A Synergetic Approach to Indoor Navigation and Mapping for Aerial Reconnaissance and Surveillance

Silvia Prophet, Jamal Atman
Institute of Systems Optimization
Karlsruhe Institute of Technology
Karlsruhe, Germany
{silvia.prophet,jamal.atman}@kit.edu

Gert F. Trommer
Karlsruhe Institute of Technology
Karlsruhe, Germany
ITMO University
St. Petersburg, Russia

Abstract—Unmanned Air Vehicles (UAVs) lend themselves to provide rescue forces with important information beyond their own field of vision. In this paper, we present a two-part yet synergetic navigation and mapping system for indoor reconnaissance and surveillance through aerial platforms. It faces inherent drawback of common Simultaneous Localization and Mapping (SLAM) approaches: map errors cannot be excluded and will directly afflict the positioning. With a flexible navigation filter and an efficient 2.5D mapping tool as centerpieces, our system facilitates appropriate mutual feedback of supporting information. That is map-based navigation aiding in terms of ego-motion estimation and improved mapping in terms of accuracy, robustness and efficiency. Hereby both modules remain independent in their basic function and are therefore guarded against overlapping errors. Finally, the system is validated by means of real experimental data and a first proof of suitability for application within autonomous exploration is given based on simulated flights.

Keywords—UAV; Autonomous Aerial Exploration; Indoor Navigation; Hybrid Sensor; Mapping; SLAM;

I. INTRODUCTION

The field of indoor navigation systems has grown in the last years because of the manifold application possibilities concerning localization, guidance and surveillance in indoor environments. Herein, solutions based on Unmanned Air Vehicles (UAVs) are an actual area of research since they can provide security guards and rescue forces with important information beyond their own area of influence and vision: from convenient monitoring of industrial area to any scenario, that requires investigation though including risks for the human being. For example, interior space - contaminated or in danger of collapse - can be surveyed and mapped or searched for injured persons and sources of danger.

Nevertheless, with obstacles at close quarters and no guaranteed data link to the ground station, such an indoor mission makes high demands on the navigation system. Precise localization is as crucial as sufficient information about the environment. Hence, common solutions either utilize pre-supposed maps for localization or both are directly integrated within well-known Simultaneous Localization and Mapping (SLAM) algorithms. But somehow or other there are drawbacks. Pre-supposing maps makes it impossible to use the idea of a flexible supporting system to full capacity. But then, errors in a simultaneously generated map cannot be excluded and will directly afflict the positioning. To handle this inherent problem we take on the idea of functional safety within a modular concept and propose a two-part yet synergetic solution to navigation and mapping in possibly unknown indoor environment. Both modules are independent in their basic function. But connected in a coadjutant feedback approach, they provide mutual support whenever reasonable.

This paper is organized as follows: At first, we shortly overview related work to main topics indoor navigation and mapping for autonomous aerial platforms. After that, we describe both relevant constraints and our aircraft’s hardware configuration. The next sections comprise the navigation module including our motion estimator and the mapping module. Finally, the synergetic overall system is presented. Experimental results by means of both simulations and real data complete the paper along with a short conclusion.

II. RELATED WORK

Long-term stable UAV navigation in indoor environments is an actual field of research. One approach to make up for lacking Global Navigation Satellite System (GNSS) signals is to install a local positioning system (e.g. [1]). However, relying on pre-installed beacons or other a-priori information severely constrains the field of application. Then again, self-contained yet costly solutions such as stereo camera [2] or 3D laser rangefinder [3] are not broadly affordable. It is desirable to find solutions based on common sensors, which are as nonsensible to perturbation as possible. Popular approaches address monocular camera [4] or 2D laser rangefinder [5]. Indeed, both have assets and drawbacks of their own, but they lend themselves to fusion of complementary advantages. For example, one can feed separately processed sensor to a central Extended Kalman Filter (EKF) [6]. The approach presented in [7] avoids this doubled burden to computing capacity in using direct sensor integration, but it is restricted to ground vehicles.

Beyond that, it is recommendable in the context of indoor reconnaissance and surveillance to offer mapping capabilities. Hereby, high maneuverability and strict limitations regarding computing capacity pose fierce challenges to any UAV mapping system. Nevertheless, various efficient SLAM solutions exist to provide for basic indoor maps (e.g. [8]). But to meet the demands of indoor navigation, fusion of map and filter via EKF-SLAM is commonly favoured. However, due to
aforementioned limitations, on-board EKF-SLAM for UAVs utilizing common sensors is barely addressed in literature. In [9] a monocular visual SLAM is proposed, the work still in progress. The approach in [10] uses 2D laser rangefinder, but it focuses outdoor environment. And incorporating both laser and camera based features in the EKF-SLAM state [11] could become too computationally intensive. Furthermore, erroneous mapping will result in erroneous localization and reciprocal.

To the best of the authors’ knowledge, there is no two-part UAV system for EKF navigation and mapping, that facilitates both mutual benefit and guard against overlapping errors.

III. OPERATING CONDITIONS

A. Scenario Constraints

Most of the intended indoor scenarios will comprise different floors with multiple rooms and transits, vertically connected via staircases or open space. But with possibly arbitrary scenarios close to and within buildings in mind, it is not advisable to use constraints concerning the environmental structure, such as orthogonality of the surroundings. Furthermore, the intended scenarios do not provide reliable GNSS information and one cannot act on the assumption that effective maps are available. Thus, position drift and instability of heading information have to be considered.

B. Hardware Requirements

As to the hardware, an application-oriented solution is desirable. A small-sized setup guarantees high maneuverability and therefore minimized sensor and computational payload is preferable. Otherwise, sensors to bridge the GNSS gap and their on-board processing are necessary for autonomous indoor flights.

C. Specialities in Micro Aerial Vehicle Navigation

First, no odometry data as provided by Unmanned Ground Vehicles (UGVs) is available. Just as well, common aiding constraints of pedestrian navigation are inapplicable. Next, beyond hovering, it is not possible to freeze during the flight. Finally, control of the aircraft is challenging due to disturbing quantities, various control parameters and six degrees of freedom (DOF) in its motion. On the other hand, an aerial platform both enables and obligates to not restrict the considered scenarios to 2D grounded ones, e.g. facilitating vertical accessing and obstacle avoiding capabilities.

IV. AERIAL PLATFORM „AIRQUAD“

A. Hardware Configuration

Our operating agent (depicted in Fig. 1) is a self-developed quadrotor with a diameter of 0.8m and rigid rotors. As a Micro Air Vehicle (MAV), it is small enough to fly in narrow indoor environments and yet it is qualified for carrying the necessary payload to be independent from external signal sources. The centrepiece of its Integrated Navigation System (INS) is a self-designed Navigation Board, an on-board system adapted to the agile dynamic and device-specific restrictions.

V. HYBRID EKF NAVIGATION WITH FLEXIBLE STATE CLONING

The system architecture of our navigation system is depicted in Fig. 2. It comprises widely used GNSS/INS integration. Moreover, we calculate relative motion from self-contained sensors to estimate all DOFs during the flight.

A. Integrated Navigation System

The EKF is a well-known approach to general localization and navigation. Inertial measurements – in our case provided by the IMU and processed via strapdown algorithm - are utilized in the prediction step. Then, depending on their availability, further sensor measurements are incorporated during estimation step. An advantage of this technique is, amongst others, a quality estimation in addition to the actual navigation solution (i.e. position, velocity and attitude).

---

1 Analog Devices, ADIS 16255
2 VTI, SCA3100
3 IDS, UI-1240 SE -C-HQ and IDS, UI-1240 ML-C-HG
4 Hokuyo, URG UTM-30LN
5 Adlink, Cool XpressRunner GS-45 Intel Core 2 Duo (2.26 GHz)
However, in indoor environments the absence of external reference signals such as GNSS prevents long-term accurate positioning. What is more, the classical EKF does not consider relative pose measurements instead. Thus, aiming at correct integration of just those, we extend the system with Stochastic Cloning Filter (SCF) approach [13]. Its basic idea consists in augmentation of the state $\tilde{x}_{k_0}$ at time $k_0$, its corresponding covariance $P_{k_0}$ and the system matrix $\Phi$ as follows:

$$
\ddot{\tilde{x}}_{k_0} = \begin{bmatrix} \ddot{x}_{k_0} \\ \ddot{\tilde{x}}_{k_0} \end{bmatrix},
\tilde{P}_{k_0} = \begin{bmatrix} P_{k_0} & P_{k_0} \\ P_{k_0} & P_{k_0} \end{bmatrix},
\Phi = \begin{bmatrix} \Phi & 0 \\ 0 & 1 \end{bmatrix},
$$

where $I$ denotes the unit matrix. After the filter propagation step a correlation between states $\tilde{x}_{k_0}$ and $\tilde{x}_k$ respectively covariances $P_{k_0}$ and $P_k$ is established. Thereby reference to past times is available and consequently information about ego-motion between different instants of time can be used to update the state.

### B. Hybrid Motion Estimator

As previously described, relative pose measurements from self-contained sensors suggest the possibility to reduce dependency from external aiding in the Kalman filter process. Yet, most well known solutions highlighting only one aiding sensor at once are strictly limited in their availability for use. On the other hand, distributed systems require increased computing time and switchover monitoring. Hence, we use one major yet hybrid source for navigation aiding. That is the deep integration of complementary monocular camera and 2D laser rangefinder. Hereby, one benefits from the successful calibration of camera$^6$ and laser$^7$ in terms of rotation $C_{i}'$ and translation $t_{i}'$. The resulting navigation filter is ought to be flexible in terms of GNSS-denied surroundings. We already described the Hybrid Motion Estimator (HME) navigation aiding in detail [12]. At this point a short overview is given.

The basic concept is to establish precise 3D to 2D point correspondences between different instants of time, which provide input to a Perspective Three Point (P3P) problem solver [14]. The transformation of the measured world points $\tilde{w}_{c_i}$ in laser coordinates at time $k_0$ to camera coordinates satisfies the following equation:

$$
\tilde{w}_{c_i} = C_{i} (\tilde{w}_{i} - \tilde{t}_{i,c_i}),
$$

Next, the pixels belonging to $\tilde{w}_{c_i}$ are tracked by the Kanade Lucas Tomasi (KLT) feature tracker [15] until current time $k$. These pixels $(\tilde{u}_i', \tilde{v}_i')$ are described as feature vectors

$$
\tilde{f}_i' = \begin{bmatrix} \tilde{u}_i' \\ \tilde{v}_i' \end{bmatrix},
$$

where $K$ represents the intrinsic matrix. Altogether, (2) and (3) provide the metrical and angular relationship at times $k$ and $k_0$ between the observed control points in order to establish the P3P problem. It is solved using an optimized combination of RANSAC and Levenberg-Marquardt algorithm [12]. Result is ego motion $C_{i}'$ and $t_{i,c_i}'$ between time steps $k_0$ and $k$.

Using „$k_0$ by $k$” in terms of „frame by frame” motion estimation, relative measurements and their errors would be directly accumulated in the filter. To use the SCF optimally, a flexible state cloning is desirable. Therefore, a “keyframe by frame” motion estimation is used. Adequate reference frame selection and retention mitigates increasing uncertainty of the estimated state. To estimate the covariance, backward propagation [16] is applied as elaborately described in our previous publication. In short, assuming the estimation errors of $\tilde{f}_i'$ to be uncorrelated among themselves, the covariance matrix is simplified as a uniform diagonal matrix. The main diagonal elements $\sigma_{\tilde{f}_i'}^2$ are calculated using the reprojection error sample covariance [12].

### VI. EXTENDED tINySLAM FOR AERIAL PLATFORMS

The tinySLAM algorithm, introduced in [17] for the first time and further improved in [18], is an application-oriented modification and simplification of the Distributed Particle (DP) SLAM [19]. It was developed for online processing on small UGVs and is therefore dedicated to computational efficiency and minimum sensor requirements. The system architecture is illustrated in Fig. 3.

As can be seen, this approach requires odometry data. Beyond that, it contains further limitations, which restrict the availability for use to 2D motion with low dynamics. This is why, after a brief summary of the basic principle, we present necessary adjustments to extend tinySLAM applicability to agile aerial platforms.

---

$^6$ The front camera coordinate system is denoted ‘c’.

$^7$ The horizontal laser coordinate system is denoted ‘l’.
A. Basic Principle

TinySLAM is a two-dimensional SLAM algorithm based on the principle of Incremental Maximum Likelihood (IML). It processes laser measurements \( \tilde{z}_i^k = (r, \varphi)_k \) in horizontal plane to estimate the agent’s most likely pose within a 2D map\(^8\) corresponding to the data acquisition. Then the map is updated based on this localization and the current sensor data.

The tinySLAM localization module uses a Monte Carlo Localization (MCL) based algorithm to estimate horizontal position and orientation \( \tilde{x}_{MCL}^k = (x, y, \psi)_k \) (subsequently also referred to as ‘pose’) of the mobile robot at time \( k \) within the so far constructed map \( M_{k-1} \). In short, a set of particles represents hypothesized poses. These are iteratively processed, characterized and filtered to find the best hypothesis of the robot position. Hereby the estimator is initialized with a random set based on an odometry motion model starting point. Weighted likelihood characterization is performed utilizing the distance measurements. In several iterations, the search space is consecutively reduced to the best hypothesis’ neighborhood, the solution converging towards the centroid of the weighted hypotheses. Additionally, a consistency filter step, which incorporates previous poses and cost function values, is applied to detect and prevent defective localization. Every time the consistency check corroborates a hypothesis, this pose is used to incorporate the acquired range data within map update. Hereby, the measurements are transformed into map coordinates and weighted. In doing so, the map \( M_k \) is consecutively built and again – with a defined latency - used to relocate the robot in successive steps.

B. 2.5D Map Representation

Stationary mounted distance sensors of a ground vehicle generally maintain their height above ground. Also, the effective range will remain within the initial laser scanning plane. Thus, the original tinySLAM grid map model is restricted to a leveled laser rangefinder’s constant horizontal. A gray value function is used for the 2D representation. It assigns each cell at the position \( x^M_k = (x^M, y^M)^T \) a value \( p_o(\tilde{x}^M_k) \in [0,1] \) proportional to its occupancy probability.

Now in theory, one could easily expand this representation to third dimension by using positions \( \tilde{x}^{M,3D} = (x^M, y^M, z^M)^T \) and thus incorporate altitude changes during the flight. However, a cubic map representation is a comprehensive computational burden. As a result, we propose a 2.5D layer by layer map as illustrated in Fig. 4. The basic idea is to assume different yet well-defined flight levels, each represented by its height over ground and a two-dimensional tinySLAM map. This considers both computational efficiency and vertical obstacle avoidance. Furthermore, a dynamically expanding structure is implemented, which incorporates only cells that are covered by actual laser measurements.

C. Quality Criteria

Several assessment criteria are defined:

\[
Q_{map} = \frac{1}{N_l} \sum_{l=0}^{N_l} p_o(\tilde{z}_{i_l}^M).
\]

, subsequently also referred to as ‘score’, describes the conformity between the map \( M \) and the current laser scan as the averaged occupancy \( p_o \) of cells correlated with the \( N_l \) point measurements \( \tilde{z}_{i_l} \).

\[
\zeta(\tilde{z}_{i_l}^M) = \begin{cases} 
1, & p_o(\tilde{z}_{i_l}^M) < 0.3 \\
1, & p_o(\tilde{z}_{i_l}^M) > 0.7 \\
0, & \text{else}
\end{cases}
\]

, describes the map quality as the \( N_l \) point measurement’s \( \tilde{z}_{i_l} \) share in well defined – i.e. most likely empty respectively most likely occupied – cells \( \zeta(\tilde{z}_{i_l}^M) \).

---

\(^8\) The map coordinate system is denoted ‘\( M \)’.
### D. Map Update Strategy

To both broaden the tinySLAM’s field of applicability and improve its accuracy we follow and further develop the keynote of [9], who suggests adapting the map update strategy in terms of rule-based behavior. In short, a map update occurs only if reasonable: either if the map is incomplete or if the current scan is of high informative value. To ensure this triggering behavior, an adaptive lower limit replaces the original consistency check as follows:

\[
Q_{\text{map}}^{\text{mw}} > \beta_{\text{min}}(Q_{\text{map}}).
\]  

(6)

That is, exponential increase of \( \beta_{\text{min}}(Q_{\text{map}}) \) involves higher demands to the score if a map of high quality is present.

Furthermore, the agent’s motion with regard to the last update has to exceed a minimum threshold as follows:

\[
\|x_{M_{i+1}}, y_{M_{i+1}}\|^2 - (x_{M_{i+1}}, y_{M_{i+1}})^2 < \varepsilon_{\text{min}}. 
\]  

(7)

This constraint replaces the original fixed map update latency suggested in [18] to account for the MAV’s hovering capability.

Now, whenever (6) and (7) are fulfilled, the map update is carried out in such a way that both localization errors and fault-prone far-off laser measurements are counteracted. This is realized by scaling proportional to both \( Q_{\text{map}}^{\text{mw}} \) and \( r_i^{-1} \).

Overall, our implementation increases accuracy and robustness while at the same time it enables implicit loop closure behavior. This is because, in contrast to the initial tinySLAM, compensation for accumulating errors is possible whenever the agent returns to an already observed area.

### VII. Synergetic Localization and Mapping

Mutual support between localization and mapping is desirable. However, both modules should be guarded against overlapping errors.

#### A. System Architecture

We propose a synergetic two-part solution (illustrated in Fig. 5). Our hybrid EKF navigation system provides the mapping module with navigation solution and corresponding uncertainties. In reverse feedback direction, MCL information serves as the basis for an additional Kalman correction.

#### B. Adaptive 2.5D Mapping

In our synergetic approach, the tinySLAM benefits from the stable available EKF estimation by progressive stages: extended sensor data pre-processing, faster localization and improved mapping.

First, information about both the agent’s attitude and height over ground is used to remove possibly present ceiling and floor from the laser’s data set and to transform the remaining point measurements to the horizontal plane.

Incorporating information about the agent’s altitude provides for 2.5D mapping.

Next, the EKF pose estimation substitutes unavailable odometry respectively simple motion model data in the MCL initialization step. In addition, the EKF covariance estimation is used to define a two-dimensional \( \sigma \) scope and thereby dynamically adapt the MCL search space \( \Xi \) to current conditions as follows:

\[
\Xi = \left[ \begin{array}{c} \sigma_{x_k} \\ \sigma_{y_k} \end{array} \right] \times \Xi
\]  

(8)

where horizontal position uncertainties \( \sigma_{x_k} \) and \( \sigma_{y_k} \) are provided by the corresponding elements of EKF covariance estimation \( P_k \). Furthermore, contrasting the positioning of MCL and EKF in terms of consistency check is of assistance within ambiguously-structured environment.

Altogether, distance measurements of higher availability and accuracy are ought to improve the map’s quality in general while covariance based aiding aims at increasing the algorithm’s robustness.

#### C. Map-Aided Hybrid EKF Navigation

Our HME based navigation system provides long-term stable localization capabilities in absence of absolute reference information. Still it is advisable to use the enhanced tinySLAM solution for further navigation aiding. Making use of the EKFs flexible structure, we suggest feedback of relative information calculated from the MCL positioning into the EKF by means of a 2D relative movement measurement

\[
\bar{\theta}_{\text{wcl}, \text{wcl}} = \left( \Delta x_{k}, \Delta y_{k}, \Delta \psi_{k} \right)
\]  

(9)

It is calculated from successive MCL localization results. Following our presented “keyframe by frame” approach, SCF “keymap to map” selection and retention is applied.

![Fig. 5: Two-part synergetic navigation and mapping. Both modules are connected in a mutual feedback loop whereas the respective basic function is unaffected by erroneous results of each another.](image-url)
The corresponding noise matrix $R_{MCL}$ is described as:

$$
R_{MCL} = \begin{pmatrix}
\sigma_x^2 & 0 & 0 \\
0 & \sigma_y^2 & 0 \\
0 & 0 & \sigma_{\psi}^2
\end{pmatrix}.
$$

(10)

Hereby, several partially dynamical factors are considered via weighted sum: the minimum uncertainty in terms of map grid $g_{map}$, the influence of map quality $Q_{map}$ and matching quality $Q_{match}$ and the directional degree of structuring, that is $\tilde{Q}_{map} = (\tilde{\lambda}_{x}^{M}, \tilde{\lambda}_{y}^{M})^T$. The latter is most crucial since it represents a direct measure for the informative value of the 2D ego-motion $\theta^{u}_{w_{2}w_{1}}$. We suggest estimation of $\tilde{Q}_{map}$ in such a way that the spatial differences between side-by-side laser point measurements $z_i^M$ are projected to the map’s horizontal principal axes, each providing a mean value as follows:

$$
\tilde{\lambda}_{x}^{M} = \frac{1}{N-1} \sum_{i=1}^{N} \left\| y_{i}^{M} - x_{i}^{M} \right\|
$$

$$
\tilde{\lambda}_{y}^{M} = \frac{1}{N-1} \sum_{i=1}^{N} \left\| y_{i+1}^{M} - y_{i}^{M} \right\|
$$

(11)

A low rate of change in one direction indicates well-defined structures and therefore corresponding uncertainties $\sigma_{x}^2$ and $\sigma_{y}^2$ are influenced inversely quadratic.

Beyond that, map and matching quality are considered for all diagonal elements of $R_{MCL}$ via proportional factor

$$
f_{map} = \frac{c_{map,1}}{Q_{map} - \delta_{min}(Q_{map})} + c_{map,2}
$$

, where $c_{map,1}$ and $c_{map,2}$ are constants determined within optimization process.

VIII. EXPERIMENTAL RESULTS

In this section, we validate the resulting synergetic system by means of experimental data collected in real tests at the Institute of Systems Optimization (ITE) in Karlsruhe. In using the MAV’s actual recordings, we account for perturbations impairing the sensor measurements under real conditions.

A. Mapping

First, a scenario consisting of an outdoor-indoor transit followed by a hallway, an unstructured furnished room and a second hallway is evaluated. Fig. 6 depicts the mapping result. Comparison with the underlaid actual plant layout of the building demonstrates both angular and structural quality of our extended tinySLAM. The algorithm provides an almost rectangular structure apart from a slight drift in heading towards the end. That is without any orthogonality constraints.

Furthermore, broad white area outside the building indicates complete observation of the surroundings. In addition, the map thoroughly reflects not only open doors but also present obstacles (e.g. ‘1’-‘4’ in Fig. 6) with high accuracy.

Next, an office-building scenario covers hallway, lecture room, study and a laboratory. As can be seen in Fig. 7, our algorithm provides a clearly structured map for various room types. The underlaid actual plant layout of the building again confirms the mapping algorithm’s quality due to structure, physical dimensions and orientation. That is irrespective of the MAV’s dynamics especially due to 3D angular rates.

It is to say that our approach is suitable for but not restricted to well-defined indoor environment. Above all, maximum number of required MCL iterations and therefore computation time is reduced by initialization via EKF navigation solution and the proposed covariance based dynamic search space. Likewise, the map’s dynamic structure reduces memory requirements.

B. Localization

We already presented a comprehensive study on the performance of the HME aided navigation system [21]. The navigation solution meets the requirements of precise localization and appropriate self-assessment. Furthermore, the self-contained algorithm turned out to be long-term stable.

Yet there are certain locally challenging situations. That is, for example, direct view towards untextured planes in close-up range, such as as plain-colored walls. Noteworthy this kind of situation generally accompanies well-defined structure within the laser scanner’s effective range.
Therefore, our map-aided EKF estimator is ought to further reduce local drift. To validate this assumption, we focus on the local instabilities which appeared in [21] within the first two rooms, where white walls were present. Indeed, the map-aiding is suitable to assist in situations which lack visual features and their trackable motion. As illustrated in Fig. 8, local drift in position is clearly reduced compared to the initial navigation solution. Additionally, localization accuracy during the hallway flight is improved. This is due to the selective support of the east component by means of map data. Likewise, heading could be estimated with high confidence as to the lateral present walls.

In contrast, one could observe a drift of the map-aided navigation solution towards the eastern exterior wall within the first room. Hereby an aslope, dynamic view on window glass spans impaired the laser measurement quality whereas the frame notch structure misleadingly indicated observability.

However, this temporary drift does not hinder the system’s global performance. Overall, our proposed map-aided hybrid EKF provides localization which is not only consistent with the actual trajectory, but of high lateral accuracy (cp. error statistics in Table I).

C. Navigation and Exploration

Finally, we would like to present a first proof of suitability of our synergetic approach for autonomous exploration based on software in the loop tests. Our simulation environment includes identified physical and motion models of the MAV hardware and its payload as well as respective realistic error models. Beyond that, a detailed furnished and texturized 3D model of the institute ITE represents the operational environment.

In the office-building indoor scenario shown in Fig. 9 the mission’s goal was to explore the whole floor, omit the staircase and return to the starting point. This mission was achieved and each room was safely accessed and mapped. It is to mention that not only the map was accurate enough to enable successful navigation. Furthermore, velocity and attitude information from the map-aided navigation solution were directly used by the cascaded velocity-attitude-controller to supervise and regulate the aircraft’s flight.

<table>
<thead>
<tr>
<th>Lateral Deviation</th>
<th>Localization Error Quantiles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.25-Q</td>
</tr>
<tr>
<td>Reference</td>
<td>0.042m</td>
</tr>
<tr>
<td>Door frame center</td>
<td>Entry 1</td>
</tr>
<tr>
<td></td>
<td>0.095m</td>
</tr>
</tbody>
</table>

*Empirical quantile p-Q divides a sample so that p*100% values are less than p-Q (e.g. 0.5-Q & median).
autonomous exploration was given based on simulated data. Beyond that, a first proof of suitability for application within evaluated the system by means of real experimental data. feedback in terms of accuracy, robustness and efficiency. We tailored to the specific needs of agile aerial platforms was Furthermore, an extended 2.5D tinySLAM mapping module with continuous availability, both short- and long-term stable. estimation, we introduced a self-contained navigation filter overlapping errors. In the regard of localization and motion remains independent and are therefore guarded against within the respective modules whereas their basic function resulting two-part system will imply distinct improvements appropriate mutual feedback of supporting information. The facilitates – beyond pure localization and mapping – an efficient mapping tool as centerpieces, the system for indoor reconnaissance and surveillance through aerial flight through ITE 4th floor. Color gradient indicates elapsed time of flight starting at red. Purple areas are not part of the map. All rooms (except the deliberately spared staircase) were successfully accessed and mapped.

IX. CONCLUSION
In this paper, a synergetic navigation and mapping system for indoor reconnaissance and surveillance through aerial platforms was presented. With a flexible navigation filter and an efficient mapping tool as centerpieces, the system facilitates – beyond pure localization and mapping – appropriate mutual feedback of supporting information. The resulting two-part system will imply distinct improvements within the respective modules whereas their basic function remains independent and are therefore guarded against overlapping errors. In the regard of localization and motion estimation, we introduced a self-contained navigation filter based on a hybrid sensor – that is a deep integration of laser rangefinder and camera - and further supported by map-based relative motion estimation. It provides precise information with continuous availability, both short- and long-term stable. Furthermore, an extended 2.5D tinySLAM mapping module tailored to the specific needs of agile aerial platforms was presented. It likewise benefits from the vis-à-vis EKF module feedback in terms of accuracy, robustness and efficiency. We evaluated the system by means of real experimental data. Beyond that, a first proof of suitability for application within autonomous exploration was given based on simulated data.

References