Real-time Cargo Volume Recognition using Internet-connected 3D Scanners

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Abstract: Transport and logistics faces fluctuations in cargo volume that statistically can only be captured with a large error. Observing and managing such dynamic volume fluctuations more effectively promises many benefits such as reducing unused transport capacity and ensuring timely delivery of cargo. This paper introduces an approach that combines user-friendly mobile devices with internet-connected sensors to deliver up-to-date, timely, and precise information about parcel volumes inside containers. In particular, we present (1) RCM, a mobile app for unique identification of containers, and (2) SNAP, a novel approach for employing internet-connected low-cost, off-the-shelf 3D scanners for capturing and analyzing actual cargo volumes. We have evaluated the accuracy of SNAP in controlled experiments indicating that cargo volume can be measured with high accuracy. We have further evaluated RCM together with SNAP by means of a survey study with domain experts, revealing its high potential for practical use.

1 INTRODUCTION

The execution and management of transport and logistics processes strongly benefits from up-to-date, timely, and precise information about transported goods. Current technology developments such as internet-connected devices (Internet of Things), mobile and cloud computing, as well as software-based web services provide unprecedented opportunities for collecting relevant information in real-time. For example, sensors can be placed at relevant positions along a transport chain and even be attached to the transport containers and transported goods, thereby delivering real-time data about cargo. Such data can in turn be conveyed to downstream logistics partners, allowing them to better plan and manage the delivery of goods, match the actual cargo volume to the cargo capacity more precisely, consolidate shipments to benefit from better freight rates or increased cargo security, and, in general, more effectively plan transport and handling activities for the enterprise (Metzger et al. 2014).

This paper focusses on *parcel* transport and logistics as one area where real-time information fosters better, even proactive, reaction to deviations. Parcel transport faces frequent volume fluctuations. For example, the amount of parcels that should be transported from an online reseller to its customers may deviate from the planned amount of parcels for that day, as actual parcel volumes can statistically be captured only with large error. Observing and managing such dynamic volume fluctuations more effectively promises many benefits for a transport and logistics enterprise, such as reducing unused transport capacity and ensuring timely delivery of goods.

Our contribution is to combine user-friendly mobile devices with internet-connected sensors for delivering up-to-date, timely, and precise information about parcel volumes. In particular, we present[1] (1) *RCM (Roll Container Manager)*, an Android app for the unique identification of parcel-containers, and (2) *SNAP (Scan and Analyse Parcel-Containers)*, a novel approach for employing internet-connected low-cost, off-the-shelf 3D scanners to measure parcel volumes. RCM matches data observed by the 3D scanner to the parcel-container, thus providing unique identification of the container for effective process management.

3D scanners are one promising class of sensors that can be applied to "estimate" volumes of spatial

[1] Additional information about RCM, SNAP and its quantitatively evaluation is provided at https://sites.google.com/site/snaprcm

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objects. Volume scanning using 3D has been applied in various areas but mostly using proprietary, complex, and costly 3D scanning devices. Therefore, systems using low-cost 3D scanners promise to be an attractive alternative to industrial sensor systems due to their lower capital expenditures and their capability of efficient process integration (Kückelhaus et al. 2013). The quality of existing low cost 3D scanners has reached a level that makes it feasible to apply them in industrial settings. Successful applications of such scanners have been reported in cases such as warehouse picking operations (Xingyan Li et al. 2012), humanoid driving (Rasmussen et al. 2013), or object reconstruction (Izadi, Newcombe, et al. 2011; Zhou and Koltun 2013; Xu et al. 2012; Bondarev et al. 2013; Kainz et al. 2012).

To quantitatively assess the accuracy of parcel volume recognition as facilitated by SNAP, we performed controlled experiments. Results indicate that the position of the parcel-container and its payload influence the accuracy. In the best case, we were able to achieve accuracy with an average error rate of about -15%. Complementing this quantitative evaluation of our solutions, we performed qualitative evaluations of SNAP and RCM through a survey study with domain experts, indicating its high potential for practical use. Especially, knowledge about the container volume in operative transport management was perceived as high importance.

The remainder of the paper is structured as follows. Section 2 gives an overview of the foundations for 3D scanning. Section 3 relates our contribution to the state of the art. Section 4 describes the implementation of SNAP and RCM. Section 5 presents and discusses the design, execution, and results of our quantitative evaluation. Section 6 describes our qualitative evaluation.

2 FOUNDATIONS

We employ Microsoft Kinect as 3D scanner (concretely, Microsoft Kinect for Windows v1 (Microsoft 2014)) and therefore present its main foundations as basis for the remainder of the paper.

Kinect solutions have previously been experimentally evaluated against professional solutions concerning accuracy, effective field of view, and object detection (Smisek et al. 2011; Khoshelham 2011; Dutta 2012). In (Dutta 2012) Kinect solutions have been reported to perform better in some aspects than professional solutions.

With the release of the Kinect for Windows SDK v1.7, Kinect Fusion was introduced, enabling the calculation of 3D-volume from depth stream data (Izadi, Newcombe, et al. 2011; Izadi, Kim, et al. 2011; Microsoft Developer Network 2013). Several depth-pictures are integrated step-by-step to obtain a 3D representation of the depth information (Newcombe et al. 2011; Freedman et al. 2012), and then can be exported as a 3D-object. The raw-data of such a 3D-object can be exported in form of a point-cloud, an accumulation of points in a 3D space with x, y and z coordinates, and can be processed further. For example, raw-data is used to identify objects in a scene by comparing two point-clouds and identifying the changed points (Litomisky and Bhanu 2013) or by creating silhouettes from the color and depth data to separate objects from the scene (Xu et al. 2012). We use both ideas in our work to separate parcel-containers from their background.

The Kinect device is very cost effective, but has its own limitations. First, Kinect Fusion requires a graphics processor for real time image processing, which means the graphics hardware and memory can become a restrictive factor (Microsoft Developer Network 2014). Depending on the point cloud resolution, scenes up to multiple cubic meters can be scanned. Second, the depth sensor has noise and a limited range. Several algorithms address these limitations, e.g., (Bondarev et al. 2013; Roth & Vona 2012; Whelan et al. 2012; Zeng et al. 2012).

3 RELATED WORK

In this section, we describe approaches related to our work.

With depth data available from 3D scanners, various application problems can be addressed. For example, (Xingyan Li et al. 2012) present an implementation for the visual detection of objects in a warehouse order picking process. A Kinect sensor is used to identify goods each time an item is placed in a basket. Both the basket and the goods are static. The color images and depth images of the Kinect are used to compare textures and geometric shapes of detected objects against known objects in a database. Recognition rates approaching 100% have been achieved. However, the solutions does not employ the new Kinect Fusion APIs. The authors use a method for calculating the volume of objects located within the basket. The depth of the container is compared with the height of the measured object points and the difference represents the height of the object, which is then multiplied by the convex hull.

A project similar to our work was carried out by DHL. Two low-cost depth sensors (similar to Kinect sensors) were used to measure the volume of cargo on pallets. The results of the pilot phase indicated high accuracy (Kückelhaus et al. 2013). Although the project of DHL is a very similar scenario, it is significantly different in structure from the application considered in our work. In the project, the loading volume of pallets is measured. Pallets have the advantage that all sides are open. Due to the fact that two sensors are used, a complete 3D capture of the objects to be measured can be performed. From the data, for example, the volume of the point cloud can be calculated with the Delaunay triangulation (Delaunay 1934). In our work, only one sensor and parcel-containers with only one open side are used. Thereby, the Delaunay triangulation cannot be applied to the cloud point, because a full coverage cannot be ensured, yet the space has to be calculated within the container. These circumstances make it more difficult to capture volume in our case.

4 IMPLEMENTATION

In this section, we briefly describe the implementation of the 3D scanning solution SNAP and the Android App RCM.

Overview of SNAP. Our implementation for volume scanning employs a Microsoft Kinect 3D scanner for real-time volume recognition of parcel-containers, called *SNAP (Scan and Analyze Parcel-Containers)*. For the technical setting, the Kinect sensor is mounted on a tripod slightly above the parcel-container to attain a complete overview of the payload. The key idea for the volume calculation is to use the point cloud of the scene, provided by the Kinect Fusion algorithm and based upon the depth stream of the Kinect sensor, to extract the point cloud of the parcel-container and calculate its volume.

Our process for volume recognition consists of two activities with three steps each: (**cal**) calibration and (**scan**) actual scanning (see Figure 1). During the calibration activity, the background and also an empty parcel-container are scanned as baseline. The calibration of the background is a simple snapshot of the point cloud of the scene without a parcel-container in it (see **cal-1** in Figure 1), and is used for the algorithms for volume recognition, as described in detail below.

To achieve precise measurements of volumes, our algorithm performs two essential steps both during calibration and scanning. First, the point cloud of the parcel-container is scanned (**cal-2** / **scan-1**). Second, the points of the container are extracted from the scene by filtering out the background (**cal-3 / scan-2**). Based on these intermediate steps, the volume of a loaded parcel-container can finally be calculated by simply subtracting the volume of the empty parcel-container from the volume of the loaded container (**scan-3**).

Overview of RCM. In addition to SNAP, we developed the Android application *Roll Container Manager (RCM)* to control the Kinect and to integrate the prototype in a user-friendly way into given business processes to perform the scan process. As mentioned above, such integration requires a unique identification of the parcel-containers. This can be

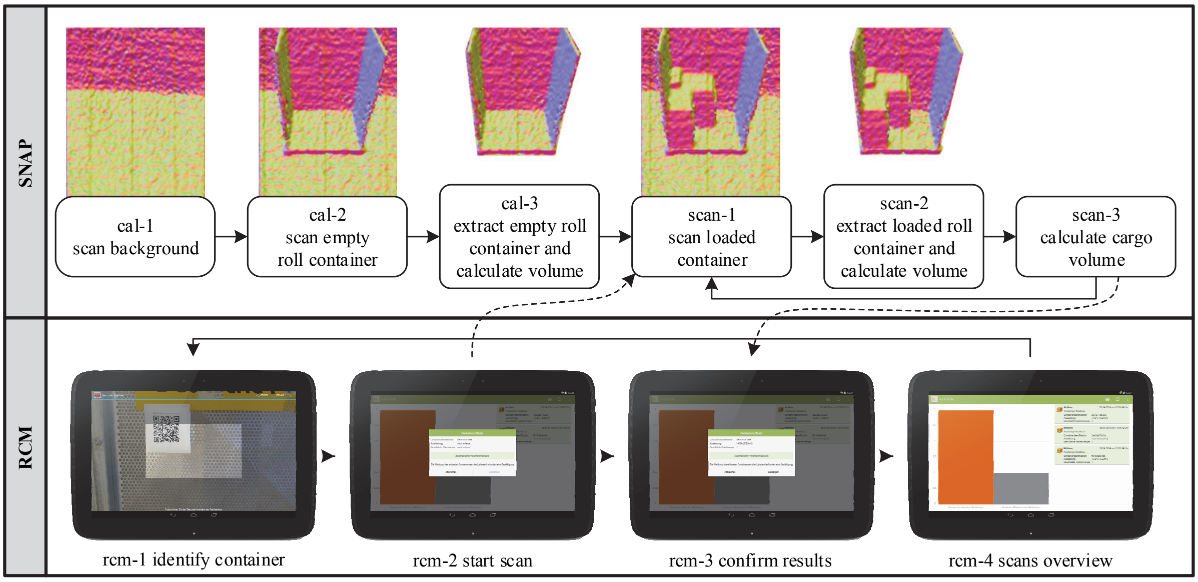

Figure 1: Abstract process for volume recognition.

done via the app by leveraging human-in-the-loop knowledge (e.g., to make sure that the 3D scanner indeed scans the parcel-container of interest).

To integrate volume recognition into a given business process, users are able to control the scanning of a loaded parcel-container by performing three steps within the RCM-App. First, they identify the container by scanning a QR-Code (**rcm-1** in Figure 1) to ensure correct data-matching to the business-process. Following this, SNAP can be started from the app to scan and analyze the volume of the payload of the parcel-container (**rcm-2**). This also ensures that the containers are only scanned after their loading has been completed. The results of volume scanning are directly sent to the RCM and is visualized for immediate confirmation by users. By confirming the results (**rcm-3**), users indicate they have checked the correctness of results. Results are then made available to the dispatcher responsible for process management (dispatchers in turn may employ control centers for process management). In addition, users may access an overview of the scans (**rcm-4**) where they can compare planned and scanned container amounts in a chart and review the details of past scans in a card view.

5 QUANTITATIVE EVALUATION

In the following, we discuss the design, execution, and results of the conducted quantitative evaluation of SNAP.

5.1 Experimental Design

We follow the definition of (Prechelt 2001) and distinguish between dependent, independent, and confounding variables. Our goal is to measure accuracy (relative error of measurement). We will investigate how the dependent variables are influenced by (variations of) the independent variables and whether there are confounding variables that might indicate wrong estimations.

5.1.1 Variables in the Experiment

Dependent Variable. We observe one dependent variable during our experiment:

- *Accuracy* of the recognition results. It is measured in the form of the relative error of measurement:

$$\text{error} = \frac{(\text{measured volume} - \text{real volume})}{\text{real volume}} \quad (1)$$

Independent variables. During the experiment, three independent variables are systematically varied to analyze their influence on the dependent variable:

- *Horizontal distance* between the parcel-container and the Kinect sensor. The analysis of this variable is crucial in practical settings since it takes some effort for the user to take care of the exact position when containers are scanned.
- *Angle* of the parcel-container to the Kinect sensor. This is measured as follows: The vertical line from the Kinect to the ground is the basis. From this point, we build a radian measure to span the field of view of the Kinect sensor. The angle from orthogonal lines of the radian measure to the container front is the independent variable. For the sake of simplicity, we took only one line in the center of the Kinect field of view.
- *Loading volume*, i.e., we want to measure whether and how the actual loading volume influences the accuracy of volume recognition.

5.1.2 Variation of Independent Variables

In order to control the variation of the independent variables, we determined the granularity of changes and the order in which the variables are modified.

Granularity. For each of the independent variables, we determined the levels for which we want to observe the influence on the dependent variable. The number of levels has been chosen such that we obtain high significance along with feasible experimental efforts (see Table 1).

For the horizontal distance of the container, the maximal and minimal levels have been restricted by the Kinect environment and the available space. Concerning the angle of the container for settings with 20° and -20° the internal space of the container is completely visible for the Kinect. For the actual loading volume, further variations beyond the ones used did not lead to new or different results.

Ordering of variable variation. According to the previously described granularities, each combination of the different levels has been evaluated, leading to 100 combinations in total. Each round consists of 35 measurements, which makes 3500 measurements in total.

Table 1: Independent Variables and Assignments.

Horiz. Distance [m]	2.58, 2.1, 1.62, 1.3
Angle [°]	0, 10, 20, –10, –20
Loading Volume [m³]	0.001, 0.131, 0.262, 0.481, 0.642

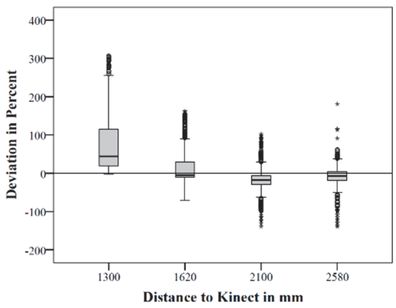

Figure 2: Distance and Deviation.

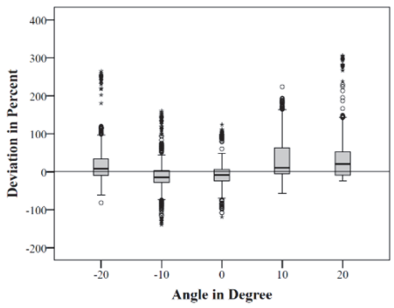

Figure 3: Angle and Deviation.

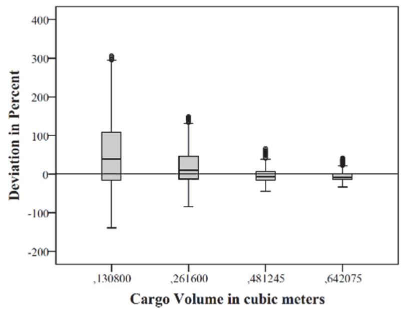

Figure 4: Cargo Volume and Deviation.

5.1.3 Confounding Variables

During the experiment, we observed three main confounding variables:

- The background and changes in the background might cause wrong volume estimations. To avoid this, a static background must be guaranteed during the experiment.
- The infrared sensor of the Kinect is sensitive to daylight. Hence, the experiment location has been protected from daylight.
- The surface of the parcel-container either reflects or refracts the infrared light. To remedy this, the inner container surface has been covered with cardboard.

5.1.4 Technical Setting and Constraints

The Kinect is located on a tripod at a height of 2.9m, the inclination angle is -38°. The range of the viewing area of the Kinect is 57° horizontal and 43° vertical. The data are processed by a computer equipped with Intel i7 3770, nVidia GT630, 16GB of memory, and Windows 7 Professional x64 SP1 as the operating system. As software, we use Microsoft Visual Studio 2012, .Net Framework 4.5, Microsoft Kinect SDK 1.8 including the Developer Toolkit, and XNA Gamestudio 4.0.

The parcel-container must be located completely in the viewing area. The size of the parcel-container is 0.92m * 1.13m * 1.67m (inside) and 0.95m * 1.2m * 1.9m (outside). The open side of the container is in front of the Kinect such that the inner space of the container is visible. The parcel-container must be optimally loaded, i.e., without empty spaces between parcels. Settings of the Kinect such as resolution, transformations, and algorithms are fixed.

5.1.5 Expected Effects

When designing the experiment, we identified expected effects caused by the variation of the independent variables, leading us to formulate three hypotheses (*H1 – H3*):

- H1/H2: "Variations of the distance/angle have no influence on the error of measured loading volume and real loading volume." The distance/angle determine the geometric position of objects. Variations of them are variable factors that are handled by Kinect algorithms.
- H3: "The larger the real loading volume is the less are the relative measurement errors." The volume is computed as the difference between the volume of the loaded container and the volume of the empty container. Due to some general variations in the scanning, lower volume has higher impact on deviations.

5.2 Experimental Results

In total, we collected 3.5GB of raw data during experiment execution, covering 3345 out of 3500 possible measurements. For the analytics, we used IBM SPSS Statistics v22.0.0.0 x64.

First, we analyzed the influence of the geometrical position of the container on the *accuracy* (measurement error).

Figure 2 and Figure 3 show the influence of the distance and the angle of the container to the Kinect. Figure 2 indicates that the Kinect delivers a low error in the 2100mm and 2580mm range. However, the error increases as the container gets closer to the Kinect sensor (1620mm and 1300mm). The angle analysis (Figure 3) shows a similar picture, with the smallest error being at -10° and 0° and increasing the further it moves away from the zero point.

We also analyzed the influence of the amount of payload. Figure 4 shows that the more payload is used, the less relative measurement error we have, starting from a very high error for lowest payload up to a very small error for highest payload.

In general, statistical influence of the independent variables is highly significant. Table 2 shows a more detailed analysis. Based on these results, we

Table 2: Significance analysis.

Independent Variable	t	Significance	Sign. Level
Distance	-33.4492941	2.3527E-205	**
Angel	9.877020051	1.26671E-22	**
Cargo Volume	-24.4620010	1.8005E-119	**

Table 3: Accuracy (measurement error) for the best case and the average case.

	best case	avg. case
std. deviation	7.31	61.41
std. error (95% confidence interval)	0.61	1.18
mean value	-16.68	17.44
median	-17.94	-1.87
minimum level (95% confidence interval)	-17.90	15.12
maximum level (95% confidence interval)	-15.46	19.76

constructed a best case scenario where we only picked the best values for the independent variables (see Table 3).

Comparing the results of the best case with the average case, a significant lower standard deviation can be identified in the best case. This means that with the choice of optimal variables, it is possible to heavily reduce the deviation to a minimum. Even if an optimal position for the container (angle and distance) cannot be ensured, a low level of deviation can be observed for high amounts of payload. Comparing a 14.90 standard deviation of the average case for the maximum payload ($0.642m^3$) used and a 7.31 standard deviation in the best case with the same amount of payload, which compares to a 28.84 std. deviation in the average case with distance set to 2.58m and 37.59 std. deviation in the average case with angle set to 0°.

5.3 Discussion

While error values showed a variance of only $\pm 15\%$ in the best case scenario, error and variance in general showed a significant movement off the desired zero baseline. This behavior is mainly caused by the distance variables to the Kinect and the angle of the container, leading to a stronger geometrical distortion. The more the container moves off the optimal orthogonal view, the more SNAP has problems with recognizing the front surface, leading to faulty volume measurements. Therefore, the user is advised to place the container as close to the optimal spot as possible to ensure accurate measurements.

Also, the amount of payload has a high influence on deviation. The more payload was used, the lower the deviation was. This leads to more results that are accurate the higher the payload is. In practice, users strive to pack the parcel-containers as full as possible, thus we can expect relatively ideal situations for this independent variable.

Considering internal validity, in total, three confounding variables have been detected. After the experiment, a manual review was performed to exhibit evidence of further confounding variables, but none with noticeable impact on the results have been observed. Considering external validity, a couple of adjustments had to be done to ensure a feasible workload and functionality. This includes using a fixed set of configuration parameters for the volume algorithms whose effects have yet to be determined. Also, the container had to be lined with cardboard, which is a very unlikely preparation for a practical use. This is yet an unlikely scenario, so either easy to apply methods or sensing technologies without this weakness need to be tested. The Kinect also needs to be placed in a static environment as changing of objects within the environment makes a recalibration of the background necessary.

6 QUALITATIVE EVALUATION

We evaluated our approach regarding usefulness, usability, and adoption by performing a survey study (questionnaire-based) with domain experts from the parcel logistics domain during a live demonstration of our prototype.

For each question of the questionnaire, we offered five choices reflecting the degree of approval, ranging from “strongly disagree”, “disagree”, “neutral”, and “agree” to “strongly agree”. A participant’s choice was quantified (1 for strongly agree, 0.75 for agree, 0.5 for neutral, 0.25 for disagree and 0 for strongly disagree), summarized and divided by the mean value, ending up with a single degree of approval. The result is summarized in Table 4.

The responses from domain experts indicate the usefulness of our approach. Especially, knowing the container volume in operative transport management (79.2%) was perceived of high importance.

Also, the usability of our volume scanning solution in practical environments has been confirmed, e.g., by a high approval of the fact that only a short training period and only few instructions are necessary. Finally, the analysis of potential adoption indicated that there is a high interest to apply our Kinect approach in general (63.9%).

However, the appropriateness of the provided functionality for the expert's individual businesses received an agreement of only 54.2 %. This may partially be attributed to the fact that the IT permeation of transport and logistics industry is still quite low in many areas and thus it may be difficult for domain individuals to relate to their current state of practice. Another mentioned aspect was an eventual vulnerability of the approach to soiled sensors.

Table 4: Results of expert evaluation.

Usefulness	
The amount of roll containers is important for operative transport management.	72.2 %
The used capacity (volume) of each roll container is important for operative transport management.	79.2 %
The interaction with the Kinect via mobile apps is useful.	70.8 %
Usability	
Using the automatic volume scan (e.g., with the Kinect) would only require a short training period.	76.7 %
Using the automatic volume scan (e.g., with the Kinect) would require some instructions.	68.3 %
Adoption	
I would like to work with the automatic volume scan (e.g., with the Kinect).	63.9 %
The provided functionality of the automatic volume scan (e.g., Kinect) is appropriate for my business.	54.2 %

7 SUMMARY AND CONCLUSION

This paper presented an approach for using Microsoft Kinect, a low-cost, off-the-shelf 3D scanner, to measure the cargo volume of a parcel-container in real-time. To quantitatively assess accuracy of payload volume recognition, we performed controlled experiments. The evaluation showed a high accuracy with only 15% relative error under optimal circumstances. However, it also revealed some weaknesses when the geometrical position of the container differs from the optimal position. Complementing this quantitative evaluation of our solutions, we performed qualitative evaluations through a survey study with domain experts, which indicated the usefulness and applicability of our approach. It thus has a high potential for practical use.

In the meantime, Kinect for Windows v2 was released and promises further improvement of our approach, especially concerning overall accuracy, noise-reduction. Furthermore, we are evaluating several other parameters to help improve accuracy and performance of volume recognition. As an ongoing step, we implement a second algorithm with Euclidean Cluster Extraction and repeat the experiments for comparison. An interesting further aspect might be to apply our solution to the Food Supply Chain, e.g., Big Box[2]. This would allow scanning parcel-containers containing objects with the same size and thus calculate the exact amount of objects.

Finally, we are going to bring our solution into the cloud, using distributed thin-clients with connected Kinect for Windows v2. This facilitates scaling our solution to extend the visible space and scan multiple containers as well as outsourcing computational-intensive algorithms.

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