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Abstract

The Inventory Verification through Detectors on Robotic Inspection Platforms project is developing methods and technologies to enable robotic platforms to autonomously perform Safeguards-relevant inspection tasks. The two inspection tasks we are working to address are automated design verification and radiation-based nuclear material accountancy inspections. Our approach to development focuses on integrating our Scene Data Fusion (SDF)-based radiation detection systems, with robotic platforms and developing autonomy algorithms within the SDF software ecosystem. The SDF technology, developed at Lawrence Berkeley National Laboratory (LBNL), is approximately ten years old and couples radiation imaging techniques with computer vision technologies to create context-informed 3D maps of radioactivity. It has been most widely applied to contamination mapping and radiation search applications, but has also been applied to object inspection in materials accountancy problems in the past. This project represents LBNL's first effort at integrating SDF with autonomous systems in a safeguards context. For the design verification task, we focus on indoor applications, where we are integrating our detector systems with a Boston Dynamics Spot robot which is given navigation instructions by the SDF computer. The Spot/SDF system will autonomously create a 3D map of a facility, concurrently note areas that present heightened radiation hazards, and automatically locate clutter objects, as well as pipes and ducts. For accountancy inspection tasks, we plan to leverage previously-developed computer vision technologies to identify and count nuclear material containers, either using the Spot system indoors or a similar small unmanned aerial vehicle (UAV)-based system for outdoor inspections. Once the nuclear material containers are identified, we are developing autonomy algorithms that automatically navigate to the containers and conduct SDF-based radiation measurements to assess whether the containers' contents match declarations within pre-specified confidence levels (e.g., empty vs. full). When the number of containers is too high for each to be individually surveyed, we will implement randomized sampling strategies in order to gain various levels of statistical precision on a broad set of items, yet randomly select a subset for additional scrutiny. This project, funded by Defense Nuclear Nonproliferation Research and Development (DNN-R&D), is in its second year of a three-year project.

1 Introduction

The Inventory Verification through Detectors on Robotic Inspection Platforms (IV-DRIP) project is a 3-year exploratory research effort that is a collaboration between Lawrence Berkeley National Laboratory (LBNL) and Remote Sensing Laboratory (RSL) supported by the Safeguards portfolio of Defense Nuclear Nonproliferation Research and Development (DNN-R&D) in the United States' the National Nuclear Security Agency (NNSA). The main premise of IV-DRIP is that both International Atomic Energy Agency (IAEA) inspectors' time and their radiation doses are limited and therefore technologies that can autonomously perform simple inspections tasks can allow for inspectors' time to be better spent on more complex and/or higher-level safeguards activities, particularly when those simple inspection tasks involve subjecting inspectors to radiation fields substantially above background. As a specific example, the number of facilities subject to IAEA inspection grew by 12% in the 2010 decade and the number of nuclear material significant quantities being safeguarded grew by 24% while the overall time inspectors spent in the field only grew by 0.4%[1]. Meanwhile, capabilities of robots to perform menial have reached a level where their adoption for nuclear safeguards inspections tasks may be fairly easy, and robots can be subjected to many orders of magnitude higher dose rates than people without adverse effects. Conversely, robot mobility and battery lifetimes remain limiting factors, and a robots repeatedly performing a task identically is likely more susceptible to spoofing. With these observations in mind, we set out to identify nuclear safeguards tasks that could be suitable for robotic automation and begin asking how best to implement those tasks.

Computer vision and mapping techniques are highly effective for automatically creating detailed three-dimensional (3D) renderings of facilities. The idea of doing so in a safeguards context is over 15 years old (see e.g., [2, 3]), and in 2015, the Join Research Centre in Ispra created the Mobile Laser Scanning Platform (MLSP), which is a free-moving LiDAR scanning system for nuclear safeguards in 2015 that could be person-carried or mounted on a vehicle [4]. Conceptually, allowing robots to support design verification tasks is a continuation of the MLSP concept, yet we also couple computer vision technologies to facilitate comparisons between facility design drawings and as-built and cluttered operational facilities. Such comparisons are bolstered by coupling semantic segmentation and imagery with the 3D rendering, as was done in Ref [5]. This effort is described in Section 3.

Another task for which robots are well-suited is menial and repetitive item inspection activities such as ensuring nuclear material storage containers' contents are consistent with declaration. For this task, we are working to leverage the advances of our sister project, the DNN-R&D-supported Container Counting project[6], where nuclear material containers are automatically identified in camera imagery and then located within a concurrently-generated 3D model. With the locations of containers, an autonomous robot can navigate toward the container and perform a radiological measurement from either a fixed and consistent pre-specified vantage, or from a perspective the more accurately mimics how an inspector might select any of a variety of measurement configurations that are roughly equivalent. Creating robotic techniques that behave like the latter results in a more robust inspection regime because performing measurements in a variety of configurations makes spoofing significantly more difficult than the alternative, which is widely held as a benefit of robotic inspections. Specifically, it is often stated that robots can perform the exact same measurement (or at least to sub-cm precision) repeatedly and that repeated performance of the same measurement in an identical configuration facilitates comparisons between measurements, which helps identify changes and trends. However, nuclear safeguards measurements are typically less interested in identifying trends, and are rather focused on robust measurements that can identify material diversion. An operator intent on deceiving safeguards can determine how to create the same radiological signature at the measurement point, once it is known, while removing a substantial portion of the radiological material that is creating the signature (e.g., by reducing the amount of shielding in the material container or by packing all radioactive material within a container at the side closest to the measurement point). We refer to such procedures as 'spoofing'.

A significant technological advancement that allows for robotic technologies to perform measurements in configurations that appear more ad hoc, yet remain capable of statistical inference is the LBNL-developed technology, Radiological Scene Data Fusion (SDF)[7]. The SDF technology couples 3D models with free-moving radiation measurements in a manner that attributes the measured radiation to the constituents of the scene, which is measured on-the-fly using co-located 3D mapping sensors such as cameras and lidar. Section 2 describes the SDF technology, a SDF-capable imaging system we have developed, and the recent preliminary results of measurements made at the Nevada Nuclear Security Site (NNSS).

Section 4 briefly describes our approaches to autonomous navigation, both for facility mapping and for safeguards material accountancy inspections. We have integrated our SDF-capable sensor system with both an unmanned aerial vehicle for outdoors inspections at, e.g., a uranium hexafloride (UF_6) storage yard and with a Boston Dynamics Spot quadruped robot[8], which we envision being more representative of an autonomous system used indoors at a safeguarded facility. Section 5 concludes, summarizes the upcoming activities in the IV-DRIP project, and provides perspectives beyond the upcoming year.

2 Scene Data Fusion

Scene Data Fusion has been well-described elsewhere[7, 9, 10] yet remains subject of active development. The initial motivation behind SDF was to enable gamma-ray imaging from free-moving radiation detector systems, particularly in indoor and/or disaster response environments. In order to support a free-moving imager system, simultaneous localization and mapping (SLAM) has been integrated into the software stack[11]. SLAM algorithms process continuously updated imagery data to create both a map of the environment based on that imagery and a self-consistent series of poses that describe how the image sensor was oriented during data collection. In SDF, we most typically use a lidar sensor for image data and couple that with an inertial measurement unit, which helps to constrain the search space in SLAM.

Free-moving gamma-ray imaging can be conducted by analyzing each gamma-ray interaction that can be imaged (e.g., Compton events) and simply projecting each events' potential directions into space, which is analogous to static Compton imaging, except the origin of each projection changes according to the detector's stance at the time of measurement. However, it was noted early on, that using the true 3D map generated by SLAM to further constrain the potential positions of source activity reduces the reconstructed spatial extent of point-like sources[7], which is suggestive of improved overall performance. This fusing of the spatial information with a radiation imaging-inspired representation of the measurement is the underlying premise of SDF. Further development of the SDF technique result in approaches that are now able to quantify the activity of the reconstructed radioactive distribution[12, 13] and to constrain the uncertainty in those activity estimates[13, 14].

The ability to quantitatively reconstruct radioactive source activities is central to our work within IV-DRIP, wherein we envision a robotic system that autonomously performs radiological surveys of nuclear material containers. The containers are declared to the inspector to contain certain quantities of nuclear material. The robotic system performs a series of measurements, making statistical tests on each container to determine how confident one can be regarding whether the SDF measurements are consistent (or inconsistent) with the declaration. Ref.[15] describes recent work within the IV-DRIP project to consider what levels of confidence can be obtained in such an approach for UF_6 containers when using a fairly simple radiation detector system. In short, while systems incapable of gamma-ray imaging are useful in many scenarios, if containers are configured in rows and the inner rows are inaccessible, detector systems capable of gamma-ray imaging appear to be valuable tools. To this end, we have developed the Inventory Verification Localization and Mapping Platform (IVLAMP), which builds upon previous SDF-capable sensor systems, but features a Compton-imaging capable M400i cadmium zinc telluride (CZT)-based radiation detector, built by H3D Inc.[16], and a lidar-based mapping system called the Hovermap ST-X, built by Emesecent Ltd.[17]. A rendering of the developed IVLAMP package as well as two mounting systems is shown on the left of Figure 1 and a photo of it being flown by a UAS during testing is shown on the right. The Hovermap handle attachment can also allow for IVLAMP to be hand-carried.

Figure 1: (Left) Rendering of the IVLAMP system. The rendering shows two mounting systems. The lower mounting system is used to attach the IVLAMP to the Spot robot, using four thumb-screws to attach to the Spot payload rails. The higher mounting system attaches IVLAMP to our UAV, using four screw points. (Right) A photograph of IVLAMP carried by our UAV at our UAV testing facility in Richmond, California, USA. Note, in this photo, the Spot mounting system is not present.

Visible on the exterior of the IVLAMP is the Hovermap package (atop), the M400i (below) and an e-con Systems See3CAM_CU20 camera (below the Hovermap lidar). Inside the carbon fiber frame of IVLAMP is a intel nuc computer, an inertial navigation system, the battery bay and power management system. The entire system weighs about 5 kg when carrying two Lithium polymer (LiPo) batteries, which provides approximately 3 hour battery life. The batteries can also be hot-swapped for continuous operation. The IVLAMP computer saves and processes the collected data and functions as a web server for the IVLAMP user interface (UI), which is accessed as a web page. The UI provides a measured spectrum, a time-based strip-chart of system count rate, a first person camera view with a first-person projection of the SDF reconstruction overlaid, and a top-down view of the map created by SLAM, with the trajectory and SDF reconstruction overlaid. Whereas normally SDF systems produce SLAM maps online, during acquisition, the Hovermap software provides an occupancy map in real-time, which is later converted to a 3D point cloud map that is better fidelity and more reliable than typical SLAM solutions.

We recently used both the IVLAMP system and an older neutron-sensitive SDF system called neutron-gamma localization and mapping platform (NGLAMP)[18] during a measurement campaign at NNSS in Mercury, Nevada, USA to collect data to train our autonomy algorithms. Here, AT400 nuclear material containers, were placed on the bottom rows of four storage racks (24 positions in total) within a warehouse and in a few of the AT400's, depleted uranium (DU) was emplaced. NGLAMP and IVLAMP were carried by hand and on by Spot, making 3D maps of the environment and also performing radiation measurements and running SDF algorithms.

An example of the type of 3D model that is made using the LAMP systems is shown on the left-hand side of Figure 2, while a top-down view showing the trajectory of the detector system, colorized by count rate in the context nearby objects in the 3D model is shown on the right. The extents of the facility are approximately 30m (y) by 20m (x) by 12m (z) and only the left half (y>-15) of the facility was actively being used for this exercise. In the right-hand graphic, points between 30 and 60 cm above ground are

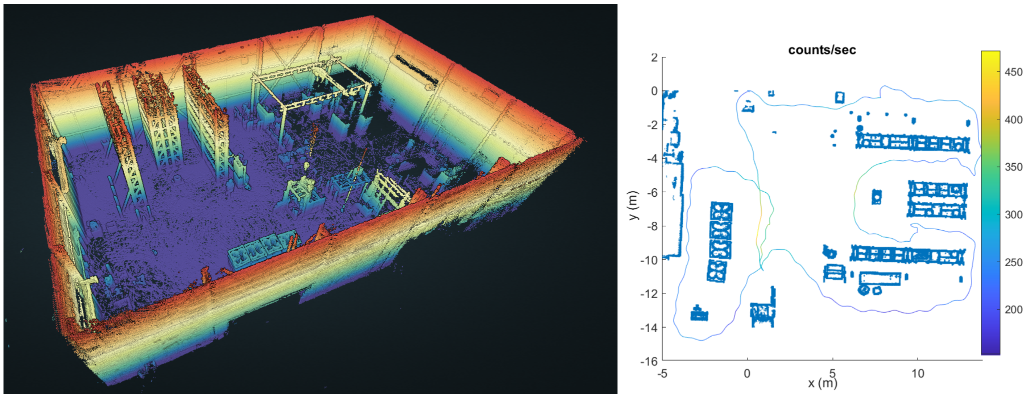

Figure 2: (Left) A 3D point cloud, created at a NNSS warehouse wherein AT400 nuclear material containers are being positioned in storage racks. The point cloud is colorized by elevation. (Right) a horizontal cut-through of 30cm of the point cloud (shown in blue) with the storage racks and staged pallets of AT400 containers visible. The trajectory of the NGLAMP system, that created this model is also shown, and colorized by count rate.

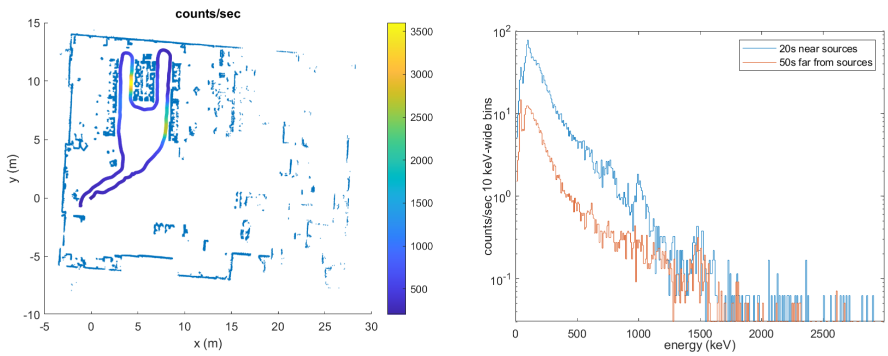

Figure 3: (Left) A top-down view of another measurement, akin to the right-hand graphic in Figure 2, yet this measurement is even shorter. (Right) Spectra generated from the measurement at tow times, one when count rates were greater than 700cps, corresponding to the 20s when the sensor system was relatively near the AT400's that contained DU and another from the 50s in the measurement when the gross count rate was less than 500cps.

plotted and it is evident that in this scenario, there was a single AT400 with 360μCi of DU placed on a small cart near the storage racks, at (x,y)=(7,-6) and numerous other AT400's were staged on pallets near (-2, -6 to -11). Additional DU was also being handled during this measurement, which resulted in an appreciably elevated count rate near (1, -6 to 10). Despite the very limited measurement time (150s) and small fraction of the entire warehouse, a fairly detailed rendering of the warehouse is created. The four storage racks (R1 through R4) are positioned at y= -3, -6, -7 and -10m, respectively and R1 and R4 span x=6 to 13m and have room for 8 containers while R2 and R3 are shorter, ranging only x=9.5 to 13m and have room for 4 containers. We number the 24 container positions in a serpentine fashion starting with position 1 at (6,-3) in R1, position 13 is at (9.5, -6) in R2, and position 17 is in R4 at (13,-10).

A second example of SDF-informed measurements is shown in Figure 3, and several views of the 3D output of the SDF reconstruction are shown as Figure 4. The NNSS warehouse was been reconfigured to have AT400's in 22 of the 24 positions, with a rectangular box also on R4 at positions 19 and 20. There are square sheets of DU of activity 360μCi inside containers in positions 2 and 4 and 1.5mCi of DU in the containers in positions 10, 11, 21 and 24. This measurement lasted 80s with NGLAMP and was processed using a reconstruction algorithm that leverages the geometry of the measurement and the anisotropic sensitivity of the four scintillator crystals within NGLAMP.

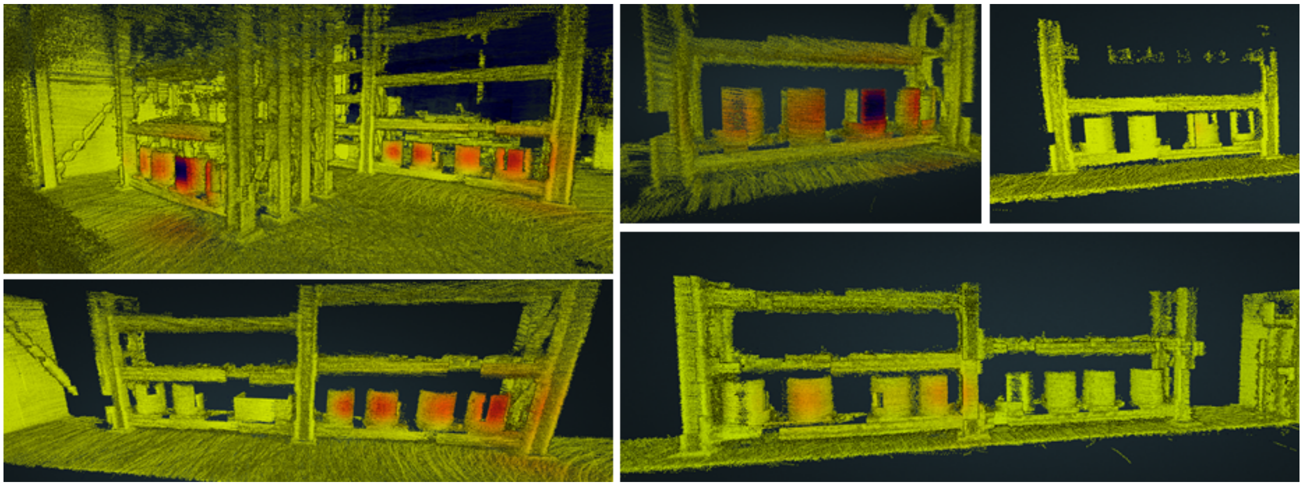

Figure 4: A series of views of the reconstructed gamma-ray activities emitted from the surfaces reconstructed from SLAM during the measurement of the AT400 storage area at NNSS. The full dynamic range of the color scale spans 0 to 4 emitted photons/cm^2/s. From top-left, clockwise: (1) Perspective looking at filled containers in R2 and R4 from position 1 in R1; (2) R2, where the two right-hand containers are filled with 1.5mCi of DU; (3) R3, where all containers were empty; (4 - bottom-right) R1, where the 2nd and 4th containers from the left are filled with 375μCi of DU; and (5) R4, where the right-most and 3rd from the right containers are filled with 1.5mCi of DU.

The images in Figure 4 are examples of the types data products that the automated IVLAMP system would provide to an inspector in support of any material accountancy determinations that an autonomous system could make. Here, all the AT400's in R2, six containers in R1 (#'1,3,5-8), and #'s 17 and 18 in R4 would be accurately described as containing no DU. The AT400's in positions 2 and 4 in R1 have emission rates consistent with containing 350μCi of DU while the contents in R2 and the right side of R4 clearly have higher DU content. It is also worth highlighting that these images are based only on an unconstrained reconstruction using a non-imaging detector system. We expect significantly better fidelity when our IV-DRIP analysis pipeline is complete because:

- Algorithms will be run to attribute radioactivity to semantically-identified containers, as is being developed by the Container Counting project[6], rather than just to volumetric emission rates;
- The algorithms will make comparisons between measurements and priors, based on declarations, rather than the unconstrained solutions shown here;
- Reconstruction algorithms will also leverage gamma-ray imaging modalities enabled by the M400i, rather than just geometric considerations; and
- When comparisons between discrete priors and measurements are inconclusive, an autonomous system can loiter longer and/or move slower as it traverses such regions to obtain better counting statistics.

The work from Ref. [15] describes how container composition priors can be leveraged in support of determinations to whether longer loiters are necessary. Ref. [12] summarizes the use of quantitative Compton imaging, but we have yet to calibrate the efficiency of the M400i in IVLAMP in the manner that is necessary to perform such analyses.

Once the M400i is calibrated for quantitative Compton imaging, we can both support future free-moving quantitative measurements and re-analyze the data collected at NNSS. Although only a few runs were shown here, the NNSS data collection featured a wide variety of container configurations, different movement patterns and IVLAMP and NGLAMP being hand-carried, mounted on Spot and some outdoor collections were conducted using the UAV.

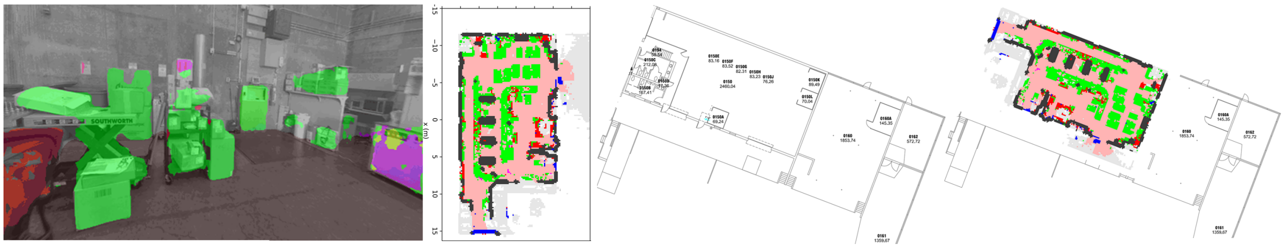

Figure 5: From left: (1) A semantically labelled imaged, (2) a floor plan derived from a series of labelled images projected into the 3D model and aggregated, (3) actual floor plan (4) floor plan with semantically-derived floor plan overlaid.

3 Semantically-informed facility mapping

We imagine that 3D maps collected during facility familiarization and design verification activities could feature sufficient clutter that automated comparisons between facility design documents provided by the facility and the 3D map could become challenging, owing to rearrangements of equipment within the facility. To address these types of challenges, we have also augmented the mapping data our LAMP systems create with semantic information. We use the IVLAMP camera imagery and process it with the DeeplabV3+ semantic segmentation neural network[19] trained on the ADE20K dataset[20] to create labelled imagery, as shown in the left of Figure 5. These labelled images are then projected into the 3D map and further collapsed into the categories: wall, floor, ceiling, stairs, door/window, movable objects, and immovable objects. This information is aggregated and a 2D floor plan is created, like shown in the 2nd image of Figure 5. These can be automatically aligned and compared, as shown in the rest of the figure, although this example does not feature any disagreements.

4 Inspection autonomy

We are considering two sets of applications for our autonomous system: facility familiarization and design verification and the performance of material accountancy through radiological measurements. The former is a common problem that has been well-studied[21, 22, 23]. The latter requires coupling navigation strategies, computer vision, and radiological investigations. As we work to implement the SDF and computer vision tools into an autonomous system, we rely on four technological underpinnings: 1) The robotic platforms that will carry our payload can accept local navigation inputs. Therefore, we only need to decide where to go and when, rather then mechanically how to move the robot. 2) Technology developed in the Container Counting project will provide a list of ‘seen’ nuclear material containers that are of interest for inspection. 3) Ray-tracing and statistical techniques being developed within IV-DRIP and summarized in Ref. [15] will help inform whether an individual container is visible from a particular vantage and whether it has been sufficiently surveyed. 4) Decision trees are used to manage the autonomy logic. The fourth point is further detailed below.

Conceptually, we are building a system that will be provided as input a spatially constrained region to survey. The robot, carrying an IVLAMP system will navigate to that region and the camera’s coverage will be aggregated in the map that is built of the region. This is akin to the semantic labeling described in Sec. 3, but only logging whether portions of the model have been seen by the camera. Concurrently, any material containers identified by algorithms running on the IVLAMP system will be logged. Ideally, the locations of the entirety of the containers of interest will be determined promptly. Thereafter, the autonomy logic will create a survey plan based on e.g., a greedy solution to the travelling salesman problem. Another input to the autonomy algorithm is whether to plan for reaching pre-set levels of statistical confidence in surveys, or to maximize confidence given a time constraint. Either way, a plan will be made with some buffer time. As

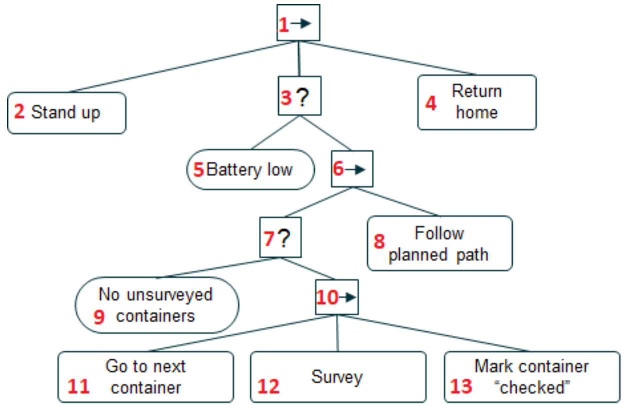

Figure 6: Example simple decision tree structure. The red labels are shown to facilitate description .

each container is inspected, statistical logic is applied to determine when to move to the next. We also plan to create logic to randomly select a subset of containers that are inspected to a higher statistical threshold. One could imagine scenarios where most containers are inspected to 10% uncertainty in relatively little time, yet perhaps, 10 of the 50, are inspected to 3% uncertainty through 10-minute dwells. With the buffer time, any surveys that take longer than anticipated can be lengthened on-the-fly. The result of such a survey is a statistical confidence statement as to whether or not the measurement of each container is consistent with expectation. Images (and data) for each container, similar to those provided in Figure 3, but also featuring the Compton imaging reconstruction modality, can be automatically produced and available to the inspector.

Practically, we have implemented much of this logic using decision trees. A simple decision tree example is shown as Figure 6. Here, the top level (1) node simply conveys that the three nodes (2-4) should be conducted in order. Therefore, the robot first initializes by standing up (2), then proceeds to continually check battery (5) and if the battery is not low, descends into the next subtree (6). If the battery is low, or when the subtree 6 logic is complete, the robot returns home (4). Subtree 6 first checks whether there are containers to survey (7). If there are none, the pre-programmed path is followed (8) until unsurveyed containers are found (9). At that point, the planning algorithm would decide which to go to first (the 'next container' (11), then that container would be surveyed until the statistical logic marks it as satisfactorily surveyed (12), at which point it would be marked as 'checked' (13) and the next container would be subject to the same logic (11-13). Once all containers are surveyed, the logic of node 7 becomes false and the pre-planned path (8) is resumed and followed until it is completed, at which point the subtree below nodes 6 and 3 are finished and the robot returns home (4).

In this example decision tree, the logic behind the creation of the planned path (8), the selection of the next container (11), and the container survey (12) can all be quite complicated and each is the subject of active algorithm development. It is within nodes 11 and 12 that we can also implement randomization, where surveys are not repeatedly conducted in the same way. We could also extend this decision tree to accommodate planned buffer time and performing follow-up surveys of those container that had the lowest statistical confidence with remaining time. Such a modification would entail creating another subtree branching off node 6, between nodes 7 and 8.

The implementation of such decisions trees in conjunction with SDF analyses has already been demonstrated in an autonomous radiological search problem with our UAV [24], which features an Ardupilot flight control software[25]. We are now working to implement and test it on Spot in conjunction with the container counting project's object recognition software (as node 9), a greedy traveling salesman solution (for node 11) and heuristics for survey methods and statistical tests for item survey completion (as node 12).

5 Conclusions

This paper has summarized the IV-DRIP project, which in its first year primarily focused on acquisition and familiarization of the Hovermap mapping system and the Spot robot as well as developing and familiarizing ourselves with autonomous control interfaces for Spot and our UAV. Now, in our second year, we have completed the IVLAMP detector system and have integrated it with both robots, allowing us to use the IVLAMP computer as the brains behind our autonomy schemes. We recently collected data at NNSS that will support development of lower-level autonomy logic and are now both analyzing that data and beginning to implement a full decision tree-based logical control system for autonomous inspections. We plan to return to NNSS and conduct tests of the autonomous systems next fiscal year. Concurrently, we have implemented methods to distinguish walls versus clutter in active facilities and will soon demonstrate the automatic acquisition of such data and subsequent automated creation of an annotated facility map for comparison with blueprints.

Acknowledgment

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References

[1] Yukiya Amano and IAEA Director General. Challenges in nuclear verification. `https://www.iaea.org/newscenter/statements/challenges-in-nuclear-verification`, 2019. Accessed: 2024, June 18.

[2] L et al. Mihailescu. Combined measurements with three-dimensional design information verification system and gamma ray imaging. In *2006 INMM Annual Meeting*, 6 2006. URL `https://www.osti.gov/biblio/893171`.

[3] Stephanie Poirier. Laser based applications: Existing and future solutions. In *JAEA-IAEA Workshop on Safeguards Technologies. Tokai, Japan*, 2007.

[4] Erik et al. Wolfart. Mobile 3d laser scanning for nuclear safeguards. *ESARDA Bulletin*, 53:62–72, 2015.

[5] Marco et al. Salathe. A multi-modal scanning system to digitize cbrne emergency response scenes. In *2022 SSRR*, pages 74–79, 2022. doi: 10.1109/SSRR56537.2022.10018826.

[6] Marco Salathe et al. Multi-sensor fusion for nuclear material container counting and inventory. In *2024 INMM Annual Meeting*, 2024.

[7] Ross et al. Barnowski. Scene data fusion: Real-time standoff volumetric gamma-ray imaging. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, 800:65–69, 2015.

[8] Spot specifications. `https://support.bostondynamics.com/s/article/Robot-specifications`, 2024. Accessed: 2024-07-01.

[9] Andrew et al. Haefner. Handheld real-time volumetric 3-d gamma-ray imaging. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, 857:42–49, 2017.

[10] Kai et al. Vetter. Advances in nuclear radiation sensing: Enabling 3-d gamma-ray vision. *Sensors*, 19 (11):2541, 2019.

[11] Wolfgang Hess et al. Real-time loop closure in 2d lidar slam. In *2016 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1271–1278, 2016. URL `https://github.com/cartographer-project/cartographer`.

[12] Daniel Hellfeld et al. Free-moving quantitative gamma-ray imaging. *Scientific Reports*, 11:1504, 2021. doi: 10.1038/s41598-021-99588-z.

[13] Jayson R. et al. Vavrek. Surrogate distributed radiological sources—part ii: Aerial measurement campaign. *IEEE Transactions on Nuclear Science*, 71(2):224–233, 2024. doi: 10.1109/TNS.2024.3351611.

[14] Jaewon Lee et al. Radiation image reconstruction and uncertainty quantification using a gaussian process prior. *Submitted to Nature Scientific Reports*, 2024.

[15] Mark S. Bandstra et al. Estimating uranium hexafluoride cylinder contents using autonomous measurement systems. In *2024 INMM Annual Meeting*, 2024.

[16] M400 product brochure. `https://h3dgamma.com/M400Specs.pdf?`, 2024. Accessed: 2024-07-01.

[17] Hovermap st-x product brochure. `https://emesent.com/wp-content/uploads/2022/11/Hovermap-ST-X-product-brochure.pdf`, 2024. Accessed: 2024-07-01.

[18] R et al. Pavlovsky. 3d gamma-ray and neutron mapping in real-time with the localization and mapping platform from unmanned aerial systems and man-portable configurations. *arXiv preprint arXiv:1908.06114*, 2019.

[19] Liang-Chieh et al. Chen. Encoder-decoder with atrous separable convolution for semantic image segmentation. In *Computer Vision – ECCV 2018*, pages 833–851, 2018.

[20] Bolei Zhou et al. Scene parsing through ade20k dataset. In *Computer Vision and Pattern Recognition (CVPR), 2017*, 2017.

[21] Héctor H. et al. Navigation strategies for exploring indoor environments. *The International Journal of Robotics Research*, 21(10-11):829–848, 2002. doi: 10.1177/0278364902021010834. URL `https://doi.org/10.1177/0278364902021010834`.

[22] Sebastian Thrun et al. Robotic mapping: A survey. 2002.

[23] Julio A et al. Placed. A survey on active simultaneous localization and mapping: State of the art and new frontiers. *IEEE Transactions on Robotics*, 39(3):1686–1705, 2023.

[24] Brian J. Quiter et al. Ongoing advancement of free-moving radiation imaging and mapping. In *Hard X-Ray, Gamma-Ray, and Neutron Detector Physics XXIV*, volume 12241, page 122410H. International Society for Optics and Photonics, SPIE, 2022. doi: 10.1117/12.2635752. URL `https://doi.org/10.1117/12.2635752`.

[25] Ardupilot web page. `https://ardupilot.org/`, 2024. Accessed: 2024-07-01.