Designing a Mixed Reality Interface for Autonomous Robot-Based Change Detection

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ABSTRACT

Robots, equipped with powerful modern sensors and perception algorithms, have enormous potential to use what they perceive to provide enhanced situational awareness to their human teammates. One such type of information is changes that the robot detects in the environment that have occurred since a previous observation. A major challenge for sharing this information from the robot to the human is the interface. This includes how to properly aggregate change detection data, present it succinctly for the human to interpret, and allow the human to interact with the detected changes, e.g., to label, discard, or even to task the robot to investigate, for the purposes of enhanced situational awareness and decision making. In this work we address this challenge through the design of an augmented reality interface for aggregating, displaying, and interacting with changes detected by an autonomous robot teammate. We believe the outcomes of this work could have significant applications to Soldiers interacting with any type of high-volume, autonomously-generated information in Multi-Domain Operations.

Keywords: human robot interaction, mixed reality, change detection, autonomy

1. INTRODUCTION

Imagine a squad patrolling a visually complex environment, such as in Fig. 1, searching for signs of recent activity. The squad's robot navigates in advance of the team autonomously, and compares its sensor readings to previous measurements taken by the last team to move through the area. The robot's perception and change detection algorithms are capable of detecting small variations between those measurements that human eyes would normally miss. But interpreting those detected changes is difficult for the robot. A human teammate is much better equipped to reason about the mission context in order to determine which changes are innocuous and which could be informative and useful.

With one or more Soldiers in the squad equipped with augmented reality head-mounted devices (AR-HMDs), the robot can easily stream its detections to a Soldier for interpretation and potential action. An autonomous robot equipped with powerful sensors and perception algorithms will have access to a large amount of raw and processed data, however. Therefore, a significant challenge for this important and valuable robot-human communication is how to determine what information should be shared and how it should be presented to the human Soldier for interpretation and interaction.

In this work, we address this challenge through the design of an augmented reality interface that aggregates change detections taken from a robot operating in the real world and provides a display to a human via an AR-HMD for interpretation and interaction. We present initial results from our change detection aggregation approach and corresponding visualization design. We believe that this is the first work to address the design of a robot-to-human mixed reality interface for communicating change detections from an autonomous mobile robot. The outcomes of this work have potentially broader applications to Soldier interaction with the sort of high-volume information generated by autonomous agents in Multi-Domain Operation (MDO)[1] settings.

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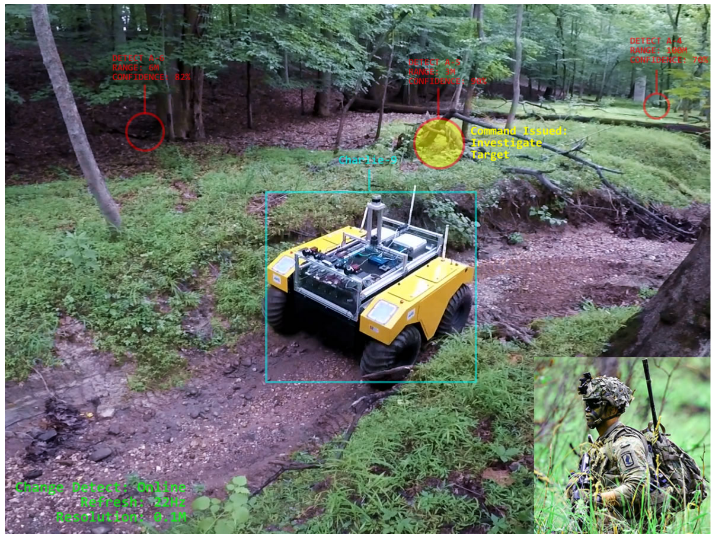


Figure 1: The autonomous robot-based change detection concept. A robot patrols a visually complex environment and conveys information via augmented reality about its position (cyan box) and aggregated change detections (red circles) to a nearby Soldier wearing an AR head-mounted display (inset). The aggregated change detection visualizations support interaction to allow the Soldier to task the robot to further investigate a suspicious change.

2. BACKGROUND AND RELATED WORK

The system presented here builds upon previous works by the authors in enabling robust human-robot teaming using mixed reality.[2,3] Augmented, virtual, and mixed reality technologies have a strong potential to address issues of communication in human-robot interaction.[4] The significant challenge of course is knowing how to share the appropriate information in a positively impactful manner.

Autonomous robot-based change detection has applications in many areas, such as inspection,[5] surveillance,[6,7] safety and security,[8] and robust outdoor navigation.[9] In recent work, communication of novel change detection from an autonomous robot to a human teammate was enabled, and the impact of different resolution point clouds from 16 and 32 bit LiDAR sensors on the change detection communication interface was examined.[10] In general, novelty detection is a research area where differences in *test* data from *training* data or a *model* learned from that data are identified.[11] The type of environmental change detection we employ here is an application of novelty detection where physical changes are continuously identified through comparison of new "test" data with a previously generated model.

In this work we look beyond communication of all changes detected as was done previously,[10] which in large, complex environments with many change points could be visually and cognitively overwhelming. This work addresses that shortcoming through aggregation of change detection data to reduce the volume of visual information and support interaction with groups of individual change detections.

3. APPROACH

Our approach assumes a mobile robotic platform capable of autonomously performing simultaneous localization and mapping (SLAM) which requires continuous perception and construction of an accurate representation of the environment. We then utilize this perceptive capability specifically for the purpose of performing change detection using a point-cloud-type model.

Motivating our approach is the belief that while a robot is better capable of *perceiving* an environmental change, a human teammate will have access to more contextual information that critically will enable the human to better *process and reason* about possible changes in the environment, i.e., what changes are real, and of those what changes are important given the mission context. Further, given a robot equipped with high fidelity sensors operating in the type of complex real-world environments where MDO will occur, we expect there will be a large number of changes for the human to process.

In anticipation of large volumes of potential change information, we therefore incorporate into our approach aggregation of real-world change detection data and visual presentation through an AR-HMD to a human teammate.

3.1 Change Detection

Our change detection approach utilizes a point-cloud-based knowledge representation of the environment. In our implementation, this is generated from a robot using a LiDAR laser scan sensor, but generalizes to other functionally equivalent sensors (RGB-D, structured light, stereo motion, etc.). The representation is generated by our SLAM process discussed previously.[10] Fundamentally, the output of the SLAM process is a point cloud that accurately represents the environment, which is accumulated and optimized as the robot maneuvers through the environment.

Algorithm 1: Change Detection Process

Result: *Change* model of all changes in the environment
while *Making initial scan* **do**
  Navigate the environment;
  Create an *initial* model of the environment.
while *Looking for changes* **do**
  Navigate the same environment;
  Create a *test* model of the environment;
  Compare the *test* against the *initial* model;
  Output the changes between the models as a point cloud for Aggregation and Visualization.

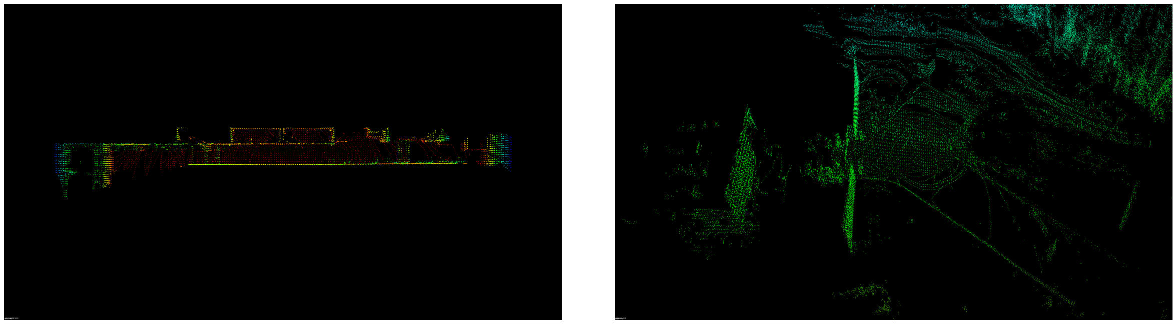
The general process for change detection is shown in Alg. 1 and is composed of two major steps: *Making an initial scan*, which generates the *initial* model point cloud, and *Looking for changes*, where a *test* model cloud is collected and compared against the *initial* model. Example initial models can be seen in Fig. 2. Note that the **Compare** and **Output** steps of change detections in the second while loop (*Looking for changes*) can be performed either online, as the robot is patrolling the environment, or as an offline process after the *test* model is created.

For the **Compare** step, the *initial* and *test* models begin in approximately the same reference frame, and the alignment is refined with a generalized Iterative Closes Point (ICP) process.[12] With fully aligned models, the change detection can then be performed in PCL[13] using a set of difference segmentation functions and outlier filters as described in.[10] In the **Output** step, the changes are accumulated into a new *change* model point cloud which is used as input for the Aggregation and Visualization process. For our experimental purposes, we focused on change additions to the environment, but the general approach is appropriate for both additions and deletions.

3.2 Change Aggregation and Visualization

Once the changes have been detected and outputted, they can be presented to the human for interpretation, as was done previously.[10] However, even in the test environments we chose there were hundreds to thousands of point changes, so that even if they are collectively interpretable, they are not individually actionable. Therefore, in this work we propose aggregating changes and presenting information about those aggregations to the human teammate via mixed reality. The human teammate can then more easily interpret, as well as interact with, the changes.

To aggregate changes we utilize Density-Based Spatial Clustering of Applications with Noise (DBSCAN).[14] DBSCAN has several properties that are advantageous for our application, including not requiring a pre-specified



(a) Alley environment, side view (b) Driveway environment, top-down view

Figure 2: Example initial model point clouds

number of clusters, ability to find arbitrarily-shaped clusters, incorporation of noise, and robustness to outliers. For our application of DBSCAN we used $\epsilon = 1.0$, $min\_samples = 5$, and the *euclidean* distance metric.

The change aggregation and visualization process is shown in Alg. 2. The raw *change* model from Alg. 1 is used as input. When a *change* model is received, we **Cluster** the changes using DBSCAN and convert each cluster to **Create** a visualization and interaction object. The final step is to **Publish** each object from the robot to the AR-HMD worn by the human.

When designing the visualizations for the aggregated changes, we noted that despite the relatively high density of the point clouds generated by the LiDAR, finding a distinct edge of a change is difficult. Therefore, we design our change locations as spherical regions, similar to the concept image Fig. 1. We also label each with a unique text identifier to facilitate voice commands (not covered in this paper). Finally, to aid in visual differentiation and to convey the size of each cluster, we scale the radius of the visualization relative to the radius of the clustered change detection.

Algorithm 2: Change Aggregation and Visualization Process

Result: Change detection visualizations $\{(x, y, z), radius\}$ based on clustered point changes

while *Looking for changes* **do**
    if *Received change model* **then**
        Cluster changes using DBSCAN;
        for *each cluster* **do**
            Create a data visualization and interaction object based on cluster location and radius;
            Publish the visualization via the robot-AR-HMD interface.

4. EXPERIMENTS

We validate our approach using data collected from a robot operating in two real-world environments performing change detection.

4.1 Hardware

The hardware used in these experiments is shown in Fig. 3. In particular, for the robotic platform we used one Clearpath Robotics Jackal mobile ground robot (Fig. 3a). The Jackal measures $0.508 \times 0.430 \times 0.250$ m and has a maximum linear velocity of 2.0 m/s. Ours is equipped with an Intel Core i5-4570TE CPU and used Ubuntu 16.04 and the Robot Operating System (ROS)[15] for its operating system and middleware, a Velodyne VLP-16 LiDAR for creating the point-cloud models, a MicroStrain 3DM-GX4-25 inertial measurement unit (IMU) for improved

(a) Clearpath Robotics Jackal robot and sensors (b) Microsoft Hololens AR-HMD

Figure 3: Experimental Hardware

mapping and state estimation performance, and a Ubiquiti Bullet M5HP 5GHz WiFi radio for communications. For the AR-HMD, we used a Microsoft HoloLens shown in Fig. 3b.

4.2 Environments

The two environments used in these experiments, referred to as the "alley" and "driveway" environments are shown in Figs. 4a and 4b, respectively. The alley environment is purpose-constructed to emulate a narrow alleyway in an urban setting, complete with multi-story buildings and doorways. The driveway environment is an approximately 7m-wide paved lane with an adjacent paved parking area for three vehicles, surrounded by grass and trees. Example 3D point clouds for the *initial* models of each are shown in Fig. 2.

4.3 Experimental Procedure

For these experiments, the robot first collected data and built an *initial* model of the environment, similar to Fig. 2. Then, the environment was changed through the deliberate addition of objects. After the change, the robot re-visited the environment and performed the change detection steps detailed in Sec. 3.1. The resulting *change* model was then used to perform the aggregation and visualization process from Sec. 3.2. For this work, this process was performed offline using the complete *change* model because of restrictions limiting in-person

(a) Alley environment (b) Driveway environment

Figure 4: Experimental Environments

experimentation due to COVID-19. As noted in Sec. 3, our method is designed to work interchangeably for both online and offline processing.

5. RESULTS AND DISCUSSION

Using the *change* model, our results show that we are able to successfully process the model, aggregate changes using the clustering method selected, and visualize the changes. Fig. 5 shows the overall outcomes. In Figs. 5a and 5b, we see the objects introduced to the empty environments from Fig. 4.

In Figs. 5c and 5d, we see the result of the aggregation process where individual changes are clustered, with the gray sphere indicating the cluster centroid. For these results we identify both true and false positive detections; of course in a real application this information would not be known to the robot. Because few change points fell upon the soccer ball in Fig. 5a, these points were discarded and therefore no change cluster is found for that object in Fig. 5c. Of significant note is there are many more false positive detections in the outdoor environment, most likely due to small changes from wind moving leaves, grass, and trees between the *initial* and *test* models.

In Figs. 5e and 5f, we see the results of our aggregated change visualization design. Each change cluster is localized, given a unique text label, and the radius of the visualization marker is scaled to match the radius of the cluster. These text and symbolic visualizations will facilitate interaction by speech and gesture (e.g., virtual "clicking" on a marker in mixed reality) in future work.

6. CONCLUSION

In future applications of MDO, human Soldiers and autonomous robotic platforms will be teamed together and operate in complex environments. One significant application for team operation is detection of changes, where the robot uses its sensing and perception capabilities to detect changes, and must convey those detections to its human teammates. One significant challenge for this vision to be realized is how the robot should distill, aggregate, and present those changes to the human for successful interpretation. Previous work[10] presented a system where a robot autonomously navigates and environment, performs change detection, and presents that information to the human; however, it did not address this important challenge. In this work, we have presented an approach to address this challenge, and demonstrated its capabilities by incorporating our expanded approach into a complete human-robot change detection system.

Future work will include experimentation with human participants to validate the data aggregation and visualization design decisions. Further, incorporation of methods robust to noisy environments, both from a robot intelligence and interface design perspective, will be explored. We believe that this work has significant potential implications for useful and practical human-autonomy teaming in real-world MDO environments.

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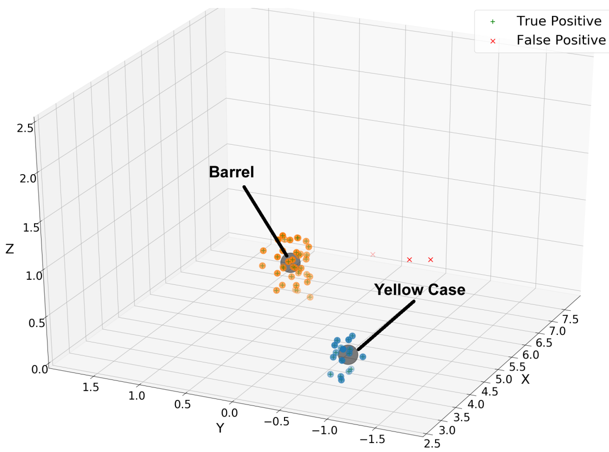
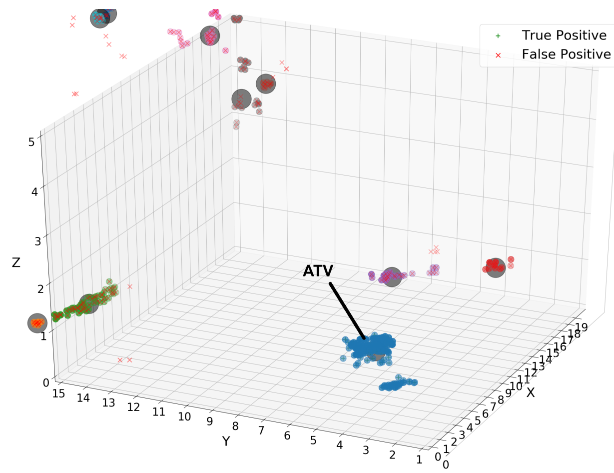
(a) Changes introduced to the alley (circled)

(b) Changes introduced to the driveway (circled)



(c) Plot of clustered change detections in alley. Gray sphere indicates centroid. Note that change detections for soccer ball were few and were discarded as outliers.



(d) Plot of clustered change detections in driveway. Gray sphere indicates centroid. Note that in this outdoor environment, there were many false positive detections.

(e) Visualization output of aggregated and scaled changes for alley.

(f) Visualization output of aggregated and scaled changes for driveway.

Figure 5: Change detection aggregation and visualization.