Algorithms



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Task force raw measurements members

HKA Redesigned Ambiguity Function Method (RAF)

Phase

Observation Equations

$$\lambda_R^{i,t} = \left(\sqrt{(x_s - x)^2 + (y_s - y)^2 + (z_s - z)^2} \right)^t - (N^i \cdot \lambda + D^{i,t} \cdot \lambda)$$

$$\underbrace{\frac{\lambda_R^{i,t}}{\lambda} - \frac{1}{\lambda} \cdot \left(\sqrt{(x_s - x)^2 + (y_s - y)^2 + (z_s - z)^2} \right)^t}_{x^i} = \underbrace{-(N^i + D^{i,t})}_{y^i}$$

Euler-Theorem: $e^{iz} = \cos z + i \cdot \sin z$

$$\sum_1^{n \cdot m} \left| e^{i \cdot (2\pi \cdot x^i)} \right| = \sum_1^{n \cdot m} \left| e^{i \cdot 2\pi \cdot \left(\frac{\lambda_R^{i,t}}{\lambda} - \frac{1}{\lambda} \cdot \left(\sqrt{(x_s - x)^2 + (y_s - y)^2 + (z_s - z)^2} \right)^t \right)} \right| = n \cdot m$$

Classical Ambiguity Function Method

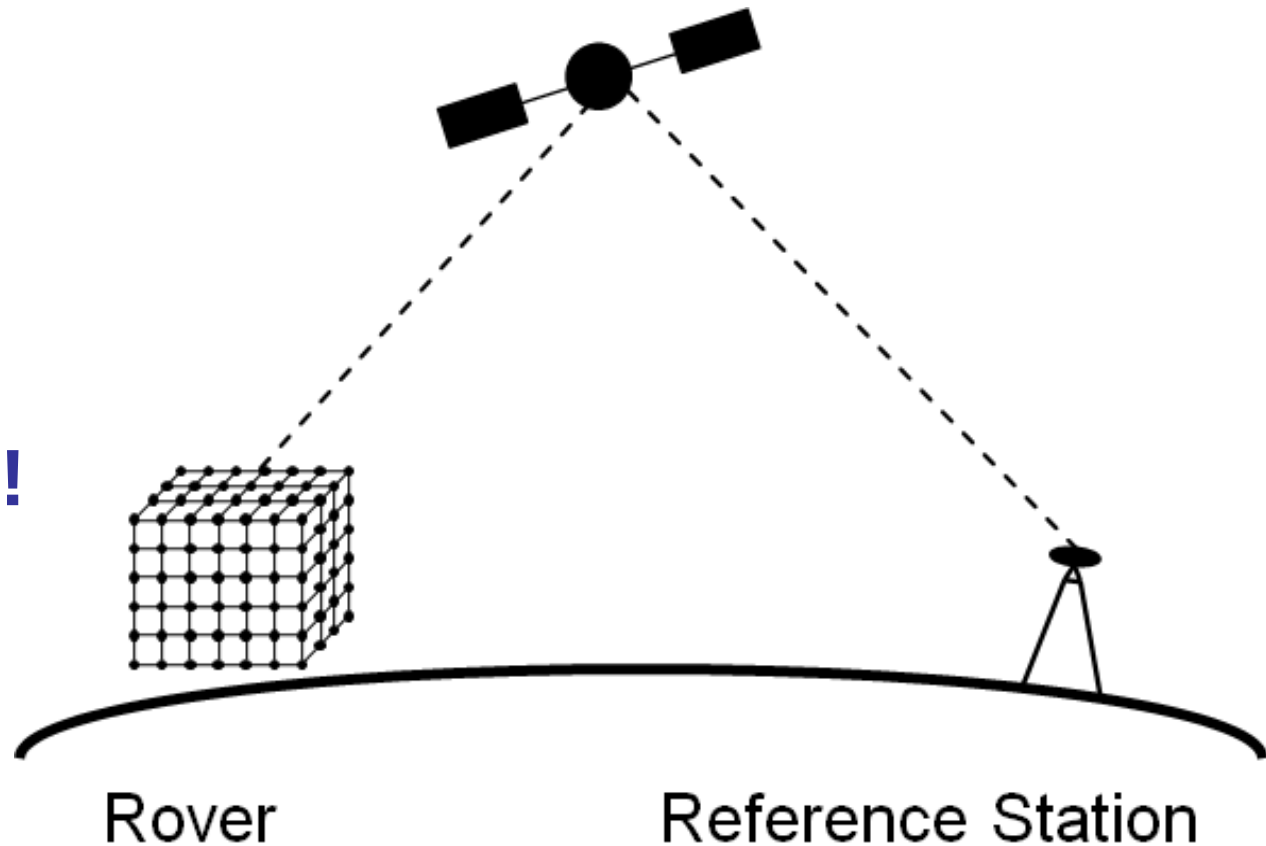
$$\sum_1^{n \cdot m} \left| e^{i \cdot 2\pi \cdot \left(\frac{\lambda_R^{i,t}}{\lambda} - \frac{1}{\lambda} \cdot \left(\sqrt{(x_s - x)^2 + (y_s - y)^2 + (z_s - z)^2} \right)^t \right)} \right| - n \cdot m = 0$$

DGNSS

PPP

3D Grid Search

Postprocessing!



HKA Redesigned Ambiguity Function Method (RAF)

Code Observation Equations

$$\rho(t_i)_{\text{Obs}} = \left| \tilde{\mathbf{x}}_R(t_i) - \tilde{\mathbf{x}}_S(t_i - \frac{\tilde{\rho}_i^j(t_i)}{c}, \mathbf{o}^j) \right| + c \cdot \Delta \bar{t}_{R,i} - c \cdot \Delta \bar{t}_{S,j} + \Delta \rho_{i,\text{ION}}^j + \Delta \rho_{i,\text{TROP}}^j$$

Phase Observation Equations

$$\underbrace{\frac{\lambda_R^{i,t}}{\lambda} - \frac{1}{\lambda} \cdot \left(\sqrt{(x_s - x)^2 + (y_s - y)^2 + (z_s - z)^2} \right)^t}_{x^i} = \underbrace{-\left(N^i + D^{i,t}\right)}_{y^i}$$

Euler-Theorem right side

$$z =: 2\pi \cdot y^i \xrightarrow{\text{yields}} \begin{cases} \cos z = \cos(2\pi \cdot y^i) = \cos(-2\pi \cdot (N^i + D^{i,t})) = 1 \\ \sin z = \sin(2\pi \cdot y^i) = \sin(-2\pi \cdot (N^i + D^{i,t})) = 0 \end{cases}$$

HKA Redesigned Ambiguity Function Method (RAF)

Non-linear Phase Observation Equations

$$f_1(\hat{l}_i^t, \hat{\mathbf{x}}) = \cos \left(2\pi \cdot \underbrace{\left(\frac{\lambda_R^{i,t}}{\lambda} - \frac{1}{\lambda} \cdot \left(\sqrt{(x_s - x)^2 + (y_s - y)^2 + (z_s - z)^2} \right)^t \right)}_{x^i} \right) - 1 = 0$$

$$f_2(\hat{l}_i^t, \hat{\mathbf{x}}) = \sin \left(2\pi \cdot \underbrace{\left(\frac{\lambda_R^{i,t}}{\lambda} - \frac{1}{\lambda} \cdot \left(\sqrt{(x_s - x)^2 + (y_s - y)^2 + (z_s - z)^2} \right)^t \right)}_{x^i} \right) = 0$$

Ambiguity-Parameters N are neutralized

Doppler Cycles D and cycle slips ∇D are neutralized

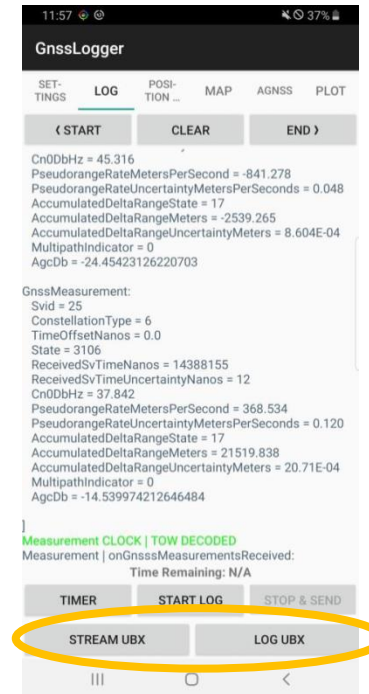
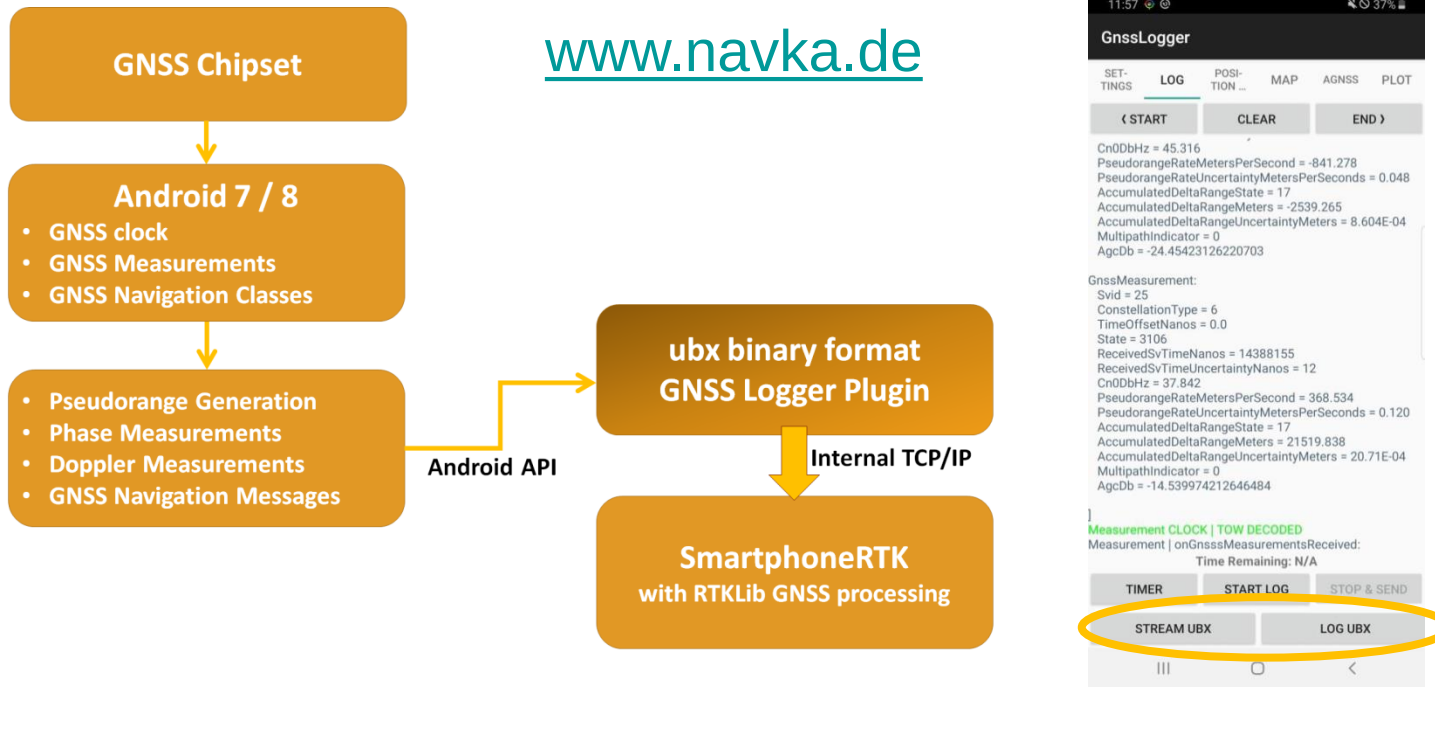
Solution of the overdetermined problem on $\mathbf{x}$ by SIMPLEX-based minimization of absolute sum of weighted residuals (L1-Norm) – Robust estimation

HKA Redesigned Ambiguity Function Method (RAF)

Transition from External GNSS to Internal GNSS

- Same GNSS Algorithms integrated into NAVKA Smartphone RTK developed by NAVKA Team (Karlsruhe University of Appl. Sciences)
- Realtime stream plugin integrated into Google GnsLogger
- Both for prototype and educational purpose

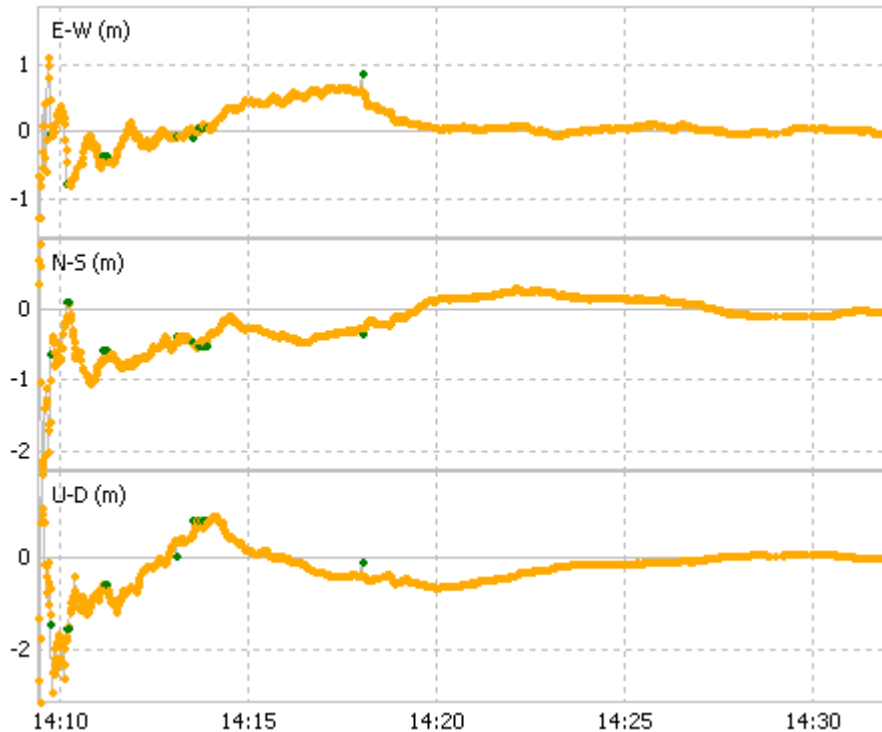
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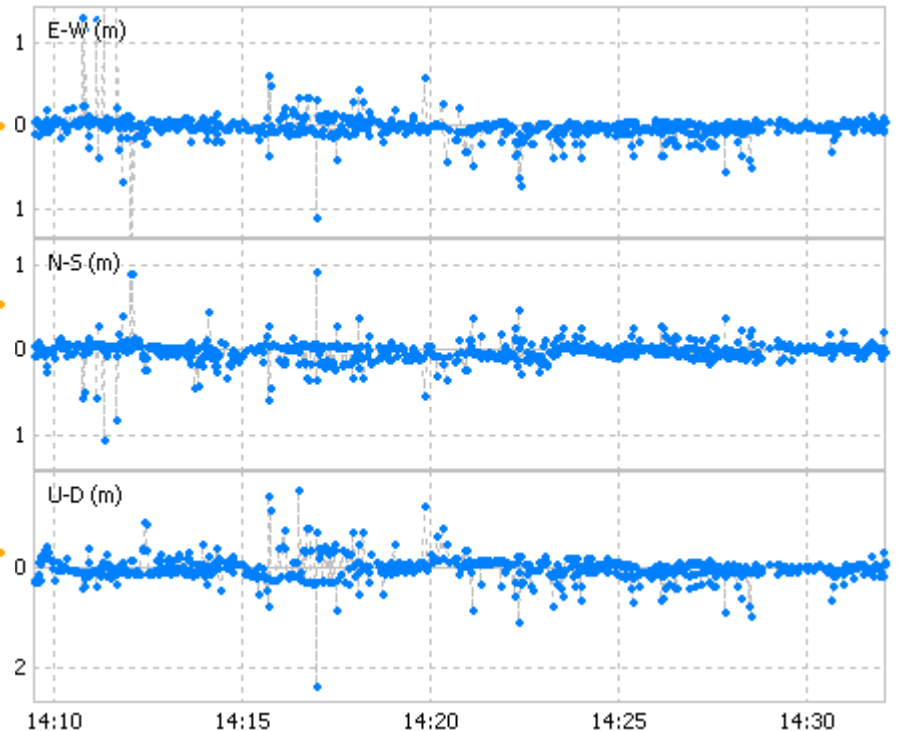
HKA Redesigned Ambiguity Function Method (RAF)

Comparison of Lambda vs. RAF

- RAF by L1-norm stable and „ready for positioning“ from the start. No initial fixing and no ambiguity refixing times in between are wasted.
- RAF noise (right) is non systematic. From the single positions a high precise solution can be computed by a sequential L1-adjustment.



Lambda with KalmanFilter (RTKLIB)



Redesigned Ambiguity Function (RAF)

GNSS/MEMS/Optical Sensors

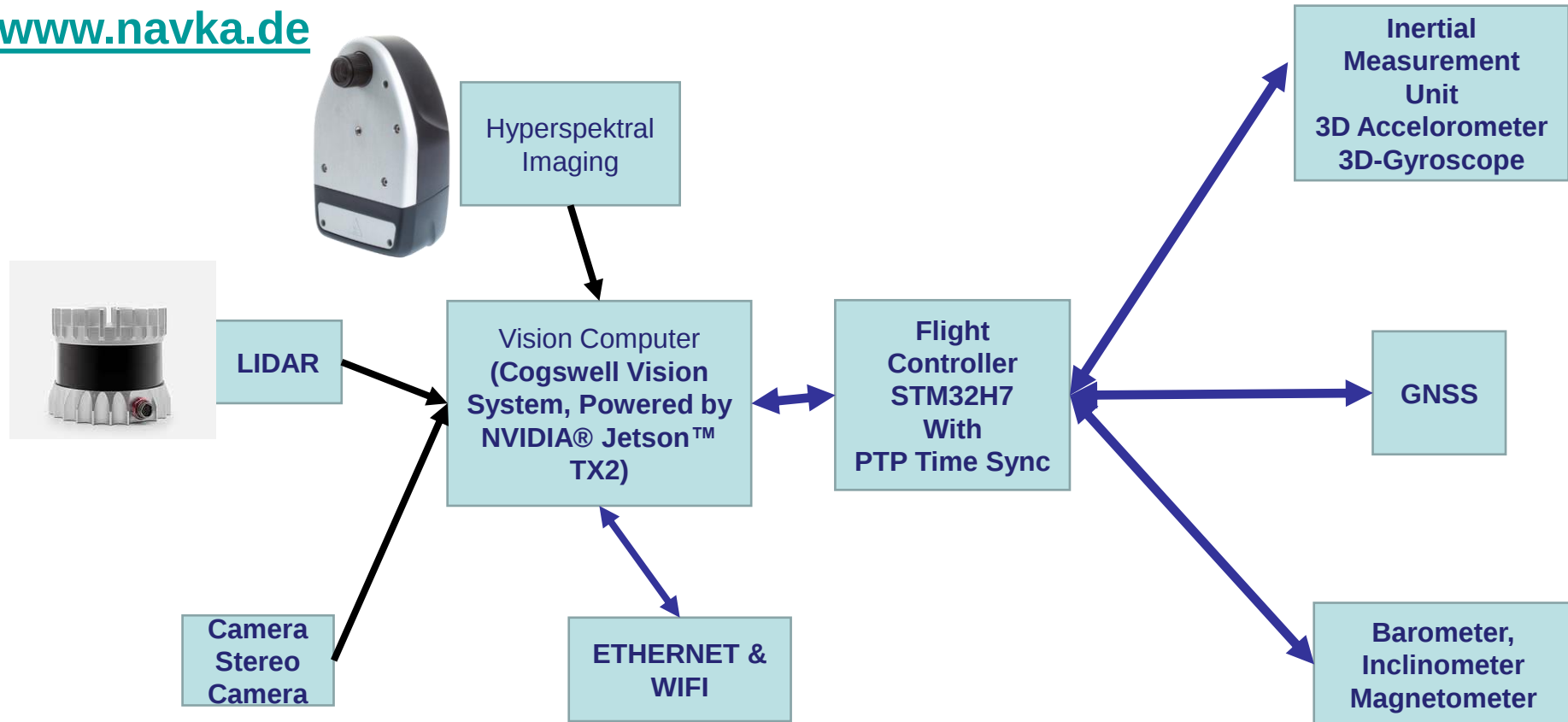
Navigation, SLAM, Georeferencing, Robotics



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$$y(t)' = [y(t), m(t)]$$

$$= \begin{bmatrix} x^e & y^e & z^e & \dot{x}^e & \dot{y}^e & \dot{z}^e & |\ddot{x}^e \ddot{y}^e \ddot{z}^e| & r^e p^e y^e \\ \omega_{eb,x}^b & \omega_{eb,y}^b & \omega_{eb,z}^b & \dot{\omega}_{eb,x}^b & \dot{\omega}_{eb,y}^b & \dot{\omega}_{eb,z}^b & |m(t)| \end{bmatrix}$$

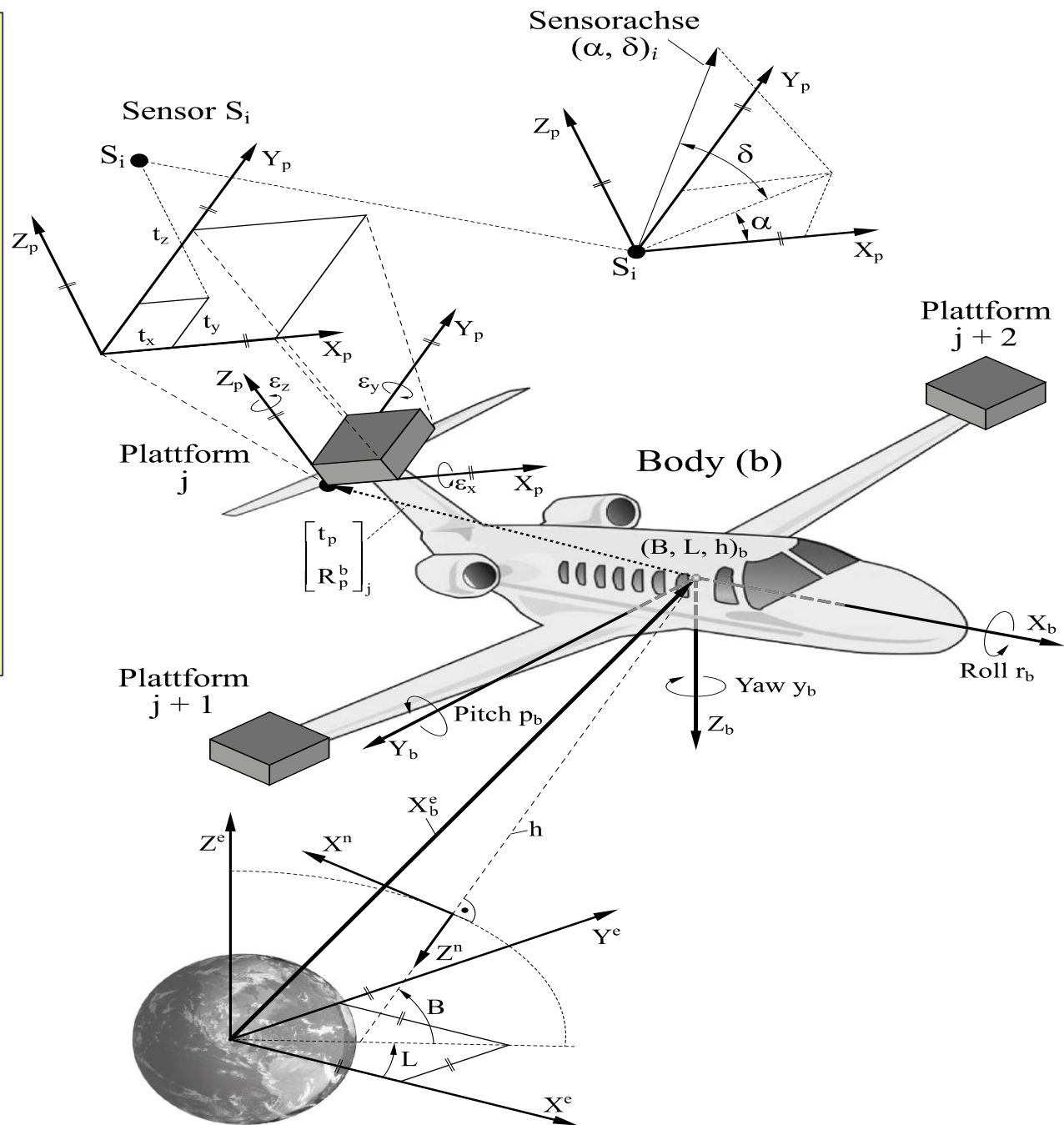


Navigation and SLAM with distributed GNSS/MEMS/Optical Sensors: Sensor leverarm parameter array $sl(i,j)$.
 Leverarm Index i for 5 leverarm parameters of sensor i on platform j .
 Index j for 6 leverarm parameters platform i on body(b)

$$(\alpha, \delta)_{s_{ij}}$$

$$\mathbf{x}_{s_{ij}}^e = \mathbf{x}_b^e + \mathbf{R}_b^e(r, p, y) \cdot [\mathbf{t}_{p_j}^b + \mathbf{R}_{p_j}^b \cdot \mathbf{t}_{s_{ij}}^{p_j}]$$

$$l(i,j)_t = l(\mathbf{y}_t, \mathbf{sl}(i,j))_t$$



Navigation and SLAM with distributed GNSS/MEMS/Optical Sensors

Formal description

Target of Multisensory Navigation & Georeferencing Systems: State Estimation

$$\mathbf{y}_t = (x^e y^e z^e | \dot{x}^e \dot{y}^e \dot{z}^e | \ddot{x}^e \ddot{y}^e \ddot{z}^e | r^e p^e y^e | \omega_{eb,x}^b \omega_{eb,y}^b \omega_{eb,z}^b | \dot{\omega}_{eb,x}^b \dot{\omega}_{eb,y}^b \dot{\omega}_{eb,z}^b)^T$$

Start: Event Chain or Markov Chain

$$\mathbf{e}_{0:t} = (\mathbf{l}_0, \mathbf{l}_1, \dots, \mathbf{l}_{t-1}, \mathbf{l}_t, \mathbf{u}_0, \mathbf{u}_1, \dots, \mathbf{u}_{t-1}, \mathbf{u}_t) = (\mathbf{l}_{0:t}, \mathbf{u}_{0:t})$$

Hypothesis: Present State as result of Markov Chain and starting state $\mathbf{y}_0$

$$\mathbf{y}_t = \mathbf{y}_t(\mathbf{e}_{0:t}, \mathbf{y}_0) = \mathbf{y}_t(\mathbf{l}_{0:t}, \mathbf{u}_{0:t}, \mathbf{y}_0) = \mathbf{y}_t(\mathbf{l}_0, \mathbf{l}_1, \dots, \mathbf{l}_{t-1}, \mathbf{l}_t, \mathbf{u}_0, \mathbf{u}_1, \dots, \mathbf{u}_{t-1}, \mathbf{u}_t, \mathbf{y}_0)$$

Now: Turning to Stochastic Process and Conditioned Probability Densities

$$\text{bel}(\mathbf{y}_t) = p(\mathbf{y}_t | \mathbf{y}_0, \mathbf{l}_{0:t}, \mathbf{u}_{0:t}) = p(\mathbf{y}_t | \mathbf{y}_0, \mathbf{l}_{0:t-1}, \mathbf{l}_t, \mathbf{u}_{0:t})$$

Now: Inversion of the Problem by Bayes Theorem to exploit information

$$\text{bel}(\mathbf{y}_t) = p(\mathbf{l}_t | \mathbf{y}_t, \mathbf{y}_0, \mathbf{l}_{0:t-1}, \mathbf{u}_{0:t}) \cdot \frac{p(\mathbf{y}_t | \mathbf{y}_0, \mathbf{l}_{0:t-1}, \mathbf{u}_{0:t})}{p(\mathbf{l}_t | \mathbf{y}_0, \mathbf{l}_{0:t-1}, \mathbf{u}_{0:t})}$$

Navigation and SLAM with distributed GNSS/MEMS/Optical Sensors

Formal description

Rewriting Bayes Inversion by abbreviating constant term

$$p(\mathbf{y}_t | \mathbf{y}_0, \mathbf{l}_{0:t}, \mathbf{u}_{0:t}) = \eta \cdot (\mathbf{l}_t | \mathbf{y}_t, \mathbf{sl}(i,j)) \cdot p(\mathbf{y}_t | \mathbf{y}_0, \mathbf{l}_{0:t-1}, \mathbf{u}_{0:t})$$

1. Markov-Assumption

Chapman-Kolmogorov-Equation to integrate previous state $\mathbf{y}_{t-1}$

$$p(\mathbf{y}_t | \mathbf{y}_0, \mathbf{l}_{0:t-1}, \mathbf{u}_{0:t}) = \int p(\mathbf{y}_t | \mathbf{y}_0, \mathbf{l}_{0:t-1}, \mathbf{u}_{0:t}, \mathbf{y}_{t-1}) \cdot p(\mathbf{y}_{t-1} | \mathbf{y}_0, \mathbf{l}_{0:t-1}, \mathbf{u}_{0:t}) \cdot d\mathbf{y}_{t-1}$$

Prediction or State
Transition Equation

2. Markov-Assumption

$$p(\mathbf{y}_t | \mathbf{y}_{t-1}, \mathbf{u}_t)$$

Preceding Estimation
Prior Information

$$p(\mathbf{y}_{t-1} | \mathbf{y}_0, \mathbf{l}_{0:t-1}, \mathbf{u}_{0:t}) = \bar{p}(\mathbf{y}_{t-1}) = \text{bel}(\mathbf{y}_{t-1})$$

Final Bayes and Chapman-Kolmogorov-Equation based State Estimation

$$\underbrace{p(\mathbf{y}_t | \mathbf{y}_0, \mathbf{l}_{0:t}, \mathbf{u}_{0:t})}_{\text{bel}(\mathbf{y}_t)} = \eta \cdot \underbrace{p(\mathbf{l}_t(\mathbf{sl}(i,j)) | \mathbf{y}_t)}_{\text{Gau\ss-Markov-Model of Sensor observations}} \cdot \underbrace{\int_{-\infty}^{+\infty} p(\mathbf{y}_t | \mathbf{y}_{t-1}, \mathbf{u}_t) \cdot \underbrace{\bar{p}(\mathbf{y}_{t-1})}_{\text{bel}(\mathbf{y}_{t-1})} \cdot d\mathbf{y}_{t-1}}_{\overline{\text{bel}}(\mathbf{y}_t)}$$

Navigation and SLAM with distributed GNSS/MEMS/Optical Sensors

Formal description

Final Bayes and Chapman-Kolmogorov based State Estimation

Particle Filter

$$bel(\mathbf{y}_{t-1}) = \sum_{i=1}^N w_{t-1}^i \cdot \delta(\tilde{\mathbf{y}}_{t-1} - \mathbf{y}_{t-1}^i) \text{ with } \sum_{i=1}^N w_{t-1}^i = 1$$

Any Distribution

Prediction Equation

$$\underbrace{p(\mathbf{y}_t | \mathbf{y}_0, \mathbf{l}_{0:t}, \mathbf{u}_{0:t})}_{bel(\mathbf{y}_t)} = \eta \cdot \underbrace{p(\mathbf{l}_t(\mathbf{sl}(i, j)) | \mathbf{y}_t)}_{\text{Gau\ss-Markov-Model of Sensor observations}} \cdot \underbrace{\int_{-\infty}^{+\infty} p(\mathbf{y}_t | \mathbf{y}_{t-1}, \mathbf{u}_t) \cdot \underbrace{\bar{p}(\mathbf{y}_{t-1})}_{bel(\mathbf{y}_{t-1})} \cdot d\mathbf{y}_{t-1}}_{\bar{bel}(\mathbf{y}_t)}$$

Exponential Distributions, e.g. Gau\ss, Laplace

Exponential Distributions Gau\ss, Laplace

M-Estimation Type

- LS Kalman Filter
- Robust L1 KF
- L1 SIMPLEX

$$\bar{bel}(\mathbf{y}_t) = \exp(\mathbf{y}(t)_{t-1}, \mathbf{C}_{\mathbf{y}(t)_{t-1}})$$

$$\hat{\mathbf{y}}_{t_M} = \underbrace{\operatorname{argmax}\{p(\mathbf{l}_t(\mathbf{sl}(i, j)) | \mathbf{y}_t) \cdot \bar{bel}(\mathbf{y}_t)\}}_{bel(\mathbf{y}_t)}$$

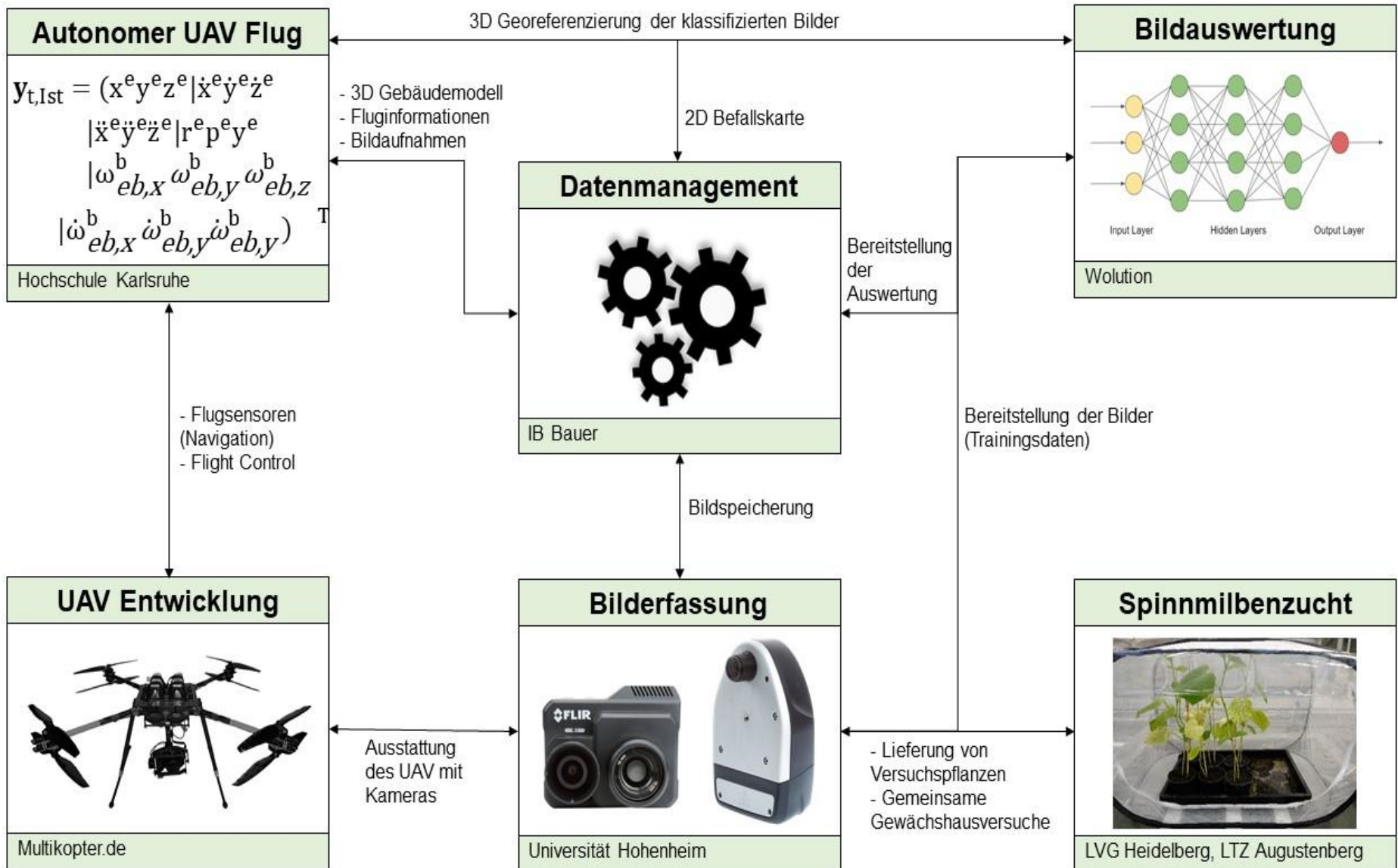
Product again exponentially distributed

Agriculture 4.0 / Horticulture 4.0

UAS for Mites-Detection, Navigation, Flight Control Autonomous UAS-Flight in Buildings, BIM Model



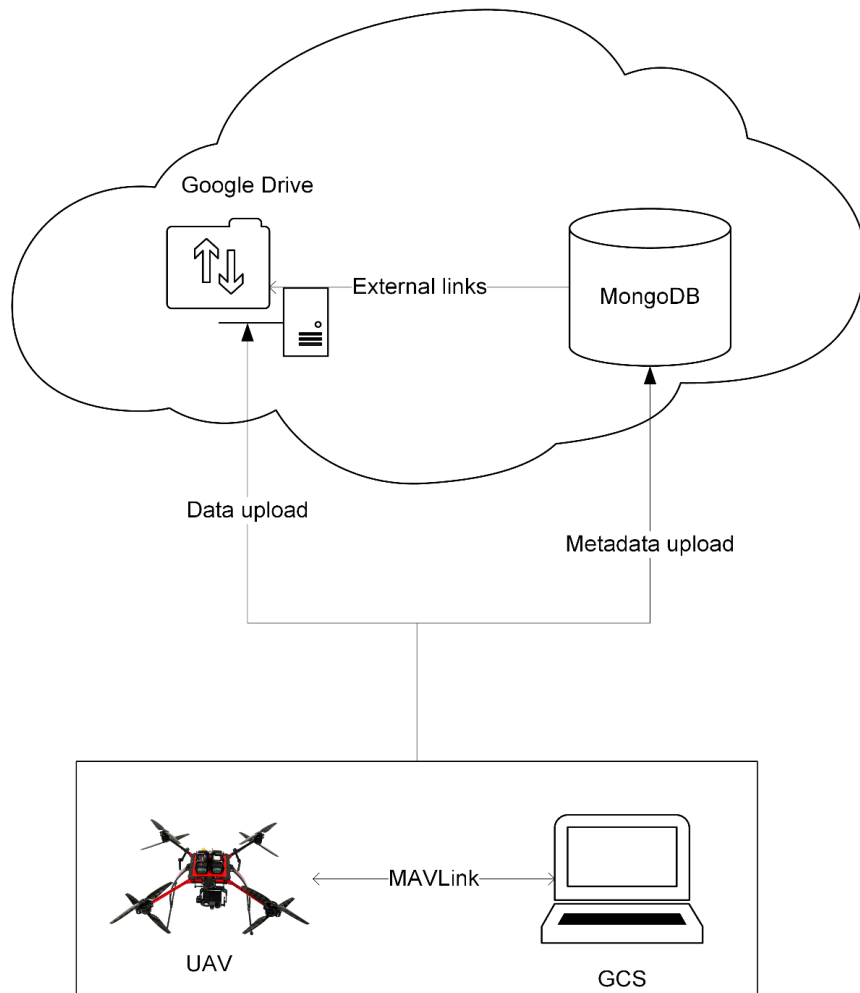
MITESENS - RaD Concept & Components - Consortium



MITESENS - RaD Concept & Components HKA

$$\mathbf{y}(t)' = [\mathbf{y}(t), \mathbf{m}(t)] = \left[\begin{array}{c} x^e \ y^e \ z^e | \dot{x}^e \ \dot{y}^e \ \dot{z}^e \ | \ddot{x}^e \ \ddot{y}^e \ \ddot{z}^e | r^e p^e y^e | \\ \omega_{eb,x}^b \ \omega_{eb,y}^b \ \omega_{eb,z}^b | \dot{\omega}_{eb,x}^b \ \dot{\omega}_{eb,y}^b \ \dot{\omega}_{eb,z}^b | \mathbf{m}(t) \end{array} \right]$$

Basicdata: Navigation-Statevector $\mathbf{y}(t)$ of UAS and unique Time Stamp t



Cloud level processes:

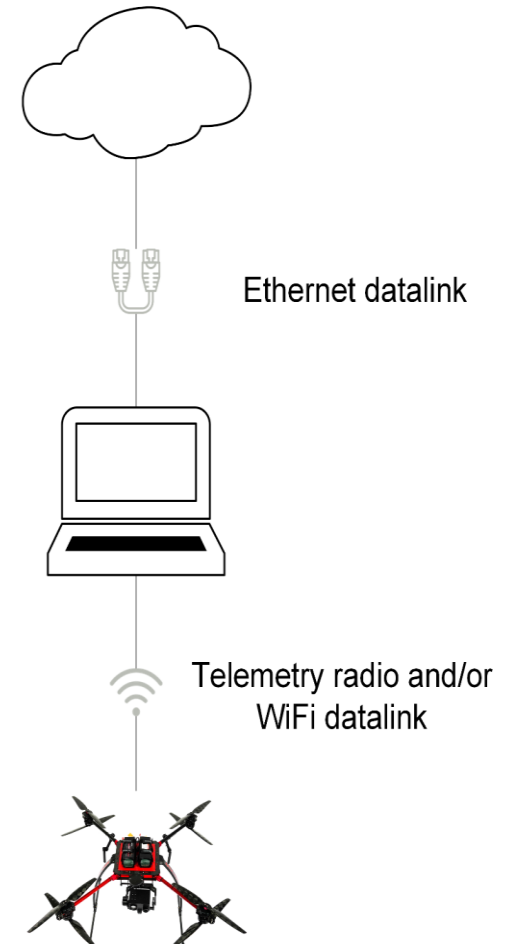
Storage, machine learning (training), photogrammetry (CloudODM)

Desktop level processes:

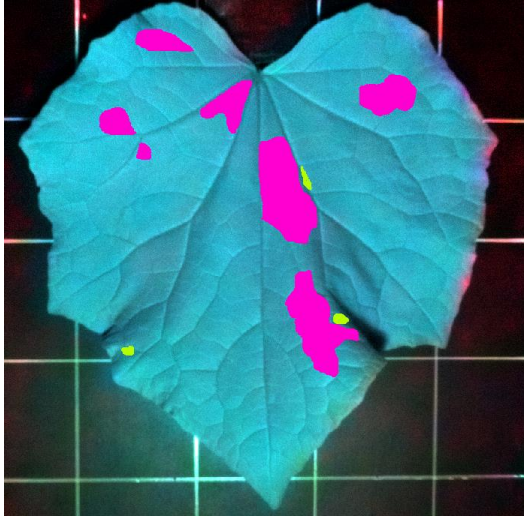
Photogrammetry, navigation/SLAM post-processing, visualization, flight planning

Embedded level processes:

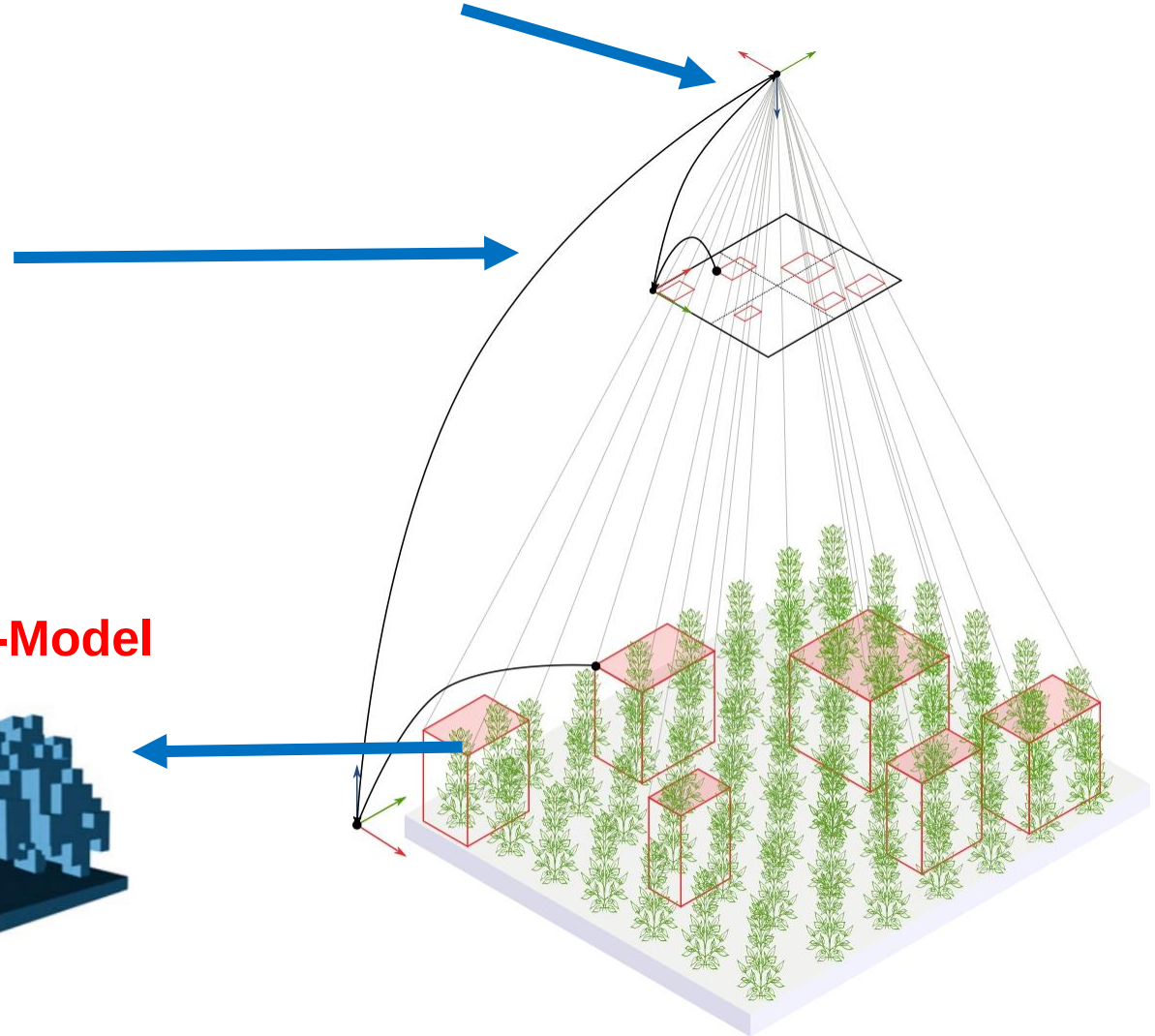
Flight control, state estimation, obstacle avoidance, SLAM and synchronized data capture



$$\mathbf{y}(t)' = [\mathbf{y}(t), \mathbf{m}(t)] = \begin{bmatrix} x^e & y^e & z^e & \dot{x}^e & \dot{y}^e & \dot{z}^e & \ddot{x}^e & \ddot{y}^e & \ddot{z}^e & r^e & p^e & y^e \\ \omega_{eb,x}^b & \omega_{eb,y}^b & \omega_{eb,z}^b & \dot{\omega}_{eb,x}^b & \dot{\omega}_{eb,y}^b & \dot{\omega}_{eb,z}^b & \mathbf{m}(t) \end{bmatrix}$$



ETRF89/ITRF 3D Voxel-Model



Georeferencing of Point Clouds

Algorithm for direct georeferencing of Pointclouds Navigation State Vector

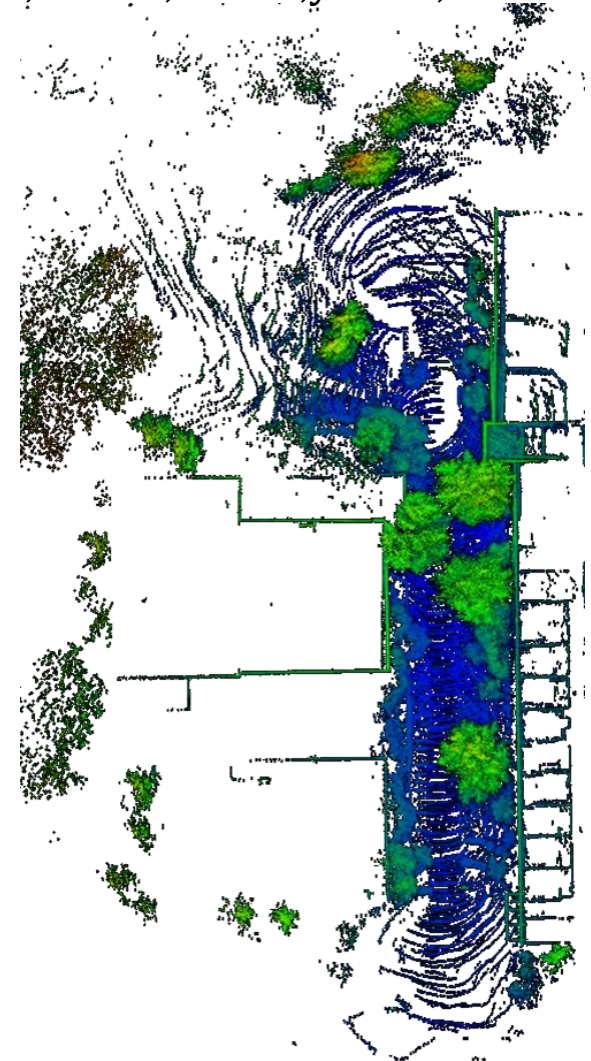
$$\mathbf{y}(t) = (\mathbf{x}^e \mathbf{y}^e \mathbf{z}^e | \dot{\mathbf{x}}^e \dot{\mathbf{y}}^e \dot{\mathbf{z}}^e | \ddot{\mathbf{x}}^e \ddot{\mathbf{y}}^e \ddot{\mathbf{z}}^e | \mathbf{r}^e \mathbf{p}^e \mathbf{y}^e | \omega_{eb,x}^b \omega_{eb,y}^b \omega_{eb,z}^b | \dot{\omega}_{eb,x}^b \dot{\omega}_{eb,y}^b \dot{\omega}_{eb,z}^b)^T$$

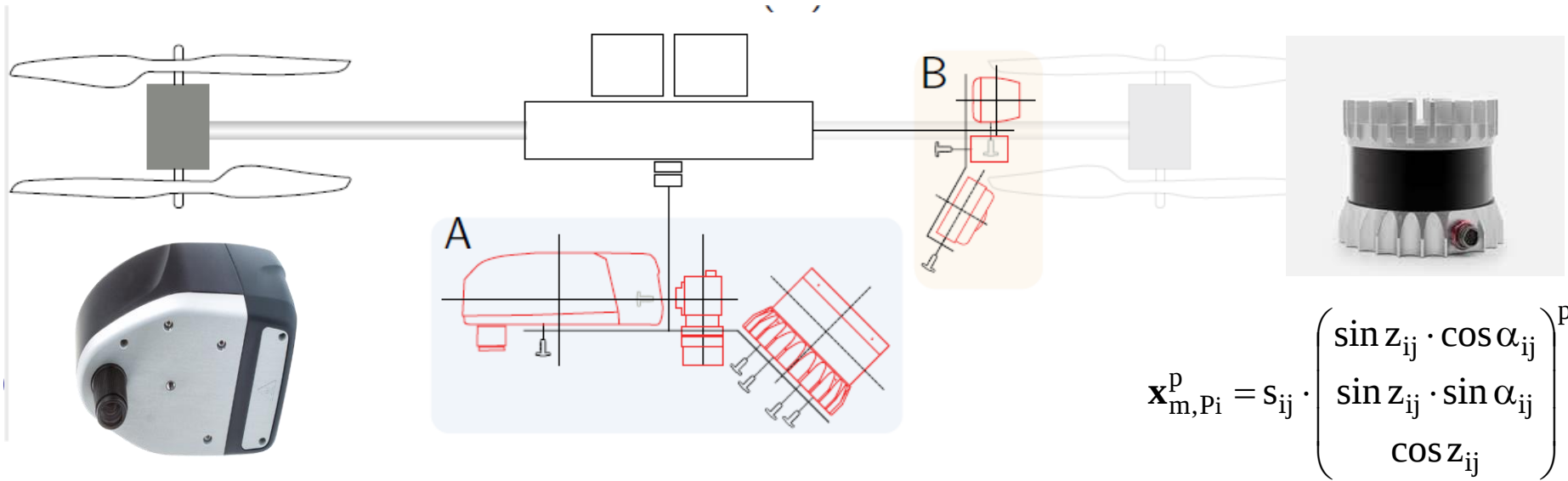
Algorithm 1: Non-rigid direct-georeferencing

input : $\mathbf{r}^s, \mathbf{R}_s^b, \mathbf{l}^b$,
 $\mathcal{T}(\mathbf{t}_i, \mathbf{P}_{gps}^l, \mathbf{R}_b^l)$

output: $\mathbf{P}_G^l$

```
1 forall  $\mathbf{r}_i^s \in \mathbf{r}^s$  do
2   /* Boresight and lever-arm correction
3    $\mathbf{r}_i^b = \mathbf{R}_s^b \mathbf{r}_i^s + \mathbf{l}^b$ ;
4   /* Interpolate pose at  $\mathbf{t}_i$  from INS trajectory
5    $\xi_{b_i}^l = \text{Interpolate}(\mathcal{T}, \mathbf{t}_i)$ ;
6    $\{\mathbf{R}_b^l, \mathbf{P}_{gps}^l\} \leftarrow \xi_{b_i}^l$ 
7   /* Apply transformation
8    $\mathbf{P}_{G_i}^l = \mathbf{R}_b^l \mathbf{r}_i^b + \mathbf{P}_{gps}^l$ ;
9 end
10 return  $\mathbf{P}_G^l$ 
```





Georeferencing Equation

$$\mathbf{y}(t) = \begin{bmatrix} x^e & y^e & z^e & \dot{x}^e & \dot{y}^e & \dot{z}^e & \ddot{x}^e & \ddot{y}^e & \ddot{z}^e & r^e & p^e & y^e \\ \omega_{eb,x}^b & \omega_{eb,y}^b & \omega_{eb,z}^b & \dot{\omega}_{eb,x}^b & \dot{\omega}_{eb,y}^b & \dot{\omega}_{eb,z}^b \end{bmatrix}$$

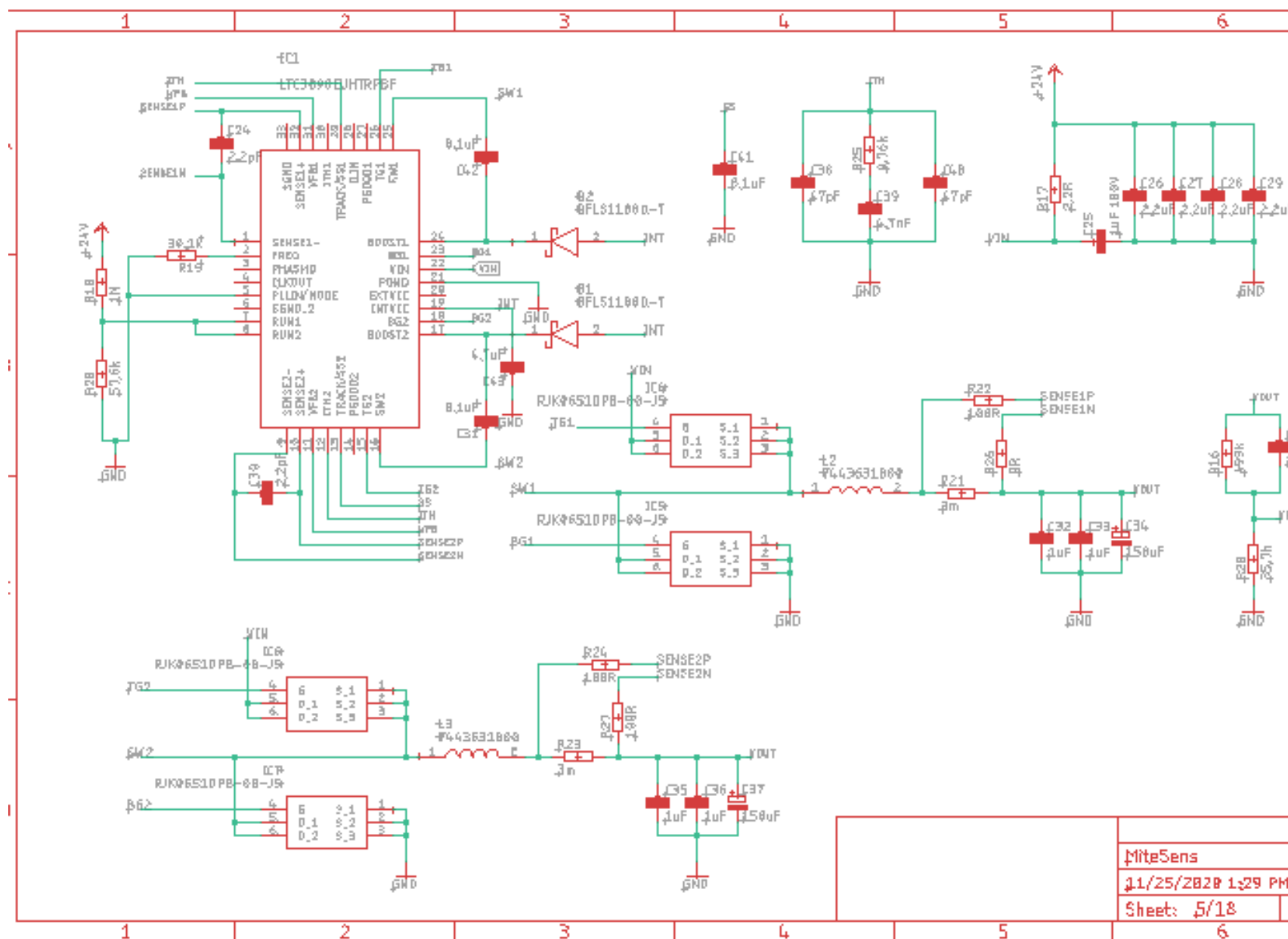
$$\mathbf{x}_{m, Pi}^e = \mathbf{x}_b^e + \mathbf{R}_b^e(r, p, y) \cdot (\mathbf{t}_p^b + \mathbf{R}_p^b \cdot \mathbf{x}_{m, Pi}^p)$$

SLAM Observation Equation

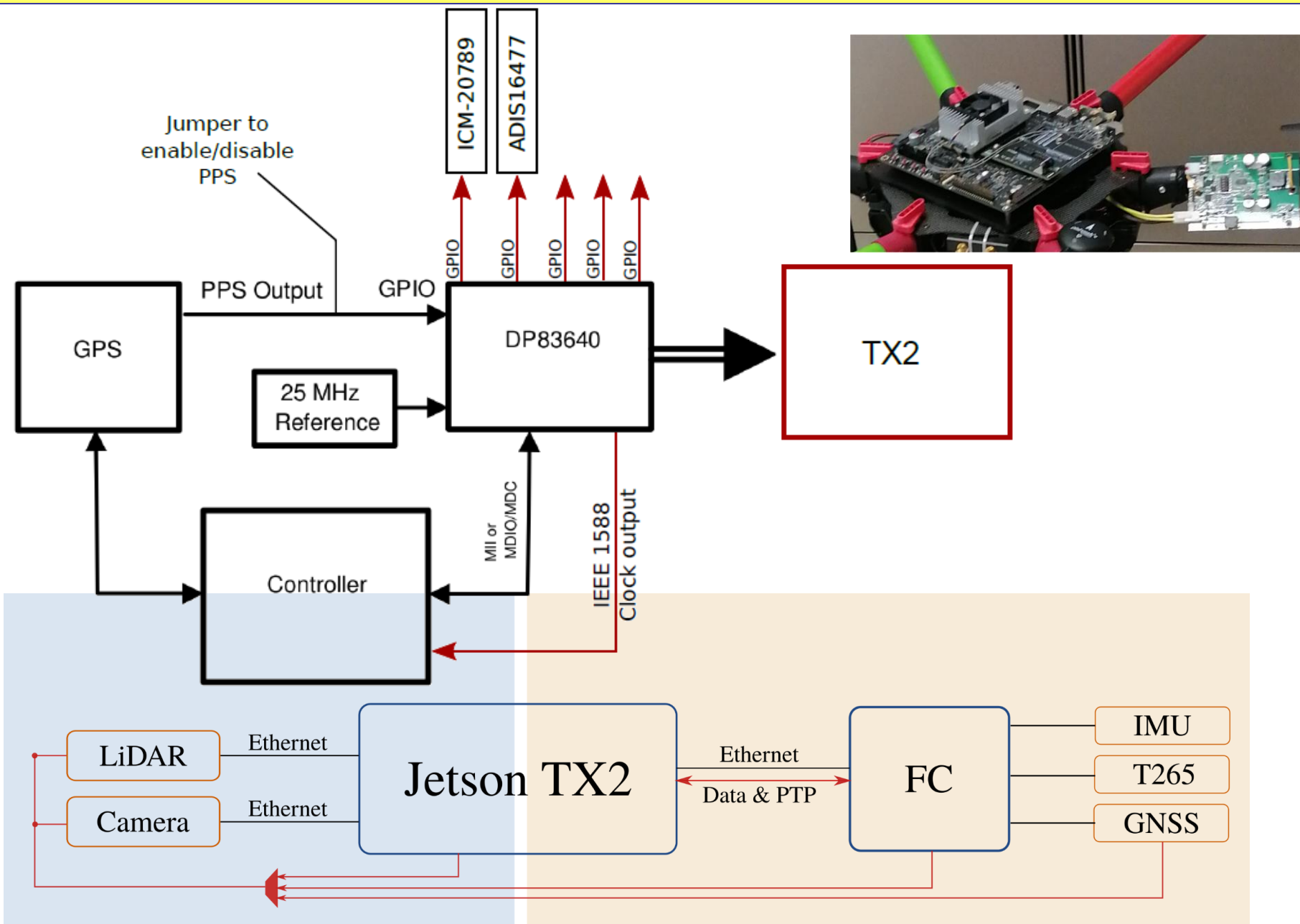
$$\mathbf{x}_{m, Pi}^p = \mathbf{R}_p^{bT} \cdot [\mathbf{R}_b^e(r, p, y)^T \cdot (\mathbf{x}_{m, Pi}^e - \mathbf{x}_b^e) - \mathbf{t}_p^b]$$

$$\mathbf{y}(t)' = [\mathbf{y}(t), \mathbf{m}(t)] = \begin{bmatrix} x^e & y^e & z^e & \dot{x}^e & \dot{y}^e & \dot{z}^e & \ddot{x}^e & \ddot{y}^e & \ddot{z}^e & r^e & p^e & y^e \\ \omega_{eb,x}^b & \omega_{eb,y}^b & \omega_{eb,z}^b & \dot{\omega}_{eb,x}^b & \dot{\omega}_{eb,y}^b & \dot{\omega}_{eb,z}^b & \mathbf{m}(t) \end{bmatrix}$$

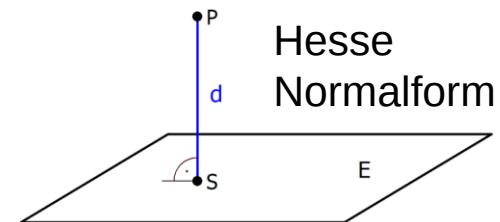
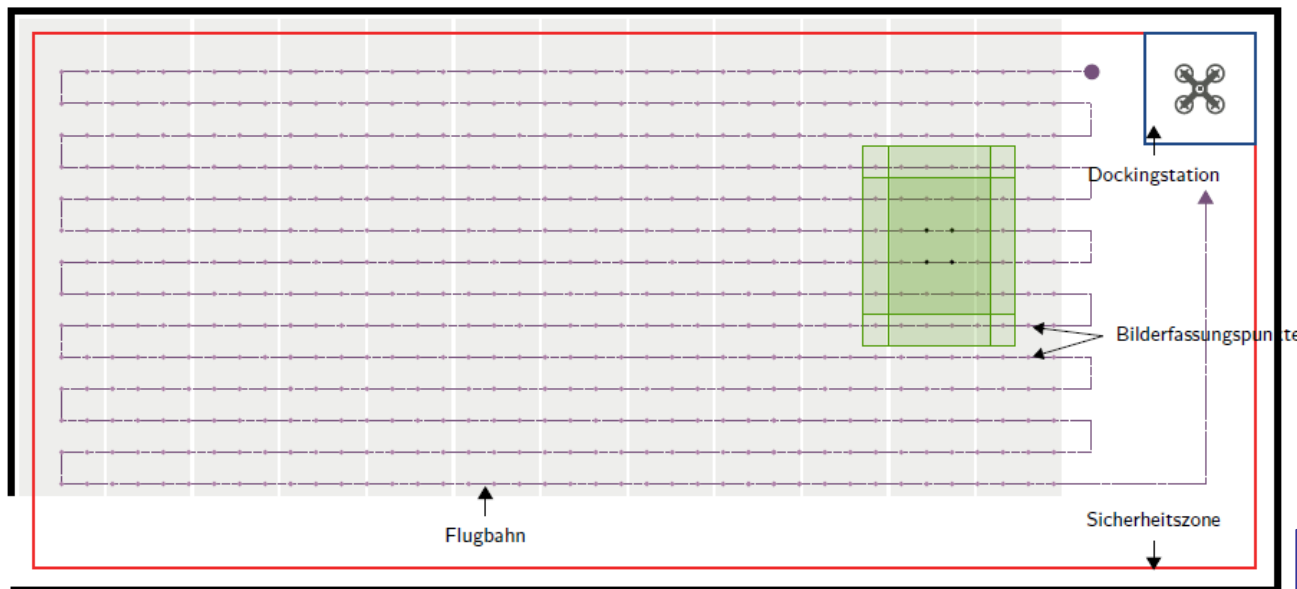
MITESENS – Flight Control Hardware Development



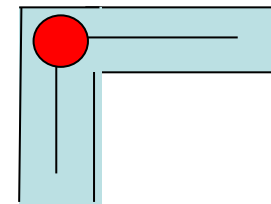
MITESENS – Flight Control Hardware Development



MITESENS – Flight Control for Autonomous Indoor UAS Flights

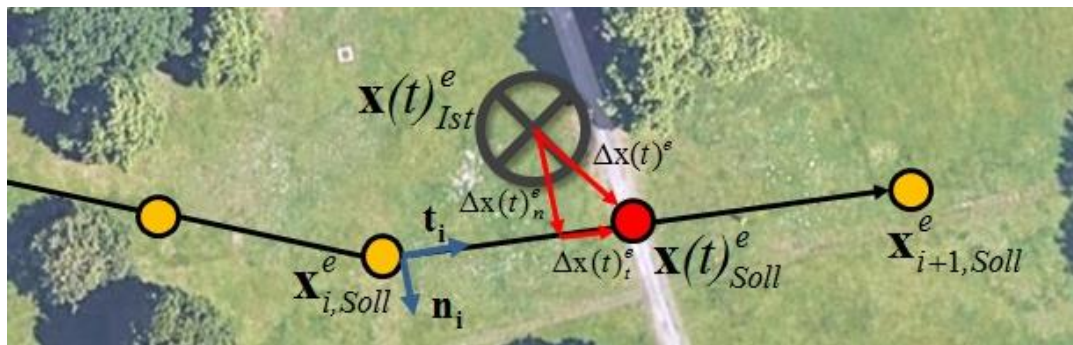


Inequations on position

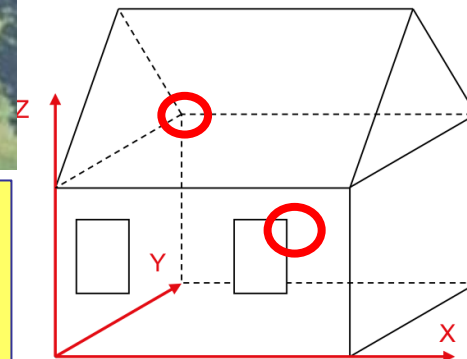


Robust L1-Norm Kalman-filter based on SIMLEX-Algorithm with space-related inequations, e.g. on distances to walls. Using ETRF89/ITRF BIM model

Out-/and indoor UAS flights

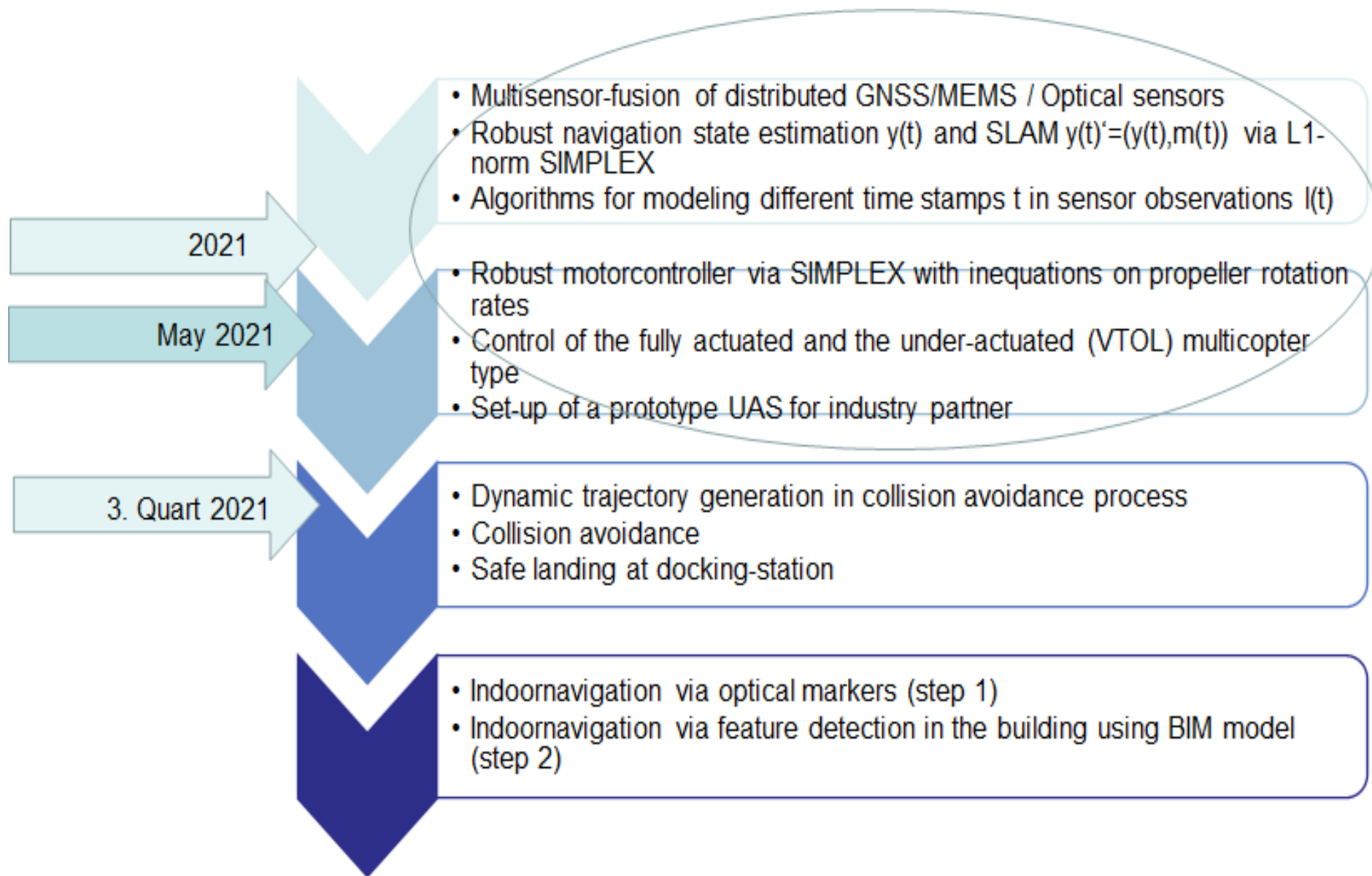


Waypoints completed to fully trajectory $y(t)_{desired}$
Control-deviation $\mathbf{d} = y(t)_{desired} - y(t)$
as flight-control input



BIM model as coordinate marker by camera-based feature detection

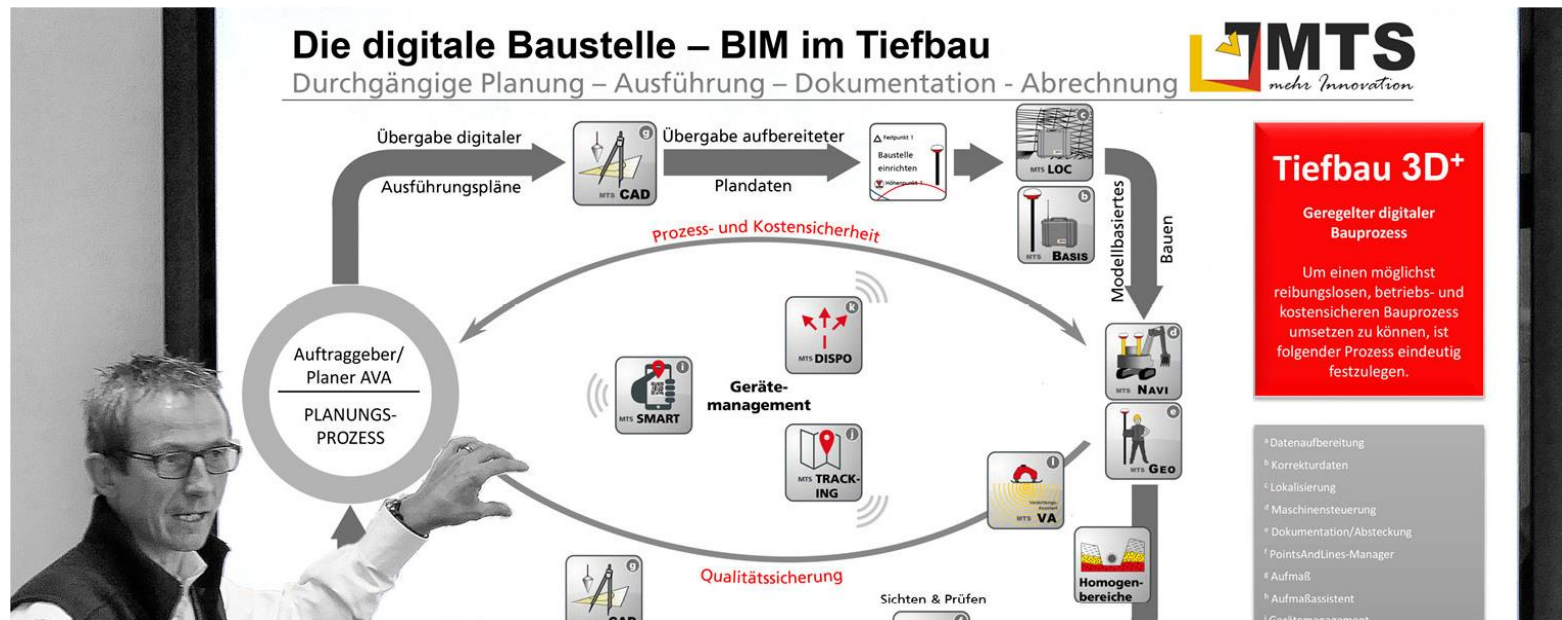
MITESENS – Flight Control for Autonomous Indoor UAS Flights



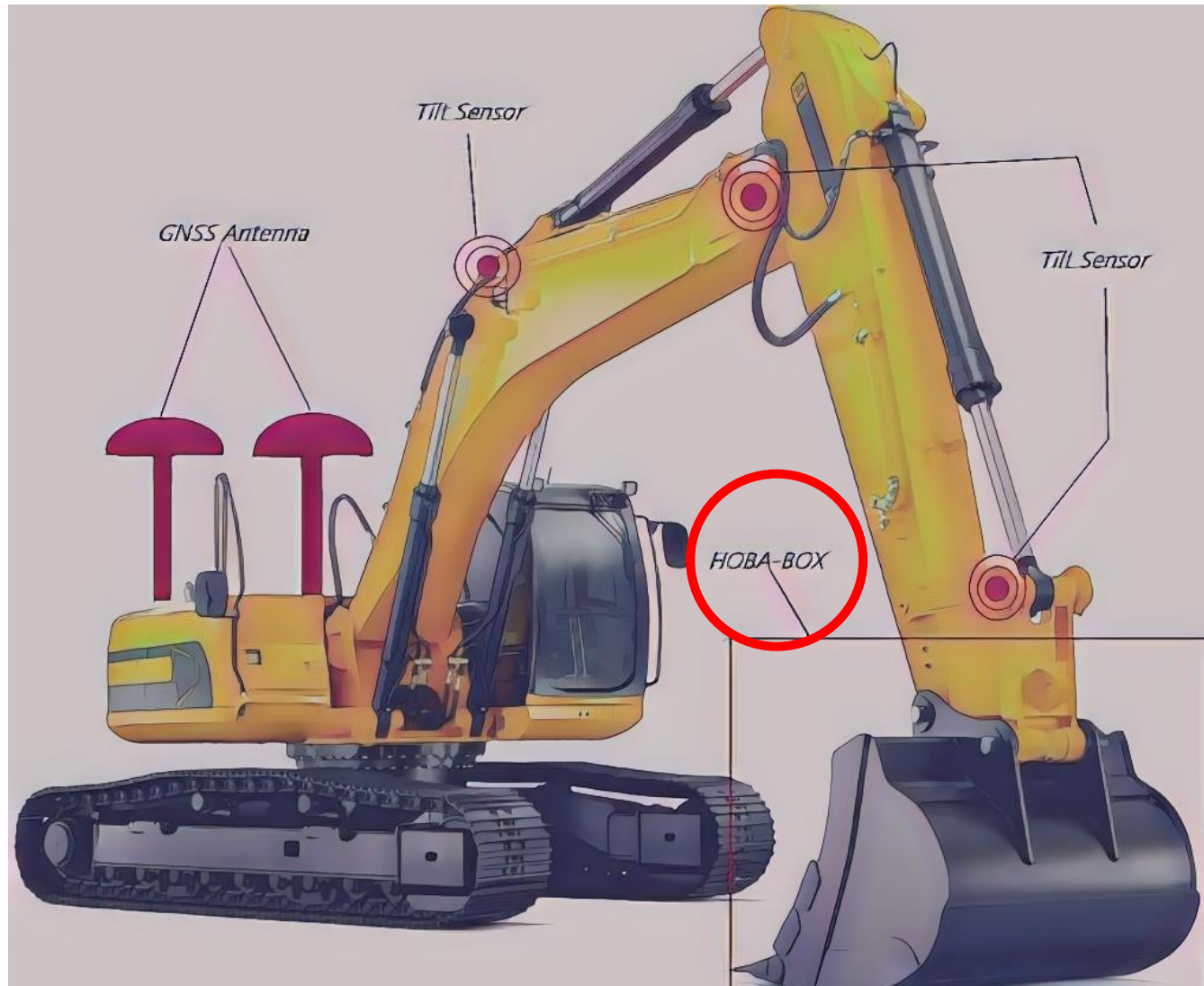
Project 2 HOBA

The R&D project "Homogeneous soils assistant for the automatic, construction site-specific recording of soil classes according to the new VOB 2016, shortly HOBA. HOBA deals with the development of a system for an automatic classification, detection & segmentation and a georeferenced voxel-based 3D-volume model generation for excavation site specific soil types according to the new BIM regulation called "VOB 2016".

Cooperation Partner www.mts-online.de

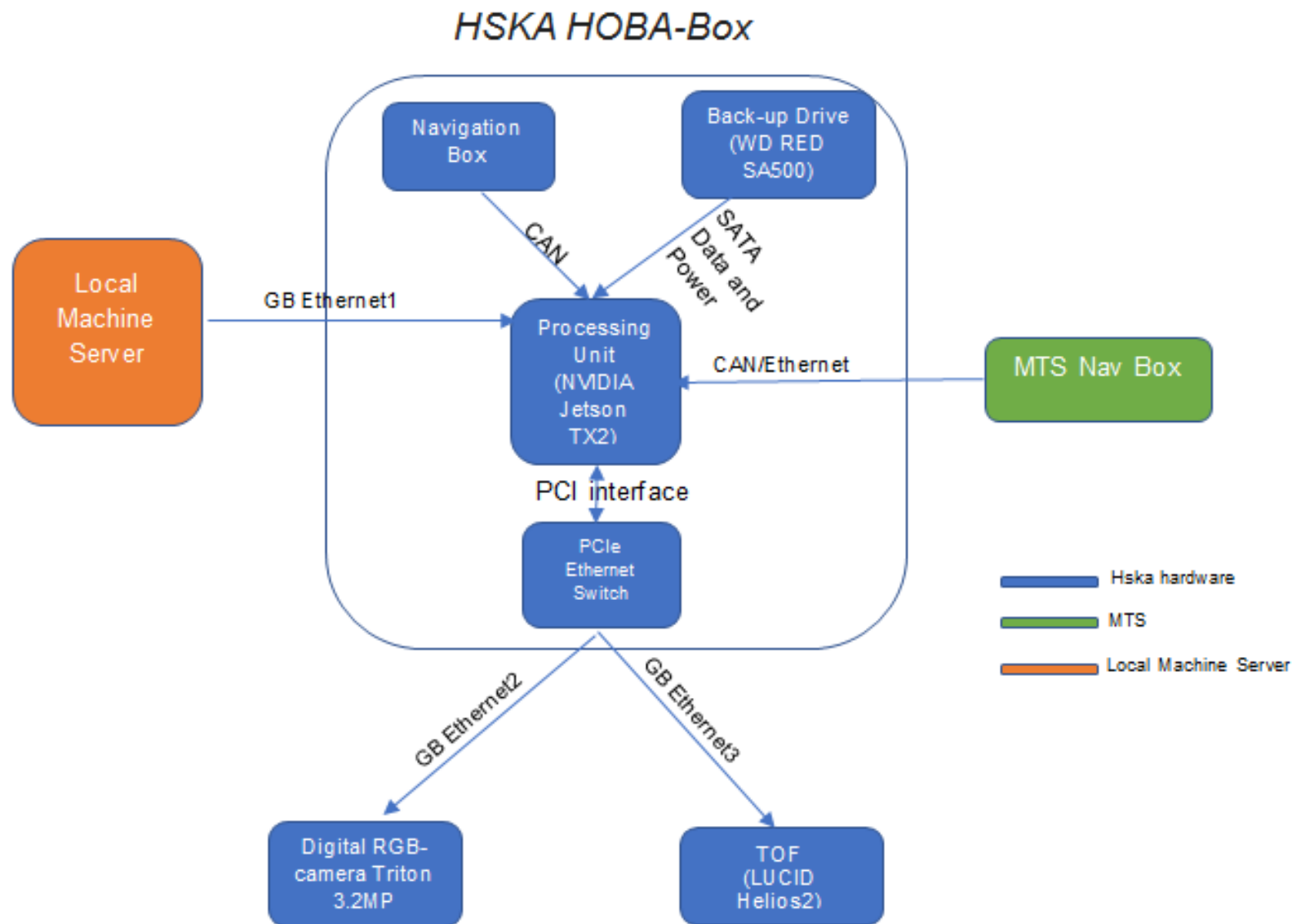


HOBA – Box



Excavator with distributed MTS sensors and HKA HOBA-Box
located in the area of the excavator bucket

HOBA Box – Hardware, Software and Algorithms Design



HOBA Box – Hardware, Software and Algorithms Design

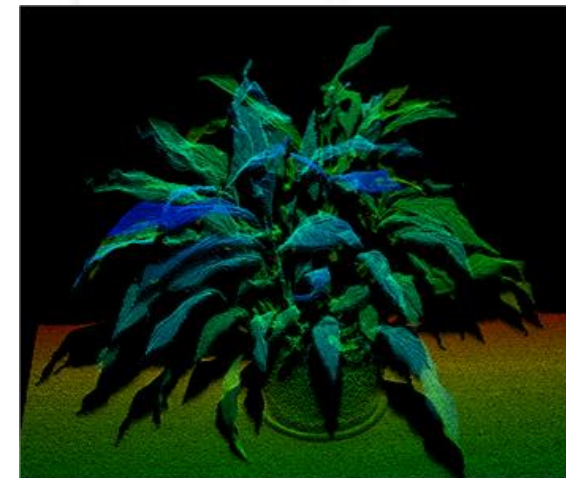
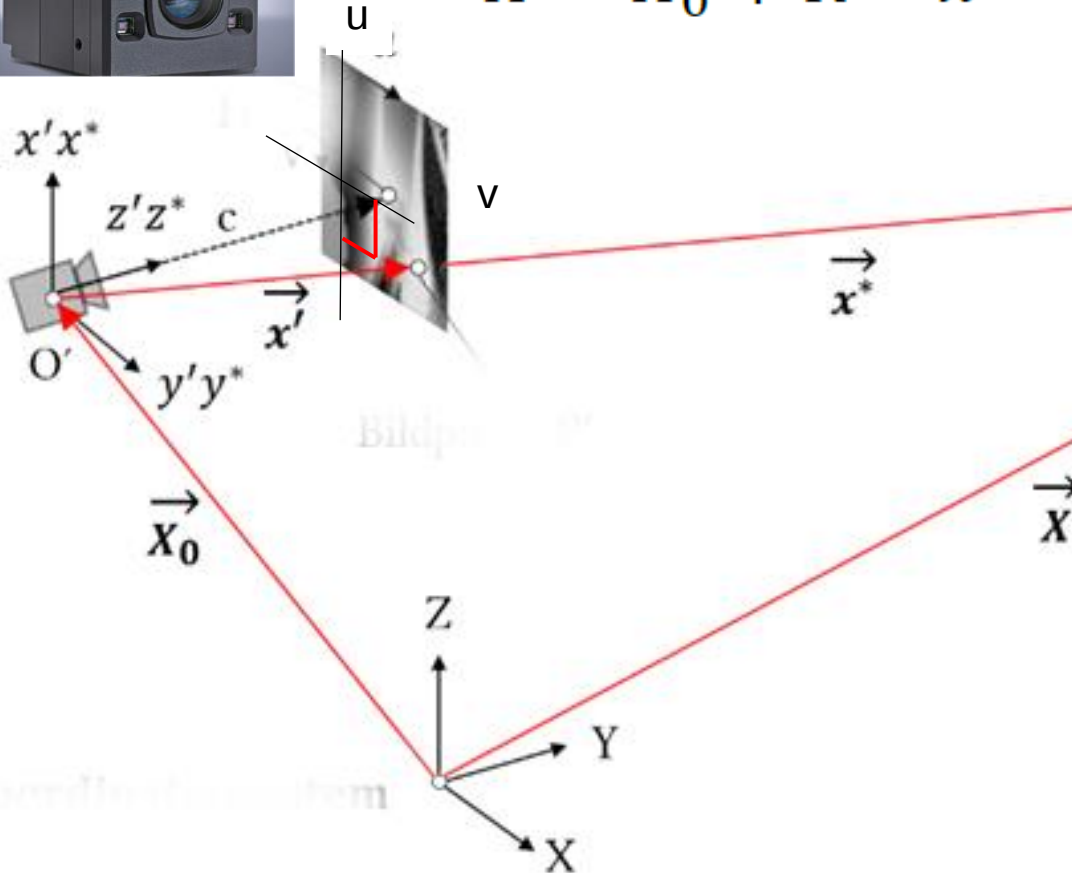
$$\mathbf{y}(t)' = [\mathbf{y}(t), \mathbf{m}(t)] = \begin{bmatrix} x^e & y^e & z^e & \dot{x}^e & \dot{y}^e & \dot{z}^e & \ddot{x}^e & \ddot{y}^e & \ddot{z}^e & r^e & p^e & y^e \\ \omega_{eb,x}^b & \omega_{eb,y}^b & \omega_{eb,z}^b & \dot{\omega}_{eb,x}^b & \dot{\omega}_{eb,y}^b & \dot{\omega}_{eb,z}^b & \mathbf{m}(t) \end{bmatrix}$$



Time of Flight Camera

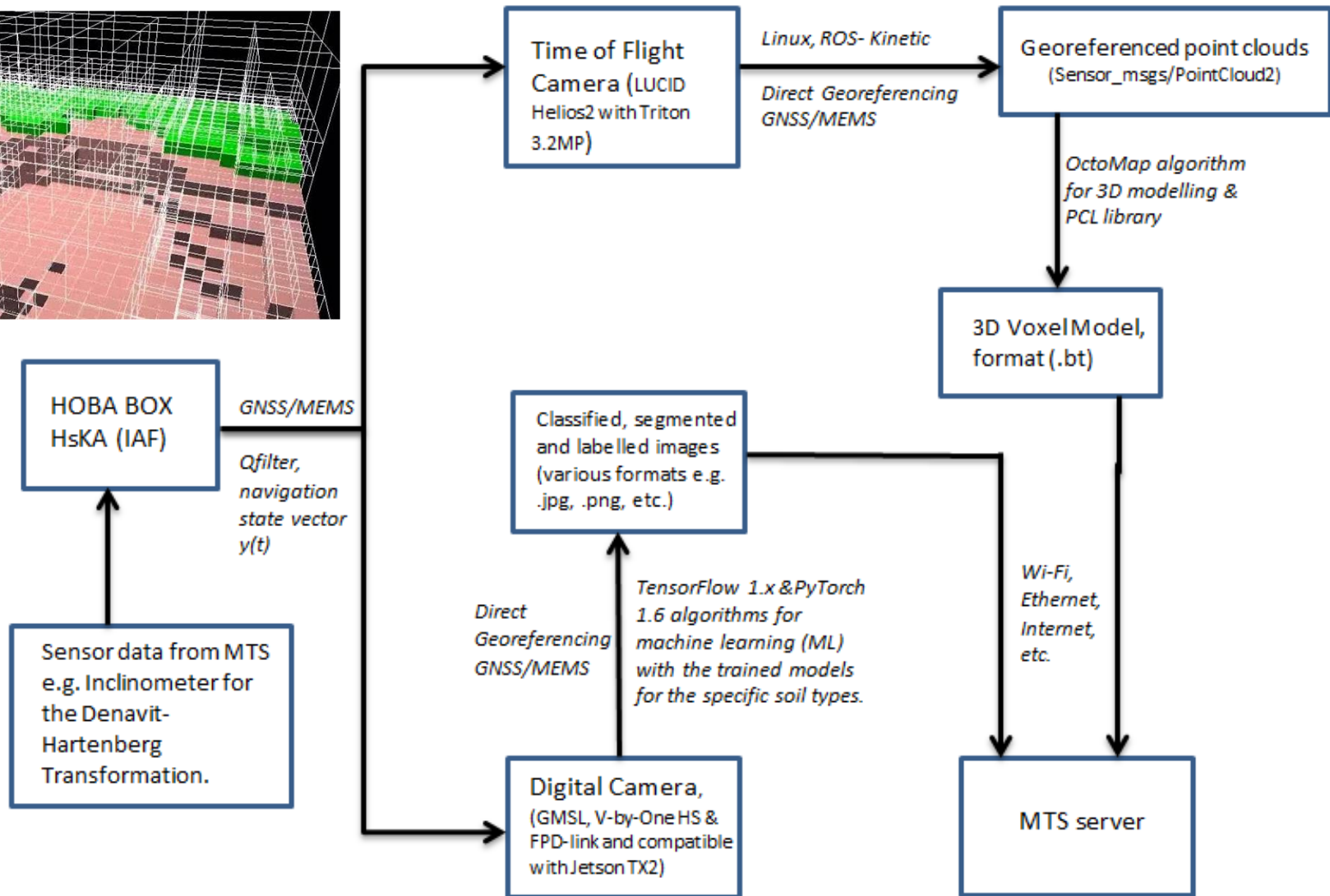
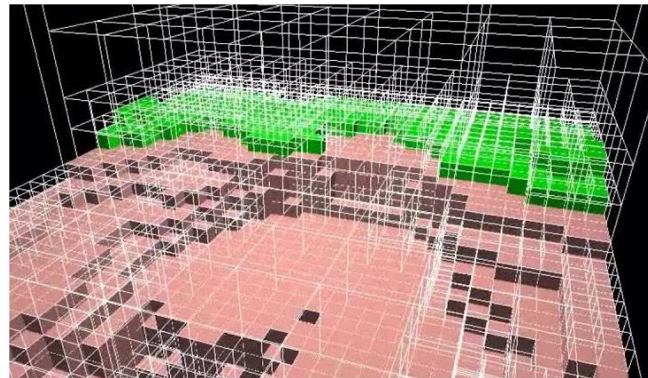
$$\vec{X} = \vec{X}_0 + R * \vec{x}^*$$

Helios-2, Lucid



HOBA Box – Hardware, Software and Algorithms Design

Target: Realtime ITRF/ETRF89 georeferenced voxel-model with classified soils of excavation





Further Information on projects: www.navka.de