An aerial robotic system for inventory of stockpile warehouses

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Abstract
This article describes the development and evaluation of an aerial robotic system for smart inventory of stockpile warehouses. The system was developed to automatically measure piles of different bulk materials, such as phosphorus and potassium compounds, which are stored in bays of different sizes inside a warehouse. This warehouse configuration is very common among fertilizer and animal food industries in Brazil. While an inventory can be executed by a human technician, the insalubrious environment, the imprecision of the manual volume estimation, and the time spent by the technician to access the information motivate the automation of the process. The proposed system uses a multirotor electrical drone that navigates autonomously inside the warehouse while it acquires light detection and ranging (LIDAR) point cloud data. This data is used to build a three-dimensional (3D) model of the environment, which is then processed to identify the stockpiles of material and calculate their volumes. Since the environment is GPS-denied and its characteristics, including symmetry, illumination and texture, do not favor visual- or LIDAR-based localization, a drone navigation strategy that relies on relative positioning with respect to simple structures of the warehouse was developed. This article also presents our approach for autonomous stockpile volume estimation, which was numerically evaluated both in simulation and with real data, yielding in accuracy and precision of about 98%. The results presented in the article show that the aerial system is able to substitute the previously adopted manual procedure, highly increasing its accuracy, repeatably and safety, and drastically reducing its time of execution and cost.

Keywords
drone, LiDAR, UAS, volume estimation, warehouse automation

†Guilherme A. S. Pereira was with the Federal University of Minas Gerais, Brazil, during the first steps of this work.
The automation of warehouses is one of the challenges imposed by the Industry 4.0 revolution. Important tools of that revolution are small unmanned flying vehicles, also known as Drones. Several commercial applications for Drones exist, but it is still not very common to see such vehicles executing automation tasks inside warehouses and other indoor environments, where localization, guidance, and control are still challenging. Motivated by the critical need for automatic inventory of agricultural products and supplies in large agricultural countries such as Brazil, this article describes an unmanned aerial system (UAS) based on a commercial quadrotor equipped with a light detection and ranging (LIDAR) Sensor for smart inventory of piles of products stored in a warehouse. Figure 1 shows pictures of the warehouse where the system was used. Notice that both flying a drone and estimating the volume of the piles using point cloud data are very challenging tasks in this environment. The proposed system was deployed operationally in March of 2019 and, since then, has been successfully used for frequent (once a month in average) inventory of stockpiles in the warehouse of Figure 1.

As discussed in Reference 4, there was a recent upsurge in the development of robots for warehouse automation, which became a new drive for robotics. Several companies are now providing robots with important capabilities such as shelf picking, product packing, and autonomous navigation, which is a key skill for a successful warehouse robot. As one of the first works in this area, Reference 5 describes the challenges that a (ground) robot would encounter in a warehouse and how navigation systems developed for office-like environments should be adapted to such a nonstructured environment. To efficiently solve this problem, most of the early solutions embedded infrastructure into the robot’s workspace such as radio-frequency and visual tags.

More recently, researchers are focused on infrastructure-free navigation inside warehouses by using only the sensors of the robot, or infrastructure already installed on the environment, such as surveillance and security cameras. For the system we present in this article, it was a requirement from our client that no modifications on the warehouse were made. This was justified by the necessity of fast and inexpensive replication of the system to several other

**Figure 1** Stockpile warehouse. Starting at the top and rotating clockwise: (1) An irregular pile of product with restricted access due to risk of collapse; (2) Warehouse view from the top side: poor illuminated environment with multiple bays with piles of products and several structures on the ceiling; (3) top view of a pile: irregular structures and low light make it difficult to manually estimate the volume of the pile; (4) View from the front of two regular piles inside bays
facilities. This strong constraint would not impact only the robot navigation system but also our choice of robot. An apparently simpler solution using cable robots, for example, was immediately discarded. Also ground robots were made impractical due to the nature of the products in the warehouse, which occupy parts of the warehouse floor. This led us to propose the use of aerial robots, as will be discussed along the article. Even with this solution, it is important to mention that our final system required small modifications in the warehouse to allow full autonomy during data acquisition.

Some recent works have presented solutions that use drones in warehouse automation. Reference 11 describes a drone that navigates in a warehouse using a LIDAR and three stereo cameras. The drone use radio-frequency identification (RFID) technology for product inventory. Reference 1 presents the design and evaluation of a drone-based system aimed at automating inventory tasks and keeping the traceability of industrial items, which are also attached to RFID tags. Reference 12 presents a multisensor fusion framework for navigation of drones inside warehouses.

Although some navigation ideas presented in the previous articles could be adapted to work in our warehouse, none of the inventory solutions presented could be applied to our problem, which consists in estimating the volume of stockpiles stored in bays distributed along the warehouse (see Figure 1). Some previous work have used photogrametry techniques based on the images obtained from an unmanned aerial vehicle (UAV) to estimate the volume of large stockpiles in outdoor environments. Although promising and very inexpensive, this strategy is not suitable for poorly illuminated environments, as is the case of warehouses.

Leveraging the recent advance of LIDAR technologies, which is accompanied by weight and cost reduction, several researchers and companies are equipping drones with such sensors to solve the most diverse sensing and estimation problems. Although, the authors did not find a previous work that specifically solve our problem by using a LIDAR mounted on a drone, its apparently natural that such systems will be used to this end, given the current state-of-the-art of mapping using moving LIDARs. Successful commercial systems for LIDAR based 3D mapping in GPS-denied environments such as the ones offered by Kaarta, Emesent, and Exyn Technologies, for example, are generic enough to be directly used in our warehouse inventory solution. It is also important to mention that LIDARs fixed on the ground are already extensively used for mapping and volume estimation.

The robotic system presented and evaluated in this article consists of (i) a quadrotor equipped with a commercial visual/inertial/sonar system for low-level state estimation and a 3D LIDAR for localization and stockpile inventory, and (ii) a software that processes the data collected by the drone and provides the inventory of the warehouse. Both, the drone and the software, are automatic and require minimum human intervention. The rest of this article is organized as follows. Following section describes the problem we have solved and presents the previous adopted solutions to this problem. Section 3 details our aerial solution in terms of hardware and software, including the strategy adopted for stockpile volume estimation. Simulated and real-world experiments are presented in Section 4 and the lessons learned along the project are discussed in Section 5. We also discuss some limitations of the solution and possible extensions in Section 6. Finally, Section 7 presents conclusions and final remarks.

2 WAREHOUSE INVENTORY

The active management of the flow of services and goods in a commerce, also known as supply chain management, is a key process that involves the movement and storage of raw materials and finished goods from point of origin to point of consumption. In this process, the knowledge about the type and quantity of material stored in warehouses is critical. Activities such as production, selling, acquisition of raw product, and transportation logistics are directly impacted by this information. Eventual differences between actual and estimated quantities may generate delivery delays, productions interruptions, and increase in logistics costs. Unfortunately, these differences are common due to errors in the stock measurement system, loss of material during transportation, uncontrolled movement of material caused by operational errors, or even theft. To maintain a better control of its inventory, many companies need to frequently measure their stocks and update their production data. Although this can be a simple process for warehouses with boxes identified by barcodes or RFID tags, for example, it is not straight forward to estimate the quantity of production in stockpile warehouses. For this type of warehouse, the manual procedure for stockpile volume estimation, which is usually executed only once a month, due to its inherent difficult, is described in the next subsection.
2.1 | Manual procedure

The manual adopted procedure for stockpile volume estimation in most warehouses consists in determining, for each pile, known and easy to calculate geometric shapes (cubes and pyramids, for example) and then measuring with laser meters the dimensions of these shapes. There are many issues involved in this task:

- The human technician must climb the piles to make the measurements, which creates ergonomic and environment risks such as falling or even pile collapse.
- The warehouse environment and pile access make it difficult to obtain precise measurements. To reduce error, two different teams are assigned to measure each pile, so the results are compared. It is common to have more than 10% deviation between two measurements of the same pile.
- If the material is forming an irregular shape, it needs to be first accommodated into a known shape. In this case, wheel loaders are required to move the material, thus reducing production time.
- For granting pile access to technicians, production must be stopped during measurement, which may require about 3 h for a typical warehouse.
- The approximation of a pile using simple shapes highly reduces the accuracy of the calculation. A 5 cm deviation, for example, may represent 15 tons (1.0%–3.0% of a pile) of material in piles whose volume ranges from 500 to 1500 tons.

To increase accuracy, reduce execution time, and, most importantly, reduce or eliminate risks for the human workers, some solutions were studied to automate the entire process. The warehouse administrators impose some requirements for a viable solution: the total time between data collection and volume estimation should not exceed a few hours; there should be no need for human technicians in the piles; the same solution should be applied for similar warehouses; no human intervention on data collection and volume calculation should be required; volumes should be estimated with accuracy in the order of 98%; fixed electronic solutions should be avoided, due to the corrosive atmosphere inside the warehouses. Next subsection presents preliminary studies performed to achieve these requirements and automate stockpile inventory.

2.2 | The path for an automatic solution

Prior to the fully automated solution presented in this article, some improvements on the manual procedure have been pursued. Through the use of a Microsoft Kinect camera and a point cloud manipulation software, some tests were made to reconstruct piles and estimate volumes. Since the surfaces of the piles are mainly homogeneous (a feature poor environment) and the Kinect’s range is small (about 6 m), the results were not satisfactory—point cloud correspondence was low and final map had many geometric errors, stretching or increasing areas and resulting in large volume calculation errors. In addition, for this solution it would be still necessary workers access to the piles, one of the risks that needs to be mitigated. At this point, it is important to mention that some bays are loaded from the top center of the warehouse through a conveyor belt. This causes the piles to have a higher peak that occludes the back of the pile when it is observed from its front, where workers usually have access. Because of these, a complete survey of the pile requires that the sensor is carried around the pile. Thus, LIDAR-based systems carried by a human, such as Reference 21, even with a larger range, were also discarded due to the same risk.

Some known solutions for stockpile volume estimation were proposed. Radar systems, commonly used on mining sites, could be positioned above the piles and provide precise measurements of the volumes without human interference. However, the initial costs were considered high, since, for each warehouse, similar investments would be necessary. In addition, the solution would be installed inside the warehouse, in contact with its atmosphere, requiring more expensive shells for electronic equipment and increased maintenance costs. Similar solutions that used fixed equipment (such as cameras or LIDARs) were also put aside for the same reasons. Using cameras should be cheaper, but there are additional problems, such as lack of illumination, what would require more investments in the warehouse.

Due to the restrictions on installing permanent infrastructure in the warehouse and the difficulties detected for the systems proposed above, a mobile robotic system became the first option. Because of the difficulty of moving in the floor of the warehouse, which is frequently occupied by parts of the piles, and on the piles themselves, a ground robot was not
considered to be the best solution, leading us to propose an aerial vehicle-based solution. Following section will present this approach, which is consisted by an infrastructure-free, self-flying drone equipped with LIDAR, and an automatic map reconstruction software.

3 | SYSTEM DESCRIPTION

The proposed solution for stockpile estimation inside warehouses is described in this section. A block diagram with an overview of the system is shown in Figure 2. Notice that we divide our system in two major blocks, namely, (i) UAS and (ii) Map Rebuild and Volume Calculation. We will start in the next subsection by describing the UAS.

3.1 | Unmanned aerial system

This section describes the hardware and the navigation strategy of our UAS. A picture of the proposed platform is shown in Figure 3.

3.1.1 | UAS hardware

As the main hardware platform for our solution, we chose a commercial drone that would have enough payload to carry a 3D LIDAR, and, at the same time, facilitate the development of its navigation system, which is supposed to work in a GPS-denied, poorly illuminated, and cluttered environment. After researching some options, we have decided on the following components for our system:

FIGURE 2  Block diagram of the overall solution
FIGURE 3  Front and back view of the assembled drone with selected hardware—detail shows light detection and ranging and the mirror installed over it, used to change the direction of some laser beams. On the right is the remote controller with operator’s panel.

- DJI Matrice 100 quadrotor platform: this drone was chosen because it is a development platform, with adequate payload and flexibility to add sensors. In addition, the drone flight controller is compatible with DJI Onboard SDK, which is a library ready to communicate with an onboard computer running the robot operating system.\textsuperscript{28} It is important to point out that, although the selected platform was adequate for the expected payload, the final payload turned out to be heavier than expected, as will be discussed in the end of this section.

- DJI Guidance navigation system: this visual/inertial/sonar system is used to stabilize the drone and estimate its velocities in a GPS-denied environment; Guidance, described in Reference 26, when installed in a Matrice 100, allows velocity-based commands, which simplifies the vehicle control if compared with attitude commands that rely on fast feedback loops and must consider the drone dynamics.

- Velodyne VLP 16 Puck Lite: this sensor is a LIDAR with 16 beams that provides 360 degrees horizontal field of view (FOV) and 30 degrees vertical FOV with a maximum range of 100 m and a typical accuracy of $\pm 3$ cm. It is used to scan the environment for reconstruction and pile estimation, and also for UAV navigation.

- UDOO x86 on-board computer: this lightweight, single board computer saves mission data and process high-level navigation commands to the drone.

- DJI N1 video encoder: this device receives data through an HDMI cable and sends it to a proprietary DJI application running in a tablet. In our application, the on-board PC sends display information to the human pilot/operator, including video from Guidance cameras, distances extracted from the LIDAR, and the mission status.

- DJI remote controller and tablet: these devices receive display information from N1 video encoder and allow the operator to assume manual control of the vehicle during missions.

The system assembled with these components is shown in Figure 3. Unfortunately, the selected components did not fulfill all initial requirements, as will be shown along the article. For example, we were required to include objects in the environment to aid the Guidance vision system. Regarding payload, we also had an unexpected issue. After including all the hardware, the robot total weight was 3.9 kg, which was above DJI’s maximum specification of 3.6 kg. With this payload, average rotor speed in a stable position in flight was kept close to 80%–85% of the maximum speed, while the desirable speed for a stable flight in disturbance situations, would be less than 75%. Unfortunately, we could not reduce even more the payload, which although high, was only achieved after we removed some accessories, such as propeller guards and electronics protective shells. With the extra weight of the removed accessories, some rotors frequently saturated in their maximum speed, causing instability. With the current weight (extra 300 g) we achieved a stable flight most of the time, since no wind is present inside the warehouse. The system will not be used in other flight conditions.

As shown in Figure 3, the original camera support of the drone was removed and the LIDAR was mounted in its place, in the bottom-front, in an angle perpendicular to the platform. This position best suited the application, allowing us to collect range information from underneath the drone, thus maximizing the view of the piles. This decision may have compromised the use of the sensor for localization, as we discuss in Section 3.2.1. We also placed a small mirror ($2 \times 2$ cm) over the LIDAR, in order to redirect some laser beams to the front of the drone, so we could measure distances from objects and walls in front of the vehicle.
3.1.2 Navigation strategy

The vehicle’s navigation strategy was proposed considering the characteristics of the environment, the space available for maneuvers, and, mainly, the path required to map the stockpiles. Since the structure of the environment is static, except for changes in the piles themselves, we decided to use a feature-based navigation approach in which the vehicle is controlled to have relative position to known and easily detectable features of the warehouse. This approach does not require the global localization of the drone. In this way, our strategy relies on the attitude data provided by the drone controller and on the LIDAR point cloud to determine a sequence of high-level commands to the vehicle. These commands, which include “takeoff,” “straight flight,” “turn,” and “land” were coded as velocity-based controllers. To implement our whole set of high-level commands, it was only necessary to control the height of the drone and the lateral, frontal, and vertical distances between the drone and some structure (e.g., walls or ceiling) of the warehouse, and the heading of the drone. For example, the “straight flight” command would keep a constant height, a constant lateral distance to the wall, and a constant heading until the front sensor detects an obstacle, which is probably when it finds the end of the warehouse.

With the designed set of high-level commands, a complete loop of the drone inside the specific warehouse where our system was tested can be performed with the sequence of commands shown in Figure 4. It is important to mention that a different warehouse would need distinct set of commands with different parameters. In Figure 4, the previous example with the “straight flight” command is represented as the blockStraight. Notice that this block has two parameters, namely, height and right distance, and a transition block, in orange, representing the front distance. The block Straight in the first column of Figure 4, for example, indicates that the drone must move forward at 10 m above the ground and with a constant distance of 3.5 m from the right wall until it detects a frontal obstacle closer than 7 m.

While height and velocity control rely on internal information estimated by the drone’s commercial controller, which is resultant from the fusion of pressure sensor, compass, inertial measurement unit (IMU) and Guidance odometry, lateral, frontal, and vertical distance control rely on plane detection using the LIDAR point cloud. Assuming that the drone coordinate frame has X as the longitudinal direction, Y as the lateral direction, and Z as the vertical direction, once planes are detected using the point cloud library (PCL), the distance between the drone and the plane, computed in the intersection between a given axis and the plane, is used by a proportional controller to achieve and maintain a specified distance to that plane. For example, the lateral controller would find the distance between the drone and the plane at

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**FIGURE 4** Sequence of high-level commands required to complete an entire mission inside the specific warehouse considered in the project (see Section 4). Orange boxes show transition conditions for each state.
the intersection between the Y axis and the plane. A vertical distance controller, which is used to make the drone enter and leave the warehouse passing through lower ceiling corridors, would use the distance computed at the intersection between the Z axis and the plane that represents the ceiling. Figure 5 illustrates a plane detected during flight at a lateral distance of approximately 2 m. In the warehouse, this plane is the banister of a footbridge.

3.2  |  Warehouse 3D reconstruction and inventory estimation

In parallel to the challenge of developing an autonomous vehicle to acquire data from the warehouse, we developed a postprocessing strategy to reconstruct the warehouse and estimate the volume of all products inside the bays. This resulted in a completely automatic software, with no need for human intervention, for 3D reconstruction and stockpile volume estimation. This software complies with the requirement of removing human subjectivity from the estimation.

3.2.1  |  Warehouse 3D reconstruction

Before the development of a specific method for warehouse reconstruction, two SLAM approaches freely available on-line, namely, LOAM\(^{19}\) and BLAM\(^{30}\), were tested. After adjusting several parameters of the methods without success, we noticed that, due to the position of the LIDAR in our vehicle (installed vertically) and the high level of symmetry of the warehouse, those methods always generated a reconstructed warehouse that is shorter than the actual and curved. Figure 6 shows an example of a warehouse reconstructed using LOAM. Although some other approaches, such as RTAB-MAP\(^{31}\), are known to perform better if vision information is added to the SLAM process, we discarded those solutions due to the lack of illumination inside the warehouse. Once our drone navigation solution does not require global localization, our final strategy was to create an offline mapping strategy to reconstruct the 3D model of the warehouse, as described next.

Since a precise model of the warehouse is mandatory for a reliable volume estimation, we chose to detect and use known and abundant geometric properties of the environment to register the LIDAR data collected. More specifically, we detect the structural arcs of the warehouse, which are 5 m spaced from each other along the longitudinal dimension of the warehouse, and match the detected arcs with the warehouse blueprint. These arcs can be seen in the two right-hand side photos of Figure 1. The block diagram in Figure 7 presents a general description of our environment reconstruction approach. Notice that this procedure is executed after the flight, using data saved on ROSBag files during the flight.

After correcting the point-cloud orientation using roll and pitch information given by the vehicle’s on-board state estimation, the first step of our warehouse reconstruction strategy is arc detection, as shown in Figure 8, followed by the estimation of the relative position of the drone with respect to this arc. Our strategy for arc detection in point clouds is to look for parallel planes in a specific region of interest (ROI) on the right side of the drone. In our case, the ROI is represented by a 1 × 1 m squared region projected on the closest right obstacle detected by the LIDAR, which is, in most of the time, the warehouse walls/roof. A specific PCL-based algorithm looks for two parallel planes that are slightly
FIGURE 6  Warehouse reconstruction using LOAM. The longitudinal length is 15 m shorter than the actual warehouse, which is a building without the curve presented in the reconstruction.

FIGURE 7  Warehouse reconstruction strategy diagram

inclined in the drone perspective. If two parallel planes are found with approximately 1.3 m distance from each other, an arc is detected (one plane represents the arc and the other plane is the roof). Using this information together with the warehouse’s blueprint and the approximate route taken by the drone, the relative position of the drone in the warehouse can be estimated and the correspondent point cloud can be registered. If no arcs are detected, the drone is flying between two arcs. In such situation, the LIDAR data is ignored and will not compose the final 3D model. In the large majority of the time, this wasted data is redundant with some data already registered. However, we could identify a few situations where important data was lost, what generated small “holes” on the final 3D model.

For each arc detected, the associated point cloud is then processed. Some warehouse features are automatically detected (Figure 9) and the drone relative position is estimated: the longitudinal position \( x \) is determined by the number of arcs detected up to that point and the distance to the center of the current arc; the height \( z \) comes from the distance to the rooftop; and the lateral position \( y \) is the distance from the footbridge, present along the whole warehouse; the attitude angles are given by the drone’s IMU, but are refined if floor planes are detected (which also corrects height estimation). Each point cloud with arcs detected, after processed, are then registered in the warehouse map. With all arcs detected.
Arc detection using LIDAR. Images from the Drone’s cameras are shown for an easier understanding. Blue axis in the Drone’s coordinate frame (RGB frame in the center of figure) points to the front. A structural arc of the warehouse, as seen marked in red in the right camera image, is detected automatically when both roof and arc plane, marked yellow and red, respectively, are found in the same region of interest of the LIDAR Data. For a better understanding of the scene, blue rectangles and ellipses mark the footbridge and a barrier, as seen in by the cameras and LIDAR. RGB axes size is 1 m, for scale. LIDAR, light detection and ranging

(27 for each side of the current warehouse), the warehouse is fully reconstructed and ready for segmentation and piles’ volume estimation.

### 3.2.2 Warehouse segmentation and inventory estimation

The strategy adopted to process the registered point cloud data and automatically estimate the volume of the piles of products is shown in Figure 10. The segmentation of the point cloud in regions of interest (bays) is straight forward. Because the point cloud is already registered to the blueprint of the warehouse using the arc detection approach described in the previous subsection, the limit of each bay is extracted directly from the blueprint as fixed $x$ and $y$ coordinates. After that, we start treating the point cloud of each bay separately.

The next step of our approach is to detect barriers and walls by looking for planes perpendicular to the floor and removing them from the point cloud. This will avoid considering these objects as part of the piles. For this step we again applied PCL’s plane segmentation. After that, some other objects are removed. Supports for barriers, pillars and pillars’ bases have known positions and are simply cut from the point cloud. The metal rods that hold the barriers together and may be installed in any position are detected as lines above the piles and also removed from the cloud.

A density-based filter is then applied to the point cloud to remove outliers. For this we used PCL’s Statistical Outlier Removal described in Reference 32. The remaining data consists only of points on the pile surface. It is still possible that there are “blank spots” in the data due to occlusion from objects and irregular piles, or even some “holes” due to failures in map registration process, which discards point clouds obtained in positions where no arcs are detected. These blank areas are then filled with points interpolated based on the average of the nearest neighbors points, which is a good approximation considering common pile shapes.

Finally, a simple integration method is used to compute the volume of material. Volumes of fixed structures (like pillars’ bases) that are under the stockpile and are only detected using the warehouse blueprint are removed from the final
FIGURE 9  Pose estimation using point cloud data (image information is shown only to facilitate understanding and is not used by the software). Regions indicated by red and purple polygons are arc and roof, respectively, detected as parallel planes. Along with the warehouse blueprint, this information is used to estimate the longitudinal position of the drone. The white circle shows points of the rooftop used to estimate height, and the blue marked area is the footbridge, detected as a plane and used to estimate the vehicle’s lateral position. The white polygon on the right indicates the circulation area, used to correct height estimation and attitude angles. In the images of left and down camera, a pile of material can be observed. This pile is represented by the large point-cloud beneath the Drone’s frame (RGB frame in the center of the figure—blue axis is not visible). RGB axes size is 1 m, for scale.

FIGURE 10  Warehouse segmentation and pile volume estimation strategy
result. For visualization, volume is multiplied by the density of the material (resulting in the total weight of the material) and a mesh of resulting point cloud is provided. An example of how the results are presented to the user is shown in Figure 11. Each line of the web-based interface represents a bay (Box, as it is called inside the company) and indicates the kind of material, its density, the weight of material stored in the bay as given by the production system, the weight estimated by our system (iBox), and the capacity of the bay. In addition, the interface shows, graphically and in percentage of the total bay capacity, the difference between the stock information stored in the production system and the one measured with the drone, and the total occupancy of the bay. By clicking on a given bay, the software also shows the 3D mesh of the pile. This visualization increases the confidence of the user on the system, since it can visually check the similarity between the actual stockpile and the reconstructed one.

4 | EXPERIMENTS

All the results shown in this article were obtained in a warehouse with a stock area of 140 × 38 m, divided by barriers in 17 bays with different lengths of 5, 10, 15, and 20 by 38 m in width. In front of the stock area, there is a 9 m wide corridor for the transit of trucks and loaders, where we chose to start our drone. Thirteen meters above the bays there is a footbridge and a conveyor belt that is used to load material from ships to the warehouse. For every 5 m along the warehouse there is a pillar supporting the arcs and the roof. The blueprint of such a warehouse is shown in Figure 12.

Regarding the shape of the piles in each bay, it is important to mention that several different shapes are possible for at least three reasons: (i) the conveyor belt is not exactly in the center of the warehouse, (ii) there is a wall in the back of the warehouse, against which the material will accumulate, and (iii) material can be loaded and unloaded from the front of each bay by trucks and loaders.

4.1 | Simulations

Prior to actual flight tests, simulations in Gazebo were performed to test the navigation strategy and the inventory estimation. A model of the warehouse, as shown in Figure 13, was built using Google SketchUp 3D based on the building
blueprints and other information collected locally. Stockpiles with known volume were added to some bays of the model. To simulate the drone, Hector Quadrotor\textsuperscript{34} was used. Because our navigation system sends velocity commands to the vehicle (instead of attitude commands, for example), the simulator behavior was very similar to the one presented by the actual drone. To simulate the sensors, we used the Velodyne simulator\textsuperscript{*} and a simulated ultrasound sensor in front of the drone to estimate the distances to obstacles, as is done with the aid of a mirror in our robot (see Figure 3). These simulated sensors are corrupted by Gaussian noise and behave similarly to their real-world counterparts.

\footnote{\url{https://bitbucket.org/DataspeedInc/velodyne_simulator/}}
A typical flight in our simulated warehouse can be seen in https://youtu.be/6z5b7gBdyiI. The reconstruction of the warehouse after one of these experiments is shown in Figure 14. It is important to remember that our system collects the data generated by the sensors in a ROSBag file and postprocess the data to reconstruct the warehouse and compute stockpile volumes after the flight.

Table 1 shows numeric results for our volume estimation method in the simulated environment when three stockpiles were available. Notice that the errors are very small (the largest one is 1.74%), thus validating our method. The differences between actual and estimated volumes are mainly due to our algorithm strategies for “filling in” the places of each pile that were not captured by the LIDAR due to eventual occlusions.

### 4.2 Actual hardware experiments

Once our strategy was validated in the simulated environment, several flights were performed with the actual platform to validate our navigation strategy and evaluate the system capacity to reconstruct the warehouse and to perform automatic segmentation and volume estimation. Our results are presented in the next subsections, starting with the navigation. Part of the data obtained in our experiments, including drone state, LIDAR point clouds and images from the Guidance cameras is publicly available as a dataset. This data is accompanied by the 3D models we have generated using the proposed approach.

#### 4.2.1 Navigation

We performed several navigation tests and experiments from December 2017 to March 2019. From the beginning of the project until the product was delivered to its final user, more than 1000 takeoffs happened inside the warehouse. A skilled pilot followed all flights and was prepared to take control of the drone in case of problems. Despite some incidents, which caused some damage on the vehicle, it is important to mention that a single platform was used during the entire project.

![Simulated warehouse rebuilt using proposed reconstruction strategy](image)

**Figure 14** Simulated warehouse rebuilt using proposed reconstruction strategy

**Table 1** Stockpile estimation results obtained in simulation

| Pile # | Actual volume (m³) | Estimated volume (m³) | Error (m³) | Error (%) |
|--------|-------------------|-----------------------|------------|-----------|
| 1      | 76.42             | 75.38                 | −1.04      | 1.36      |
| 2      | 139.60            | 137.17                | −2.43      | 1.74      |
| 3      | 312.04            | 307.77                | −4.27      | 1.37      |
During our experiments, each of the high-level commands (see Figure 4) was tested and tuned independently. Once they presented satisfactory behaviors, the commands were then composed to perform the whole task. A video showing the execution of the four first commands of Figure 4 can be seen at https://youtu.be/WuHEMvpHePA.

As mentioned before, our high-level commands rely on low-level velocity controllers running in the Drone’s proprietary hardware. Those controllers rely on velocity estimates provided by the DJI’s Guidance system. Because Guidance is mostly based on vision (it relies on five stereo pairs of cameras), it suffers from the absence of features in the environment and poor illumination. We have noticed that when the drone was flying over homogeneous stockpiles, Guidance was unable to estimate the vehicle’s velocity, causing the drone to diverge from its path, sometimes moving towards an obstacle. It was then necessary to add artificial features to the environment, what was made by hanging inexpensive pool noodles on the top of the piles. This simple solution, which does not require precise installation or a specific color or shape, solved the problem along most part of the path, but we also noticed that at the corners of the warehouse, where the drone must make a 90 degrees turn, the environment was too dark to allow visual estimation. It was then necessary to install extra illumination in these parts of the warehouse. Even with these modifications, some failures would still occur. To make the system reliable, a backup attitude-based controller was then developed: when a failure is detected (Guidance system outputs a sequence of linear velocities equal to 0.0), the controller switches to attitude control, which will keep the drone going forward until Guidance is restored and the command can be switched back to velocity-based control. When the DJI M100 drone is switched to attitude control, we are able to send roll, pitch and yaw set-points to the drone. In our case, we generate these setpoints differently for each angle. For roll, we have a proportional-derivative controller for the distance between the drone and the lateral wall, as measured by the LIDAR. For yaw, we have a proportional controller for the angle between the drone and the lateral wall, also computed using LIDAR data. Finally, for pitch, because we do not always have detection in front of the drone, due to the dimensions of the warehouse, we set the pitch setpoint to be a very small constant that makes the drone to move forward until Guidance estimation is recovered or the end of the warehouse is detected. Although the results obtained with the backup controller were good, we opted to keep the original velocity-based as the main controller since it was more reliable for some movements, specially turns.

After initial tests and adjustments, the system executed several missions without any additional problem. As contracted with the client, the product was only delivered for production after 20 successfully consecutive flights, during which there were no pilot intervention, minimal human risks (obtained with a single operator inside the warehouse at a safe distance from the drone), and measurement of all piles inside the warehouse with at least 98% of accuracy. All the flights should also have a duration of less than 15 min and the inventory should be provided less than 60 min after the flight. All these criteria were met in March of 2019, when the system officially became a tool for the supply management team of the company. A video of the drone performing the inventory of a warehouse can be seen at https://youtu.be/YeVQRjrSLRY. A point cloud of the reconstructed warehouse obtained in a typical flight is presented in Figure 15.
4.2.2 Inventory estimation

To evaluate the volume estimation system using data obtained by the drone, a series of experiments were performed. In the first one, a qualitative assessment was made by visually comparing the actual stockpile with the reconstructed pile. To check for discrepancies, this test also verified some parameters of the pile, such as length and height. Figure 16 shows a picture of a pile and its reconstructed counterpart.

Our second experiment aimed at assessing the accuracy of the whole volume estimation process. After four complete flights of the drone followed by volume estimation, we changed the volume of one of the bays and execute other four flights. To change the volume, a rectangular rigid body with known volume of 37.924 m$^3$ was introduced into the bay, thus changing the volume of the pile. We then compared the average difference of the estimated stockpile volume before and after the volume was changed with the inserted volume, as shown in Table 2. Notice that the percent error in the volume estimation is very low and is consistent with the accuracy found in simulation.

To verify the precision (repeatability) of the system, we performed 19 mission flights in the warehouse while keeping the stockpile volume in five bays unaltered. Flights happened in a single day but in different times of the day. Figure 17 shows the reconstruction of one of the piles in 18 flights. Table 3 shows numerical results with these experiments. Notice that the system is very precise with a maximum coefficient of variation of 0.91%.

In our last experiment, we tested the volume estimation of empty bays. This special case was considered because we would like to test if fixed structures on the warehouse could be considered as material of the pile, thus generating a false volume. We then executed six flights in a day when there was a bay completely empty (bay 04). The result is shown in Table 4. Although the system did estimate that there was some material in the bay, the estimate (0.72 m$^3$) was insignificant if compared with the full capacity of the bay, which in this case is 1500 m$^3$.

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**Table 2** Accuracy assessment

| Estimated volume of the pile (m$^3$) | 268.556 |
|-------------------------------------|---------|
| Estimated volume of the pile with inserted volume (m$^3$) | 306.480 |
| Estimated volume difference (m$^3$) | 38.760 |
| Actual volume difference (m$^3$) | 37.924 |
| Absolute error (m$^3$) | 0.836 |
| Percent error (%) | 2.2 |

*Note: Estimated volumes are the average of four flights.*
**Figure 17**  Precision assessment: Same pile (bay 15) reconstructed with information from different flights

**Table 3**  Precision assessment: Estimated volume of material for each pile/bay after 19 flights

| Bay | Mean (m³) | SD (m³) | Coefficient of variation (%) |
|-----|-----------|---------|-----------------------------|
| 08  | 867.95    | 7.94    | 0.91                        |
| 13  | 2686.05   | 13.24   | 0.49                        |
| 14  | 1067.69   | 9.21    | 0.86                        |
| 15  | 2841.34   | 24.68   | 0.87                        |
| 17  | 3914.79   | 16.71   | 0.43                        |

**Table 4**  Estimated volume of material for an empty bay after six flights

| Mean (m³) | SD (m³) | Coefficient of variation (%) |
|-----------|---------|-----------------------------|
| 0.72      | 0.42    | 58.33                        |
5 | LESSONS LEARNED

The system described in this article is the result of a project between IHM Stefanini (an automation and industrial IT company) and a large fertilizing company with operations in Brazil. The project was the first in IHM that involved knowledge in the areas of UAS and LIDAR mapping. The development team was really excited by the opportunity to work with such a challenge. This excitement turned out to be really useful to withstand the probation imposed by lack of experience during the development phase.

As any project, we were subjected to budget and time constraints. The aerial platform and the sensors chosen for the development and later deployment presented some limitations that would not make them a perfect fit for the warehouse environment. Due to our constraints, we had to accept some design mistakes and then stressed the initially chosen hardware to the maximum, so we could have at least a minimum viable solution, which we assume that is not the most adequate solution.

Using DJI Guidance, for example, was really valuable during the development, since it simplified drone control. But, when real tests started, we realized that the environment was not well suited for the system: low-light conditions and homogeneous surfaces underneath the drone. The result was that Guidance failed constantly during flights—we have diagnosed that Guidance depends mainly in features detected by the downward camera (the other four stereo cameras acts mainly for obstacle detection) but we could not change this behavior, once its firmware is protected. Since we could not change the whole sensor (the system was developed using velocity-based commands and changing it would cause a huge delay in the product delivery), we found some workarounds to provide minimal conditions for safe flights, as described in Section 4. For future developments, some alternative and more open solution than Guidance will be considered. For example, a complete SLAM system using a rotating LIDAR such as References 36,37 could not only provide the vehicle’s state estimation, but also facilitate 3D mapping and inventory estimation.

Drones are also limited in payload. Again, it may seem obvious, but when there is not enough payload to install protective shells, add a new sensor, or to have some extra minutes of flight time, one realize that there are important choices to make. Selecting hardware and choosing paths that are short enough for the battery capacity available were the most challenging parts of the project.

Other truth acknowledged by the development team is that drones will eventually crash and fall. Although this may look obvious, until the vehicle falls for the first time the team was not believing it would happen. Even with the presence of an experienced pilot during the experiments, some minor coding mistakes or wrong assumptions may result in an unexpected behavior and, frequently, there is not enough time or space to actuate and stop the vehicle from crashing. Due to our initial high confidence in our work and our lack of experience with aerial vehicles, some field tests were postponed because we did not have enough spare parts, or even another platform to continue the flights. The initially estimated budget for the project did not considered enough resources for having more than one aerial platform, and it took some months until we got experienced in repairing the drone and reallocated resources to have the needed spare parts to keep tests going on.

From the perspective of project management and delivery, the most valuable lesson learned was the need for expectations alignment with our customer. Initially, there was some misunderstanding between the two parts: while the development team expected to deploy a rough prototype that would prove value, some representatives of the customer expected a fail-proof solution for warehouse inventory. The realignment occurred during the project and caused unnecessary stress and focus deviation.

6 | SOLUTION LIMITATIONS AND OUTLOOK

After some months of the deployment of the solution, it is possible to discuss some of its limitations and future directions. Since the project was concluded, we have been presenting our case for many fertilizer’s companies in Brazil and other countries in South America. Some logistical companies that manage stocks of grains and other materials for agribusiness also looked avidly for our solution. This confirms our perception that the volume measurement problem in stockpile warehouses is indeed relevant.

One may argue that a drone-based solution may be very limiting and difficult to adapt to different warehouses. Indeed, by visiting different plants, we noticed that, although our system is suitable for stock estimation in several warehouses, it is clear that it may fail in some others. Although, we think that it is possible to find a simple set of rules for flying the drone inside most of the warehouses that we have been visiting, we found some different scenarios, which include
warehouses with ceilings very close to the stockpiles or bays with walls that restrict the access from many directions, where it would be not possible to fly a drone at all. In fact, during our visits, it was common to find plants with multiple warehouses where some are suitable for drone flight and some are not. Since most companies have the intention to solve their inventory problems for all of their warehouses, we are currently trying to develop a set of solutions that would fit all the scenarios. These would include the current drone-based solution and also fixed or manually transported sensors.

A clear drawback of the current system is the necessity of detecting warehouse structures and use blueprint information to create a reliable map. Although this guarantees the expected accuracy and precision of the measurements, it also resulted in an algorithm that highly depends on specific characteristics of each warehouse. Roll-outs of the solution for new warehouses, where structures and blueprint may differ, will require a significant initial configuration time and increasing costs. Alternative strategies, such as the installation and detection of inexpensive visual fiduciary markers (such as ARTag, AprilTag, and ARUCO) inside the warehouse may accomplish the same results while using a more generic algorithm.

Another fact that limits the reproducibility of the proposed system is the fact that, some months after our first deployment, the DJI Matrice 100 vehicle was discontinued by the manufacturer. This implies that next developments should focus in more generic platforms with different, and perhaps open-source, flight controllers. For our solution, changing the flight controller also means that the high-level velocity commands based on the Guidance system velocity estimation will need to be replaced, creating the need for the development of a more robust attitude-based controller.

7 | CONCLUSIONS AND FINAL REMARKS

This article presented a UAS for smart inventory of stockpile warehouses. For at least 1 year, this system has been an active part of the production system of an fertilizer company in Brazil, which now counts with an automatic system to perform the inventory of one of its warehouses. Although all missions of the system still need to be supervised by a technician/pilot, who only takes over in exceptional situations, the full integration of this system in the production process prevented at least four human technicians from monthly executing a dangerous and unhealthy inventory operation that now could be executed daily by the robotic drone. In fact, after the project was delivered, our client reduced the production of the warehouse (due to a business strategy) what yielded in a slow variation of the stockpiles’ volume. Due to this, the proposed solution is being used only once a month. With this frequency, after 1 year of use (approximately 12 flights), two repairs were executed by our company. In both cases, the technician that was supervising the drone felt unsafe, assumed the manual control of the vehicle, and was not able to land it properly. These events led the customer to think that, although the solution met the initial expectations, it is still not ready for replication. In a future project, which is still in commercial discussion, it is expected that we completely remove the need for a human user/supervisor.

As a result of the first automatic inventory after delivery, the fertilizer company realized that they had more than 1000 tons of a product above its own production estimation—each ton of this specific material costs 150 US dollars. Later, they found out that some ships have loaded more products than accounted, resulting in this difference. This kind of problem would take weeks to be traced and would imply in increase of costs for logistics operation. The company estimates a reduction of 75,000 US dollars/year of logistics costs for each warehouse that adopts the UAS solution. This number was not confirmed yet, but the authors expect that it can be even higher if it includes theft prevention, performance increase, and eventual losses caused by work accidents.

The project was executed in 18 months (6 months more than expected) and final costs of development exceeded initial budget in more than 50%. Although there were some expectations that we would provide a ready-to-market solution for warehouse inventory, there are still many developments and tests to be made. Different warehouses with distinct light conditions, different structures, and other unknown factors will impose new challenges, which could impose major modifications on the current system.

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