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Title: Robots Against Infectious Diseases: A Technologically Grounded, Human-Centered Exploration

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Robots have the potential to protect health care workers, provide patient care, and ultimately save lives in infectious disease outbreaks. Nevertheless, infectious disease outbreak scenarios present unique technological and social challenges for robotics. This work explores what robots *can* and *should* do in the fight against infectious diseases. We present two major contributions, each of which is a starting point for answering these larger questions about robots and infectious disease outbreaks.

First, a real-time contamination tracking and modeling system for robotic health care support is demonstrated and evaluated. The system models contamination of the environment and people, directs decontamination efforts of a simulated scrubber robot, and alerts users when nearing contaminated areas. The transmission model design choices are discussed, as based on Ebola virus disease,

and the system is evaluated against the spread of a physical substance. This system, the first of its kind, would allow medical teams to take appropriate actions to carefully enter, avoid, or decontaminate contaminated areas, reducing infection risk for themselves and their patients.

Second, three hypotheses relating to patients' comfort and trust of a proposed teleoperated robotic solution are tested. Human participants lay in a simulated Ebola treatment unit while a human-sized robot performed tasks in the space. The patient's visibility of the operator was altered based on two conditions, full visibility and no visibility. Our findings suggest patients trust the robot teleoperator more when they can see the teleoperator. This yields guidance for how to design future robotic treatment units and raises questions for envisioned telepresence medical systems.

Robots Against Infectious Diseases: A Technologically Grounded, Human-Centered Exploration

by

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Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Kory Kraft, Author

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This work exists due to the efforts of many. I am grateful for the help and suport of my advisor Dr. William D. Smart, everyone in the Personal Robotics Group, the faculty and staff of Oregon State University's Robotics program, those at Corvallis Christ Central Presbyterian, my family, and especially, my wife. Much of the thesis comes from two previously submitted conference papers. The specific contributions of those involved are outlined in Appendix A.

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This manuscript is dedicated to the brave and determined health care workers that died in the midst of caring for those with the Ebola virus disease.

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Chapter 1: Introduction

The 2014 - 2016 Ebola virus disease (EVD) outbreak was unprecedented in its scale and impact. More than ten thousand died in the West African outbreak [1]. The epidemic ravaged three countries for over a year and sent fear throughout the world. Governments and organizations spent tremendous time, money, and effort treating and containing the disease [2]. Health care workers on the ground, both locals and foreigners, spearheaded the fight at the risk of their own lives.

Due to a variety of factors, health care workers fighting the disease on the front lines faced disproportionately higher infection rates than the general public. By May 2015, the infection rates for health care workers compared to the general population in Guinea, Liberia, and Sierra Leone were 1.45% to 0.02%, 8.07% to 0.11%, and 6.85% to 0.06% respectively [3]. The high mortality rate and virulence of EVD make it a risky disease for health care workers to treat, even in well-resourced settings. West Africa's limited medical infrastructure, demanding climate, and diverse cultures only intensified the challenge and risk [4, 5].

The recent EVD outbreak reminds us of the dangers infectious diseases continue to present, both to the world at large, and health care workers in particular. EVD, while a severe and serious disease, is not unique in the disporportionate danger posed to health care workers. Providing medical care to people with highly infectious diseases exposes health care workers to a heightened risk for developing

an infection themselves, requiring them to take sometimes burdensome precautions like wearing person protective equipment in hot and humid climates [4, 6].

Robotic health care systems designed for infectious disease outbreaks could lighten this burden while still ensuring quality patient care. The current toolbox for fighting infectious disease outbreaks is a big one; it includes high-tech and low-tech solutions, grass-roots and top-down approaches, individual as well as community-wide responses. Vaccine development, strategic social advertising campaigns, and complex macro-level disease modeling are all examples of tools included. Robotics, though, is largely missing.

This is somewhat surprising considering the benefits robots are poised to offer. Robots cannot catch infectious diseases, will not contribute to medically-resistant disease strains, and can be general tools for a variety of diseases. Robots then are positioned to be powerful tools in future infectious disease responses, just as they are lauded to be in other domains. Despite the potential foreseeable benefits, there remain enormous and complex technical, cultural, and social-psychological challenges to deploy robots in infectious disease outbreaks.

This work showcases potential benefits while exploring and overcoming some of the difficulties. The meta questions of the work closely align with those originally posed by the White House Office for Science and Technology Policy in response to the EVD outbreak [7, 8]. Namely, what *can* robots do in the fight against infectious diseases, both in the short- and long-term? To this I include the socially and culturally sensitive question - what *should* robots do in the fight against infectious diseases?

I present two central pieces, Chapters 3 and 4, which begin to address these admittedly broad questions. Chapter 3 underlines the increasing technological feasibility of what robots *can* do in infectious disease outbreaks. In Chapter 3, I describe and evaluate a real-time contamination modeling and tracking system for robotic health care support. The smart treatment unit models contamination and relays this information to decontamination robots. The treatment unit also warns people when they near a contaminated area. The system is the first end-to-end contamination modeling and tracking system for robotic health care support.

Chapter 4 explores the question of what robots *should* do, from the patient's perspective. In Chapter 4, I focus on the human side of the problem to explore the dynamics between patients, robots, and operators in a teleoperated robot context. This chapter examines patients' levels of comfort and trust in such a setting. The results from the study presented therein suggest that it is better to have a robot's operator in the patient's line of sight. This informs how treatment units utilizing robots should be designed to cultivate patients' trust.

Taken together, these two pieces show that robots can be beneficial in infectious disease outbreaks, that proposed robotic solutions need to at least acknowlege people's understanding, fear, or misgivings, and that this new subdomain of robotics should be further funded and explored. These points will be further argued in Chapter 5, which concludes the work. Before going any further though, Chapter 2 gives background and related work relevant to both pieces.

Chapter 2: Background and Related Work

2.1 Ebola Virus and Infectious Diseases

2.1.1 Overview

EVD was first identified in 1976 [4]. Its characteristic filamentous particles make it a filovirus and, along with Marburg, is in the family Filoviridae [9]. It is endemic in regions of central Africa [9]. There are five Ebola virus species. The recent outbreak was caused by the Zaire strain [10]. Early symptoms include high fever and body aches. This can then lead to severe vomiting, diarrhea, and nasusea. Haemorrhagic symptoms, which vary in their severity, occurs at the peak of the illness in 50-70% of patients [11]. The World Health Organization reports an incubation period for the virus between 2-21 days. During this time, humans are asymptomatic [12].

2.1.2 Impacts

EVD is highly infectious and can be highly virulent (with mortality ranging from 20-90%)[13, 14]. EVD, while serious, is not unique in its impacts; infectious disease outbreaks can take lives, disrupt economies, and set back an entire region's development[15, 16, 2].

The recent EVD outbreak is a good example of the potential destruction caused by infectious disease. The outbreak, declared in March 2014, took over eleven thousand lives out of an estimated twenty-eight thousand cases [1]. These outbreak occured primarily in Guinea, Liberia, and Sierra Leone, countries already beset by medical fragility [3]. Despite ample fear and political pressure it still took a year to begin extensive human trials of a promising EVD vaccine [17, 18]. The long-term complications for EVD survivors is being closely studied. Current findings suggest suvivors are at increased risk for hearing loss, neurological abnormalities, occular deficits, sleep disturbance, and other complications [19].

2.1.3 Transmission

Humans and apes are end hosts for EVD [9]. Human-to-human transmission of EVD is through direct contact of an infected person's body fluids through broken skin or mucous membranes [20]. Humans are not contagious until they are symptomatic [12]. One study suggests that the virus can be spread sexually from EVD survivors months after recovery [21]. The medical community is still uncovering the natural reservoirs of EVD [20]. Nevertheless, one has to be in close proximity (<1m) to a disease vector in order to contract the disease under most ordinary circumstances [12].

The disease transmission model developed for our system, discussed in Section 3.3.3, is an appropriate fit for this type of close-proximity, non-airborne disease transmission.

2.2 Medical and Health Care Robotics

Robots are used in the medical and health care field in a variety of ways. For example, there are commercial robots that transport and deliver goods in hospitals[22], peform surgery [23], calm and comfort patients [24], and connect physicians to remote patients [25]. Okamura et al. broadly segment the medical robotics field into these areas: surgical and interventional robotics, robotic replacement of diminished/lost function, robot-assisted recovery and rehabilitation, behavioral therapy, personalized care for special-needs populations, and wellness/health promotion [26]. This partitioning, while helpful in its specificity, misses a large part of what happens in many hospitals and doctors' offices: general medical diagnosis and treatment involving complex patient-doctor interactions. They also miss the behind-the-scenes organizational and logistical work needed for stable medical infrastructures.

An ultraviolet disinfection robot is used by some hospitals to prevent hospital acquired infections. The robot is placed into a room by an operator, set-up via a touch screen, and then irradiates the room while stationary [27]. However, the robot can only decontaminate a space that does not have humans present.

The mobile robots described above would benefit from knowing whether they are in, or nearing, a contaminated area. This information would allow them to be properly decontaminated before entering a contamination-free zone rather than spreading the contamination around.

Surprisingly there has been little intersection of the medical robotics literature

with the disaster robotics literature, aside from looking at how to use robots to provide limited remote care to patients in disaster search and rescue scenarios [28]. This leads us to believe that the specific benefits and challenges of deploying robots in situations of infectious disease outbreaks has been overlooked.

Chapter 3: Contamination Modeling and Tracking

This chapter is from under-review work [29] submitted to The International Conference On Intelligent Robots and Systems (IROS), 2016. My specific contributions, as well as those of others, are outlined inSection A.1.

3.1 Introduction

Health care workers are not the only ones at risk in outbreaks. In any health care setting patients are at an increased risk of acquired infections. These can turn routine visits and surgeries into life-threatening situations.

Robots and automation can perform meaningful tasks in these biohazardous areas, protecting both health care providers and patients. However, robots need actionable information to perform such tasks intelligently. In particular, awareness of the location of contamination would allow them to deliberately avoid these spaces or target them for decontamination. We develop and evaluate an end-to-end system for modeling contamination in health care facilities and provide two demonstrations for how this real-time information can be used to further protect health care workers: a simulated floor cleaning robot that selectively targets contaminated areas and a warning system for nearing health care workers.

Our principal contributions lie in the novelty of the system, the person tracking

mechanism, and the evaluation methodology. While the system was designed with the transmission of Ebola in mind, it also has relevance to similarly transmitted infectious diseases.

3.2 Background and Related Work

This section gives background pertaining disease modeling and tracking. We also note the non-existence of systems for real-time infectious disease contamination tracking for robots and health care worker support.

3.2.1 Disease Modeling and Tracking

Disease spread can be modelled at various scales. Epidemiological modeling is concerned with the macro scale as it attempts to model disease levels in populations [30]. These models allow organizations to predict future outbreak areas and make strategic high-level responses [31]. They do not, however, provide relevant information for the immediate needs of health care workers or robots in health care spaces.

At the other end of the spectrum, microbiological predictive models attempt to model the the growth of a culture of bacteria or spread of a virus through an organism [32]. These aid in understanding the transmission of a disease, but again do not yield immediate, actionable information for robots or workers in health care spaces.

Air sampling systems are used in operating rooms and health care filtration systems to monitor air quality and evaluate microbial contamination. These systems cannot identify diseases in real-time and are only capable of detecting airborne diseases [33]. Some work has been done using computational fluid dynamics to model the aerosol contamination of surfaces in a hospital room [34]. The work was performed in simulation and made no attempt to develop an end-to-end real-time contamination modeling system.

Our system addresses the gap between micro- and macro-scale disease modeling. Furthermore, we demonstrate the uses of such a system utilizing a physical environment with a real robot.

3.3 System Overview

Our contamination modeling system is composed of four main subsystems seen in Figure 3.1 and described in detail below. The system is built on top of the Robot Operating System (ROS) using the publish-subscribe communication paradigm [35]. The hardware costs less than USD $1,000 per room, making it an affordable option for resource-constrained deployments. The system currently relies on a pre-specified occupancy map of the environment. The initial location of contamination is also needed (e.g. area of a patient's cot).

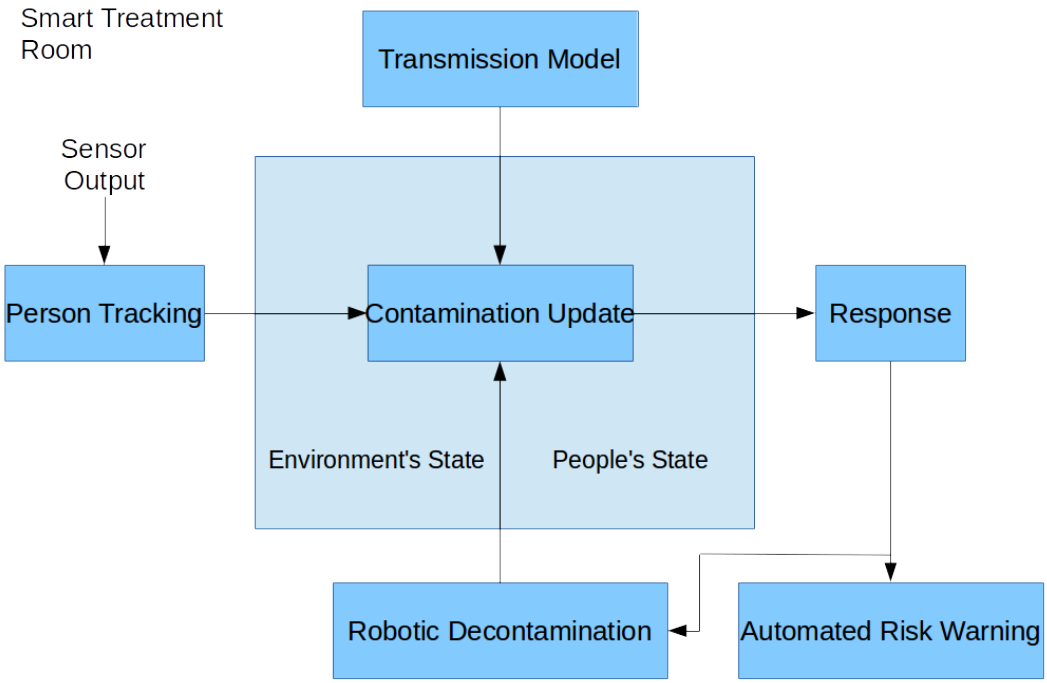

Figure 3.1: Contamination modeling system diagram.

3.3.1 Smart Environment

A smart, sensored environment is the container for the contamination modeling system as shown in Figure 3.1. The environment must have sensors capable of tracking the location of people and/or objects. External tracking frees up workers from having to individually sensor each movable object in the environment. This freedom is particularly important in resource-constrained environments where shipments may run late and time is limited.

The specific environment used in our system resembles an Ebola treatment unit built according to information found from *Médicins Sans Frontièrs* [36]. It is a scaled-down version of a high risk zone within a larger Ebola treatment center. It is approximately 4m x 5m x 2.5m and is covered in anti-static, fire retardant, white plastic with a cement floor. The space contains two single cots and various medical supplies. The treatment unit serves as both a primary subsystem within the contamination modeling system and a testbed for system validation.

The treatment unit is equipped with a wall-mounted SICK LMS 291 rangefinding laser. The laser is mounted 1.5m from the ground on a wall of the room. Three web cameras (2 of which are ultra wide angle) are mounted on the ceiling. The laser and web cameras are running ROS wrapped drivers and tethered to a desktop [37, 38].

3.3.2 Person Tracking

Person tracking is a necessary component in the contamination modeling system because real-time disease contamination sensors do not exist. To overcome this, person tracking along with *a priori* contamination regions are used as a proxy for a contamination sensor. The sensor information comes from the smart treatment room as seen in Figure 3.1.

Person tracking is done using a wall-mounted laser rangefinder and custom ROS nodes. The laser is mounted at chest height and has full visibility of the room. Before use, we capture a number of scans of the empty treatment unit, to determine where the static objects are. Since the laser is mounted at chest height, there are no (significant) objects other than the walls.

To determine the position of people in the Ebola treatment unit, we first filter the data from the laser rangefinder to remove the static obstacles. The remaining contact points are then spatially clustered with the DBSCAN algorithm [39]. We then fit an ellipse to each cluster, on the assumption that humans are approximately elliptical at chest height.

To fit the ellipse, we follow the approach of Fitzgibbon, Pilu, and Fisher [40], where the parameters to the implicit form of the general conic equation

$$ax^2 + bxy + cy^2 + dx + ey + f = 0 \tag{3.1}$$

are estimated, subject to the constraint

$$4ac - b^2 = 1. \tag{3.2}$$

The constraint ensures that the resulting parameters specify an ellipse, and not some other conic section. Once the parameters are estimated, the major and minor axes of the ellipse are calculated, and checked to ensure that their size is appropriate for a human.

Since we assume that there will be few people standing in the treatment unit, we do not explicitly track the ellipses over time with a filter. Instead, we simply associate ellipses that are close to each other in space and orientation, from the angle of the major axis, in subsequent detections. This has proven to be robust in our experiments. A ROS node publishes the position of the detected ellipses, along with a unique numerical identifier for each one.

3.3.3 Transmission Models

Different diseases have different transmission methods which impact how each propagates through an environment. The perfect transmission model would have its predicted contamination location set be equivalent to the real contamination location set. If this goal proved to be intractable, then it would be better, in a medical context, to tend to overestimate rather than underestimate contamination. That is, false positives are better in this case than false negatives.

All transmission models must account for the fact that contamination can be spread from people to the environment and from the environment to people. Figure 3.1 highlights how the transmission model is a distinct component in our system. Our system allows for the input of different transmission models and is thus adaptable to use for a variety of diseases.

Our system is currently targeted for the Ebola virus disease. We created a binary transmission model, a relatively simple 2D transmission model, to approximate the true, complex transmission of Ebola. The binary transmission model assumes people or an environment's grid cell are either fully contaminated or not contaminated at all. If one part of a person is contaminated, the whole person is considered contaminated. An distance threshold, α, controls the how close objects have to be spread or catch contamination. A person "spreads" contamination to every nearby grid cell less than a distance of α away from the center of the ellipse. Similarly, the environment "spreads" contamination to every person less than a distance of α away.

The binary nature of the model fits Ebola well since the disease is highly virulent. Since the disease transmission requires close contact, an α distance of 1.5m is a good conservative estimate for transmission distance.

3.3.4 Contamination Update

Figure 3.1 shows how the contamination update is dependent upon the current transmission model in use, the current contamination states of the environment

and people, the location of people, and decontamination efforts. The two-way propagation of environment-to-person contamination requires that the contamination update occur simultaneously for the environment and people. Thus, the contamination update block must have access to the master copy of the contamination state of the environment and people. In our system, the contamination update occurs during a callback method for each person's location update. The contamination update must handle spreading and removing contamination.

In our system, environment contamination levels are stored in a 2D occupancy grid native to the navigation stack in ROS [41]. This data structure allows for easy integration when directing decontamination robots, as cost-maps utilize the same data structure. Similarly, built-in display types in Robot Visualization (RVIZ) provide real-time visual updates of current contamination levels to personnel.

3.3.5 Intelligent Response

The purpose of the system is to protect lives by providing actionable information to robots and people. Below are two use-cases to this end.

3.3.5.1 Optimized Decontamination Robots

We implemented and deployed a scrubbing robot protocol on a real TurtleBot 2 in our Ebola treatment unit[42]. The bleach-scrubbing protocol path plans the robot to the nearest contaminated locations based on the model. The robot continuously

cleans a given radius of the location where it is located. The cleaning radius of the robot was modelled as a circular region proportional to the diameter of the robot's base.

Future methods could take into account the current contamination levels of the environment, available robotic resources, and space priorities to perform more sophisticated path-planning.

3.3.5.2 Automated Warning System

A personnel monitoring node tracks the locations of personnel over time. If the system detects personnel nearing high-level contamination regions, they are audibly alerted from speakers in the treatment unit. This allows health care personnel to take extra precautions when entering these areas and allows them to relax when they are not in this areas. This could be extended to other forms of alert via vibrating wristbands, smart phone alerts, etc.

3.3.6 User Interface

A view of the RVIZ-based graphical user-interface (GUI) for the contamination modeling system is shown in Figure 3.2 [43]. The GUI displays the 2D contamination grid overlaid on the environment map and represents the people as labeled cylinders. GUI mouse tools allow users to demarcate regions as contaminated or contamination-free. ROS Camera Views show the contamination over the web

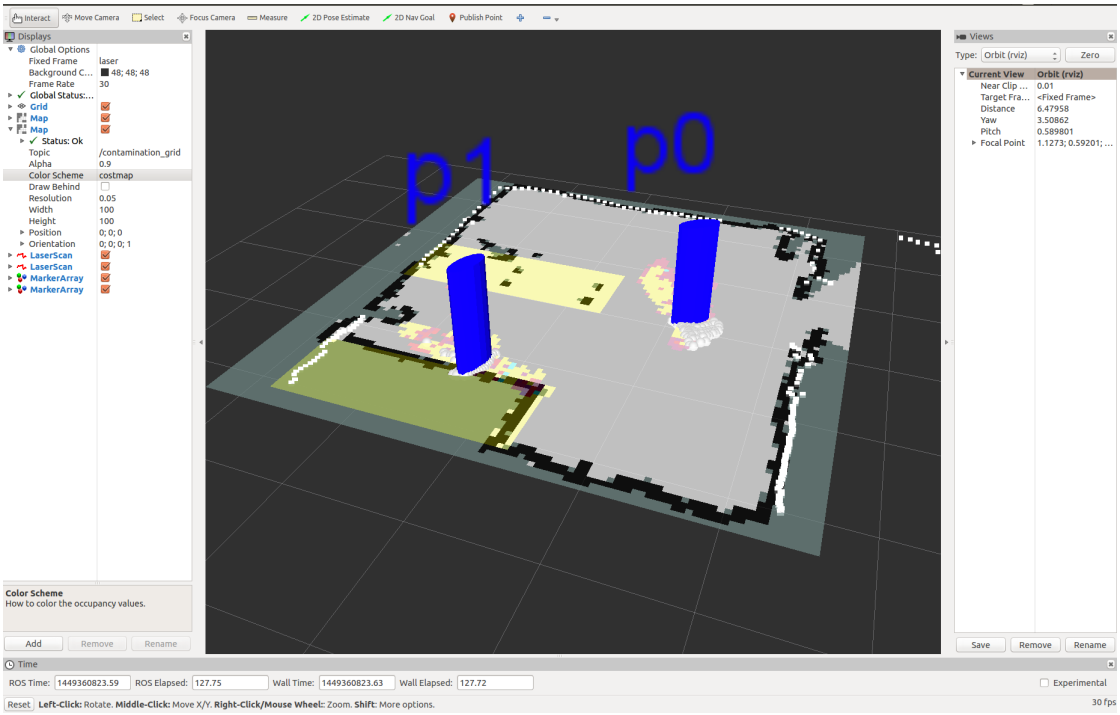

Figure 3.2: RVIZ gaphical user interface of the contamination modeling system. Two people have been tracked and are represented by the blue cylinders.

camera images in real time. The GUI can be used by environment managers to visually monitor spaces, manually direct decontamination robots, and track contamination history over space and time for internal review.

3.4 Experimental Validation

3.4.1 Methodology

It is important to verify that the system accurately predicts what happens in the real world. Ideally, we would test our system against another real-time sensor or model for our chosen scale and transmission modality. Since no such things exist, we instead show that the system provides an accurate superset of a physically tracked substance, *post hoc*. This validates that the system does not include false negatives (i.e. truly contaminated locations that are not marked as such by the system). This is important in a medical environment as it is better to overestimate, rather than underestimate, contamination.

To do this, we used an analog for contaminated bodily fluids, performed tasks in the space, and then compared *post hoc* image results of the location of the bodily fluids with the final contamination map of the system.

The bodily fluid analog was a mixture of corn syrup and green fluorescent powder. This liquid was then spread about the room in different configurations and densities. These known locations were tagged as contaminated areas by a manager using the GUI tools. Participants then went into the room and performed various

tasks for two minutes, such as removing a bucket and checking the simulated patient's temperature. During this time, the contamination modeling system was running, tracking their locations and modeling the contamination spread.

The contamination map was saved once the participants finished with their tasks and left the room. Next, the lights were turned off and a centrally located black light was turned on. Still images were captured from each of the three web cameras in the treatment unit to record the final spread of the fluids. See Figure 3.3 for pre- and post-trial views of the contamination spread in the room.

The images were blurred, thresholded, and masked to provide only the pixels with green in them. Using the transformation matrix obtained from the cameras to the treatment unit map, and with the pinhole camera model from ROS image geometry, each of these green-contamination pixels was transformed to a location in the world [44]. These physical contamination regions can then be overlaid onto the treatment map. This allows for a comparison to the system-predicted contamination regions.

3.4.2 Results

Figure 3.4 is an example screenshot from one of the evaluation trials. An RVIZ Camera View (on the left) is displayed alongside a high level map view (on the right). In this particular instance, a person is walking to the other side of the room after stepping in contamination fluid next to the patient's bedside. The dark grey in both images is the predicted contamintion.

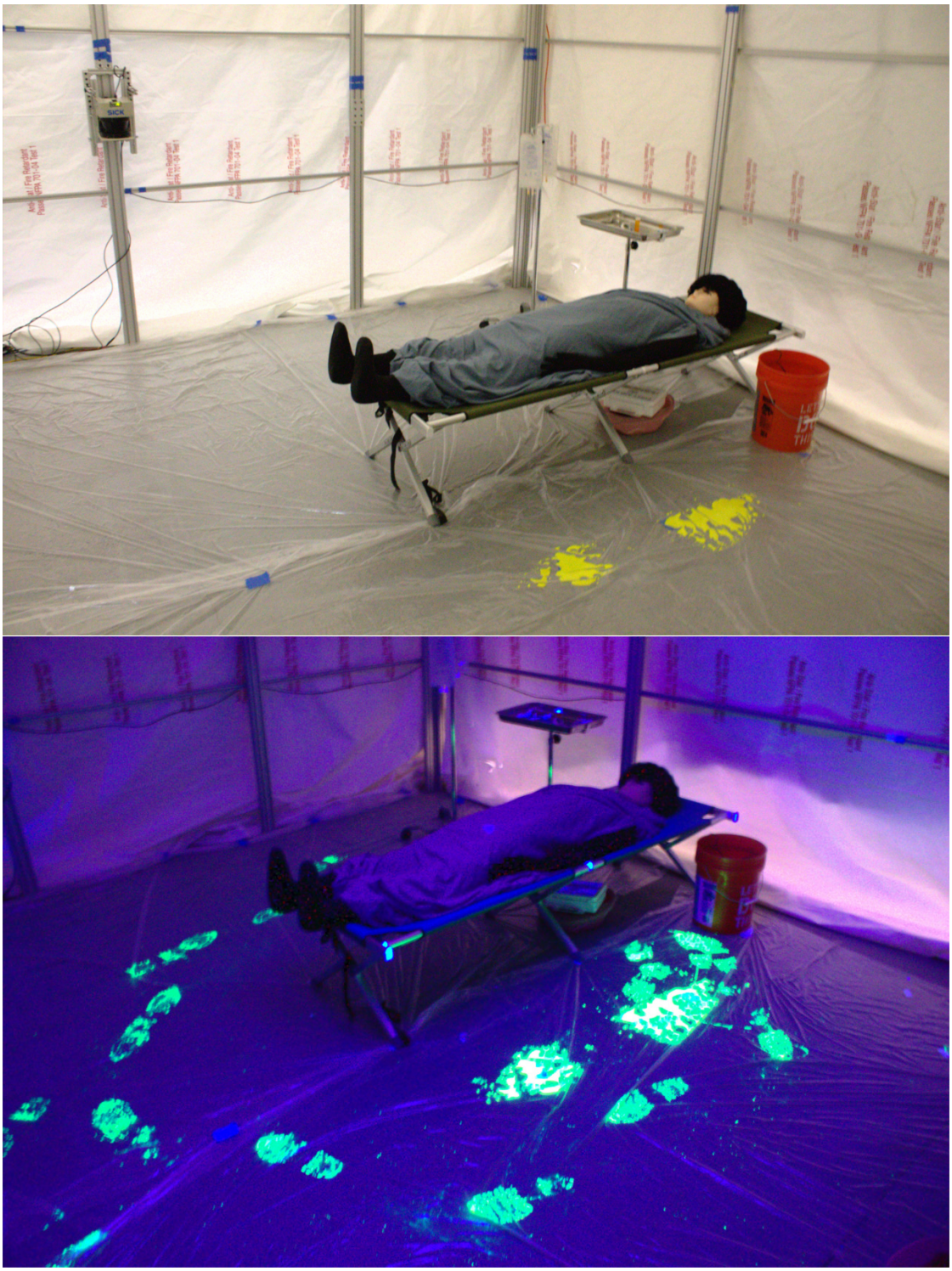

Figure 3.3: Contamination modeling in a simulated Ebola treatment unit. Pre-trial view (top) and post-trial view with blacklight on (bottom).

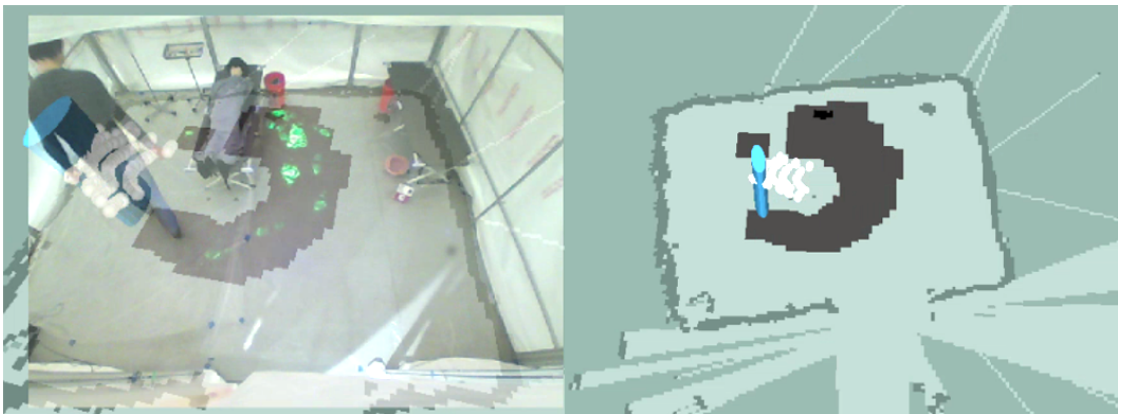

Figure 3.4: Left: RVIZ Camera View during trial run. Right: RVIZ map view of the treatment unit map overlaid with the modelled contamination in black.

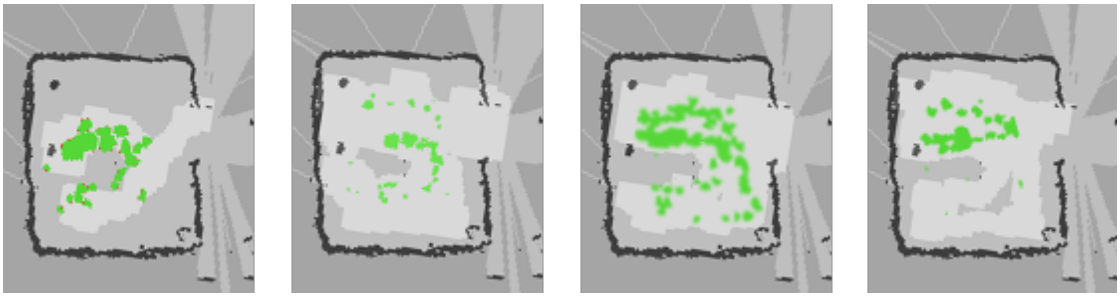

Figure 3.5: Treatment unit maps overlaid with modelled contamination in lighter grey and tracked substance in green.

The blue cylinder is a visual representation of the person's location in the treatment unit map. The white dots are sets of filtered scans over the previous half second period. Notice how each of these forms a partial ellipse since the laser is at chest height. Further note in the left image of Figure 3.4 that the predicted contamination in dark grey covers all of the *post hoc* imaged fluid in the environment. This fits with the goal, as described in Section 3.3.3, to have the system-predicted contamination be at least a superset of the real contamination.

Figure 3.5 shows the treatment unit maps of four separate example trial runs. Each map is overlaid with the contamination predicted by the system in lighter grey. The real fluid contamination is overlaid in green. The real fluid contamination was imaged from a camera opposite of the entryway. Each map in Figure 3.5 has the green contamination regions inside or on the edge of the virtual contamination model regions. The three rightmost maps in Figure 3.5 have most of the green contamination spots strictly inside the predicted contamination sets, with the exception of a few outliers. The leftmost map in Figure 3.5 contains some of the real fluid spots inside non-system predicted contamination regions.

Both Figure 3.4 and 3.5 have physical contamination regions that are more sparse than the virtual model. This was consistent across trials and fits with the goal to tend to overestimate rather than underestimate the true contamination.

Note, there are differences between the multiple camera angle's *post hoc* fluid contamination locations that are not shown. This means that the green contamination regions shown in 3.5 are not necessarily the exact location of the fluid in the world. These variations are due to compound tranformation errors in the eval-

uation procedure. First, the transformations of the cameras to the treatment unit map contain inaccuracies as these camera-to-world transformations were done by hand. Second, the pinhole camera model used to project rays from each image pixel into the world makes assumptions that do not fit our wide angle web cameras. Despite these compounding errors, the physical contamination evaluation procedure provides a realistic comparison.

3.5 Discussion

Our results show that the system modelled contamination provides an approximate superset of real fluid contaminated regions; most of the real fluid contamination is within the system tracked contamination. In accordance with our trasmission model design goals there are more false positives than false negatives. This suggests that our method of tracking contamination via tracking person location in relation to *a priori* contamination is an acceptable analog for a contamination sensor.

Our system demonstrates both the feasibility and usefulness of a contamination modeling and tracking system for robotic health care support. In its current form, the system is useful for low-fidelty training excercises with health care workers and for developing robotic applications that utilize the contamination information.

While the contamination modeling and tracking system in its current form is helpful, there are still avenues for future work. Most importantly, better transmission models need to be developed and tested before the system can be utilized in health care settings. The current disease transmission model would only be

appropriate for dealing with agents with similar transmission modalities as Ebola in low fidelity conditions. We noted that the density of the fluid decreased over time. That is, with each step, the amount of contamination trasmission decreased. The current transmission model employed could see improvements by moving from a binary contamination level to a probabilistic contamination level that decreases over time.

Airborne agents, like influenza, would present many interesting modeling challenges. Modeling airborne agents would likely require more and varied sensors, and necesitate modeling and mapping the environment in 3D.

The system also needs to be tested for scaling, both in the number of lasers used and in the number of rooms monitored. Multiple lasers need to be integrated and tested so that multiple personnel can be consistently tracked, without risk of occlusions. This is a conceptually easy next step, but will increase the financial and computational costs. Similarly, the system needs to be tested in a multi-room configuration as this is how most treatment units are laid out.

Lastly, more thought needs to be given to how to effectively warn workers when entering contaminated areas that include patients. Voicing over a loud speaker that a worker is entering a contaminated or dangerous area could be both jarring and disrespectful for patients.

3.6 Conclusion

This work represents a major first step in developing a rapidly deployable, low-cost, real-time contamination modelling system for health care support. Our contamination modelling system provides important information that can be used to help and protect both health care workers and patients. We demonstrated that the information can be used by decontamination robots to clean more intelligently, so that humans do not have to risk contamination. We also showed how the system can autonomously alert health care workers when nearing high-risk zones. Lastly, we evaluated our modeling system by comparing it to a bodily-fluid analog and provided concrete avenues for future work.

Chapter 4: Patient Visibility of the Operator: Effects on Comfort and Trust

This chapter is from previously published work [45]. My specific contributions, as well as those of others, are detailed in Section A.2.

4.1 Introduction

Health care professionals had to wear high levels of personal protective equipment (PPE) in order to safeguard against infection [6, 13]. This PPE, when coupled with the high heat and humidity of the region, meant that health care workers could only work for 45 to 60 -minute shifts before being at risk for heatstroke [4]. This dramatically decreased the quality of care that they were able to provide and contributed to the high mortality rate of the outbreak.

We are investigating the use of teleoperated robots in this setting to allow health care workers to perform some of their duties at a safe distance from infected patients. However, these robots can be scary things, especially when hovering over a medical cot with a patient in it. In this paper, we investigate whether being able to directly observe the human teleoperator makes the patient feel more trusting and comfortable, when being attended to by a robot.

Specifically, we address the following hypotheses:

- **H1:** A patient's increased visibility of the operator leads to higher levels of patient trust in the **operator**.
- **H2:** A patient's increased visibility of the operator leads to higher levels of patient trust in the **robot system**.
- **H3:** A patient's increased visibility of the operator leads to higher levels of overall **patient comfort**.

We test these hypotheses under two conditions where the operator was either visible or not visible to the patient. The patient lay in a simulated Ebola Treatment Unit (ETU) while a human-sized mobile robot performed various tasks via teleoperation. Questionnaires and psychophysiological responses were used to evaluate the hypotheses.

Our major contribution suggests that greater visibility of the operator gives patients higher levels of trust in the operator. Our results raise important questions regarding the current adoption and style of telemedicine systems, as companies currently sell remote medical telepresence devices [25] and pursue remote telesurgery platforms [46]. These results also have immediate practical implications for the design of a teleoperation control unit to be deployed in the field.

While the latest Ebola outbreak was the stimulus for our work, the principles and practices learned here generalize to other types of infectious disease outbreaks, especially those requiring workers to wear PPE.

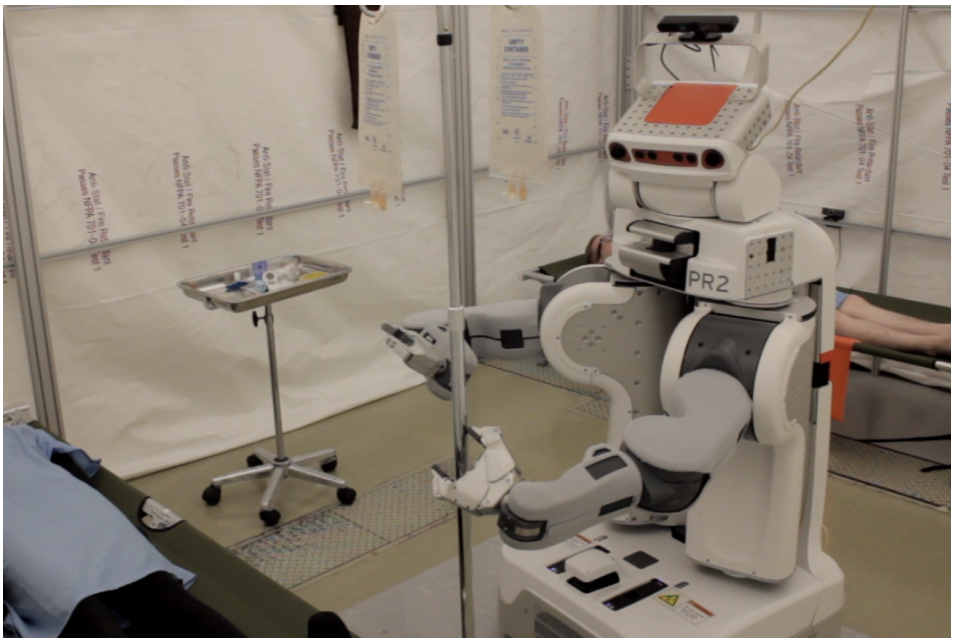

Figure 4.1: The robot moves an IV fluid pole during a study session.

4.2 Background and Related Work

We give background information and related work pertaining to social health care robotics as well as the importance and measures of trust and comfort in medicine and human-robot interaction.

4.2.1 Social Health Care Robotics

There has been research on general nursing robots that involve physical interactions with patients [47][48]. Despite some advances, most commercial robotic systems are either 1) stationary manipulator platforms for executing precision tasks or 2) mobile platforms without manipulators meant to connect people together, move

goods around, or perform static ultraviolet decontamination. In this work, however, we are interested in exploring a more general robotic platform that is mobile and manipulator-capable in a domain that has been largely ignored – responding to infectious disease outbreaks.

4.2.2 Trust in Medicine

Trust is an important component of medical care, yet it is multifaceted and culturally dependent. Trust in medical systems can be influenced by a variety of factors (e.g., payment method) and is linked with a variety of outcomes (e.g., patient retention and likelihood to seek medical services in the future) [49, 50, 51, 52].

One important factor in our study is the link between trust of physicians and the willingness of patients to seek future medical treatment. This is especially important in outbreak conditions. PPE obscured the human appearance enough that it distanced potential patients from health care providers. *Médicins Sans Frontièrs* (MSF) doctors value physician-patient trust so highly that they have learned to go into new communities, regardless of contamination risk, without wearing their PPE in order to gain communities' trust [53].

The Wake Forest Physician Trust Scale (PTS) is one standard measure for patient-physician trust and has undergone verification and testing[54]. We use the PTS in our pre-experiment survey.

In our post experiment survey, we examine both the patient's trust of the robot system and the operator of the robot using similar language and style to the PTS.

This is discussed more in Section 4.4.5.1.

4.2.3 Trust in HRI

Trust has been examined in a number of contexts in HRI. For example, Freedy et al. developed a task-specific, objective measurement of trust for a collaborative human-robot task [55]. Desai et al. found that reliability impacts user trust in shared-autonomy robots as evidenced by increased switching to manual mode in driving a robot [56]. Bainbridge et al. examine the trust of a robot versus a video-displayed agent both by using questionnaires and examining the likelihood of participants to follow through with certain actions [57]. Similarly Salem et al examine participants likelihood to trust a "faulty" robot versus a properly functioning robot [58]. All of these studies include quantitative measures for trust using post-hoc questionnaires.

There is a growing trend to quantitatively evaluate trust by counting the number of times participants allow a robot to do an action autonomously or, as in [55] and [58], follow through with a request from the robot. In each of these studies the participants played a much more active role in interacting with the robot than a hospitalized patient would. The passive role of the patient in our experimental setting requires the use of subjective, self-reported data instead of more objective, observational data.

4.2.4 Comfort in Medicine

Comfort is seen as "central" to medical practice amongst practitioners[59]. MSF doctors in the Ebola outbreak went through the trouble of putting a picture of themselves with their handwritten name next to it on the front of their PPE. This offset the unease brought on by the obfuscating PPE and made patients feel more comfortable with doctors[53].

The nursing literature provides a rich set of theory and tradition for measuring and valuing patient comfort. The literature includes studies that assess comfort for both patients and caregivers using questionnaires and ethnographic interviews [60, 61].

The health care and medical literature sometimes defines comfort as the absence of pain and use measures such as the Visual Analog Scale for Pain [62, 63]. However, this is not relevant to our study because our study did not induce physical pain.

4.2.5 Comfort in HRI

Comfort has been studied in the context of socially-aware robots that optimize for people's comfort when navigating around them [64][65], in human-robot handovers [66], and in response to robot touch in a nursing context [48]. [64] uses a 5-point Likert scale questionnaire to evaluate comfortable approach paths, speeds, and distances by robots. [67] developed a unique hand-held device that allows users to input current comfort ratings for the duration of the experiment; this method

has the obvious drawback of requiring the participant to continually assess and report their comfort level. [65] defined and modelled pedestrians' walking comfort as the "subjective impression of one's easiness of traversing an environment." They recorded pedestrians' traversal using laser range finders and then averaged three 7-point Likert items to calculate comfort.

Robots like the Paro and MEDi (built on the NAO robot) are being trialled in health care settings to provide comfort to patients [68, 69, 24, 70].

We define comfort as the relative absence of stress and arousal and test this using questionnaires and physiological methods. Following Chen et al. we use a Galvanic Skin Response (GSR) system to measure skin conductance which is linearly correlated with valence and arousal [48]. Our methods are described more in Subsection 4.4.5.

4.3 Implementation

This section outlines the robot, robotic control, and environment used in the experiment.

4.3.1 Robot Description

For this study, we used a PR2 humanoid robot [71]. The PR2 has two 7 degree-of-freedom arms. The mobile base allows for semi-holonomic motion. In addition, the PR2 has a telescoping spine and ranges in height from 1.33-1.64m.

The PR2 is equipped with a variety of sensors: two laser range-finding sensors (one on the base and one on the head), an Asus Xtion RGB-D camera mounted on top of the robot's head, a wrist camera for each arm, and stereo cameras. Each of these sensors, except for the stereo cameras, was used to provide situational awareness to the robot operator.

The robot ran on battery power, but was tethered via Ethernet for data transmission. To simplify networking, a remote desktop was connected via Ethernet to the service port of the robot.

4.3.2 Robot Control

An operator teleoperated the robot using the ROS PR2 Surrogate package [35, 72]. This allows the teleoperator to control the position of the robot's arms via Razer Hydra motion sensing controllers [73].

The operator holds the controllers, moves his/her hands freely, and presses the enable button when he/she desires the robot's end effectors to match that of the operators. An open gripper, close gripper, and killswitch button are mapped to the controller. The killswitch immediately disengages the robot's joint actuator forces.

The operator relied on an RVIZ-based GUI to perform the teleoperation. The operator's GUI gives access to a variety of information including a live feed from the robot's sensors, the three ETU environment cameras, and a model of the robot as it appears in the world. The operator relied solely on the vizualization found

on the monitors to move the robot and complete each task.

The operator was trained by repeatedly completing the tasks in the ETU without any human subjects. The training time took roughly 2 hours. The primary author of this paper acted as the operator.

4.3.3 Environment

The robot performed tasks in a simulated Ebola treatment unit (ETU) built according to information found from MSF [36]. Our scaled-down ETU is resemblant of a high-risk zone within a larger Ebola treatment center.

The ETU is an enclosed space approximately 4m x 5m x 2.5m. It is covered in anti-static, fire-retardant white plastic for a ceiling and walls and has a concrete floor. There is only one entryway measuring approximately 2m H x 1m W. The space includes: 2 single cots (195cm L x 66cm W x 40.6cm H), an IV pole and bags, 2 bedpans, a medical tray, and sundry first aid supplies. The full-size simulated patient's cot is located in the middle of the room, while the human subject's cot is next to the walls.

The ETU is equipped with 1 regular webcam and 2 ultra wide angle webcams. These provide greater situational awareness for the teleoperator and the safety attendant. The sensors were controlled via ROS drivers on a desktop machine on the outside of the ETU.

Figure 4.2: Patient's perspective of the room, including view of simulated patient and medical supplies.

4.3.4 Safety

The PR2 robot is equipped with both onboard and wireless emergency stops. A human safety attendant continually monitored the scene via a remote screen with live feed from 3 different cameras in case intervention was needed. The robot's maximal gripper effort was set to 30N. Participants were given an orange flag with instructions to raise it in case they desired to stop the experiment.

A thorough explanation of the experiment and the inherent risks was given to each potential participant before the experiment started. Consent was required, and each participant was free to stop or leave the experiment at any time, for any reason. The university's IRB approved the study.

4.4 Methods

4.4.1 Experimental Design Overview

To test our 3 hypotheses we conduct a 2 condition, between-subjects experiment wherein we vary the participant's visibility of the operator. Participant visibility of the operator is broken into 2 conditions described below.

The study is broken into 3 stages and takes roughly 35 minutes. The initial stage consists of informing the participant of the study via a brief overview, obtaining written consent to participate, and filling out an initial questionnaire. The participant is then taken to the simulated ETU and shown how the E-stop works on the robot. Following that, the participant puts on an exercise heart rate monitor and the patient gown. This stage takes approximately 10 minutes.

In the second stage the participant is led into the ETU. The GSR is attached to the participant's left hand. The subject is then instructed to lay down. Recording of the psychometric signals begins, as well as video and audio recording if the subject gives consent. A 2 minute baseline of the signals is collected, with the operator in the ETU standing beside the robot for roughly 1 minute. The operator then leaves the ETU and closes the door based on the visibility condition. The robot is activated and executes 5 tasks in close proximity to the participant via teleoperation. Execution of the tasks takes approximately 8 minutes.

The participant is then led out of the ETU and instructed to take off the gown. The post-hoc survey is administered. The participant takes off the exercise heart rate monitor, is paid $20 for their time, and allowed to ask questions.

4.4.2 Participant Visibility Conditions

In both conditions, the teleoperator is located outside the ETU approximately 5m away from the the participant's cot. The only thing changed between conditions is the material of the entryway door covering. Participants are randomly assigned a condition.

In the **no visibility** condition an opaque sheet of plastic, of the same material as the rest of the ETU, is drawn over the entryway to the room. Thus, the operator is not visible to the participant at all during the robot's task execution. In the **visibility** condition the participant and operator are physically separated by a sheet of 4mm clear plastic drawn over the entryway to the room, allowing the participant full visibility of the operator, constrained by the participant's requirement to stay on the cot. The participant's view of both conditions is shown in Figure 4.3 .

4.4.3 Robot Tasks

The robot performed five tasks in the ETU, in close proximity to the participant:

1. Deliver wrapped gauze to the medical tray
2. Pick up a no-touch thermometer and hold it over participants torso
3. Move IV pole closer to the participant's cot
4. Remove the wash cloth hanging on the wall next to the participant and place

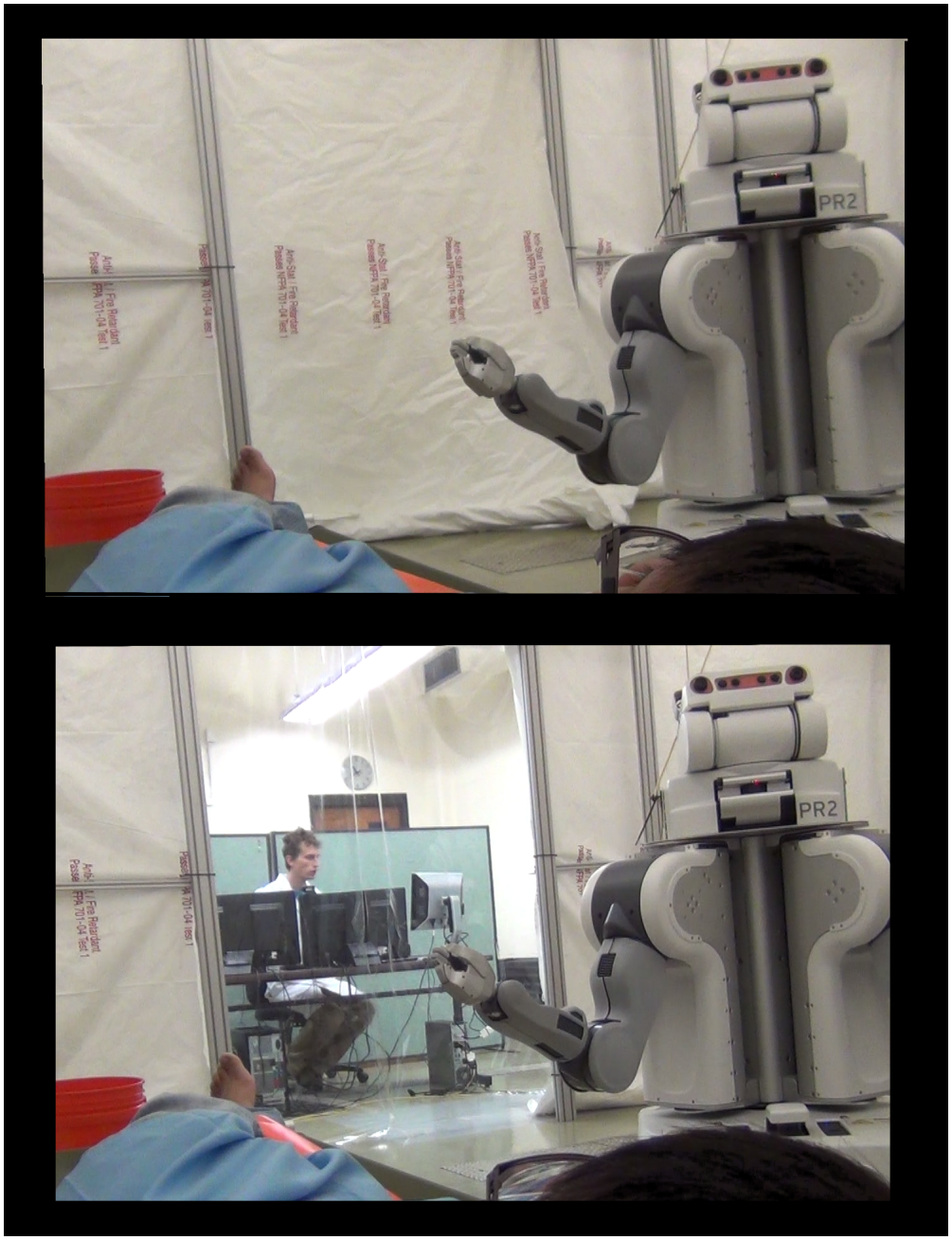

Figure 4.3: The participants view in the no visibility (top) and visibility (bottom) conditions.

it in a bucket

5. Move the bucket from the end of the cot to the other side of the ETU entrance

The primary criteria for task selection is that each had to be feasible and consistently repeatable. This was a two-fold decision. First, we were interested in what robotic technology could actually do in the near-future. Second, we wanted standardize robot performance between participants.

We also wanted realistic tasks that would lighten the workload of the health care staff. The selected tasks were deemed helpful based on conversations with trained medical personnel (nurses and doctors), some of whom were principal leaders in the latest Ebola response [53].

Lastly, we wanted tasks that are generalizable to other tasks in this domain. The selected tasks involve the robot picking up objects of various sizes, stiffness, textures and colors that requires the robot to use its full range of height and to traverse much of the ETU space.

4.4.4 Participant Arrangement

Participants were recruited from the surrounding community and campus. They were required to proficiently speak and read English and be at least 18 years old. 23 people participated in the study (8 females and 15 males, ages 18 to 55, median of 24). All but one had at least some college experience. 19 participants gave consent to allow us to record audio and video.

We wanted the participant to feel like he/she was in a medical environment as much as possible. Not only was our ETU realistically modelled, we also sprayed a small amount of bleach under the participant's bed before entering to give the room a sterilized smell.

In the initial briefing for the experiment, the participant was told that we were interested "in human-robot interactions" and "how to use robots to help in the fight against infectious diseases." We framed the robot to the participant as "a robot, controlled by a human operator" twice in the study overview and once in the consent form. With the exception of specifying that the robot would be "moving the IV pole from one cot to another," the actions of the robot were not specified in advance. We characterized the robot's actions as "general health care tasks in the ETU." It was not disclosed to the participants that we were studying their levels of comfort and trust. The initial briefing and surveys were conducted outside of the ETU, with partitions blocking the subject's view of the ETU.

The participant was shown how the emergency stop functions on the robot in the ETU before putting on a heart rate monitor in another room. Then the participant put on a standard hospital gown over his/her clothes. He/she was led into the ETU where the GSR was hooked up. Further questions by the participants were deferred until the end of the study unless the questions regarded safety practices.

4.4.5 Measures

4.4.5.1 Questionnaires

An initial questionnaire was administered to each participant following the consent process. Basic demographic information was collected, including 4 items relating to age, gender, level of education and current employment status. Each participant then took the Negative Attitude Towards Robots (NARS)[74] survey and the PTS.

Following the robot task execution stage, the participants returned to the initial study area to take a post-experiment survey. The post-experiment survey is broken into three categories: operator trust, robot trust, and comfort (see Table 4.1). Each question is on a 5-point Likert scale, with 5 being "Strongly Agree." The operator and robot trust questions were designed to follow the language and spirit of the trust questions found in the PTS and the work by Chen et. al [54, 48]. Means are calculated per category. Negative questions are inverted to follow the same scale as the other questions. Analysis of variance and 1-sided t-tests are done to test the significance of the comparisons.

4.4.5.2 Pyschophysiological Response Measures

We measured participants' GSR and heart rate during the robot task execution, but in this paper only report GSR data. Baseline monitoring began two minutes before the robot started its task execution. The participant lay down on the cot during baseline monitoring. Monitoring stopped after the robot returned to its

Operator Trust, Cronbach's $\alpha = 0.68$
I trust the operator.
The operator is extremely thorough and careful.
I thought the operator would hit something.
I would allow the operator to lay a sheet over me using the robot.
The operator was skilled.
The operator ensured my safety while performing the tasks.

Robot Trust, Cronbach's $\alpha = 0.78$
I trust the robot system.
The robot system is extremely thorough and careful.
The robot system frightened me.
I would allow the robot system to lay a sheet over me.
The robot system accomplished its tasks well.
The robot system made sure I was safe while performing tasks.

Comfort, Cronbach's $\alpha = 0.95$
I was comfortable in the room.
I liked being in the room.
I felt scared in the room.
I felt relaxed in the room.
My time was peaceful.

Table 4.1: Survey questions per category.

starting location and folded its arms.

Following Chen et al. we used Qubit System's S220 GSR with the C410 LabPro Interface and C901 Logger Pro software to measure GSR [48, 75]. Since the sensor is highly sensitive to physical movement, the participant was instructed to lie on his/her back with his/her instrumented hand on the cot for the entire robot task execution stage. The GSR outputs 0-5v and was sampled at a rate of 3.3 Hz.

The second minute of recording was used to calculate a baseline for the individual participant using Equation 4.1. A baseline is needed since the gain has to be hand-adjusted in the initial reading period and since the initial reading period varies per individual.

$$Baseline(gsr_p) = \frac{\sum_{t=200}^{400} volt_t}{200} \tag{4.1}$$

This is used to calculate a proportional GSR value:

$$PropGSR_t(gsr_p, baseline_p) = \frac{volt_t}{baseline_p} \tag{4.2}$$

Task-phase proportional means (TPPM) for each participant are calculated using Equation 4.3. Start and end times for the task-phases were calculated by taking the mean of hand-coded times from the recorded sessions.

$$TPPM(g_p, b_p) = \frac{\sum_{t=phase_{start}}^{phase_{end}} PropGSR_t(g_p, b_p)}{phase_{end} - phase_{start}} \tag{4.3}$$

This is used to calculate the proportional mean during a task-phase for an entire conditional group using Equation 4.4.

$$CondTPPM([p],[g],[b]) = \frac{\sum_{i=1}^{n} PPM(p_i, g_i, b_i)}{n} \tag{4.4}$$

One-sided t-tests are performed on TPPMs between significance to check for significant differences.

4.5 Results

4.5.1 Questionnaire Results

For the survey responses, n=11 for the no visibility condition and n=12 for the full visibility condition.

Figure 4.4 is a boxplot for trust in the operator between conditions. A higher y-value represents a higher level of trust in the human operator. The median and mean are above the neutral line for operator trust for both conditions. However, the full visibility condition had a higher mean than the no visibility condition (M=4.38 vs. M=3.95). Thus, the full visibility group expressed higher levels of trust in the human operator than the no visibility group. This difference is significantly explained by the condition (p<0.05, Cohen's d=0.81) and supports H1.

Figure 4.5 shows the boxplot for trust in the robot by each condition. Again, a

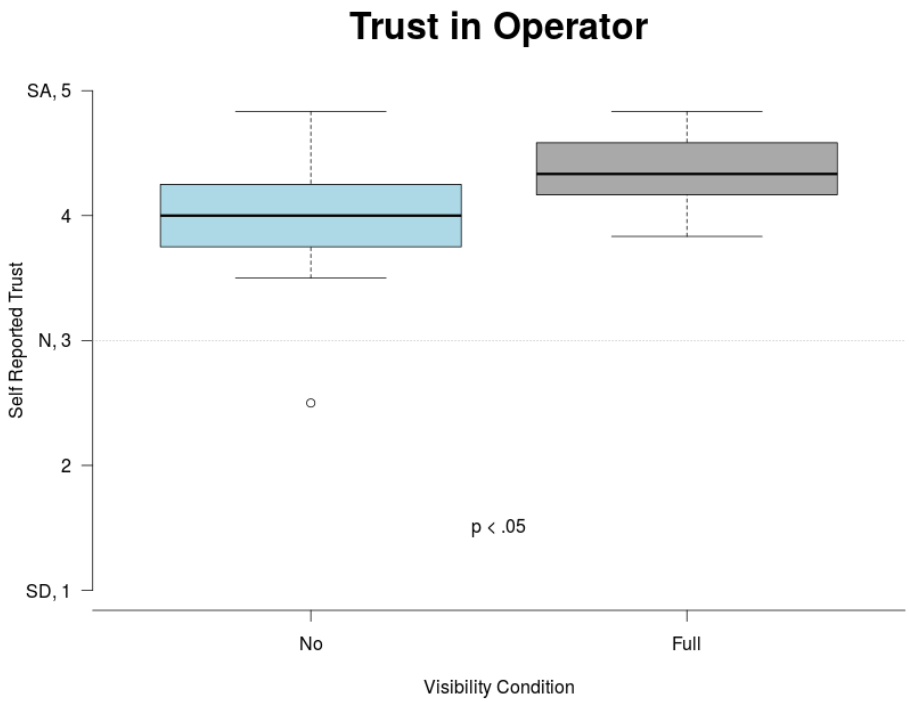

Figure 4.4: Boxplot of operator trust means per condition.

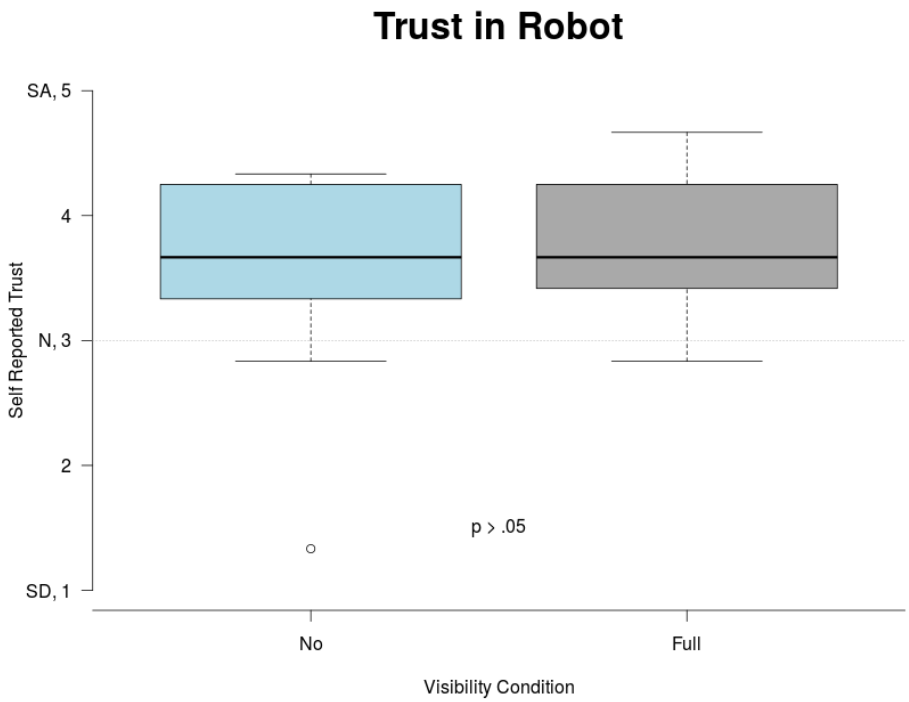

Figure 4.5: Boxplot of the robot trust means per condition.

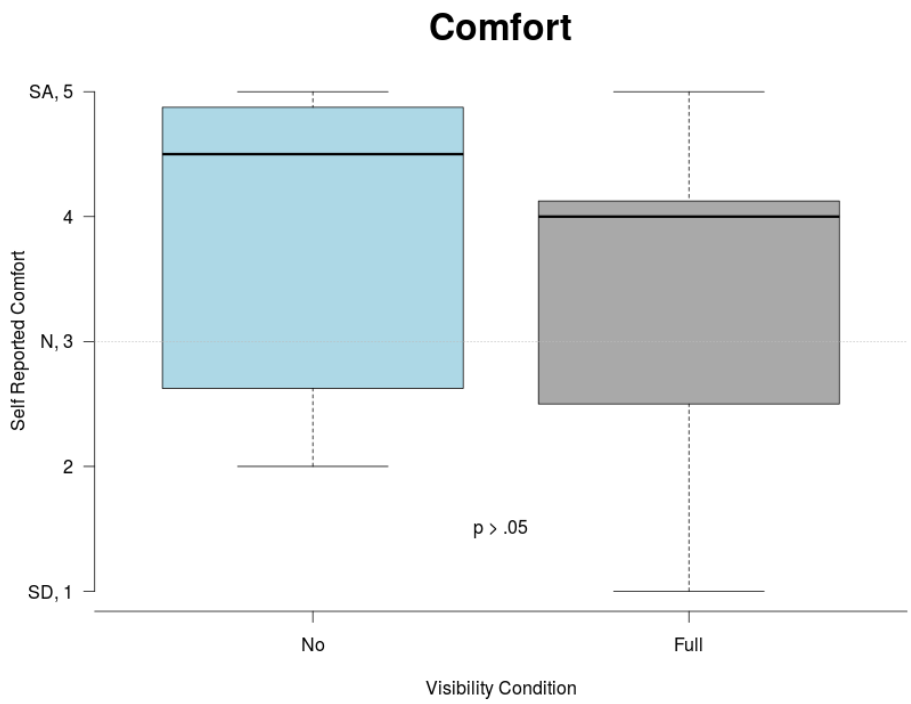

Figure 4.6: Boxplot of comfort means per condition.

higher y-value indicates higher levels of trust. The medians are equal whereas the mean in the full visibility condition is higher than the no visibility condition mean (M=3.77 vs M=3.56). While interesting, this result is not statistically significant enough (p>0.1, Cohen's d=0.30) to support H2.

Figure 4.6 shows the self-reported level of comfort for the each condition. Comfort levels determined by the questionnaire show a lower mean and median in the full visibility group. While in contrast to our initial inclination, these results are not significant enough to reject H3 (p>0.1, Cohen's d=0.34).

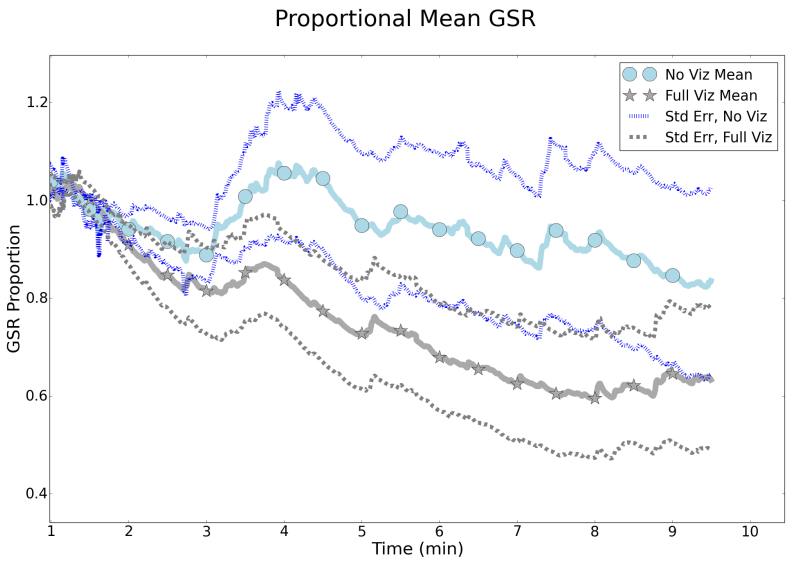

Figure 4.7: Mean proportional GSR over time, per condition.

4.5.2 Galvanic Skin Response Results

Three of the participants' data had to be excluded from analysis because the signal was saturated immediately following the baseline time period, indicating a poor gain setting. Thus, for the GSR data, n=9 for the no visibility condition and n=11 for the visibility condition.

Figure 4.7 shows the average proportional GSR reading for both conditions (note again that minute 2 was used as a baseline and the robot did not start moving until after minute 2). A higher proportional GSR reading indicates greater levels of arousal and excitement. The no visibility group had a higher level of arousal compared to the full visibility group throughout the trial. Both conditions experienced an increase between minutes 3 and 4, but the rise for the no visibil-

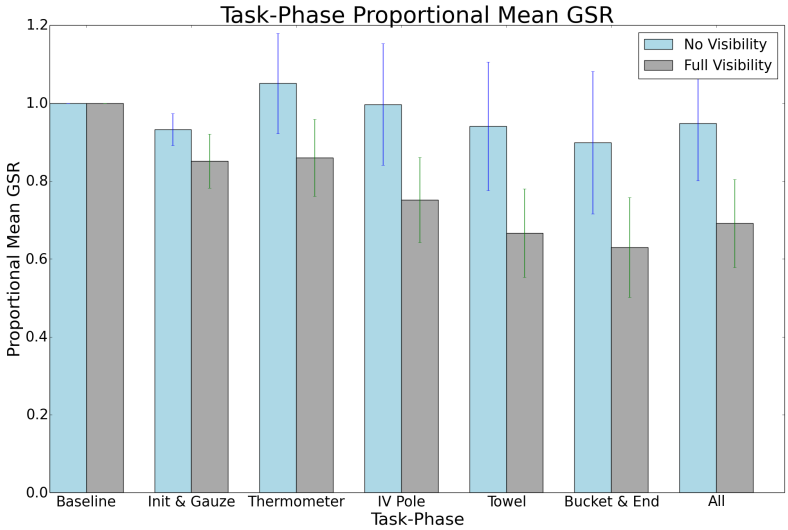

Figure 4.8: TPPM GSR for each task phase and whole experiment, with standard error bars.

ity condition was much higher. The full visibility condition's signal looks much smoother, indicating fewer changes in arousal across time.

Figure 4.8 shows the proportional task-phase mean GSR values by condition. The no visibility condition's mean is higher than the full visibility condition at each stage and across all time. The difference in the proportional mean across all time yields a marginal degree of significance ($p<0.1$). This suggests that the no visibility condition had higher levels of arousal/valence compared to the full visibility group during the robot's task execution, and only marginally supports H3.

In agreement with our intuition, Figure 4.8 suggests that the "Thermometer" phase, where the robot held a no touch thermometer over the torso of the par-

ticipant, is the most arousing/exciting task-phase for both groups, aside from the baseline reading.

4.6 Discussion

In support of H1, our results suggest that people are less trusting of the the human operator when the operator is unseen. The reason for this effect is still unknown. The patients may tend to project more autonomy on the robot when the operator remains unseen during task execution, and this might lead them to doubt the operator's ability to command and control the robot. Contrast this to the full visibility condition where the patient is continually reminded of the operator's role in the control and manipulation of the robot. This might bolster the patient's trust of the operator because the patient can constantly link the operator's capabilities and power to the robot's actions.

In this experimental design, the operator was introduced to the patient before the robot even began to move and had at least 5 minutes of interaction with the patient during the consent process and safety explanation. The patient even walks by the operator's control unit. We hypothesize that the effect size may have been much greater if the patient did not meet the operator beforehand or see the control station. A less-rational state due to medication or symptoms may also increase the effect, causing patients to project more autonomy to the robot, further decreasing their perceived ability of the operator to control the robot.

From the support of H1 it follows that a patient-centered robotic ETU would

feature a mobile teleoperator control unit that could be temporarily stationed outside of patients' rooms. This would allow each patient to see the operator while the operator controls the robot. This would be in contrast to a central teleoperation control unit which would not allow patients to see the person manipulating the robot.

The deeper implication of H1 is to question the current and imagined-future form of telemedicine. Obscuring the operator behind the robot could be disconcerting and off-putting for many people in regards to their trust of the operator unless, as with most current robot surgery, the patient is unconscious. A loss of operator trust could mean a decrease in long-term physician-patient relations and a lower likelihood to seek future medical care. More work needs to be done to evaluate how things such as screens, speech communication, or even greater familiarity with robots can help overcome this specific barrier to operator trust in telemedicine applications involving physical action around the patient.

Our results do not support H2; nevertheless, it is very interesting to find that the patient's trust of the operator varied significantly while the trust in the robot did not. Participants may have been assessing different attributes of trust when evaluating the operator versus the robot. The trust attributes assessed for the operator (e.g., level of control) may have varied greatly between conditions. The same measured trust attributes might not have varied as much for the robot. This might help explain why there was not a significant difference in robot trust.

Our results are somewhat mixed in regards to H3. The survey responses do not support H3, and if anything, point the other way. The GSR data however

shows that the no visibility condition experienced significantly more arousal across time compared to the full visibility condition in support of H3. The higher levels of excitement in the no visibility condition coincide with their lower levels of operator trust. The lower levels of arousal in the full visibility condition coincide with their higher levels of operator trust. Our results then fit an inverse pattern between trust levels (in the operator) and GSR response. This seems to make intuitive sense that, all else being equal, the more trust a person has in the human operator, the calmer he/she would be. Thus, the GSR data not only supports H3, it also fits with H1.

Participants may have responded to the comfort questions with more regards to the physical attributes of the ETU rather than the overall situation of the robot moving around in the space. This could explain variation in the results.

There appears to be a general downward trend in the GSR results for both conditions. This may suggest that people adjust to the robot over time. The downward trend could also be explained by the variation in the tasks. People were more excited when the robot hovered over them with a no-touch thermometer than when the robot dropped the towel in the bucket. To better understand the overall downward trend the GSR baseline should not start until the person's GSR voltage stabilizes and tasks should be varied. Also, these results are drawn from a limited interaction time between the robot and test subject; it is unclear how longer interaction times, on the order of days or hours, would impact the levels.

There are limitations to the current study. While the support of H1 is statistically significant with a large effect size, the result is limited in statistical power. Ideally, at least double the number of participants is needed to increase statistical

power. Lastly, interviews may have aided in the interpretation of the results.

4.7 Conclusion

In this work we explored how patients' visibility of the teleoperator affects their own levels of trust in the operator, robot, and their overall comfort. We tested our three respective hypotheses by having a human-sized robot complete general health care tasks around participants under two conditions of operator visibility. The experiment took place in a simulated Ebola treatment unit.

Our major contribution suggests that a patient's increased visibility of the operator leads to higher levels of patient trust in the operator. More needs to be done to assess the reasons for this effect and ways to potentially overcome this barrier to trust. The mixed results regarding H3 invite more research and clarification into how visibility impacts patient comfort.

Robotic technology in infectious disease outbreaks is poised to offer tremendous benefits to health care worker safety but the particular challenges of deploying these systems around human patients needs to be further explored.

Chapter 5: Conclusion

Robots can bring enormous benefits to the fight against infectious disease outbreaks. In Chapters 3 and 4, I presented three concrete use cases of this, with EVD as the target disease. Namely, smart robotic treatment centers can track disease propagation alerting other robots and health care workers of danger. Scrubbing robots can autonomously and efficiently decontaminate treatment center floors utilizing supplied contamination knowledge. Health care workers can safely provide basic health care using teleoperated or shared-autonomy robots. These examples are just the beginning what robots and automation *can* do in infectious disease outbreaks.

Along with these demonstrated technical capabilities, Chapter 3 raised questions regarding best practices for alerting health care workers in the presence of patients. Chapter 4 explored in detail the effects of operator visibility on patient comfort and trust. The results of the study suggest that people are more trusting of the operator when they can see the operator. This suggests that it would be better to have a robot's operator be in the line of sight of the patient. This work, again, is just an example of what robots *should*, and *should not*, do in infectious disease outbreaks.

It is important to remember that, even though EVD was the target disease for the work, the principles generalize to other similar infectious agents and contexts.

Though the EVD outbreak was the catalyst for the research, the work should not stop because the latest outbreak is officially over. This time 'in-between outbreaks' should only spur on more creativity to prepare for the next outbreak, whether EVD or something else. It is the time for organizations to freshly reexamine their responses to infectious diseases, to refine their methods, and to develop and test new technologies. It is also the time, especially in light of the above research, for roboticsts to do their part and to do the same. The above work provides initial results regarding how robots and automation *can* and *should* be used in infectious disease outbreaks, but more work needs to be done.

First, the robotics community needs to acknowledge and embrace the infectious disease outbreak scenario as a new working domain, or at the very least subdomain, of disaster robotics and medical robotics. This domain deserves our attention and effort due to the large potential impact and uniqueness of the domain. Disaster robotics, search-and-rescue robotics, and medical robotics research have not addressed the specific issues that arise in infectious disease outbreak response due to different underlying assumptions, even though there is overlap and intersection with these areas. A taxonomy and characterization of robotic infectious disease outbreak responses needs to be developed. This needs to be done in comparison with disaster, search-and-rescue, and medical robotics. It is suggested to define the domains in the areas of purpose, assumed environmental conditions, resources, duration of interaction, anticipated patient and work cultures, organizational structures, intended users, and technical abilities required.

For example, disaster and search-and-rescue robotics assumes the full spectrum

of resource availability surrounding the response environment. However, they assume the worst in regards to environmental and structural conditions. Medical robotics research assumes the best in regards to environmental, structural, and resource conditions. Infectious disease response robotics, on the other hand, can occur across the entire spectrum of environmental, structural, and resource conditions.

The treatment duration is also widely different than current search-and-rescue and disaster robotics anticipate. Their medical focus primarily deals with pinpointing the initial location of the patient and providing first response medicine until extraction. Infectious disease response robotics needs to account for sustained, longer-term patient care, possibily lasting through a quarantine period. Thus, human-robot interaction studies in this domain should include longer term interaction studies.

As mentioned, differences also exist in the structural assumptions made by the various domains. In infectious disease responses, large governmental and non-governmental organizations may wield considerable say over the layout and structure of treatment facilities. However, these structures must be rapidly-deployable anywhere on the globe. Once deployed, they may be surrounded by severe resource constraints. Infectious disease robotics therefore makes unique structural assumptions; the evironment can (and should) be altered to make it more robot-friendly, allowing robots to effectively perform a larger variety of tasks. This would increase the robotic technology adoption rate resulting in saved lives. The general robotics research goal to enable robots to work well in all environments can

and should be abandonded in this context. Future research then should examine possible structural designs that would provide the highest cost-benefit for robotic abilities. It is further suggested to collaborate with teams that are already working on next-generation rapidly deployable treatment units as well as design one from the ground up with robotics and automation in mind.

It is also important to examine uniquenesses within the infectious disease response robotics domain, as not all infectious diseases are the same. The benefits of robots will likely vary based on the microbiological and epidemiological nature of the target disease. Particular axes of interest include the virulence of the disease, the transmission mode of the disease, portal of entry/exit, the mortality rate of the disease, and other options for treating and preventing the disease. Work needs to be done to pinpoint the diseases that robots would be most beneficial in fighting.

Understading the overlap and uniquenesses of the domain when compared to others, and the role that specific diseases have on outcomes, should result in the identification of particularly challenging areas. It should also yield a projected timeline for when robots can be effectively tested and deployed in real situtations. This would then guide various research entities to understanding and exploring the short- and long-term applications as desired.

This domain will push the boundaries of human-robot interaction research. The questions raised in Chapter 3 and findings from Chapter 4 reinforce the idea that any proposed robotic solution needs to acknowledge and understand the responses and attitudes of end-users and projected beneficiaries. Studying these responses and attitudes is particularly challenging in the context of infectious disease out-

break response due the variability of cultures and mental states of the people the robots may interact with. Human-robot interaction will need to focus on a more differse subject population that it has historically, likely requiring the use of novel methodology.

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APPENDICES

Appendix A: Contributions

Parts of the introduction and background sections come from [76, 77]. The contributions for comprise Chapter 3 and 4 are described in detail below.

A.1 Chapter 3

Chapter 3 is drawn largely from work submitted to the 2016 IROS conference and is undergoing review [29]. It is work done in collaboration and guidance with my advisor Dr. William D. Smart. Tiffany Chen and Patrick Hansen are also coauthors on the paper. Tiffany Chen developed the initial system code, which I then heavily refactored, debugged, and extended. Dr. William D. Smart developed the initial ellipse fitting code. Kyle Wizzard helped with the manual labor during the evaluation procedure.

I designed and set up the test environment and tools, guided and initialized the ideas, refactored, debugged and extended the initial tracking and contamination code, implemented the warning system, implemented the scrubbing protocol on the Turtlebot, developed the evaluation method, performed the evaluation, analyzed the evaluation results, and wrote the conference paper.

A.2 Chapter 4

Chapter 4 comes from work published at the 2016 ACM/IEEE Human-Robot Interaction Conference, which was nominated for a best paper award [45]. It is work done in collaboration and guidance with my advisor Dr. William D. Smart. Many people deserve credit for the roles they played in making the work a reality. Matthew Reuben helped move and reconstruct the treatment unit. William Curran introduced me to the PR2 and PR2 Surrogate package. Duy Nguyen and Cameron Bowie manned the emergency stop button in the event that a participant signalled to stop the experiment or the robot appeared to do something dangerous. My advisor and lab mates each gave considerable feedback for each iteration of the paper. A number of people volunteered to pilot the study.

My contributions include formulating the original research question, developing the experimental design, implementing the study, perfoming the study as the operator, analysing the data, and writing the conference paper.

Appendix B: Author's Note

While the 2014 - 2016 Ebola outbreak began its spread across West Africa, I began my drive across the continental United States for graduate school. Ebola brought with it fear, mistrust, and death. Graduate school brought excitement, optimism, and opportunity. The two events could not be more disparate.

The White House Office of Science and Technology Policy responded to the outbreak, in part, with a challenge to universities and businesses to provide innovative solutions to help in the Ebola crisis. The group also initiated several workshops around the country to brainstorm ideas and foster collaboration (Innovation on the Edge: Accelerating Solutions in the Fight against Ebola).

Our Personal Robotics Group accepted the challenge with sticky notes in hand. The goal of the workshop was to provide near- and long-term solutions for protecting health care workers and saving lives. We mocked-up a demo video of the PR2 removing bed linens in a couple days using a standard off-the-shelf package and our PR2 robot. The video was decent enough quality to help win us the award, but did not provide clear direction for moving forward. Thus, the real work for this project and myself began.

In laying out a work such as this, one that seeks to convey the benefits of technology against the realities of disease and death, it is important to acknowledge my own current standing of ignorance. I have never set foot in West Africa. I

have not been the victim of a deadly disease. My first-hand knowledge of the medical field consists of routine visits to well-resourced doctors, a few emergency room visits, and one extended hospital stay due to a collapsed lung. Thus, to a large degree, I am out of touch with the realities of the situation. Nevertheless, I hope to make the case that using robots against infectious diseases is, and should continue to be a, fruitful endeavor. It's an endeavor that is not just beneficial for the priviledged few (an abstract pursuit to help earn folks like me degrees), but hopefully an enabling and supportive technology for all of humanity.

Interestingly, this is not the first time I have found myself building a 'career' in response to a terible situation, though this is a first for how disconnected I feel from the situation. As a white, well-educated male, I often find myself somewhat removed from the pain and suffering of those I seek to help. For example, my color and class put me on different sides of the street and law than those I worked with in South Carolina. My nationality put in a different dorm than the locals in Honduras. This time though, my graduate work put me an ocean and continent across from those who were the intended beneficiaries of my work. Aware of this reality, my hope is that the distance does not trivialize the work presented. I believe there is great potential in using robots against infectious diseases in all parts of the world.