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Multisensor SLAM-Robotics for the Automatic Generation of 3D-Building Models

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The automated creation of 3D building models is gaining importance in light of the smart cities concept, the use of building models for seamless out- and indoor navigation and yet, through the introduction of BIM (Building Information Modeling) in construction. It has come evident that, the interdisciplinary practice of BIM is one of the driving forces behind digitization and Industry 4.0. In this regard, the development of high accuracy geodetic measurement systems for automated creation of building models makes (Fig. 1) an important contribution to the 3D building information acquisition and monitoring components of BIM.x

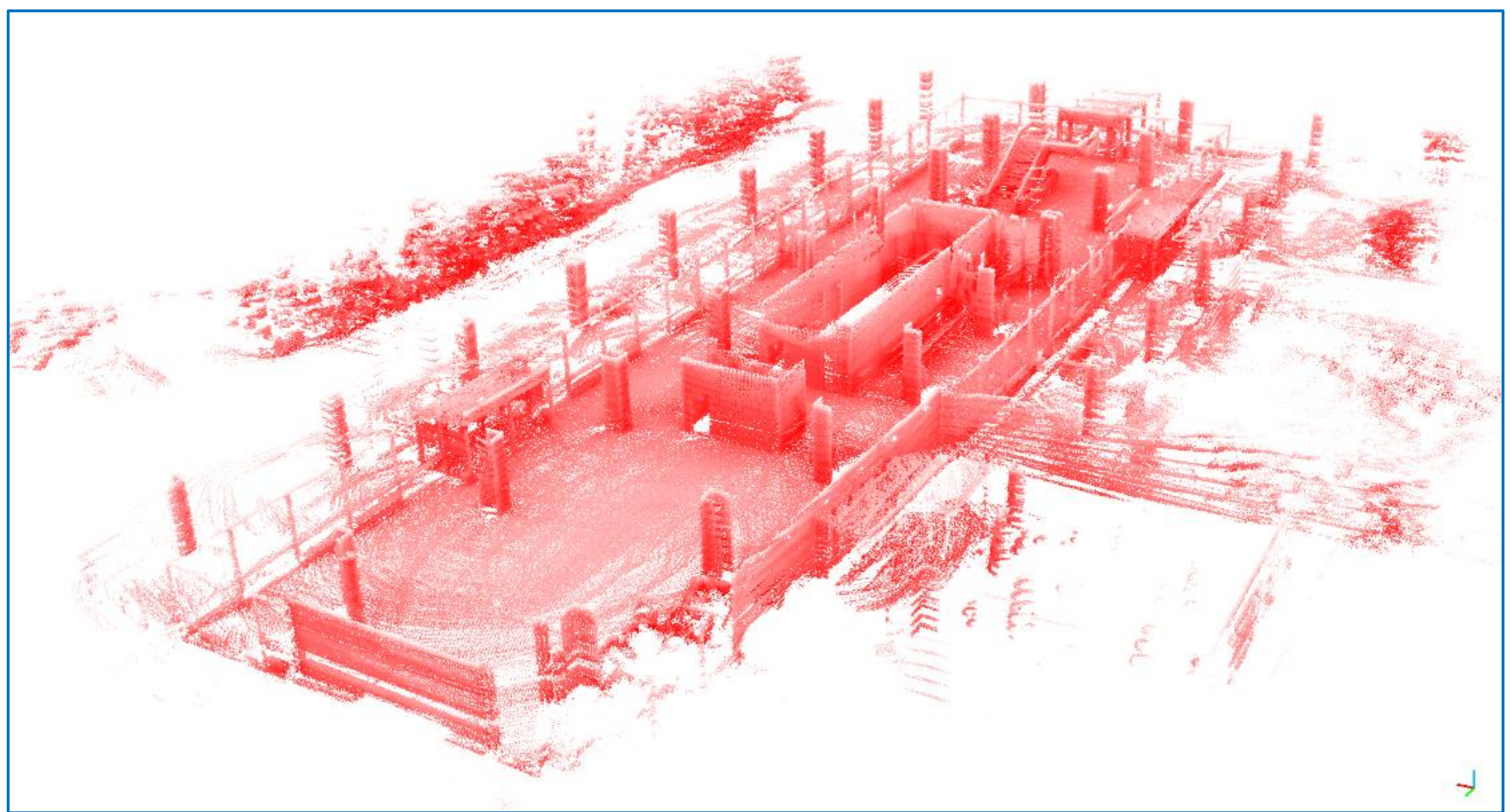


Fig. 1: Georeferenced 3D point cloud as result and further processing interface of the 3D mapping system MSM. The picture shows the interior of the HSKA B-building

Due to GNSS signal deprivation, indoor scenarios present a special challenge for georeferenced 3D mapping (Fig. 1). Even though the primary purpose of the 3D mapping system MSM developed at HSKA in the NAVKA project (www.navka.de) as "Innovative Projekte" project" in its first stage, is to overcome this challenge, while MSM it also provides a possibility to integrate a GNSS com-ponent. So the MSM robotic system can work in and outdoors.

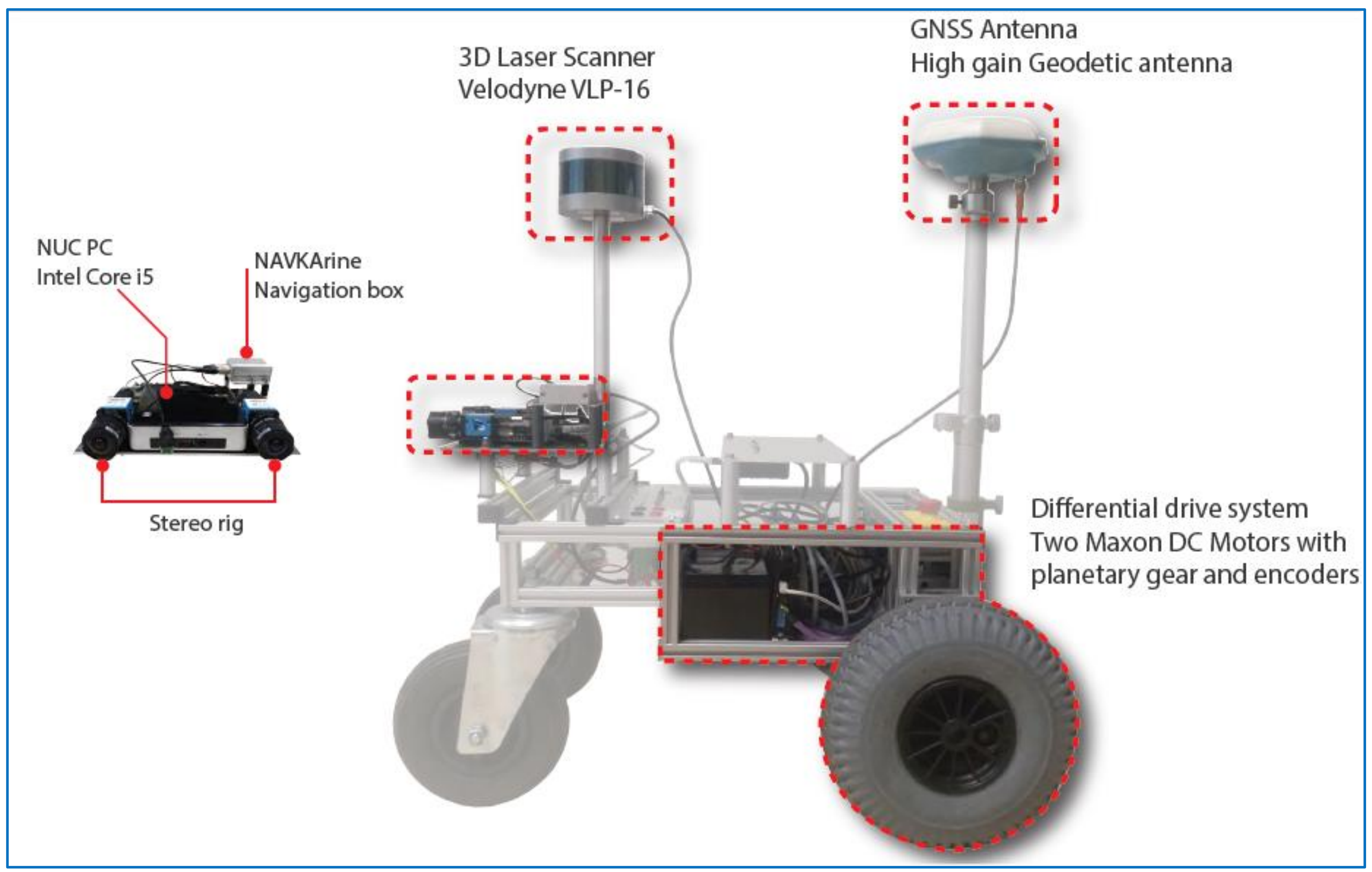


Fig. 2: Sensor and Leverarm Schematic of the 3D robotic mapping system MSM.

So the MSM robotic system (Fig. 2) can work in and outdoors. The typical use cases for such 3D mapping system are:

- Cost effective acquisition of 3D building models
- Parallel autonomous navigation and 3D mapping
- Construction monitoring and BIM

The navigation state estimation $\mathbf{y}_t$ and the associated control of navigation objects or bodies (b) (here the robot) is done by means of distributed GNSS, MEMS (Micro Electro Mechanical System) sensors, and optical sensors, e.g. laser scanners and cameras (Fig. 2). The sensor observation equations $\mathbf{l}(i,j)_t$ in a general leverarm $\mathbf{sl}(i,j)$ of distributed sensors in a multisensor (i) multiplatform (j) design (Fig. 2) read:

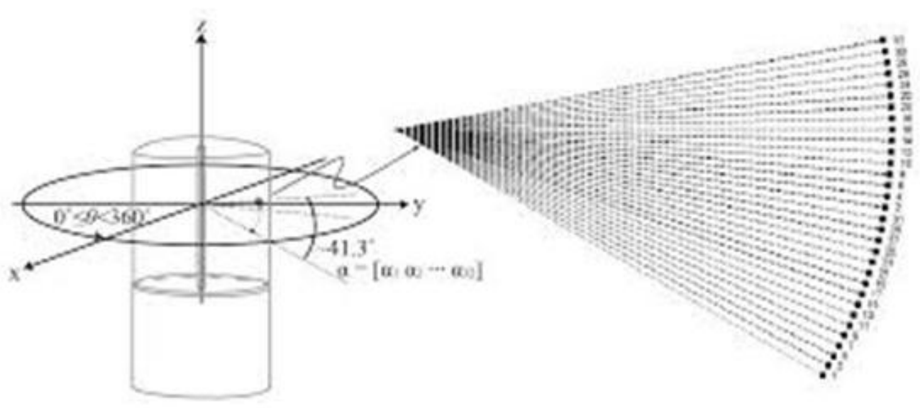
$$\mathrm{l}(\mathrm{i,j})_t = l(\mathbf{y}_t, \mathbf{sl}(i,j))_t \qquad (1)$$

Based on the presentation of the navigation state vector $\mathbf{y}_t$ as an event-based markov chain of measurements $\mathbf{l}(i,j)_{0:t}$ and control measures $\mathbf{u}_t$ following an initial state $\mathbf{y}_0$, the Markov chain is transformed into a Bayesian approach. This Bayesian basis allows further the integration of the physical assumptions on the motion model, the subsequent transition model $\mathbf{y}_t|\mathbf{y}_{t-1}$ for consecutive navigation states, as well as on all discrete controls $\mathbf{u}_{0:t}$. Based on two assumptions about Markov chains of 1st order, the final Bayes-based density function of the navigation state estimation $\mathbf{y}_t$ - inluding the so-called Kolmogorov-Chapman integral equations - reads:

$$\underbrace{p(\mathbf{y}_t|\mathbf{y}_0,\mathbf{l}_{0:t},\mathbf{u}_{0:t})}_{bel(\mathbf{y}_t)} = \eta \cdot \underbrace{p(\mathbf{l}_t|\mathbf{y}_t)}_{\text{Error density related to (1)}} \cdot \underbrace{\int_{-\infty}^{+\infty} p(\mathbf{y}_t|\mathbf{y}_{t-1},\mathbf{u}_t)\cdot \overline{p}(\mathbf{y}_{t-1}) \cdot d\mathbf{y}_{t-1}}_{\overline{bel}(\mathbf{y}_t)} \qquad (2)$$

Kolmogorov-Chapman equations

In case of Gaussian density functions for all components on the right side of (2), the optimum estimation of the so-called belief ($bel(\mathbf{y}_t)$) of the navigation state $\mathbf{y}_t$ is the Maximum-Likelihood (M) estimation type, the M-estimation Kalman-Filter type. Else, the so-called particle filter is optimal to estimate the belief ($bel(\mathbf{y}_t)$) of $\mathbf{y}_t$ (2). integrating laserscanners or cameras into a robotic system (Fig. 2), the following observation equations hold for laser-scanners:



$$\mathrm{x}^{\mathrm{p}}_{\mathrm{m,Pi}} = \mathrm{s}_{\mathrm{ij}} \cdot \begin{pmatrix} \sin z_{\mathrm{ij}} \cdot \cos\alpha_{\mathrm{ij}} \\ \sin z_{\mathrm{ij}} \cdot \sin\alpha_{\mathrm{ij}} \\ \cos z_{\mathrm{ij}} \end{pmatrix}^{\mathrm{p}} \qquad (3a)$$

$$\mathbf{x}^{\mathrm{p}}_{\mathrm{m,Pi}} = \mathbf{R}^{\mathrm{b}^{\mathrm{T}}}_{\mathrm{p}} \cdot (\mathbf{R}^{\mathrm{e}}_{\mathrm{b}}(\mathrm{r,p,y})^{\mathrm{T}} \cdot (\mathbf{x}^{\mathrm{e}}_{\mathrm{m,Pi}} - \mathbf{x}^{\mathrm{e}}_{\mathrm{b}}) - \mathbf{t}^{\mathrm{b}}_{\mathrm{p}}) \qquad (3b)$$

Equation (3b) shows, that the observation model (1) for laserscanner (Fig. 2) observations (3a) has to be extended: The state vector is composed of both, the navigation state $\mathbf{y}_t$ and the map $\mathbf{m}_t$ coordinates: We arrive at the SLAM (Simultaneous Locali-zation And Mapping) problem.

The strict, „full" SLAM implies by the big dimension of $\mathbf{m}_t$ a „big-data" problem. It's solution in realtime, the use of UAV instead of the robot type, 3D-collision avoidance, dynamic path-planning automatic cont-rol and autonmuous flying are the challenges of related PhD work.

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