Abstract—Accurate and robust pose estimation is a fundamental capability for autonomous systems to navigate, map and perform tasks. Particularly, construction environments pose challenging problem to Simultaneous Localization and Mapping (SLAM) algorithms due to sparsity, varying illumination conditions, and dynamic objects. Current academic research in SLAM is focused on developing more accurate and robust algorithms for example by fusing different sensor modalities. To help this research, we propose a new dataset, the Hilti SLAM Challenge Dataset. The sensor platform used to collect this dataset contains a number of visual, lidar and inertial sensors which have all been rigorously calibrated. All data is temporally aligned to support precise multi-sensor fusion. Each dataset includes accurate ground truth to allow direct testing of SLAM results. Raw data as well as intrinsic and extrinsic sensor calibration data from twelve datasets in various environments is provided. Each environment represents common scenarios found in building construction sites in various stages of completion.

SUPPLEMENTARY MATERIAL

The dataset as well as the documentation is available at https://www.hilti-challenge.com.

I. INTRODUCTION

Robots on construction sites promise improved safety of workers, task productivity and high quality data capture [1]. Although some dangerous tasks (such as concrete chain sawing) are prime work to automate, the more repetitive and ergonomically difficult tasks (such as overhead drilling and installation) result in many worker injuries. Construction robotics offers a way to remove this worker hazard, while also improving task scheduling and progress monitoring. To achieve that goal however, automation requires a wide array of technologies and techniques to perceive, map and navigate through the environment.

With the introduction of GNSS and INS augmented systems, high performance outdoor positioning and navigation solutions are widely available [2]. Continuing that trend to indoor or complex outdoor environments however, remains a challenge. To bridge the gap, autonomous positioning systems rely on a fusion of sensors and techniques. But these hardware platforms can be a barrier to high quality research due to cost and integration complexity.

Many types of indoor and outdoor spaces remain sparsely explored in research due to a lack of reliable test data with accurate reference information. Previous efforts to collect and distribute high quality multi-sensor data have resulted in significant improvements and insights in the research areas of visual odometry, SLAM and sensor fusion [3], [4], [5], [6], [7].

In order to support the growing body of experiences in various indoor and mixed environments, we have created a suite of sensors (representing different categories of sensor techniques) with attention made to precise time synchronization and calibration. With this sensor platform, we have collected datasets in various locations with different practical deficiencies seen in real-world scenarios (Fig. 2); along with accurate ground truth for effective testing and evaluation. Whereas previous datasets have focused on automotive vehicle motion, airborne UAV motion, or provided expansive simulations, this dataset targets real spaces collected by handheld or robotic-like motion, using the latest in commercially available sensing technology. With the use of redundant sensors, this dataset also provides a direct comparison of sensor performance in different environments; which can be informative for future system designs. We believe that these collection scenarios capture a wide array of robotic and reality capture uses cases that many not be as illustrative...
with previous data. Our aim is to stimulate research on robust indoor positioning, mapping and navigation with particular application to construction environments.

II. SENSOR SETUP

Our sensor suite (the ‘Phasma’ stick, Fig. 1) consists of 3 categories of sensing modalities, along with multiple sensors operating with different ranges and noise levels. These include:

A. Passive Visual

**AlphaSense by Sevensense**

The visual data is collected from an array of rigidly mounted 1.3MP global shutter cameras. This module consists of 5 wide field-of-view cameras mounted to give an approximate 270 deg continuous field of view. Within this configuration a stereo camera is also present. Images are synchronously collected at 10Hz.

**Ouster OS0-64**

Long range point cloud data is collected by the 360 deg scanning lidar sensor. This unit has a scan repetition of 10Hz, and a point data rate of 1,300,000 points/second. Ranges are recorded from 0.3 to 50m, with typical lowest noise returns greater than 1m. Range accuracy is 1.5-5cm.

**Livox MID70**

This unit is a lidar sensor with a 70 deg circular field of view and a non repeating scan pattern. Point data rate is 100,000 points/second. Ranges are recorded from 0.02 to 200m, with typical returns between 1 and 50m. Range accuracy is 2.5cm.

B. Active Optical

**Ouster OS0-64**

Long range point cloud data is collected by the 360 deg scanning lidar sensor. This unit has a scan repetition of 10Hz, and a point data rate of 1,300,000 points/second. Ranges are recorded from 0.3 to 50m, with typical lowest noise returns greater than 1m. Range accuracy is 1.5-5cm.

**Bosch BMI085**

This IMU is embedded in the AlphaSense module. It provides a modest level of performance in terms of noise and bias stability. The data from this IMU is tightly timestamped to the AlphaSense timing system. Data is collected at 200Hz.

**InvenSense ICM-20948**

This IMU is embedded in the Ouster lidar. It provides a more modest level of performance than the ADIS16445 in terms of noise and bias stability. The data from this IMU is tightly timestamped to the Ouster timing system. Data is collected at 100Hz.

C. Inertial Sensors

**Analog Devices ADIS16445**

This IMU is rigidly mounted to the AlphaSense module. It is a high performing MEMS based sensor with relatively low noise and sensor bias drift rates. The data from this IMU is tightly timestamped to the AlphaSense timing system. Data is collected at 800Hz.

**Bosch BMI085**

This IMU is embedded in the AlphaSense module. It provides a modest level of performance in terms of noise and bias stability. The data from this IMU is tightly timestamped to the AlphaSense timing system. Data is collected at 200Hz.

**InvenSense ICM-20948**

This IMU is embedded in the Ouster lidar. It provides a more modest level of performance than the ADIS16445 in terms of noise and bias stability. The data from this IMU is tightly timestamped to the Ouster timing system. Data is collected at 100Hz.

D. Ground Truth System

For testing and validation, 2 systems are used to capture ground truth:

**Total Station**

A survey grade prism is attached to the Phasma stick. This is tracked by the Hilti PLT30 automated total station. Most datasets are collected in a “stop ‘n go” fashion, where the total station makes a precise

---

1. https://www.sevensense.ai/product/alphasense-position
3. https://www.livoxtech.com/mid-70
7. https://www.hilti.com/e/CLS_MEAOOL_INSERT_7127
measurement to the prism during the ‘stop’ periods. Range measurements to the static prism have 3mm accuracy. Total station range and angle measurements are processed to generate XYZ position information.

**Optical Tracking**

Optical tracking targets are attached to the Phasma stick. When operated in a motion capture space, the multiple targets allow for the direct computation of a 6DOF pose. Those datasets have a position accuracy of <1mm and are collected at 200Hz.

### III. DATA SYNCHRONIZATION AND LOGGING

In a dynamic multi-sensor system, time synchronization between sensors is critical in order to make best use of the sensor fusion. Special care was given to synchronization in the Phasma stick to ensure maximum performance:

**AlphaSense, Bosch IMU and ADIS IMU**

The AlphaSense manages time synchronization at the hardware level via an FPGA implementation. Camera times are computed to the mid-exposure pulse (MEP). IMU data is time tagged on arrival to the FPGA data bus. Overall time synchronization between the cameras and IMUs is <1ms.

**Ouster lidar and Invensense IMU**

The Ouster module includes an integrated IMU. The Ouster point data and IMU are hardware synchronized to the Ouster internal clock. Time synchronization between the two is <1ms.

**Cross Module Synchronization**

Synchronization between modules (AlphaSense, Ouster, Livox) is provided by the supported PTP network time protocol [8]. Each module is attached via wired Ethernet cable to the data logging device, which also hosts the PTP master clock. With this setup, the time alignment between the modules is observed to be <1ms, as shown in Fig. 3. For verification we adopted the approach from [9] and used optimization tools over the correlation signal of gyroscope data.

Data logging occurs on a dedicated computer attached to the Phasma stick. The logging computer runs a Ubuntu 18.04 OS with ROS system running during capture. Sensing modules are connected to the data logger and data streams are directly recorded in ROS bag files.

### IV. CALIBRATION

Along with time synchronization, sensor intrinsic and extrinsic calibrations are critical to achieve the highest system performance. In our setup, extensive calibration was undertaken to align the various optical and inertial systems. Intrinsic sensor calibration was conducted by each respective manufacturer. For passive camera systems the procedure was a standard checkerboard calibration; for active systems proprietary calibration models were computed and corrections applied to the data at the time of capture.

The reference point of the body frame of the Phasma stick is defined at the AlphaSense Bosch IMU centre. All other sensors are transformed back to this point. Spatial offsets were determined from the CAD model of the Phasma design and refined within a calibration procedure; rotation offsets between sensors were computed in the calibration process.

The extrinsic calibration between the motion capture markers and the AlphaSense Bosch IMU was performed by using the hand eye calibration toolbox [10].

Calibration files, CAD Models and sensor noise parameters are provided in the supplementary material. The rosbags contain the Transformation (TF) Tree [11] with all transformations between the sensors.

### V. DATASETS

Data was collected under various conditions with indoor and mixed indoor-outdoor environments. The data shows...
TABLE I

<table>
<thead>
<tr>
<th></th>
<th>Basement 1</th>
<th>Basement 4</th>
<th>Campus 2</th>
<th>Construction Site 2</th>
<th>Lab Survey 2</th>
<th>RPG Drone Testing Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-LOAM</td>
<td>0.162</td>
<td>0.288</td>
<td>13.332</td>
<td>6.395</td>
<td>0.088</td>
<td>2.838</td>
</tr>
<tr>
<td>SVO2.0</td>
<td>0.813</td>
<td>2.598</td>
<td>8.941</td>
<td>2.992</td>
<td>0.082</td>
<td>1.927</td>
</tr>
<tr>
<td>ORBSLAM2</td>
<td>x</td>
<td>10.306</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

practical challenges in different stages of construction. Challenges include variable lighting, limited features and/or highly reflective and transparent surfaces.

Data Descriptions (see Fig. 2):

(a) **Basement**

Data was collected in a windowless room (approx. 20x40m). No natural light; mixed illumination brightness. Concrete space with building infrastructure. Basement 1 is a short and easy path, and for Basement 3 and Basement 4 we mounted the sensor platform on a moving base instead of operating it handheld. Basement 3 and 4 also allow to exploit loop closure capabilities of the SLAM systems.

(b) **Campus**

Data was collected outdoors in a courtyard setting (approx. 40x60m). Good natural lighting with high illumination. Mixed features with building structure and natural flora.

(c) **Construction Site**

Mostly outdoors with some covered areas (approx. 40x80m). Strong natural light with high illumination. Unfinished natural surfaces with limited features above the ground plane.

(d) **IC Office**

Indoor space with many windows and reflective surfaces (approx. 10x70m). Mix of natural and artificial light. Strong illumination at the windows, modest illumination indoors.

(e) **Lab**

Indoor space dominated by large windows (approx. 10x10m). Strong natural light and reflective surfaces. Optitrack 6DOF ground truth.

(f) **Office Mitte**

Indoor space in finished office building (approx. 30x50m). Mix of natural and artificial light. Lots of building structure.

(g) **Parking**

Mix of indoor and outdoor space (approx. 100x100m). Parking garage from top floor to lower floor. Lighting varies from extreme bright to modest darkness. Ground plane structure on top floor; lots of building structure on lower floor.

(h) **RPG Tracking Area**

Indoor test facility (approx. 30x30m). Mostly artificial light with some natural. Single large room with random motion path throughout. Vicon 6DOF ground truth.

VI. DATASET FORMAT

Datasets are stored in binary format as rosbags which contain images and IMU measurements using the standard sensor_msgs/Image and sensor_msgs/Imu message types, respectively. The Ouster data uses the sensor_msgs/PointCloud2 format while the Livox data is stored in the custom livox_ros_driver/CustomMsg message type to not loose. Fig. 4 shows an example of the camera and lidar data from the Lab Survey 2 dataset. Reference/ground truth data is given in a separate file for each dataset, with the filename indicating the reference source (e.g. Construction_Site_prism.txt means the ground truth is in the prism frame). Rosbag contents are listed in Table II.

VII. EVALUATION

The evaluation of the datasets is based on the absolute trajectory error (ATE) after SE3 alignment of the ground truth with the estimated trajectory. The correspondences are matched based on their timestamps. Scenarios collected with a motion capture system are compared with their XYZ position components only; for the other datasets the intermittent XYZ total station observations are compared. An example of a SLAM comparison with motion capture ground truth is depicted in Fig. 5 for the dataset LAB_Survey_2. An example of what established approaches can achieve on a few datasets with total station ground truth is shown in Table I.

ORBSLAM2 (which is using stereo images) is not able to produce meaningful results in all handheld datasets because it immediately looses track of features due to fast rotational movements. The only dataset where ORBSLAM2 is not
failing is Basement 4 where the Phasma stick was mounted on a moving platform. The other tested algorithms, A-LOAM and SVO2.0, are more robust with initialization and tracking. However, depending on the scene texture and scene geometry, either the lidar based A-LOAM or SVO 2.0 which is using stereo cameras and the IMU performs better.

Fig. 5. Example comparison of SVO2 [14] using stereo and IMU, LOAM [13] using the Ouster lidar. ORBSLAM2 faild to produce meaningful results. Dataset: Lab Survey 2

VIII. KNOWN ISSUES

Despite careful design and execution of the data collection experiments, we are aware of different issues which pose additional challenges for processing and limit achievable accuracy when comparing to ground truth. These include:

- Clock Drift and Offset: The clocks from motion-capture system and the data logging computer are not hardware-synchronized. We used Ethernet connection and a time-of-arrival time stamping to keep the offset to a minimum, however we observed a difference of around 1-3 ms in the two clocks.
- Some frames in the lidar and camera data have been dropped due to high load on the controller.

IX. CONCLUSION

In this paper we have described a new public dataset captured with a highly redundant multi-sensor platform. Our goal is to improve the use of SLAM algorithms in construction robotics to assist in task automation and execution. This data captures a series of real-world examples collected with current sensing technologies with a high quality time synchronization. Based on the results we showed, it is clear, that for using SLAM in real world construction use cases like progress monitoring or surveying, the robustness and accuracy has to be improved significantly. We hope to expand this data offerings into various other environments, to further spur research on positioning and navigation issues commonly encountered in indoor and mixed environments.

ACKNOWLEDGMENTS

The authors are grateful for the support of the whole team from Sevensense for their continuous support and helpful discussions, and IVISO for the calibration verification using the tool Camcalib.

REFERENCES

<table>
<thead>
<tr>
<th>Topic</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>/alphasense/cam0/image</td>
<td>sensor_msgs/Image</td>
<td>front facing camera 1</td>
</tr>
<tr>
<td>/alphasense/cam1/image</td>
<td>sensor_msgs/Image</td>
<td>front facing camera 2</td>
</tr>
<tr>
<td>/alphasense/cam2/image</td>
<td>sensor_msgs/Image</td>
<td>upward facing camera</td>
</tr>
<tr>
<td>/alphasense/cam3/image</td>
<td>sensor_msgs/Image</td>
<td>right facing camera</td>
</tr>
<tr>
<td>/alphasense/cam4/image</td>
<td>sensor_msgs/Image</td>
<td>left facing camera</td>
</tr>
<tr>
<td>/alphasense/imu</td>
<td>sensor_msgs/Imu</td>
<td>Bosch IMU, 200Hz</td>
</tr>
<tr>
<td>/alphasense/imu_adis</td>
<td>sensor_msgs/Imu</td>
<td>ADIS16446, 800Hz</td>
</tr>
<tr>
<td>/livox/lidar</td>
<td>livox_ros_driver/CustomMsg</td>
<td>Livox MID70</td>
</tr>
<tr>
<td>/os_cloud_node/imu</td>
<td>sensor_msgs/Imu</td>
<td>InvenSense, 100Hz</td>
</tr>
<tr>
<td>/os_cloud_node/points</td>
<td>sensor_msgs/PointCloud2</td>
<td>Ouster OS-64</td>
</tr>
<tr>
<td>tf_static</td>
<td>tf2_msgs/TFMessage</td>
<td>all transforms between frames</td>
</tr>
</tbody>
</table>


