Mobile 3D LiDAR-based Object and Change Detection in Production and Operations Management

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***Abstract*—As an ongoing robot-related trend, intelligent mobile robots can create an accurate digital three-dimensional (3D) model of the environment using Light Detection And Ranging (LiDAR) scanners. This paper presents a new solution concept, which enables change detection and thus more efficient visual 3D data utilisation in production and operations management. As a result, use cases for mobile, real-time 3D LiDAR-based change detection are identified. In these cases, Autonomous Mobile Robots (AMRs) equipped with LiDARs detect changes automatically while moving around the factory in, e.g., internal logistics tasks. The solution studied may be useful for, e.g., detecting large items left in the wrong places, obstacles on AMRs' routes and blocked fire doors and emergency exits. The as-is 3D model of the factory can also be used as a basis for factory renovation and modernisation and progress monitoring.**

Keywords-Autonomous mobile robot; AMR; LiDAR; object and change detection; real-time

I. INTRODUCTION

Modern factories are full of fixed sensors on production lines and machines, as well as in the building itself. There have been plenty of discussions and actions taken in smart factories in order to unleash the potential of Industry 4.0 and enormous amounts of data [1]. AMRs and digital twins are among central technologies when companies proceed in Industry 4.0 and 5.0 [2][3]. AMRs use LiDAR scanners in mapping their environment, localisation and autonomous navigation [4]-[8]. With 3D LiDARs, an accurate digital reconstruction can be created of the environment where the AMR is moving while conducting, e.g., internal logistics tasks. However, data gathered by LiDARs remain under utilised in factories, and new mobile LiDAR solutions can enable new use cases and benefits for production and operations management.

The aim of this study was to study the way mobile 3D LiDAR-based object and change detection can enhance production and operations management (POM). The study consisted of two tasks: 1) development of a new mobile, real-time 3D LiDAR-based solution concept for object and change detection and related testing in real industrial environments and 2) identification of potential use cases for such solutions within the production and operations management domain. The findings of the study propose new potential use cases for object and change detection in, e.g., production, intra-logistics and security operations. The strengths of the solution are especially related to cases in which rather large visual objects and changes need to be detected. Then, for example, obstacles blocking AMR traffic or emergency exits can be pinpointed real-time leading to prompt reactions and thus ensuring smooth logistics flows and safety.

This paper is organised as follows: Section 1 provides an introduction for the paper. In the Section 2, we provide a theoretical background regarding digital smart factories, AMRs, LiDARs and related applications, as well as methods for object and change detection. Section 3 describes the methodology of the study. Section 4 presents the study results: a) a technical solution concept for object and change detection and testing results in a real industrial environment, and b) potential use cases for the solution. Finally, in the Section 5, conclusions are drawn on the most potential use cases and the ways the solution may enhance POMS in the future.

II. THEORY

A. Intelligent production and operations

Industry 4.0, also known as the Fourth Industrial Revolution, is drastically renewing manufacturing companies' production and operations [2]. Digital technologies make machines more self-sufficient, highly data intensive and able to communicate and even "talk" to one another. Automation and data analytics emerge as major forces to enhance efficiency in operations management [9]. The ultimate aim is to enhance production and operations efficiency and business growth.

Hand in hand with the phenomenon goes the trend of making all businesses smarter and more automated [9]. Manufacturing is in an increasing manner equipped with sensor and autonomous systems. Dull, dirty and dangerous labour involves in an increasing manner robots instead of people. Robotics and digital twins are two out of five central disruptive technologies in the Industry 4.0 and beyond [9]. Robots are more intelligent and autonomous and support automation of production and intra-logistics operations. In addition to robotics, holistically digitalised models of products and factories are developed for smart factories [10]. Industry 5.0 also includes edge computing, digital twins and collaborative robots also encompassing stronger human

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perspective in terms of critical thinking and decision making [3][9].

Industry 4.0 and 5.0 go hand in hand with the Big Data phenomenon [12], and huge amounts of various data from machines and operations are collected and used nowadays in factories. Data supports rehal-time monitoring and more intelligent decision making concerning, for example, production and inventory management [1][4][12]. Fifth-generation (5G) network enables further advances in data gtransfer, remote monitoring and operation [13].

B. Autonomous mobile robots in smart factory

Traditionally, motives for automation have been cost savings, quality improvements and safety [14]. Use of AMRs is increasing in production and intralogistics operations [5][14]. AMRs are typically equipped with a wide set of sensing technologies providing input data. Laser scanners, 3D cameras, accelerometers, gyroscopes, ultrasound sensors and wheel encoders ensure accurate position and heading data at all times, thus enabling safe autonomous navigation [5][6][15][16]. Although huge amounts of data are often collected with fixed sensors in factories, data that AMRs collect while driving around remains underutilised. We suggest that data collected with laser scanners, 3D LiDARs, could also be used more in production and operations management.

Figure 1. SPOT robot as an example of an AMR.

During the past ten years, the use of 3D LiDARs has grown rapidly. LiDAR stands for Light Detection And Ranging. LiDARs uses light pulses, typically emitted by a laser, to measure distances of its surroundings. LiDARs provide a precise distance point cloud relative to the AMR of its environment, which is then used for Simultaneous Localisation And Mapping (SLAM) and collision avoidance [6]-[8][17]-[19]. As a result, a point cloud consisting of as many as millions of dots is created, and a digital twin of the environment is created (Figure 2). More knowledge is needed on, how point clouds formed by AMR 3D LiDARs could be used to accrue benefits for production and operations management.

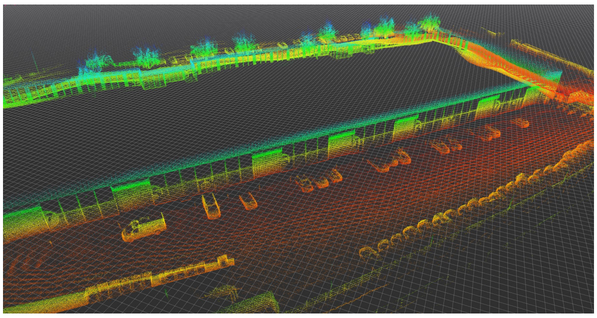

Figure 2. Point cloud created with 3D LiDAR scanner.

C. 3D LiDAR applications in various business fields

LiDARs are widely in use in various business fields. In the manufacturing industry, one of the most common applications of LiDARs is for autonomous navigation of AMRs and automated guided vehicles (AGVs) in internal logistics operations [4]-[8]. Accurate, as-built 3D models of industrial sites could be used more in the manufacturing sector [4] for, e.g., site modernisation projects, inspection, safety analysis, simulation and change detection.

In addition to AMRs and AGVs in industrial use, another common application area for LiDARs is transportation. LiDAR data can be collected, e.g., by cars on the ground, by airplanes or drones in the air or by satellites in space [20]. In these cases, LiDAR data is mobile, whereas in some cases, data can also be collected statically, e.g., when modelling a building. In this paper, we concentrate on mobile laser scanning, which is LiDAR mounted on a mobile platform, moving on a factory floor or outdoor at a factory site. Mobile LiDAR scanning is the most common approach for collecting data in transportation applications, since roads and various features of urban environments can be captured with a high level of detail [20]-[22]. Further applications for LiDARs include, e.g., mapping mines [23][24], cities and buildings [25]-[28], forests [29], plants and fields [30] and historical landscapes in archaeological research [31].

D. 3D LiDAR-based object and change detection

LiDAR sensors target the surrounding surfaces with a laser beam and produce range data by measuring the time for the reflected light to return to the receiver. For instance, Ouster OS0-128 LiDAR has a 360°×90° field-of-view and a measuring range from 0.5m up to 100m. These wide angle, high resolution LiDARs provide opportunities not only for localisation, navigation and mapping, but also for detection and monitoring temporal changes.

3D-change-detection tasks aim to find differences in a scene or for particular types of objects using multiple acquisitions of 3D data. 3D LiDARs scan the environment at

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a high speed (e.g., 20 times per second), and every time, a point cloud consisting of as many as millions of dots is created. For instance, with an angular resolution of 0.2°×0.7° Ouster OS0-128 LiDAR is able to provide up to 2621440 points per second, with a precision of ±1.5–5cm. Point clouds collected at different times are then compared for detecting changes. The changes in the 3D geometry can be further categorised as additions (previously free space is now occupied), subtractions (previously occupied space is now free) or discrepancies, where the apparent change is caused by sensor noise or other sources of error [32]. In addition to data differentiation, change detection may also include identification of changes for meaningful objects. For instance, monitoring of an on-street car park included 1) vehicle detection, 2) classification in terms of defined categories of vehicles and 3) change detection in terms of whether a car had changed from a certain spot in order to estimate parking duration [33].

3D object detection can be divided into three kinds of methodologies: 1) fusion-based approaches, combining RGB images and 3D point cloud data, 2) two-dimensional (2D) detection-driven methods, based on 2D bounding boxes defined from RGB images and 3) point-cloud-based methods, exploring features and topology of points to detect 3D objects [34]. In this paper, we concentrate on the latter one, point-cloud-based methods. 3D LiDARs can create a very accurate digital 3D model and map of the environment, even in environments where there are people [35]. When a mobile robot gathers 3D LiDAR data, object steric size and location information are included. Another benefit of LiDARs is that they are insensitive to natural light, which makes them a potential sensor for 3D detection in environments with varying or poor light conditions. In many cases, methods based on RGB images and image recognition are feasible for object and change detection [36]. However, while comparing LiDAR-based methods with the 2D object detection, LiDAR-based methods can provide new potential applications for production and operations management.

One state-of-the-art point-cloud-based object and change detection method is a method called PointPillars, in which point cloud data is combined with voxel-based feature extraction [37]. First, it organises raw point clouds as pillars (voxels) and then uses PointNet to learn the representation of point clouds. Finally, a standard 2D convolutional is used to enable efficient real-time detection. This method has been used, e.g., in autonomous vehicles for pedestrian and cyclist detection [38][39].

E. *Literature synthesis, research gap and research question*

3D LiDARs have been traditionally used for mapping the environment, robot localisation and autonomous navigation [4]-[8]. In recent years, the advances in LiDAR technology have improved their range, accuracy and resolution. At the same time, laser scanners' prices have gone down significantly in relation to their improved capabilities. Object detection, classification and 3D change detection can be done in a more detailed level than before and new use cases can be identified in factories. Still, within the production and operations management domain, there is scarcity of research concerning future mobile 3D LiDAR-based concepts, solutions and potential use cases that can emerge in this context. Object and change detection done with 3D LiDARs may offer new benefits for the industry. It is one way in which mobile LiDAR data collected by AMR on site can be taken into more efficient use in so-called smart factories. Thus, the main research question of this paper is the following: *"How can mobile 3D LiDAR-based object and change detection enhance production and operations management in smart factories?"*

III. METHODOLOGY

There is quite limited research within the POMS domain regarding the way LiDAR-based object and change detection could enhance operations in smart factories. Therefore, this study applies a qualitative case study approach, which is suitable for increasing the understanding of a phenomenon previously under investigated and thus to answer "how" questions [40]. The studied case includes the development of a solution concept for LiDAR-based object and change detection, its testing and collection of qualitative data on the research topic from the companies participating in the same project. VTT Technical Research Centre of Finland developed the technical solution. The solution is based on a LiDAR point-cloud comparison and helps identifying changes between the point clouds scanned at different times.

The solution can be used on a mobile platform, such as an AMR, which is moving around an industrial site anyway during its preliminary task (e.g., in intra-logistics). The aim is to develop a solution, which would enable mobile, real-time object and change detection in factories both indoors and outdoors. Parts of the solution were tested, and experiences gathered already in the course of this study, but development work is still ongoing based on the results so far. However, the solution concept is presented in this paper.

The solution was developed and tested in two phases. The first scanning round was done in real industrial environment outdoors on a factory yard. The changes that took place on the yard were related to the trash containers (present/absent), the factory doors (open/closed) and cars. The test results were gathered and used for further development. The version of the solution presented in this paper was finalized and tested again in office environment.

In addition to technical development work, qualitative data were gathered in discussions with company representatives. Nine companies attended the same publicly funded "Multi-purpose service robotics as operator business" R&D project in 2021-2022. The companies represent robotics, software and end-user companies. They attended several workshops during the research project, and among other research topics, they gave their views also into LiDAR object and change detection.

Tasks and results of this study are thus twofold: 1) Technical development work regarding the new mobile LiDAR-based object and change detection solution and its testing, and 2) identification of use cases in the production and operations management domain. Finally, conclusions were drawn combining onsite test results and discussions between the researchers and the company representatives on potential use cases and limitations of the solution.

IV. RESULTS

A. Solution concept for 3D LiDAR-based object and change detection

The large quantity of produced points by high resolution LiDARs makes the point-cloud processing a challenging task, especially if this is done in real-time. To achieve real-time change detection with this kind of high resolution LiDAR, we propose a solution that is based on an open-source C++ library called Open Visual Database System (OpenVDB) [41]. OpenVDB incorporates a hierarchical data structure and tools for the efficient storage and manipulation of sparse volumetric data maintained in 3D grids. This volumetric database is typically referred to as VDB. The library has been used in the visual effects industry for simulation and rendering of water, fire and other effects that rely on sparse volume data. Despite the wide use in numerous movie production applications over the last decade, the robotics community has paid little attention to the library. The proposed solution requires a reference point cloud to be converted to a NanoVDB level set grid as described in the steps of Figure 3.

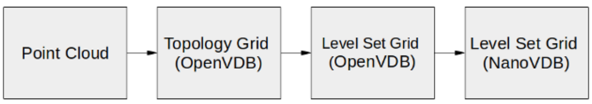

Figure 3. Steps to convert point cloud to NanoVDB level set.

NanoVDB [42] is a new addition to the OpenVDB library to leveragme the power of Graphics Processing Units (GPUs) in the processing of volumetric data, whereas OpenVDB was originally designed to be run Central Processing Unit (CPU) only. NanoVDB provides a simplified representation of the data structures being still completely compatible with the OpenVDB's tree structure. It offers functionality to convert back-and-forth between the NanoVDB and the OpenVDB data structures and to create and visualise the data. NanoVDB's compacted and linearised representation of the VDB tree structure is read-only. In other words, while values can be modified in a NanoVDB grid, its tree topology cannot. Despite this limitation, NanoVDB enables notably faster collision detection and raytracing compared to OpenVDB's CPU implementation [43]. The proposed approach for change detection follows the pipeline defined in Figure 4.

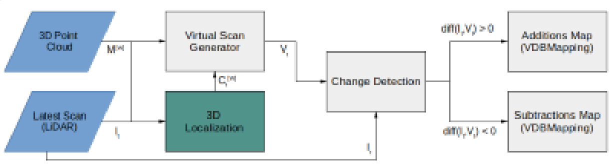

Figure 4. Pipeline for the change detection.

A NanoVDB level set grid is created from an existing 3D point cloud that represents the reference map of the environment. Because the same 3D point cloud is also used to localise the autonomously moving robot, the pose of the LiDAR scan can be used to render a matching virtual LiDAR scan from the NanoVDB level set grid. 3D localisation is done based on combining wheel or LiDAR odometry to a scan matching module that tries to minimise the cumulative drift of the odometry by registering the latest LiDAR scan or a submap created from multiple consecutive scans to the reference map [44].

The computationally expensive process of rendering virtual scans from an existing map of the environment is performed using NanoVDB on a GPU. For each new scan, the change detection is apprehended by calculating the difference between the LiDAR scan and the virtual LiDAR scan. The difference is defined according to range:

- range < 0: positive change (insert to OpenVDB grid as occluding voxel)
- range > 0: negative change (insert to OpenVDB grid as newly revealed voxel)
- range == 0: no change (optionally only update to NanoVDB grid as 'visible' voxels)

This way the positive and negative voxels are cumulated to the OpenVDB grid, done in the CPU as a NanoVDB grid cannot be modified. Afterwards, the changes are accumulated to OpenVDB grid via VDBMapping. In the following Figure 5 positive changes detected are presented:

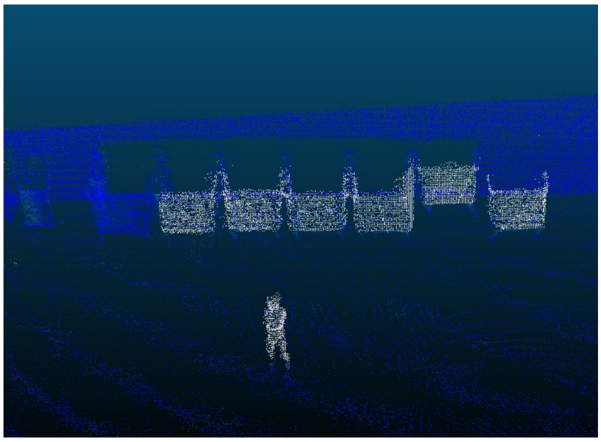

Figure 5. Positive changes detected at the industrial site.

The novelty of the presented method is in its approach to be real-time. The traditional method creates point clouds and only afterwards registers these to the same coordinate system and performs the change detection accordingly. Real-time approach enables more precise change detection on-site.

To the best of the authors' knowledge, NanoVDB is deployed in the field of robotics only to implement a GPU-accelerated mapping and simulation package called NanoMap [45]. This work extends the use of OpenVDB and NanoVDB to LiDAR-based change detection. Also, only in recent years, OpenVDB has been starting to appear in open source projects, e.g., to implement spatiotemporal occupancy grid map [46], probabilistic 3D mapping [47] and efficient Truncated Signed Distance Field (TSDF) integration of range sensor data [48]. The latter presents a 3D mapping library, called VDBFusion, which has a higher runtime, lower memory consumption and disc usage compared to older state-of-the-art 3D mapping libraries, like OctoMap [49] and Voxblox [50].

The presented work is evaluated on an embedded platform, NVIDIA Jetson AGX Orin, with data collected using two different robotic platforms, including SPOT robot (Figure 1) and ROVéo, ROVENSO's wheeled robot (Figure 6).

Figure 6. ROVENSO's ROVéo AMR.

B. *Identified use cases in production and operations management*

As results of this study, use cases for LiDAR-based object and change detection were identified. The emphasis is to complement data collected with fixed sensors in factories with LiDAR scans done continuously on a mobile platform. Real-time change detection is one central novelty value of the solution developed by VTT. When AMR detects relevant and defined changes in real-time, it can send an alarm for the respective organisation unit (e.g., security or production) with a location in which the change was detected so that the organisation can take the needed measures.

Another selection criterion for potential use cases was that purely LiDAR-based detection would be beneficial compared to camera or LiDAR-RGB camera-based detection and image recognition. Cameras and image detection is a more suitable method for detection of smaller details and items. Compared to visual light cameras, a relatively accurate 3D model of the environment can be created, and rather large items and changes can be detected. Another strength of LiDARs is in their use in poor lighting conditions. LiDARs are already commonly used in AGVs and AMRs, so no new sensor or camera investments would be needed, but the idea would be to better utilise data collected by those moving around in factories.

When identifying potential use cases for mobile LiDAR-based object and change detection, the following criteria and features of LiDAR-based detection were considered:

- Added value from AMR moving around the factory and factory site and detecting changes in real-time
- Achieving relatively accurate and up-to-date digital 3D reconstruction of the environment of the AMR with repeated LiDAR scans
- Visual detection of rather large physical items and changes
- LiDARs work also in poor or limited lighting conditions.

The next Table outlines identified use cases for LiDAR-based object and change detection in production and operations management:

TABLE I. INDUSTRIAL USE CASES FOR LIDAR-BASED OBJECT AND CHANGE DETECTION.

Industrial operation	Use cases
Internal logistics	- Pallets and other large items left in the wrong place - Blocked routes of AMRs and AGVs and sending information to the fleet management system or operators - Cars left in the wrong place (e.g., on AMR/AGV driving lanes) in the yard
Warehouse	- Pallets, trolleys or other large items left in the wrong place in the warehouse
Production	- Large items left in the wrong place on aisles or in production cells: links to lean, 5S and safety - Digital as-is 3D model as basis for machinery and production line modernisation
Security surveillance	- Blocked fire doors or large items left in the front of emergency exits that should be kept clean - Factory gate or open doors, e.g., at night when there or no people at work - Holes in factory area fence
Building maintenance	- As-is model of the factory as basis for factory renovation and modernisation and progress monitoring

V. CONCLUSIONS

RGB images and image recognition is often feasible for visual change detection [36]. However, in certain cases, an accurate digital 3D model of the environment created with LiDARs and detecting changes repeatedly in real-time accrue benefits for production and operations management. This study identified use cases for mobile, real-time LiDAR-based object and change detection. The new solution developed and presented enables efficient visual 3D data utilisation in operations management. The study shows practical implications of Industry 4.0 and 5.0 in terms of utilising autonomous systems and digital twins.

As the main results of the study, we identified potential use cases in production, internal logistics, security and maintenance operations for the developed solution. Identifying, e.g., obstacles on AGV and AMR routes and sending the information to the operators of fleet management systems helps AGVs and AMRs update their routes and continue their tasks smoothly. Thus, the solution may help in optimising traffic flows in factories. Detecting large items left in the wrong place and sending alarms for respective organisation units enhance intra-logistics operations, tidiness and safety. For security purposes, the solution identifies e.g. doors left open at nightime.

The study results contribute to the operations management literature [4]-[8] by presenting a new technical enabler for object and change detection in factories. The main novelty value of the solution is the aim of detecting changes in real-time on repetitive rounds of AMRs. Real-time approach enables more precise change detection on-site and provides many future development possibilities e.g. in terms of sending alarms of noted changes that might cause safety or other hazards. Thus, the results complement earlier studies on mobile change detection [33, 35]. Point cloud data collected with LiDARs will support more intelligent decision making in companies concerning, for example, production and intra-logistics [1][11][12].

As with any study, this one also has limitations. One limitation is that the technical solution is not ready yet, but is still under development. More testing and development will be needed in various industrial environments in order to ensure its reliability and accuracy. The accuracy of the change detection depends heavily on the accuracy of the 3D pose estimation of the LiDAR, which may be degraded due to measurement noise, motion distortion, and reflections from shiny surfaces. Moreover, major geometric changes in the environment (e.g., some walls removed) may also degrade the accuracy of the pose estimation. Another central limitation is that, in many cases, object and change detection is more feasible and cheaper to conduct with cameras. On the other hand, the use of LiDARs is already common in AGVs and AMRs, which reasons for wider utilisation of the data they collect. What remains important is to carefully evaluate which cases, e.g., RGB camera or RGB camera-LiDAR solution, are feasible and more reliable than a solution based solely on LiDAR. LiDARs' strengths remain in their ability to make a relatively accurate digital twin of the environment. Use cases that benefit from those have the foremost potential for LiDAR-based solutions.

Despite the limitations, this study inspires multiple interesting future R&D avenues. Within the production and operations management domain, autonomous systems, extensive data utilisation and so-called digital twins will provide much to study and develop in the future. For example, the fusion of multimodal data that AMRs collect can offer many possibilities for developing, e.g., manufacturing, intra-logistics and maintenance operations to be safer and more efficient. For example, one can integrate thermal camera and gas sensors onto a mobile robot platform, and data collected by those can be used in combination with LiDAR-generated maps for safety. More research will certainly arise from applying the new object and change detection method developed for various industries. Construction is one business field that would certainly benefit from real-time 3D modelling and change detection.

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