A Backpack-mounted 3D Mobile Scanning System

Ein rucksackgetragenes mobiles Laserscanningsystem

Andreas Nüchter, Dorit Borrmann, Jan Elseberg, David Redondo

Mobile laser scanning systems automate the acquisition of 3D point clouds of environments. The mapping systems are commonly mounted on cars or ships. This paper presents a mapping solution mounted on a backpack. A clever choice of hard- and software enables the system to generate 3D maps without using GPS (global positioning system) information and without relying on expensive IMU (inertial measurement unit) systems. Therefore, it enables flexible indoor mapping.

Keywwords: Mobile laser scanning, indoor mapping, personal laser scanning

Mobile Laserscannigsysteme automatisieren die Aufnahme von 3D-Punktwolken zur Erfassung von Umgebungen. Die Kartierungssysteme werden üblicherweise auf Autos oder Schiffen montiert. In diesem Beitrag wird eine Lösung präsentiert, die sich auf einem Rucksack montieren lässt. Durch geschickte Auswahl von Hard- und Software kann das System 3D-Karten ohne GPS-Information und ohne kostspielige inertiale Messsysteme erstellen. Dadurch ist es möglich, flexibel Innenräume zu kartieren.

Schlüsselwörter: Mobiles Laserscanning, Kartierung von Innenräumen, personengebundenes Laserscansystem

1 INTRODUCTION

3D mapping systems have to become more and more flexible to meet the users' requirements. There is a critical demand for indoor mapping systems, e. g. for scanning factories and production lines. Often times terrestrial laser scanning is too time-consuming and thus too costly. Robotic solutions /Nüchter et al. 2013/ or solutions with scanners mounted on carts, like the viametris iMMS /VIAmetris 2015/, /Thomson et al. 2013/, are not suitable for a large number of applications, as closed doors and doorsteps may preclude their application. A backpack mounted system, also known as personal laser scanning, is the ideal solution to overcome these issues for indoor mapping. The system architecture allows to monitor a 2D mapping progress, such that the operator knows on the fly, which areas already have been gaged. Recently, Google unveiled "The Cartographer, Its Indoor Mapping Backpack" for similar use cases /Lardinois 2015/. While they rely on Hokuyo laser scanners, which are inexpensive devices with low data rate, accuracy and range, the here presented solution features a high-end laser scanner, namely a Riegl VZ-400, for mapping. In addition, we exploit two levels of SLAM (simultaneous localization and mapping) technologies for generating precise maps. The system is ready to use and this paper presents results obtained during a presentation at

Fig. 1 | Images of the backpack system. Left: Side view with all of its sensors and equipment. Right: Detailed view of the SICK and the IMU.

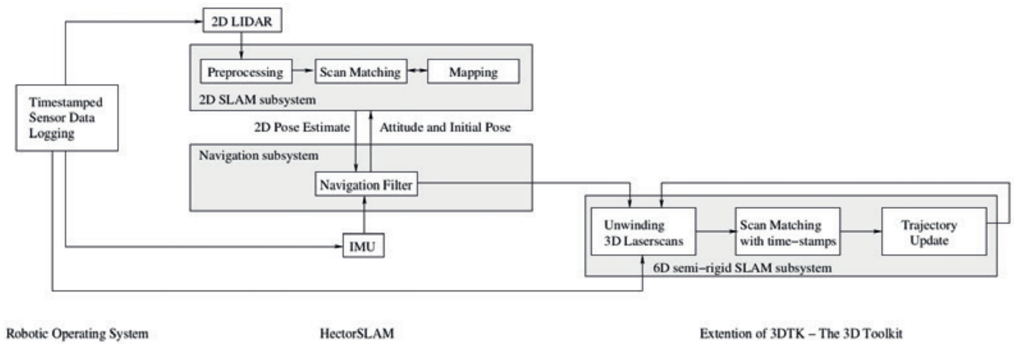

Fig. 2 | Overview of the system architecture

MoLaS: Technology Workshop Mobile Laser Scanning at Fraunhofer IPM in Freiburg, Germany in November 2014. A similar presentation was given at the 7. Anwenderforum Laserscanning an der FHWS in Würzburg, Germany.

Our backpack solution (*Fig. 1*) relies on a horizontally mounted 2D profiler, a SICK LMS100 scanner. A SLAM software called HectorSLAM /Kohlbrecher et al. 2011/ generates an initial trajectory of the backpack by registering these data. The trajectory is then used to "unwind" the data of the Riegl VZ-400. The Riegl scanner itself is rotating around its vertical axis, such that the environment is gaged multiple times. This is exploited in our calibration and semi-rigid SLAM solution. While calibration computes the 6 DoF (degree of freedom) pose of every sensor, the semi-rigid SLAM deforms the trajectory of the backpack such that the 3D point cloud aligns well.

Fig. 2 presents the overall architecture of the system. For sensor data acquisition we exploit ROS, the so-called robotic operating system /Quigley et al. 2009/ which is a middleware for Linux operating systems. ROS is a set of software libraries and tools that are used in the robotic community to build robot applications. As a middleware, it connects device drivers, programs and tools on a heterogeneous computer cluster. ROS provides standard operating system services such as hardware abstraction, low-level device control, implementation of commonly used functionality, message-passing between processes, and package management. It enables time-stamped sensor data logging and the control of the devices. Programs are running as independent processes as so-called ROS nodes. The data of the 2D Lidar (Light detection and ranging) and of the IMU are fed into the 2D SLAM subsystem HectorSLAM which is also implemented as ROS node. The output of the HectorSLAM ROS node serves as input of the six degree of freedom (6 DoF) semi-rigid SLAM, which registers the 3D data from the Riegl VZ-400, and is implemented using 3DTK – The 3D Toolkit /Nüchter et al. 2015/.

2 THE BACKPACK-MOUNTED 3D SCANNING SYSTEM

The setup of the backpacking system is strongly influenced by the robot Irma3D /Nüchter et al. 2013/. The basis is a Tatonka load carrier where aluminum components and system solutions for building fixtures, so-called item24-profiles /item24 Industrietechnik 2015/ similar to the Volksbot RT 3 chassis have been attached using pipe clamps. Energy is currently provided by two Panasonic 12 V lead-acid batteries with 12 Ah, but to save weight, these will be replaced by lithium polymer batteries. Similarly to Irma3D /Nüchter et al. 2013/, the backpack features a horizontally scanning SICK LMS 100, which is used to observe the motion of the carrier using a grid mapping variant. To fully exploit the 270° field of view of the SICK LMS 100, the sensor head is positioned slightly above the load carrier. The central sensor of the backpack system is the 3D laser scanner Riegl VZ-400. The VZ-400 is able to freely rotate around its vertical axis to acquire 3D scans. Due to the setup, however, there is an occlusion of about 100° from the backside of the backpack and the human carrier. The backpack has an inexpensive, low-end IMU, namely the Phidgets 1044 (PhidgetSpatial Precision 3/3/3 High Resolution) /Phidgets 2015/. The backpack is also equipped with a network switch to receive the data from the two scanners and to connect the 12" laptop (Samsung Q45 Aura laptop with an Intel Core 2 Duo T7100 processor), which is carried by the human.

Due to the occlusion, it is disadvantageous to constantly spin the VZ-400 as the resulting trajectory at which data was collected will have a gap. Currently, our semi-rigid SLAM solution for optimizing the trajectory (cf. Section 4) cannot handle these gaps. Thus, we programmed the scanner such that it rotates back-and-forth. *Fig. 3* compares the resulting scan patterns.

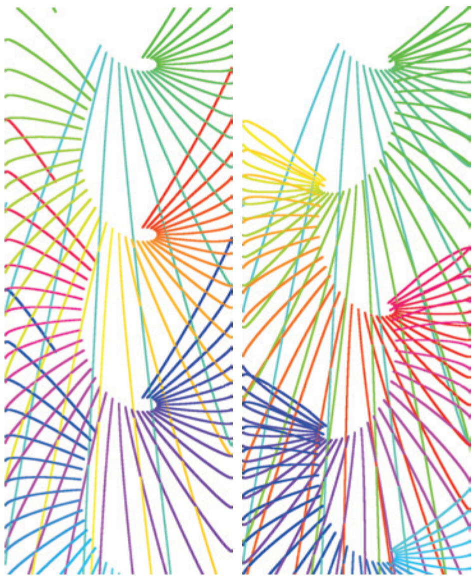

Fig. 3 | The results of simulated mobile laser scanning patterns for the backpack system. Left: Spinning 3D scanner that is affected by an occlusion of 100°. Right: System that rotates back-and-forth and thus, all laser pulses capture distance measurements.

3 2D MAPPING WITH THE HORIZONALLY-MOUNTED LASER PROFILER AND INITIAL TRAJECTORY GENERATION

HectorSLAM is a state of the art 2D SLAM solution /Kohlbrecher et al. 2011/. It represents the environment in a 2D occupancy grid, which is a very well-known representation in Robotics. Compared to other state of the art grid mapping approaches, it neither uses feature extraction as in /Durrant-Whyte & Bailey 2006/ nor a particle filter for mapping as in FastSLAM /Montemerlo et al. 2002/, /Hähnel et al. 2003/, which commonly enable reliable robot localization and mapping. The 2D Lidar performs 6 DoF motion while the backpack is carried. First, the scan has to be transformed into a local stabilized coordinate frame using the IMU-estimated attitude of the Lidar system. In a scan matching process, the acquired stabilized scan is matched with the existing map. The optimization of the alignment is done using a Gauss-Newton approach, similar to the work in /Lucas & Kanade 1981/, and therefore neither data association, i.e., point matching, nor an exhaustive search for the optimal pose transformation is needed. As "any hill climbing/gradient based approach has the inherent risk of getting stuck in local minima" /Kohlbrecher et al. 2011/ the developers of HectorSLAM mitigate it by employing a multi-resolution map representation similar to image pyramid approaches used in computer vision. Different maps are kept in memory and simultaneously updated using the pose estimates generated by the alignment process, which ensures consistency across scales. The scan alignment process is started at the coarsest map level and the resulting estimated pose is used as the start estimate for the next level.

The information of the 2D SLAM solution is exchanged using the ROS communication framework with the navigation filter, which is an EKF (Extended Kalman Filter) in a bi-directional fashion, and thus fused with the values of the IMU to produce 6 DoF pose estimates. The 2D mapping and the navigation module are not synchronized and the EKF usually runs at a higher update rate. HectorSLAM uses this EKF for the pose estimation and the EKF values are projected onto the xy-plane and are used as start estimate for the optimization process of the 2D scan matcher. In the opposite direction, covariance intersection (CI) is used to fuse the SLAM pose with the full belief state of the navigation system.

Fig. 4 shows the results of HectorSLAM using the SICK scanner on the backpack. Depicted is the first part of the trajectory, i.e., it can be seen how the map is built in an incremental fashion. Occupied grid cells are denoted in black, light-gray denotes free space, while dark-gray refers to unknown values. The trajectory of the system is drawn in red. In *Fig. 5* the complete map is shown. When no IMU information is used (left) one can see that one turn is not correctly modelled and thus an incorrect 2D map and an erroneous trajectory are produced. Using an IMU yields much better initial estimates. Overall, HectorSLAM has proven to produce a 2D map reliably.

Next, we shift our focus to processing the 3D data obtained by the Riegl scanner. We "unwind" the data using the HectorSLAM trajectory, split the 3D data into segments, match these segments and distribute the alignment in a semi-rigid fashion. In addition, we present our calibration method.

Fig. 4 | Three steps of HectorSLAM: After processing 1 second, 2 seconds and 3 seconds of 2D Lidar data

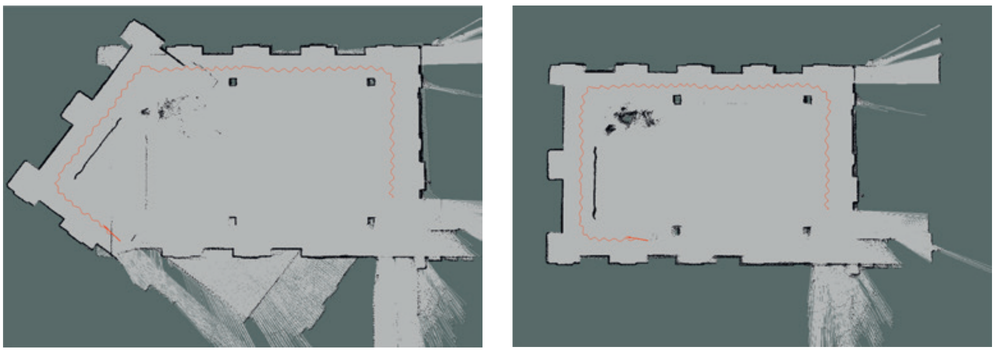

Fig. 5 | HectorSLAM without (left) and with (right) incorporating IMU data. In general HectorSLAM is able to work on raw Lidar data as only input, however, including data of an IMU leads to more reliable results.

4 MOBILE MAPPING WITH CONSTANTLY SPINNING SCANNERS

In the following subsections we summarize our work from /Borrmann et al. 2008/ and /Elseberg et al. 2013/. These algorithms are suited to turn laser range data acquired with a rotating scanner while the acquisition system is in motion into precise, globally consistent 3D point clouds.

4.1 Automatic High-Precise Registration of Terrestrial 3D Scans

The basis of our software development is the well-known iterative closest point (ICP) algorithm. Given two 3D point clouds and a rough initial pose estimate, e. g., by the odometry of a robot, ICP iteratively revises the pose estimates (translation and rotation with 6 degrees of freedom) of the second scan. For doing so, the algorithm selects closest points between the two raw scans and minimizes an error function. Current research in the context of ICP algorithms mainly focuses on fast variants of ICP algorithms /Elseberg et al. 2012b/. The key issue for fast ICP variants is the ability to find closest points efficiently. For more than two scans this procedure is repeated, always registering the nth scan against the $(n-1)$th scan.

Pairwise ICP improves the scan pose estimates, but registration errors sum up when adding more scans. SLAM algorithms use loop closings to bound this error, i. e., the pose estimates are improved when a scan is taken at a position close to the location of a previous scan. Recently, we have presented our globally consistent scan matching algorithm, which is a bundle adjustment solution for 3D scans. It extends the ICP algorithm. Given n point clouds as input improved pose estimates for all scans are computed. In an ICP-like fashion, the algorithm iteratively calculates closest points between all scan pairs as specified in the SLAM graph. Using these point pairs, improved poses for all scans based on least square error minimization are calculated. The algorithm is discussed in detail in /Borrmann et al. 2008/. *Fig. 6* shows a scene in Horn, Austria, where the scans have been registered with ICP and its globally consistent extension. Please note that our algorithm does not require any feature extraction.

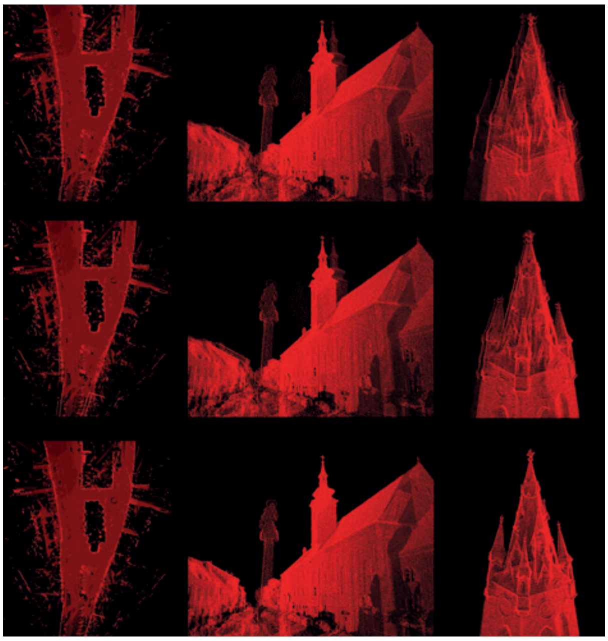

Fig. 6 | Globally consistent scan matching applied to a data set acquired in Horn, Austria, which consists of several terrestrial 3D scans. Top: Initial point cloud alignment. Middle: Intermediate step. Bottom: Final registration. From left: Bird-eye view. Middle and right: Details.

4.2 Automatic Calibration for Mobile Mapping

Calibration is the process of estimating the parameters of a system. In /Elseberg et al. 2013/ we presented a general method for this estimation problem, where the 3D point cloud represents samples from a probability density function which represents the probability that a specific location $\boldsymbol{\ell}$ has been measured.

$$d(\boldsymbol{\ell}) = \frac{1}{n}\sum_{j}^{n} G\left(\boldsymbol{\ell} - \boldsymbol{p}_j, \sigma^2 \boldsymbol{I}\right), \tag{1}$$

where $G(\boldsymbol{\mu}, \sigma^2 \boldsymbol{I})$ is a Gaussian distribution with mean $\boldsymbol{\mu}$ and covariance $\sigma^2 \boldsymbol{I}$. This is more than sufficient to capture consistency of a point cloud. As calibration errors lead to the same surfaces appearing at multiple positions in the point cloud, the entropy can be used to measure the compactness of the point cloud. /Sheehan et al. 2011/ derive the following simplified entropy measure, which depends on only the pairwise distance of every possible pair of sample points:

$$E\left(P'\right) = \sum_{i}^{n}\sum_{j}^{n} G\left(\boldsymbol{p}_i - \boldsymbol{p}_j, \sigma^2 \boldsymbol{I}\right). \tag{2}$$

Considering the enormous amount of data, calculating a measure that uses all possible pairs of sample points seams infeasible. We use an octree-based reduction /Elseberg et al. 2012a/ and use only closest point pairs to overcome the computational issues. Our automatic method treats the "unwinding" method as a function where the calibration parameters are the unknown variables. The function expresses how the trajectory, the laser measurements and the calibration parameters are combined to create the 3D point cloud. Finally, we employ Powells method for optimizing the calibration parameters.

4.3 Semi-rigid SLAM for Trajectory Optimization

In addition to the calibration algorithm, we also developed an algorithm that improves the entire trajectory of the backpack simultaneously. The algorithm is adopted from /Elseberg et al. 2013/, where it was in a different mobile mapping context, i. e., on wheeled platforms. Unlike previous algorithms, e. g., by /Stoyanov & Lilienthal 2009/ and /Bosse & Zlot 2009/, it is not restricted to purely local improvements. We make no rigidity assumptions, except for the computation of the point correspondences. We require no explicit motion model of a vehicle for instance, although such information may be incorporated at no additional cost. The semi-rigid SLAM for trajectory optimization works in 6 DoF, which implies that the planar trajectory generated by HectorSLAM is turned into poses with 6 DoF. The algorithm requires no high-level feature computation, i. e., we require only the points themselves.

In case of mobile mapping, we do not have separate terrestrial 3D scans as in section 4.1. In the current state of the art developed by /Bosse & Zlot 2009/ for improving overall map quality of mobile mappers in the robotics community the time is coarsely discretized. This results in partitioning of the trajectory into subscans that are treated rigidly. Then rigid registration algorithms like the ICP and other solutions to the SLAM problem are employed. Obviously, trajectory errors within a subscan cannot be improved in this fashion. Applying rigid pose estimation to this non-rigid problem is also problematic since rigid transformations can only approximate the underlying ground truth. When a finer discretization is used, single 2D scan slices or single points result that do not constrain a 6 DoF pose sufficiently for rigid algorithms.

Details of the algorithm are given in /Elseberg et al. 2013/. Essentially, we first split the trajectory into sections, and match these sections using the automatic high-precise registration of terrestrial 3D scans, i. e., globally consistent scan matching /Borrmann et al. 2008/. Here the graph is estimated using an heuristics that measures the overlap of sections using the number of closest point pairs. After applying globally consistent scan matching on the sections the actual semi-rigid matching as described in /Elseberg et al. 2013/ is applied, using the results of the rigid optimization to guide the optimization to its numerical minimum. To speed up the calculations, we make use of the sparse Cholesky decompositions by /Davis 2005/.

5 EXPERIMENTS AND RESULTS

The backpack has been presented and demonstrated at MoLaS: Technology Workshop Mobile Laser Scanning at Fraunhofer IPM in Freiburg, Germany. A data set has been acquired in the areaway in the Fraunhofer Institute (*Fig. 7*). The Riegl VZ-400 was rotating around the vertical axis back and forth to avoid the blind spot. The result of HectorSLAM was already given in *Fig. 5* (right). As it is a consistent 2D map, it serves as an input for "unwinding" the Riegl data yielding an initial 3D point cloud. The left part of *Fig. 8* and *Fig. 9* show the point cloud prior to the semi-rigid SLAM, the right part the corresponding views after the optimization. The final point cloud is presented in *Fig. 10*, where three different views are shown. The laser reflectance values have been mapped to greyscale and assigned to the 3D points. The red line denotes the trajectory of the backpack. The

Fig. 7 | Photos of the first author operating the backpack system

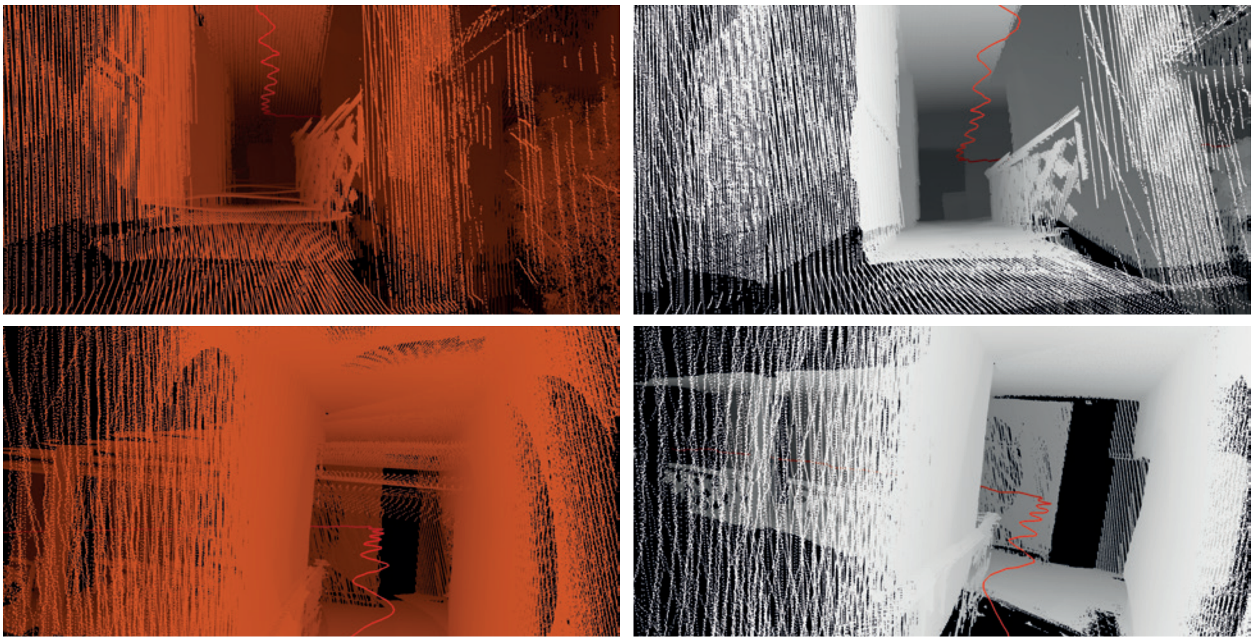

Fig. 8 | Left: "unwound" 3D point cloud. Right: Optimized point cloud using semi-rigid SLAM.

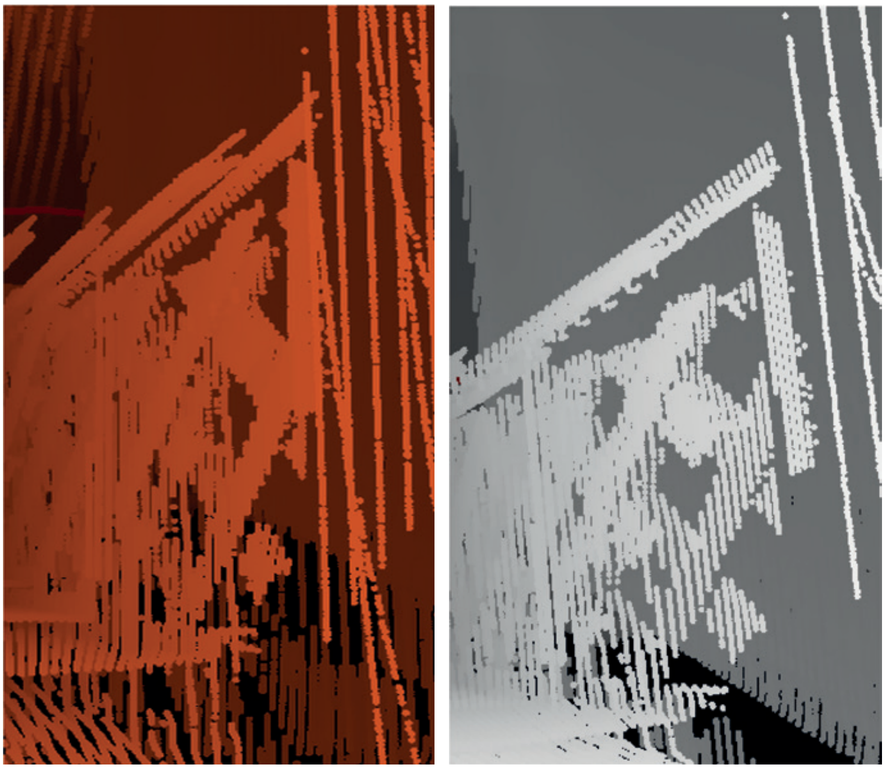

Fig. 9 | Detailed view of the balustrade in *Fig. 8* (above). Please note the improvement at the handrail.

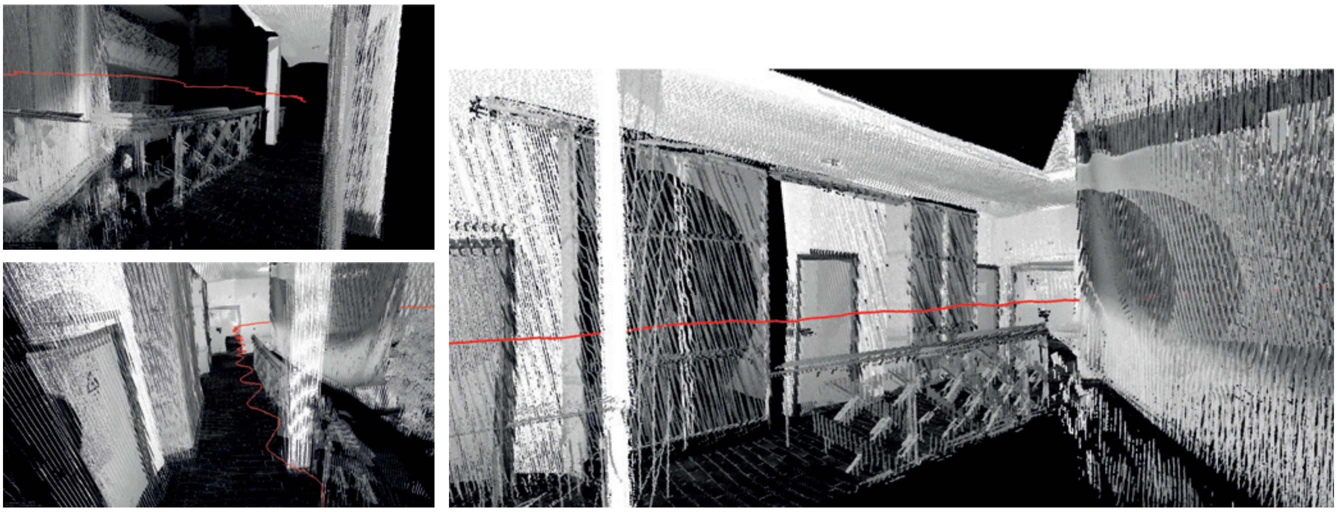

Fig. 10 | Overall view of the final result. The points have been colored using reflectances and the red line denotes the trajectory.

experiment was performed prior to the social event and thus, the oscillation originates from the normal human walking motion.

Semi-rigid optimization improved the consistency of the 3D point cloud. Nevertheless, small inaccuracies remain. The main limiting factor for the point cloud quality is the poor input quality. In previous works, we obtained highly accurate results in other mobile mapping scenarios using data from a Riegl VMX-450 and an Optech Lynx Mobile Mapper /Elseberg et al. 2013/. In addition, the Riegl VZ-400 spins with a rotational frequency with 6 seconds per revolution. Our scan matching based method relies on the fact that the same surface is measured several times. This provides information for scan matching and pose, resp. trajectory optimization. With a higher rotational speed, the time and thus the motion between the same 3D surface being measured again is shorter and thus, the maps would be more accurate.

6 CONCLUSIONS AND OUTLOOK

The paper presents the hardware and system architecture of our backpack mobile mapping system. It is currently designed for indoor applications, does not require GPS information or an expensive IMU. It is flexible and can easily be set up. Its technical basis is a horizontally mounted 2D Lidar, an effective 2D SLAM algorithm and an calibration and semi-rigid SLAM algorithm operating on the 3D point cloud.

Needless to say, a lot of work remains to be done. In future work, we aim at testing the backpack in an outdoor environment and incorporating a GPS. Furthermore, we will use an iGPS (Nikon Metrology) /Nikon Metrology 2014/ to set up an accurate metrology-enabled indoor area to acquire independent ground truth to verify our methods and to estimate the accuracy.

Acknowledgements

The project started while the first three authors were at Jacobs University Bremen, Germany. We would like to thank our former students Remus Dumitru, Araz Jangiaghdam, George Adrian Mandresi, Vaibhav Kumar Mehta and Robert Savu. An initial student video is available under the following URL: http://youtu.be/tI7kztEtEFM .

References

Bosse, M.; Zlot, R. (2009): Continuous 3D Scan-Matching with a Spinning 2D Laser. In: Proceedings of the IEEE International Conference on Robotics and Automation (ICRA '09), 4312–4319.

Borrmann, D.; Elseberg, J.; Lingemann, K.; Nüchter, A.; Hertzberg, J. (2008): Globally consistent 3d mapping with scan matching. In: Journal Robotics and Autonomous Systems (JRAS), 56(2008)2, 130–142.

Borrmann, D.; Lingemann, K.; Nüchter, A. (2015): 3DTK–The 3D Toolkit. http://slam6d.sourceforge.net.

Davis, T. A. (2005): Algorithm 849: A Concise Sparse Cholesky Factorization Package. In: ACM Trans. Math. Softw., 31(2005)4, 587–591.

Durrant-Whyte, H.; Bailey, T. (2006): Simultaneous localization and mapping (slam): Part i. In: IEEE Robotics and Automation Magazine (RAM), 13(2006)2, 99–108.

Elseberg, J.; Borrmann, D.; Nüchter, A. (2012a): Eine Milliarde 3D-Punkte mit Standardhardware verarbeiten – Processing One Billion 3D Points on a Standard Computer. In: allgemeine vermessungs-nachrichten (avn), 119(2012)1, 11–23.

Elseberg, J.; Magnenat, S.; Siegwart, R.; Nüchter, A. (2012b): Comparison on nearestneigbour-search strategies and implementations for efficient shape registration. In: Journal of Software Engineering for Robotics (JOSER), 3(2012)1, 2–12.

Elseberg, J.; Borrmann, D.; Nüchter, A. (2013): Algorithmic solutions for computing accurate maximum likelihood 3D point clouds from mobile laser scanning platforms. In: Remote Sensing, 5(2013)11, 5871–5906.

Hähnel, D.; Burgard, W.; Fox, D.; Thrun, S. (2003): An efficient fastslam algorithm for generating maps of large-scale cyclic environments from raw laser range measurements. In: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS '03), Las Vegas, Nevada, USA.

Lardinois, F. (2015): Google Unveils The Cartographer, Its Indoor Mapping Backpack. TechCrunch. http://techcrunch.com/2014/09/04/google-unveils-the-cartographer-its-indoor-mapping-backpack/.item24.

Industrietechnik (2015): Alu-Profilsystem-Baukästen für industrielle Anwendungen. http://www.item24.de.

Kohlbrecher, S.; Meyer, J.; von Stryk, O.; Klingauf, U. (2011): A flexible and scalable slam system with full 3d motion estimation. In: Proceedings of the IEEE International Symposium on Safety, Security and Rescue Robotics (SSRR '11).

Lucas, B. D.; Kanade, T. (1981): An iterative image registration technique with an application to stereo vision. In: Proceedings of the DARPA Image Understanding Workshop, 121–130.

Montemerlo, M.; Thrun, S.; Koller, D.; Wegbreit, B. (2002): Fastslam: A factored solution to the simultaneous localization and mapping problem. In: Proceedings of the AAAI National Conference on Artificial Intelligence (AAAI '02), 593–598.

Nikon Metrology (2014): iSpace – Portable Metrology System User Manual and Startup Guide. http://www.nikonmetrology.com.

Nüchter, A.; Elseberg, J.; Borrmann, D. (2013): Irma3D – An Intelligent Robot for Mapping Applications. In: Proceedings of the 3rd IFAC Symposium on Telematics Applications (TA '13), Seoul, Korea, 119–124.

Phidgets (2015): Products for usb sensing and control. http://www.phidgets.com/products.php?product_id=1044.

Quigley, M.; Gerkey, B.; Conley, K.; Faust, J.; Foote, T.; Leibs, J.; Berger, E.; Wheeler, R.; Ng, A. (2009): ROS: an open-source robot operating system. In: Proceedings of the IEEE International Conference on Robotics and Automation (ICRA '09), Kobe, Japan.

Sheehan, M.; Harrison, A.; Newman, P. (2011): Self-calibration for a 3D Laser. In: The International Journal of Robotics Research, 31(2011)5, 675–687.

Stoyanov, T.; Lilienthal, A. J. (2009): Maximum Likelihood Point Cloud Acquisition from a Mobile Platform. In: Proceedings of the IEEE International Conference on Advanced Robotics (ICAR '09), 1–6.

Thomson, C.; Apostolopoulos, G.; Backes, D.; Boehm, J. (2013): Mobile laser scanning for indoor modelling. In: ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, II-5/W2, 289–293.

VIAmetris (2015): Mobile Mapping Technology. http://www.viametris.com.

Prof. Dr. Andreas Nüchter

UNIVERSITÄT WÜRZBURG
INFORMATIK VII – ROBOTIK UND TELEMATIK

Am Hubland | 97074 Würzburg
nuechter@informatik.uni-wuerzburg.de

Dorit Borrmann, M. Sc.

UNIVERSITÄT WÜRZBURG
INFORMATIK VII – ROBOTIK UND TELEMATIK

Am Hubland | 97074 Würzburg
borrmann@informatik.uni-wuerzburg.de

Jan Elseberg, PhD

UNIVERSITÄT WÜRZBURG
INFORMATIK VII – ROBOTIK UND TELEMATIK

Am Hubland | 97074 Würzburg
jan.elseberg@uni-wuerzburg.de

David Redondo

UNIVERSITÄT WÜRZBURG
INFORMATIK VII – ROBOTIK UND TELEMATIK

Am Hubland | 97074 Würzburg
david.redondo@stud-mail.uni-wuerzburg.de

Manuskript eingereicht: 05.02.15 | Im Peer-Review-Verfahren begutachtet