Towards an Automated Checked Baggage Inspection System Augmented with Robots

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ABSTRACT

We present a novel system for enhancing the efficiency and accuracy of checked baggage screening process at airports. The system requirements address the identification and retrieval of objects of interest that are prohibited in a checked luggage. The automated testbed is comprised of a Baxter research robot designed by Rethink Robotics for luggage and object manipulation, and a down-looking overhead RGB-D sensor for inspection and detection. We discuss an overview of current system implementations, areas of opportunity for improvements, robot system integration challenges, details of the proposed software architecture and experimental results from a case study for identifying various kinds of lighters in checked bags.

1. INTRODUCTION

Created in November 2001, the Transportation Security Administration (TSA) bears the responsibility of securing the civil aviation system in the United States. By law, TSA has a mandate to screen all commercial airline passengers and baggage. Two recent reports by the Government Accountability Office acknowledge the progress TSA has made in deploying screening and explosive detection systems for checked bags at the airports it oversees.[1,2] However, a number of shortcomings of the current implementations have been pointed out: (1) 76% of all airports have optimal systems, (2) only 36% of larger airports are equipped with systems that meet the current needs for in-line and/or stand-alone baggage screening, (3) existing implementations fail to meet current standards for detecting explosives in checked luggage (4) TSA estimates 60% of existing systems will reach the end of their useful life within the next 5 years. These shortcomings are despite the TSA budget increasing to $7.91 billion dollars for the 2013 fiscal year from $4.7 billion in fiscal year 2002. The costs for securing the civilian aviation system are only expected to rise with the most recent Senate budget proposal including an increase of the September 11 security fee.[3] The fee is charged to every passenger for each leg of their itinerary up to a maximum of twice and is expected to rise from its current level of $2.50 to $5.00 and up to $7.50 by 2017.

The Electronic Baggage Screening Program (EBSP) Strategic Planning Framework outlines the goals for the TSA in the development of baggage screening systems in the airports. From the Planning Guidelines and Design Standards for Checked Baggage Inspection Systems,[4] the goals of the strategic planning framework are to:

1. Increase security through deploying explosives detection system (EDS) equipment to as many airports as practicable and implementing more labor-intensive explosives trace detection (ETD) screening protocols at those locations where ETD will continue to be used for primary screening.

2. Minimize EBSP life-cycle costs by deploying the best possible screening solutions at each airport, appropriately balancing capital investment and operating cost tradeoffs.

3. Minimize impacts to TSA and airport/airline operations through well designed and well-placed EDS solutions.

4. Provide a flexible security infrastructure "platform" for accommodating growing airline traffic and other industry changes over the next 20 years and for addressing potential new threats.

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We posit that despite the significant automation currently employed by the TSA in the Checked Baggage Inspection Systems (CBIS), the addition of innovative robotic technologies in the baggage screening process can significantly reduce the labor-intensive tasks required to manually inspect some bags. Technologies enabling robots to work in close collaboration with humans can address issues in implementing all four EBSP strategic plan goals in a cost-effective manner. For example, the labor-intensive ETD, where a piece of fabric is swabbed across a suspicious bag and placed inside the trace detection machine, can be accomplished with a robot working in collaboration with a human operator, allowing ETD to be deployed to more locations covering more potential threat entry points. Robotic technologies enabling flexible operations can simplify the design and execution of CBIS, which in turn reduces required capital investment and can standardize maintenance and operating costs across airports. In addition, because robotic technologies can rapidly be integrated with existing systems with minimal impacts to current operations, they provide a flexible path to accommodate future expansion and throughput needs while addressing yet unknown threats that will require more advanced detection. If these goals can be addressed with a cost-effective solution leveraging the recent advancements in robotics enabling human-robot teams, the TSA could perform its necessary functions ultimately with minimal increases in monetary resources.

Significant challenges exist in integrating robots into existing CBISs, not limited to technical problems. The systems need to be designed with expansion capabilities as demand scales in the future and the addition of capabilities as the complexity of threats evolves quickly. Because the systems provide safety-critical services, their performance and capabilities need to be verified and validated with very close scrutiny. This places significant regulatory and legal hurdles that would need to be cleared for an actual implementation to be successful. We also note that, even though the motivation for this research is based on the airport transportation system in the United States, the proposed system is applicable at many airports worldwide.

2. CURRENT CBIS GUIDELINES

The current TSA planning guidelines and design standards for CBIS[4] outline the 3-tier hierarchical approach that TSA utilizes to screen checked baggage. We discuss the process here for the sake of completeness and provide the context for the robotics application presented in the paper. Figure 1 provides a simplified flow chart modified from the planning guidelines, showing the progression of the bags in the CBIS, and how each level can clear a bag.

The levels correspond to the increasing attention each bag receives during its screening process. The majority of bags passing through the CBIS are cleared at Level 1, where each bag goes through the automated explosives detection system (EDS). If no anomalies are detected by the system at Level 1, the bag is placed on a conveyor out of the CBIS and passed onto the airline baggage handlers.

If any anomalies are detected by the system, then the bag goes through additional checks. If the bag is properly tracked, the bag passes to Level 2 resolution, where a human screener looks at the images from the EDS and decides if the image is clear. If the bag is not properly tracked, it automatically skips Level 2 and goes to Level 3. Any bags with images that are not cleared at Level 2 also pass onto Level 3.

Level 3 consists of explosives trace detection resolution, which is a tedious and labor-intensive task. The process requires swabbing the bag with a special cloth that is then inserted in an explosives trace detection machine that scans for trace signs of the volatile chemicals present in explosives. The process also involves opening the bag to ensure a variety of surfaces are swabbed with the cloth and also to conduct a physical inspection. If the bag is not cleared at Level 3, it is placed in a secure area to await inspection by the necessary law enforcement personnel.

Throughout the entire process, the baggage handling system (BHS) must adhere to set a requirements to guarantee efficient operation of the CBIS. All the main lines must have a minimum throughput of 1800 bags per hour at the correct spacing for the scanning machines to operate properly. TSA has specified that 95% of bags must be cleared within 10 minutes of entering the CBIS and be passed on to the airlines. In addition during the screening process, the bags must be positively identified at all times. Metrics for lost bags and error bags are 0.5% or up to 3%, respectively. Delayed, missing, or added bags must quickly be found and properly reinserted into the system. In addition, the system needs to provide detailed reports to the TSA about specific

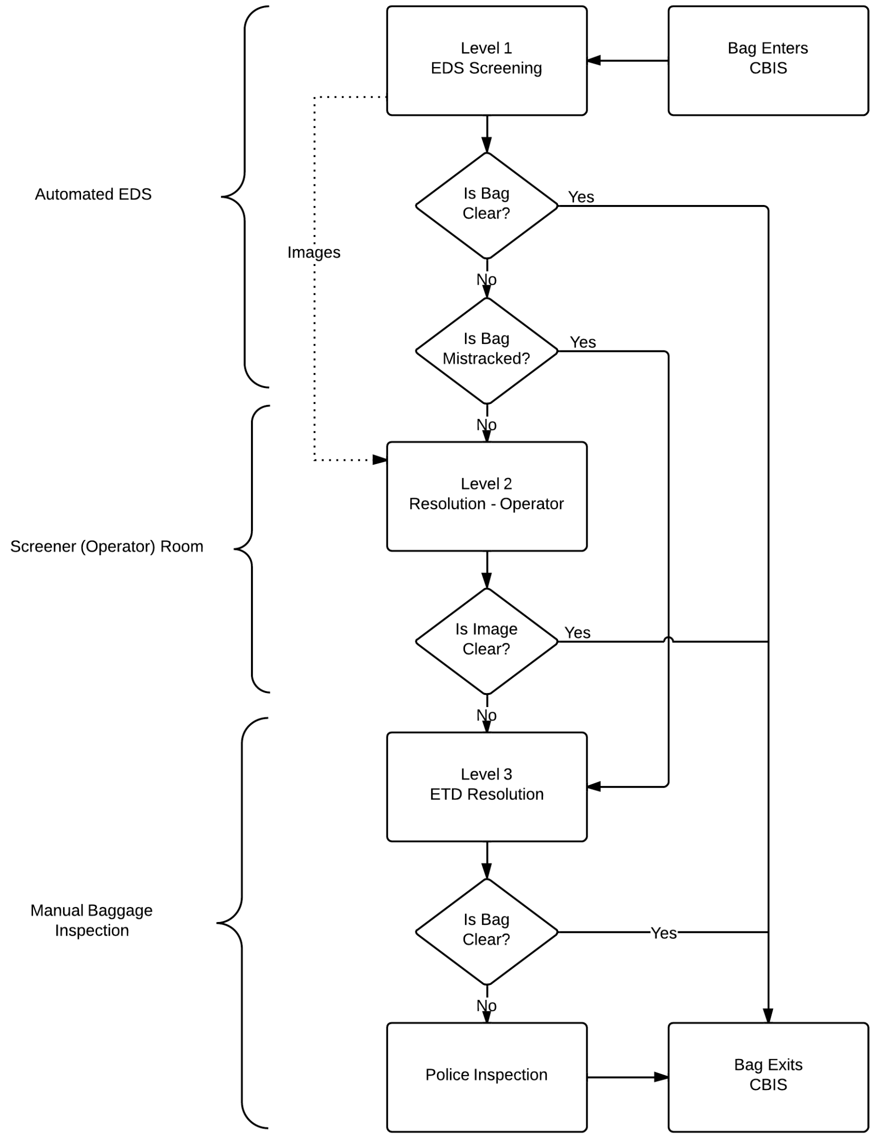


Figure 1. A simplified flow chart, modified from the TSA planning guidelines,[4] showing the hierarchical levels of the CBIS as recommended by TSA. Bags that are cleared at any point through the screening process leave the CBIS. The baggage progresses through the automated explosives detection system (EDS) and if needed, the images are viewed by a screener, and if needed pass through explosives trace detection (ETD) and physical inspection. Finally, if the bag does not clear ETD, the local police inspect the bag.

bag data (tag numbers, timestamps through each level/station, tracking ID, type, EDS machine serial number, Level 1/2 screening status, and total time in system), faults in the baggage handling system, statistics on the EDS machines, and overall system efficiency statistics. These metrics are then used to evaluate the effectiveness both in terms of throughput and security of the whole screening operation at a particular airport.

The complexity of the system required by TSA is significant, but necessary to ensure safety of the civil aviation industry. In addition to meeting all these requirements, manufacturers need to be able to scale their systems to meet the needs to airports and operations of various scales. The TSA splits the systems into four different categories: high-volume in-line systems, medium-volume in-line systems, mini in-line systems, and stand-alone systems. The in-line systems are connected to the airport-wide baggage handling conveyor belts to handle large loads. High volume systems are built to handle the largest loads: more than 1000 bags per hour through the EDS. Medium-volume systems need to be designed with the ability to easily upgrade to high-volume systems in order to accommodate future expansion needs. Similarly, mini systems needs to be able to scale throughput without significant modifications to the equipment. Stand-alone systems need to be designed with software and hardware enhancements available to allow additional bags to be loaded in the machine fast enough. The TSA guidelines make it very clear that the needs for checking baggage are expected not only to grow, but to grow very significantly requiring careful life cycle analysis of the system as a whole.

3. AREAS OF OPPORTUNITY

Because of the complexity and scale of some of the CBISs implemented at airports, there are significant areas of opportunity to improve the screening process in terms of the metrics outlined above and to minimize the associated costs with implementing some of these systems. For example, the Oakland International Airport case-study[4] places the *most* cost-effective option's life cycle cost at $23 million over 20 years and the *least* cost-effective option at $41 million. Even small optimizations in any part of the system will result in dramatic savings for airports the size of Oakland International, and even more savings for the largest US and international airports.

For the purposes of this research, we consider the areas of opportunity that could be augmented with robots, such as the Baxter described in Section 4, to provide a better screening process. An opportunity area is immediately available as the bags enter the CBIS where they have to be split up and sent to the EDS machines. The TSA has very strict performance metrics in terms of how many bags may jam since every jam slows the throughput of the EDS machine. While static deflectors and conveyor belts are used to align bags with the machines, errors still are possible and Baxter could be used to help prevent jams ahead of the EDS machines, and if a jam is detected, the robot could be used to help clear the jam before a backlog occurs.

Further along the system, for bags that are unlabeled or mistracked, they are automatically diverted to Level 3 ETD screening. ETD screening is time-consuming and labor-intensive, so the number of bags sent to ETD need to be kept to the smallest set that indicate anomalies in the EDS machines. An area of opportunity is available to utilize the Baxter robots to make sure that a bag is truly unlabeled or mistracked before being sent to the Level 3 ETD screening. Every bag entering the system is tagged with the traditional label that goes around a handle on the bag, but is additionally tagged with a corresponding small barcode sticker. A Baxter robot could be used to manipulate and scan the bag for these small stickers or remnants of a mangled large label before sending the bag to Level 3. Every bag that can simply be retagged because a sticker or label was mangled saves resources at Level 3.

Since Level 2 screening mostly involves the clearing of bags by an operator based on the images from the EDS, there are few opportunities to utilize robots. On the other hand, Level 3 ETD screening provides many opportunities to utilize robots, especially since Baxter is specifically designed to work in close proximity to humans. In order to do ETD screening, bags need to be opened and physically inspected. The robot can assist in the act of opening the bags for inspection, the actual inspection process, the placement of information cards in the bags, the closing of the bags, and finally the re-entry of the bags into the BHS. Many of these tedious tasks are currently performed by TSA agents, who could be focusing on more important and mentally stimulating tasks. Some of the items the TSA agents are looking for that are not allowed in check bags are: flares, gun powder, blasting caps, dynamite, fireworks, grenades, plastic explosives, replicas of explosives, aerosol, fuels, gas, torches, lighter fluid, lighters, strike-anywhere matches, flammable paint, turpentine, replicas of incendiaries, chlorine, compressed gas cylinders, bleach, spillable batteries, spray paint, and tear gas.[5] These are all items that Baxter could locate given the appropriate object recognition algorithms while inspecting a bag.

Because of Baxter's flexibility in completing tasks and reinforcement learning, a collection of robots in a facility could quickly transition between the identified areas of opportunity to help distribute load within the system. The TSA goes through significant research collecting data to calculate the required metrics so that the system can handle the increases in load such as on major holidays or even variations throughout the day. Providing the TSA with more tools to be able to effectively balance the load, can reduce the amount of overhead that needs to be designed in to the CBISs. In addition, many similar opportunities are present in the inspection and handling of carry-on baggage through TSA security checkpoints. This provides a convenient way to develop technologies that can address both problems at the same time, saving time and costs.

4. BAXTER ROBOT

Baxter, developed by Rethink Robotics, enables humans to intuitively interact with robots in close proximity.

Figure 2. A picture showing Baxter along with the test setup for the case study. Baxter can work in close proximity to humans and utilize an intuitive user interface enabling flexible operations in a variety of scenarios. The robot can be trained and retrained while in the field for performing different tasks.

Because one of Baxter's target markets is production floors, the robot is designed with work on a conveyor line in mind. Baxter is designed to:[6]

- work safely alongside people, without the need for protective cages;
- operate collaboratively through a unique, user-friendly UI;
- be trained manually by line workers, with no programming required; and
- respond adaptively to changes in its environment.

These features and capabilities fit well within possible solutions to achieve the goals set by the TSA for CBISs. The ability to work alongside TSA agents is especially appealing because the cost to integrate Baxter robots in the CBIS will be relatively low. Because Baxter and other robots of similar capabilities and quality are orders of magnitude cheaper than the millions that the ETD machines can cost, they could provide a compelling cost-effective solution for taking over some tasks in baggage screening. If the efficiency gained by the introduction of Baxter robots can eliminate the need for even one extra ETD machine, that can significantly reduce the life cycle cost.

The Baxter research edition robot we utilized to implement the case study has a convenient Robot Operating System (ROS) API allowing us to leverage the existing nodes, like MoveIt for motion planning and collision avoidance. Baxter has two 7-DOF manipulators with two-fingered claw grippers and cameras integrated in the wrists. The wrists incorporate an open-source hardware interface allowing custom end-effectors to be designed. Torque, position, and velocity information is provided from each joint through the API. The joints provide compliance through the use of series-elastic actuators at each joint. This built-in hardware compliance allows Baxter to operate near humans in a safe manner. A URDF model of the torso and manipulators is provided with software SDK allowing for easy integration with the ROS visualization environment, rviz, and the MoveIt library.[7]

5. CASE STUDY

With the identified areas of opportunity in mind and considering Baxter's current capabilities, we decided to focus on implementing a proof of concept system demonstrating the ability to search a bag for prohibited items. By looking at the TSA prohibited items list, one item in particular is relatively common and likely to be left in bags accidentally: the lighter. Lighters pose a risk to aircraft because they are pressurized, and if the fuel disperses as a mist in the cargo hold, due to failure of the pressure vessel, it could cause a serious fire. In addition, due to their generally small physical size, they can be difficult to detect reliably.

The aim of this case study is to create a software framework to demonstrate robotics enabled bag inspection in which the robot performs a task that would reasonably be expected to occur in reality. The case study is a first-step in an attempt to deploy robots in airport security and is by no means exhaustive as to the wide range of threats facing the aviation industry daily. By simplifying the conditions of the case study, we aim to highlight the utility of the software architecture rather than the performance of algorithms with respect to detection metrics. In actual implementations of the system, fault-tolerance, safety, and optimization need to be emphasized.

Figure 2 shows the general setup and assumptions we made while conducting this work. We assume that a bag starts in front of Baxter, open and ready to be inspected. We also assume we have access to a sensor that can provide both image data and depth data. In our case, we utilize the Microsoft Kinect sensor because of its good performance in indoor environments. To simplify the problem, we assume the mistakenly placed lighter is on top of the clothes in bag. This is not a reasonable assumption in a real-world scenario, but extending the implementation with a pick and place algorithm to search through the clothes in the bag is not within the scope of this work. For the case study, Baxter needs to locate the lighter, pick it up, deposit it in a "Prohibited Items" bin, and finally place a placard in the bag indicating to the passenger that their bag has been searched.

6. SOFTWARE ARCHITECTURE

The general structure of the software architecture follows the pipeline for processing the data from the Kinect sensor, shown in Figure 3. We use the point cloud library (PCL) to implement plane segmentation,[8] allowing us to remove the tabletop and other extra surfaces from the image data. We then create a masked image focused on the detection area. The image data is then processed using OpenCV's template matching algorithm[9] which has been trained apriori on synthetically generated distorted images of a lighter. When a lighter is detected, its 3D position with respect to the sensor is calculated. This is translated into robot-centric coordinates through ROS's TF tool.[11] The path controller generates waypoints to the pickup of the lighter and this information is forwarded into the MoveIt tool which handles motion planning using OMPL. Finally, the generated trajectory is sent to Baxter through the API and Baxter picks up the lighter. The same process using MoveIt is then repeated to place the placard in the bag.

MoveIt is a ROS library that can implement the OMPL motion planning library and integrated with ROS visualization tools and ROS message passing structure.[10] Instead of biasing MoveIt to plan a path out of the way of the suitcase, we create a simple waypoint generator that forces MoveIt to do pickups always from above the suitcase, avoiding the issue of pushing it off the table. Figure 4 shows a sample visualization of MoveIt motion planning for both manipulators.

7. RESULTS

Using the test setup shown in Figure 2, we were able to successfully locate and pickup a lighter placed on top of clothes inside a suitcase. Figure 5 shows a series of images as Baxter completes the task of finding and removing

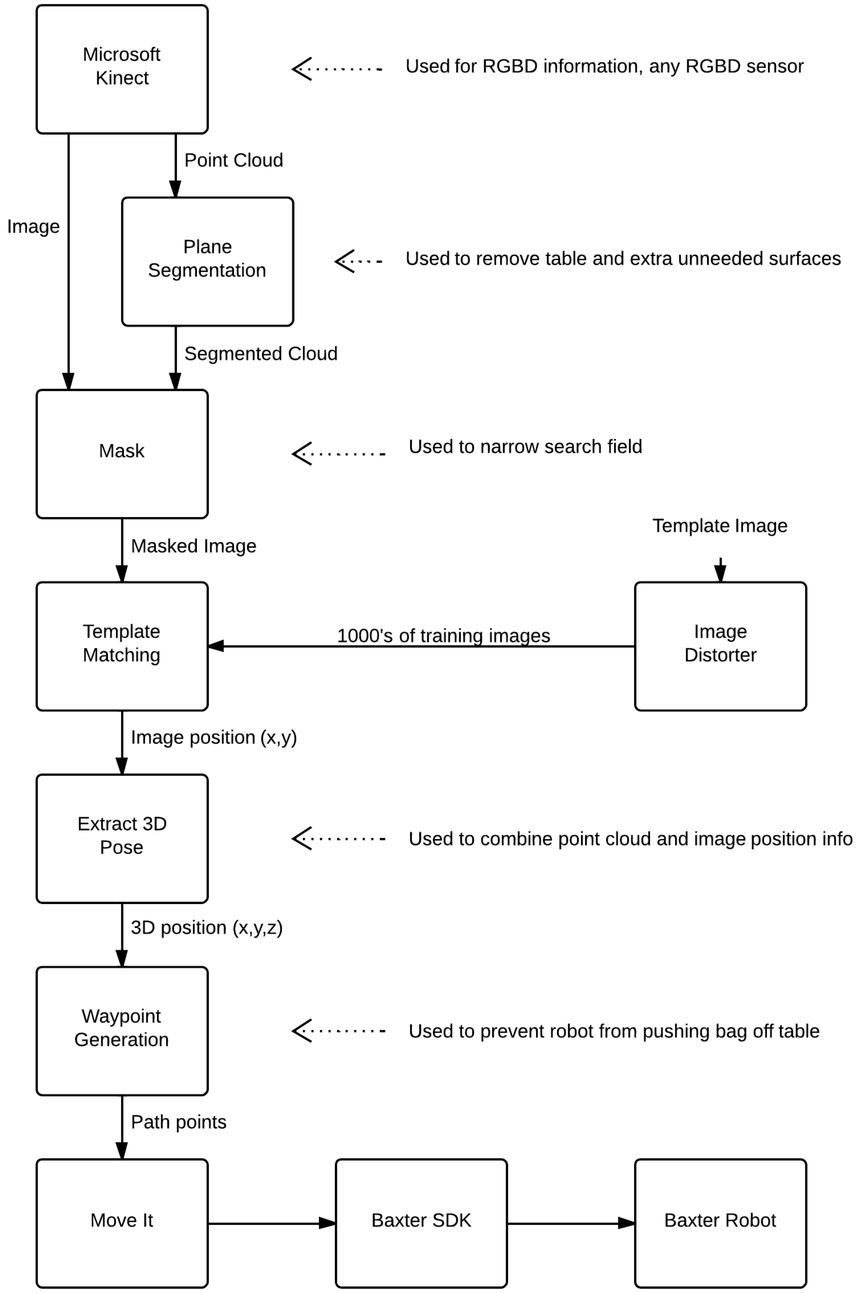


Figure 3. A flow chart showing the pipeline used to process the Kinect RGBD data and detect lighters using template matching. Point cloud library's plane segmentation[8] is used to help create a masked image which is then put into the template matching algorithm.[9] Once the 3D position of the lighter is determined, the waypoint generation and MoveIt[10] generate a trajectory to pick up the lighter without pushing the bag.

the lighter from the bag. The image sequence starts at the top left and ends at the bottom right. Robot first locates the lighter using the template matching, and then calculates the position of the lighter in robot-centric coordinates. MoveIt plans the path to the lighter and picks it up using the two finger gripper. Baxter then deposits the lighter in the designated bin. In the last couple images, Baxter picks up a standard TSA form which tells the owner that their bag was searched and places it in the bag. The entire process takes about 45 seconds

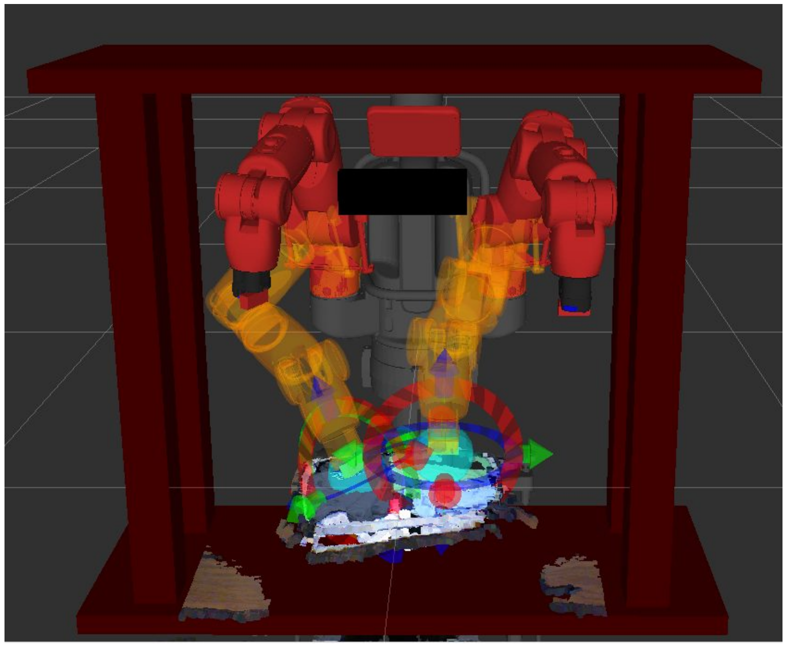


Figure 4. A visualization of the results provided by the MoveIt tool. MoveIt provides motion planning for both manipulators. The red manipulators show the current robot position, and the orange manipulators show the desired final position. In addition, the Kinect RGBD data is overlaid on the model of the scene. The alignment between the data and model indicate a good TF tree in ROS.

on average to complete.

Figure 6 shows the image data provided by the Kinect, and the result of the template matching algorithm. The dark area indicates a good match, and thus the algorithm has successfully found the lighter. We place a rectangular box around the lighter to indicate to the user where it was located. It should be noted that the object detection algorithm used in this study is not dependent on color. Color and shape based detection can be incorporated to enhance the robustness of the system. Other classifiers such as histogram of gradients cascade classifier[12] or part-based detection[13] can also be added in conjunction to the presented template matching for increased performance.

Overall, the effectiveness of the developed software architecture is demonstrated in a proof of concept system showing how Baxter or a similar robot could be used in a security inspection scenario.

8. FUTURE WORK

Multiple directions exist as future work on using robots in airport security situations. The work presented here provides the framework for a system to improve efficiency of Level 3 ETD screening process. If Baxter can be programmed to open luggage, search for prohibited items other than just lighters, and close the bags, the TSA agents will be able to focus on other important aspects of their jobs. It will also make the screening process faster, and more resilient to changes in load conditions. Idling robots do not lose focus and concentration like humans who may not have much to do during off-peak times. If Baxter is upgraded with a mobile base, the robot could also load and unload bags from the conveyor bringing bags to ETD screening.

One area of particular research interest would be to enable Baxter to search for prohibited items that are difficult to detect using x-rays. If Baxter can accurately detect these items, it could potentially be a significant improvement in security. If all baggage can be physically searched instead of just scanned as the majority of baggage is currently checked, the detection rates would likely increase significantly. In addition, concerns of privacy advocates would be at least partially addressed by using robots instead of humans to search the luggage. Enabling Baxter to detect these items though will require a concentrated effort to fuse various sensing capabilities to detect a very wide range of possible threats.

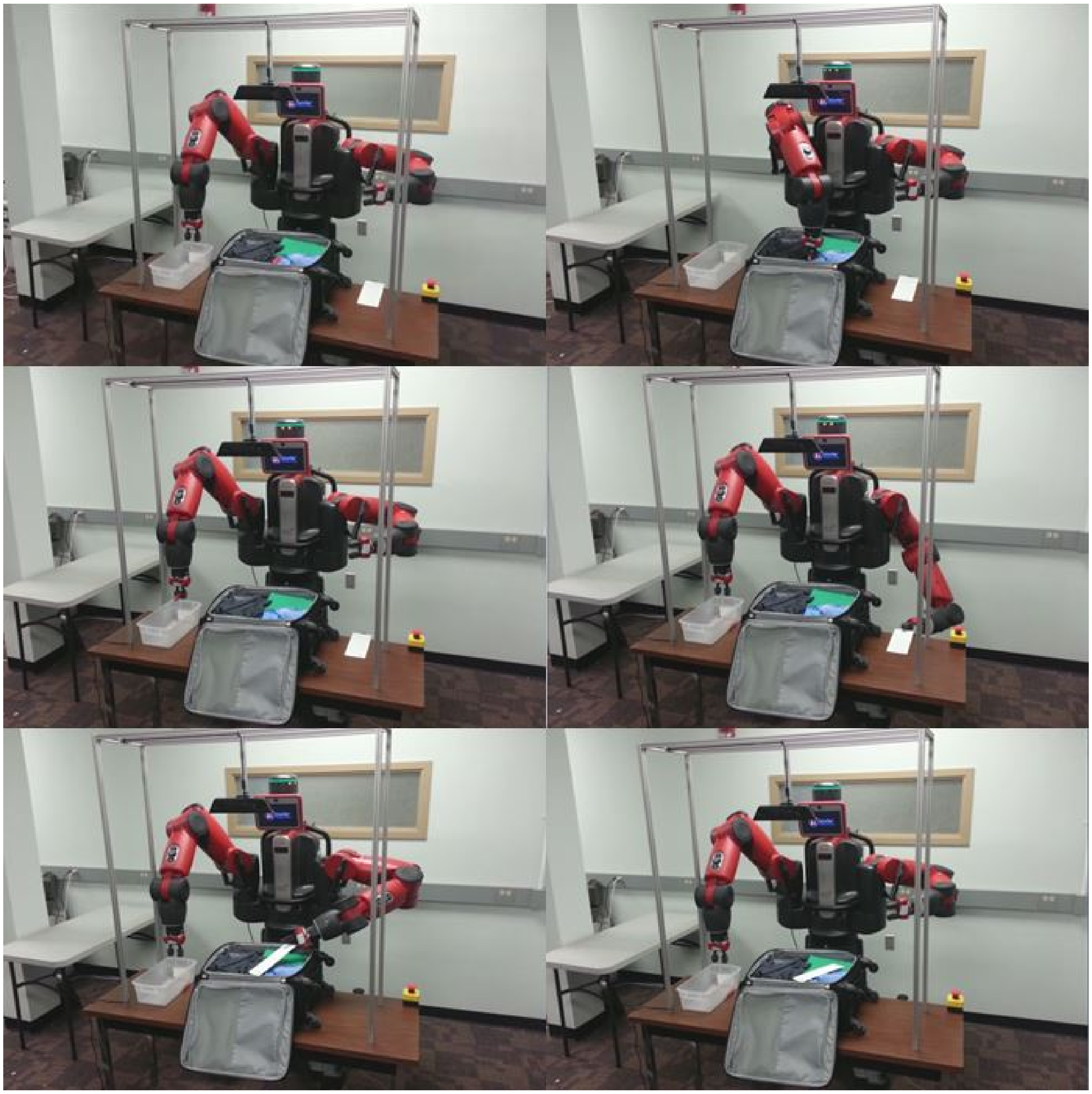
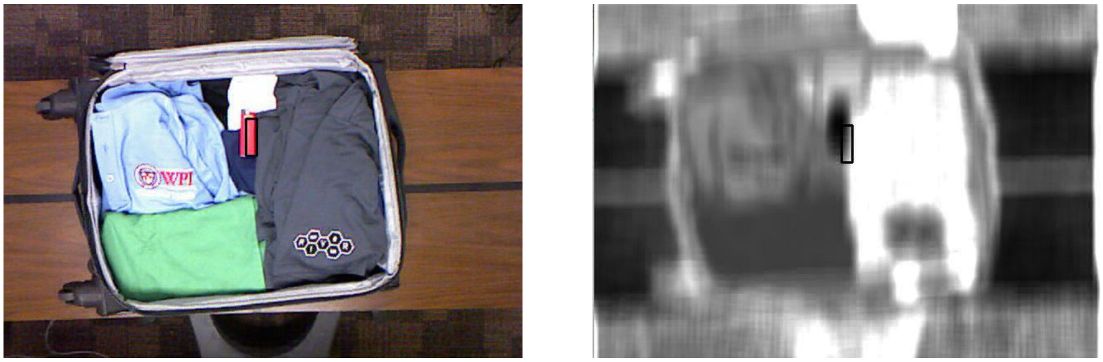


Figure 5. A series of pictures (starting at the top left, ending at the bottom right) showing Baxter locate the lighter in the bag, pick it up, place it in the designated bin, and place the informational. The template matching finds the lighter despite the range of colors, textures, and bends in the fabric of the clothes in the suitcase.

We further identified possible areas of opportunity for Baxter to augment existing systems for aligning bags to help eliminate jams at the entrance of the CBIS. Jams present serious issues and increase costs because airports need to add excess capacity to the system in order to alleviate backlog when a jam occurs. If Baxter can be used to minimize the occurrence of jams, the amount of excess capacity that needs to be added decreases with the decreased risk. Future work could explore the possibility of enabling Baxter to sense misaligned bags and with non-prehensile manipulation align bags on the conveyors.

Another area of possible future work could focus on giving Baxter the ability to search for barcode stickers. In cases where the luggage tag has been torn off or destroyed, Baxter could be programmed to search the bag for the secondary tag. Enabling this solution will reduce the rate of lost bags in the system and reduce the number of bags that have to be manually screened with the ETD machine. Similar to above, this reduces the amount of overhead capacity that needs to be factored into the system, reducing initial costs in addition to overall operating



(a) Raw Kinect Image (b) Template Matching Output

Figure 6. Pictures showing the Kinect image data. 6a shows the raw RGB output of the Kinect sensor. 6b shows the image after the template matching. The dark area indicates a good match indicating lighter has been found. In the image, the algorithm has located the lighter and placed a black box to indicate it has found it.

and maintenance costs.

In this work, we only considered the scenario of using Baxter to screen checked baggage. Potential applications exist at the screening checkpoint for passengers and carry-on baggage as well though. One of the most controversial TSA topics, the pat-down security checks, are regularly the focus of the media because of errors or misjudgments by TSA officers. Because Baxter is designed to operate safely around people, some of the pat down tasks may be delegated to the robot. Travelers may feel more comfortable due to privacy concerns to be patted-down by a robot instead of human TSA officer.

Finally, future work could focus on finding other applications for the security related capabilities of Baxter. There are many other locations though such as shipping ports, high-importance buildings, prisons, and sporting events that require the same security principles but in different contexts.

9. CONCLUSION

We have presented the current state of CBIS implementation and TSA recommendations for new CBIS in airports. We have identified several areas that could be improved using robots similar to Baxter. We also present a case study with a proof of concept system to locate and remove prohibited lighters from checked baggage. Augmenting checked baggage inspection processes with robots seems to be a feasible approach in near future.

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