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# Analysis of How Mobile Robots Fail in the Field

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by

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of the requirements for the degree of
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Dedication

To my parents for their unwavering support.

## Acknowledgments

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ABSTRACT

The considerable risk to human life associated with modern military operations in urban terrain (MOUT) and urban search and rescue (USAR) has led professionals in these domains to explore the use of robots to improve safety. Recent studies on mobile robot use in the field have shown a noticeable lack of reliability in real field conditions. *Improving mobile robot reliability for applications such as USAR and MOUT requires an understanding of how mobile robots fail in field environments.*

This paper provides a detailed investigation of how ground-based mobile robots fail in the field. Forty-four representative examples of failures from 13 studies of mobile robot reliability in the USAR and MOUT domains are gathered, examined, and classified. A novel taxonomy sufficient to cover any failure a ground-based mobile robot may encounter in the field is presented. This classification scheme draws from established standards in the dependability computing [30] and human-computer interaction [40] communities, as well as recent work [6] in the robotics domain. Both physical failures (failures within the robotic system) and human failures are considered.

Overall robot reliability in field environments is low with between 6 and 20 hours mean time between failures (MTBF), depending on the criteria used to determine if a failure has occurred. Common issues with existing platforms appear to be the following: unstable control systems, chassis and effectors designed and tested for a narrow range of environmental conditions, limited wireless communication range in urban environments,

and insufficient wireless bandwidth. Effectors and the control system are the most common sources of physical failures. Of the human failures examined, *slips* are more common than *mistakes*. Two-thirds of the failures examined in [6] and [7] could be repaired in the field. Failures which resulted in the suspension of the robot's task until the repair was completed are also more common with 94% of the failures reported in [13].

# Chapter One

# Introduction

This thesis provides a detailed investigation of how ground-based mobile robots fail in the field. Forty-four representative examples of failures from 13 studies of mobile robot reliability in the Urban Search and Rescue (USAR) and Military Operations in Urban Terrain (MOUT) domains are gathered, classified, and examined. A novel taxonomy is presented and used which draws from the dependability computing [30], human-computer interaction [40], and robotics [6] communities and is sufficient to cover any failure a ground-based mobile robot may encounter in the field. Both physical failures (failures within the robotic system) and human failures are considered.

The 13 studies come from two primary sources. The Center for Robot-Assisted Search and Rescue (CRASAR) at the University of South Florida provided five of the studies. CRASAR spends more than 200 hours per year using the robots in the field and currently has twenty-one robots from six manufacturers. The other eight come from the Test and Evaluation Coordination Office (TECO), part of the Maneuver Support Center at Fort Leonard Wood. TECO provides operational test and evaluation expertise to the Chemical, Engineer and Military Police Schools and assists in the development and execution of Advanced Warfighting Experiments (AWE) for the US Army.

Overall robot reliability in field environments is low with between 6 and 20 hours mean time between failures (MTBF), depending on the criteria used to determine if a failure has occurred. Common issues with existing platforms appear to be the following: unstable control systems, chassis and effectors designed and tested for a narrow range of environmental conditions, limited wireless communication range in urban environments, and insufficient wireless bandwidth. Effectors and the control system are the most common sources of physical failures. Of the human failures examined, *slips* are more common than *mistakes*. Two-thirds of the failures examined in CRASAR's reliability studies [6][7] could be repaired in the field. Failures which resulted in the suspension of the robot's task until the repair was completed are also more common with 94% of the failures reported in TECO's M1 PANTHER II study [13].

## 1.1 Motivation

The considerable risk to human life associated with modern MOUT and USAR has led professionals in each of these domains to explore the use of advanced technology, like robotics, to improve safety. Mobile robots are appealing for USAR and the military because they can be sent either ahead of or in place of humans in particularly hazardous situations. They are also capable of doing things humans cannot, like enduring low oxygen environments (without support equipment) and working for indefinitely long shifts without becoming fatigued (if provided sufficient power). Mobile robots can send back a wide variety of data from their on-board sensors. Despite the lure of these features, only a few mobile robots have been used in real USAR (e.g. the World Trade Center rescue response [34][8]) and military operations (such as cave reconnaissance in Afghanistan [2]). The final acceptance of robot technology in these new application areas will depend as much on their reliability, as on the capabilities of the robot platform (such as the ability to detect chemical or biological agents). A fragile robot in constant need of maintenance and repair is likely to be left behind to make room for more reliable equipment.

There are a variety of factors which make *field work* particularly challenging for robots as opposed to *lab conditions*. For example, conditions which a robot may

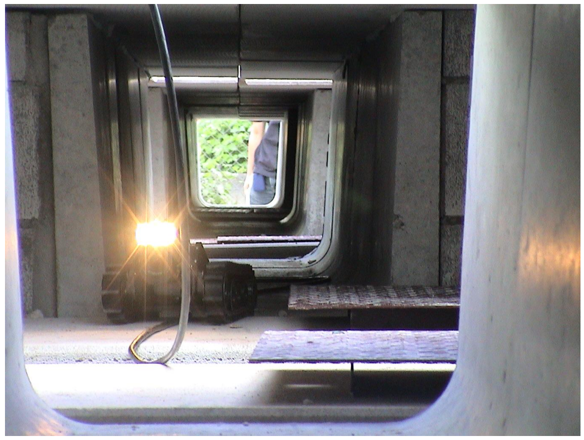

Figure 1. An Inuktun MicroVGTV Inside a Confined Space Training Maze.

Figure 2. An iRobot Packbot Climbing a Rubble Pile Used for USAR Training.

encounter in a field environment for USAR and/or MOUT include: dirt, standing water, rain, intense heat, intense cold, confined spaces (see Figure 1), uneven surfaces (see Figure 2), the presence of obstacles with unpredictable movement, and hostile agents.

Recent studies on mobile robot use in the field have shown a noticeable lack of reliability in real field conditions. In [6] the mean time between failures (MTBF) for field robots was a little over 6 hours and the availability rate was only 50%. The analysis in [34] showed that tethered robots required assistance through the tether an average of 2.8 times per minute. Studies performed by TECO have found a MTBF less than 20 hours.

*Improving mobile robot reliability for applications such as USAR and MOUT requires an understanding of how mobile robots fail in field environments.*

## 1.2 Research Question

*How do ground-based mobile robots fail in the field?*

Understanding mobile robot field failures requires knowledge of the causes of failures and their characteristics. These characteristics include the frequency, symptoms, and impact of each type of failure. It is also important to know how the robots' operating environment, and decisions made during their design affect these characteristics. A wide variety of platforms must be examined to isolate traits of failures that span all ground-based mobile robots which could be used in the field. The organizations which operate in hazardous domains, like USAR, rely heavily on interaction [9]. Even a fully autonomous mobile robot must still interact with and take orders from humans [37]. Therefore, not only the failures of the robot platform but also human operator errors must be considered when examining mobile robot reliability in these domains.

## 1.3 Contribution

This work provides two major contributions:

1. A taxonomy of robot failures built from a synthesis of failure taxonomies in three separate communities within the field of Computer Science.

2. A meta-study including 44 representative examples of mobile robot field failures drawn from 13 studies in the USAR and MOUT domains, arguably two of the most challenging field domains for ground-based mobile robots. These examples demonstrate how mobile robot failures can be classified using the new taxonomy and the challenges associated with using robots in field environments.

The taxonomy was created from experience in the *robotics* [6], *human-computer interaction* [40] and *dependability computing* [30] communities. Failures are categorized based on the source of failure (physical and human). Two attributes, *repairability* and *impact*, are used to capture the severity and repercussions of the physical failures. Though the taxonomy was designed to cover only field failures, it is expected to be sufficient to cover any application of mobile robots.

Information on how and when mobile robots fail helps to identify the weaknesses of current mobile robot technology, which in turn, illuminates the challenges which robot manufacturers and developers of fault-tolerant control systems must meet to improve their reliability. In addition, potential adopters of mobile robot technology can benefit from an unbiased, quantitative assessment of current technology. This gives them the ability to balance the capabilities a mobile robot will bring to their application domain against the actual cost of maintaining the equipment.

Data on how mobile robots fail can also be used to provide a realistic starting point for fault modeling in model-based fault tolerance systems, such as [25], [32], [48], [51], [54], and [61]. In addition, robot fault-tolerance approaches which use costly diagnosis techniques, like active probing (gathering additional information from other sensors or robots) used by Long and Murphy [31], would also benefit from the incorporation of probability data to rank hypotheses, reducing the cost of diagnosis by ensuring that the most likely hypotheses are checked first.

## 1.4 Overview of Analysis Method

This thesis examines mobile robot failure data from 13 studies from the Center for Robot-Assisted Search and Rescue (CRASAR) at the University of South Florida and the Test and Evaluation Coordination Office at Fort Leonard Wood [42]. These include the CRASAR's World Trade Center (WTC) studies [34][8], field experiments with

Hillsborough County Fire Rescue Department [10], and reliability analyses [6][7]; as well as TECO's eight mobile robot studies described in [42]. A total of 28 robots were considered in this thesis, representing 15 different models from seven manufacturers. They range from small (less than 10 pounds) tracked vehicles capable of changing their geometry, to a modified M1 tank (over 60 tons).

For the purposes of this paper, a field environment is defined as *an environment which has* not *been modified to ensure the safety of the robot or to enhance its performance*, and a *failure* is *the inability of the robot or its support equipment to function normally*. Note that both complete breakdowns and noticeable degradations are included.

As discussed in Section 1.3 a novel taxonomy of mobile robot failures was developed for this meta-study. The taxonomy shown in Figure 3 uses *classes* to capture the source of the failure which can be either *physical* (system or robot) or *human*. Five subclasses, based on common subsystems found in all robot systems, fall within the physical branch. These are *effector, sensor, control system*, *power*, and *communications*. Human failures are divided into *design* and *interaction* subclasses, the latter of which is further subdivided into *mistakes* and *slips*. Two *attributes* are also included to describe the severity of the physical failures in terms of its *repairability* and *impact* on the robot's mission at the time of the failure. The values given to these attributes are *field-repairable* and *non-field-repairable*, and *terminal* and *non-terminal* respectively.

Due to differences in data collection and reporting methods among the studies, quantitative analysis of the failure data was often not possible. Therefore, the majority of the findings are based on examination of the examples of field failures described in each of the studies. Where quantitative results could be generated, standard formulas taken from [24] were used to convert the data into common reliability metrics. One such metric was the mean time between failures (MTBF), which provides a rough estimate of how long one can expect to use a robot without encountering failures. Projected availability,

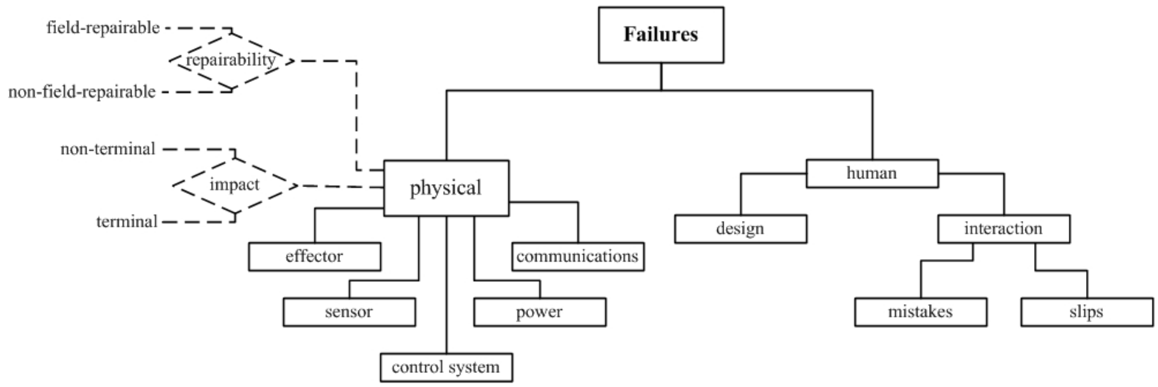


Figure 3. The Taxonomy of Mobile Robot Failures Used in this Analysis. *Classes* are shown with solid lines, and *attributes* with dashed lines.

also called reliability, was also used. This metric is reported as a percentage and should be interpreted as the probability that the robot will be free of failures at a particular point in time. All other quantitative results, such as the average downtime and probability that a failure was caused by a component in class (from the taxonomy) $c$, were also calculated using standard formulas.

## 1.5 Thesis Organization

Chapter Two provides an overview of related work in robot reliability, failure and reliability analysis approaches, and fault tolerant systems, establishing the uniqueness and potential benefits of a detailed study on how mobile robots fail in the field within the larger robotics community. Chapter Three describes the new method for examining mobile robot failures used in this meta-study including some basic criteria, a novel taxonomy developed for mobile robot failures, and formulas used to summarize the failure data in terms of reliability metrics. In Chapter Four, the 13 studies included in this meta-study are described in detail, including the robots examined, the information available from each study, their approach to failure documentation and analysis, and a summary of important results. Chapter Five presents 44 representative examples of mobile robot field failures from the 13 studies, and any numeric results available. Its organization follows the new taxonomy exactly, providing an example of how the taxonomy can be used to classify failure events and, in turn, using those examples to highlight the characteristics of failures which fall into each class. Finally, in Chapter Six, a summary of the findings of this meta-study is given followed by a discussion of the implications of these findings and recommended avenues for improvement. Chapter Six closes with an overview of future work on this topic.

# Chapter Two

# Related Literature

This chapter provides an overview of related work in robot reliability, failure and reliability analysis approaches, and fault tolerant systems. It establishes both the uniqueness and potential benefits of a detailed study on how mobile robots fail in the field within the larger robotics community. Section 2.1 compares related work on robot failure analysis and reliability. Section 2.2 examines approaches to failure and reliability analysis found in the literature, looking for suitable techniques for a meta-study of mobile robot field failures. Section 2.3 presents relevant work in fault-tolerance systems for mobile robots. Finally, Section 2.4 provides a summary of the results of this literature review.

Section 2.1 presents studies found in the literature which attempt to characterize and improve robot reliability, excluding the 13 studies included in this meta-study. This includes studies which seek to improve robot reliability through failure and reliability analyses, as well as qualitative studies of mobile robot suitability. It is shown that this thesis is unique in three respects: both human and robot failures are examined, it covers robot failures in the urban search and rescue (USAR) and military operations in urban terrain (MOUT) domains, and it is the only meta-study that covers mobile robot failures.

Section 2.2 covers two distinct approaches to failure and reliability analysis found in the literature: characterization and formal validation. Characterization approaches from the dependability computing, human-computer interaction, and robotics communities are presented. These classify failures based on a pre-defined set of categories. Formal validation approaches from the robotics and control theoretic literature are also included.

These create a complete model of the system to be studied and then examine that model to determine if it meets reliability criteria. This section establishes that no existing approach is suitable for the task of mobile robot field failure analysis. The classification schemes developed for dependability computing and HCI are not sufficient, and formal validation methods can only be applied to a single system (e.g. robot model) and/or a single task at a time. This establishes the need for a new method of robot failure analysis. This thesis contributes such a method that is described in detail in Chapter Three.

Failures appear most often in the robotics literature in studies which endeavor to create fault-tolerance systems that can detect, isolate, and/or recover from failures. Fault-tolerance work, presented in Section 2.3, is of interest to this meta-study for two reasons. First, a fault-tolerance system is created for failures with certain characteristics. It is of interest to see if the community as a whole agrees on common characteristics of robot failures. Second, fault-tolerance researchers and developers are a potential consumer of the results of this study.

This section reveals that, while none of the studies discussed presented any evidence of having investigated the kinds of failures robots encounter, each approach made certain assumptions about the characteristics of those failures. It is concluded that the fault-tolerance community can benefit from this meta-study, which provides information on common failures for field domains like USAR and MOUT. Fault-tolerance systems which use probabilistic modeling, in particular, can use the frequency of failures and relative probability of failure for robot subsystems presented in Chapter Five as high-fidelity estimates for USAR and MOUT environments.

## 2.1 Robot Failure and Qualitative Evaluation Studies

This section covers studies which are related to this meta-study by having similar goals, namely to characterize and improve robot reliability. Specifically, Sections 2.1.1 and 2.1.2

cover studies that seek to improve robot reliability through failure and reliability analyses respectively. In Section 2.1.3 qualitative studies of mobile robot suitability for the USAR domain are presented. The studies covered in this section are not included in the meta-study for one of two reasons: they study robots used in indoor, controlled environments; or they present shortcomings of mobile robots for USAR based on the characteristics of the domain, rather than the examination of documented failures.

### 2.1.1 Multiple Data Source Robotic Manipulator Failure Analyses

Two studies were found in the literature that, like this meta-study, examined robot failures from multiple sources. Both covered industrial manipulators used primarily in the automotive industry. Beauchamp and Stobbe [1] examined documented human-robot system accidents from nine different studies. Starr, Wynne, and Kennedy [52] surveyed failure and maintenance reports from two large automotive plants.

In [1] Beauchamp and Stobbe present a review of human factors[1] experimental studies on human-robot system accidents, where the robot is an automated industrial manipulator. The review included two types of studies: studies of documented human-robot system accidents (nine summarized), and related human-factors experiments (11 included). The focus of the paper was the latter. The review of the human-robot accident studies served mainly as motivation for additional work in human-factors on industrial manipulator systems. The findings of each of the nine studies were summarized individually. No classification scheme was developed to describe the documented accidents. Neither the rate of failure nor the impact of the failures (on the human involved or plant productivity) was determined. A quick summary of the accident studies provided the following overall findings: most accidents occur during programming (training the

[1]Human factors is a field of study involving research into human psychological, social, physical, and biological characteristics, and working to apply that information to the design, operation, and use of products or systems to optimize human performance and safety.

manipulator to perform a task) and/or maintenance, when a person is likely to be found within the operating envelope (area in which the robot's arm could move) of the manipulator; and the accidents frequently involved unexpected robot movement which was caused by either equipment failure (maintenance) or human error (programming).

Starr, *et al.* present in [52] a survey of the failures of robotic industrial manipulators. The survey includes failure and maintenance reports from two automotive plants. The data covered 200 robots from five manufacturers over a period of 21 weeks for Plant A and 5 weeks for Plant B. In Plant A, the robots were found to be down for repair or maintenance for 3.95 hours per week per manufacturing line, and in Plant B, the downtime rate was 1.74 hours. Robot usage was not recorded, therefore the mean-time between failures could not be determined. The analysis created eight categories to summarize the 60 and 100 different codes (used to indicate the type of failure) used in Plant A and Plant B, respectively. Non-robot failures (80% of all failures encountered) were placed in their own category and were not analyzed further. Of the robot failures, position failures were the most common at 45%, followed by drive system (hardware) failures at 25%. The data from Plant B were also analyzed in groups by manufacturer. The differences in the results for each manufacturer were determined to be due to differences in the manipulators' tasks (spot welding versus transportation) and drive system (electrical versus hydraulic). For example, the hydraulic robots had double the number of failures recorded per manufacturing line compared to the electric robots.

Tables 1 and 2 provide a summary of the differences between the two studies covered in this section and this meta-study. Table 1 lists the type of robot, type of failures (robot or human), and the method used to synthesize the data for further analysis. Table 2 provides additional information for comparison in terms of the number of robots and the failure attributes examined. These tables show that this meta-study covers mobile robot failures in a more complete (including both human and robots failures) and organized

Table 1. Comparison of Related Studies Including Synthesis Method, and Robot and Failure Types. Manipulators refers to automated industrial manipulators.

| Study | Robot Type | Failure Type | Synthesis Method |
|---|---|---|---|
| Beauchamp and Stobbe[1] | Manipulators | Human only | None |
| Starr *et al.*[52] | Manipulators | Robot only | Classified using categories developed for this analysis |
| This meta-study | Mobile robots | Human and Robot Field Failures | Classified using a complete failure taxonomy |

Table 2. Comparison of Related Studies: Number of Robots and Failure Attributes Examined.

| Study | # Robots | Failure Attributes Examined | | |
|---|---|---|---|---|
| | | Frequency | Impact | Relative Frequency of Categories |
| Beauchamp and Stobbe[1] | Unknown | No | No | No |
| Starr *et al.*[52] | 200 from 5 manu. | No | Yes | Yes |
| This meta-study | 28 from 7 manu. | Yes | Yes | Yes |

fashion than the two studies of industrial manipulator failures. Table 2 also shows that Starr *et al.*'s study is larger in scope in terms of the number of robots examined. This is due to the fact that industrial manipulators have been accepted as essential tools in the automotive industry. No such industry exists today for mobile robots.

### 2.1.2 Single Data Source Mobile Robot Reliability Studies

The Workshop on Robots in Exhibitions at IROS[2] in September of 2002 produced two studies on the reliability of mobile robots actively used for long periods of time. Nourbakhsh [41] describes a set of four autonomous robots used for a period of five years as full-time museum docents. Their robots reached a mean time between failures (MTBF)

[2] IEEE/RSJ International Conference on Intelligent Robots and Systems

of 72 to 216 hours. Tomatis, Terrien, Piguet, Burnier, Bouabdallah, and Siegwart in [58] describe a similar project. As compared to the scope of this meta-study, the analysis described by Tomatis et.al. was more narrow both in the applications and the robots analyzed. The operating environment was also indoors and engineered to assist the robot. However, their MTBF was 7 hours — similar to the 8.3 hour MTBF found in the original reliability study [6] performed by the Center for Robot-Assisted Search and Rescue (CRASAR).

### 2.1.3 Qualitative Evaluation of Mobile Robots for USAR

Three studies have concentrated on identifying the weaknesses of ground-based mobile robots for USAR based solely on the characteristics of the robot and the constraints of the domain. Blitch provides a survey in [2] of the mobility problems keeping current robot technology from populating well-suited niches within USAR, especially the confined space access niche. Tumble recovery, traction, and the (incorrect) assumption of an obstacle-free working envelope are identified as the key problems. Casper, Micire, and Murphy [9] present an overview of the USAR domain, listing tasks that robots are best suited for, followed by a discussion of the constraints that application domain places on robotic technology. Sensors are identified as the area which requires the most improvement, though weather-proofing and an invertible chassis were also mentioned as required features rarely found in robots at that time. In [37] Murphy, Casper, Hyams, Micire, and Minten discuss the same issues as Casper *et al.* [9] but provide some additional discussion on the need for *adjustable autonomy*, or the ability to change the allocation of control between the robot and its operator.

Table 3 provides a summary of the papers discussed in this section, including this meta-study, for comparison. The types of robots analyzed, the variety of models, the target environment or application domain, the kinds of failures (human or robot) examined, and

Table 3. Comparison of Robot Failure and Qualitative Evaluation Studies. For the meta-studies, the number of data sources is indicated in parentheses after the group name.

| Group | Robots | Models | Environment | Failures | Analysis |
|---|---|---|---|---|---|
| This meta-study (13) | Mobile robots | Varied | USAR & MOUT | Human and Robot | Failure |
| Multiple-source Studies[1][52] (13 total) | Industrial Manipulators | Varied | Factory | Human or Robot | Failure |
| Single-source Studies[41][58] | Mobile robots | Single | Museum | Robot | Reliability |
| Qualitative Evaluation [2][9][37] | Mobile robots | Varied | USAR | Robot | Suitability |

the analysis type are included. Table 3 shows that this meta-study is unique in that it covers both human and robot failures, it is focused on robot field failures in the USAR and military operations in urban terrain (MOUT) domains, and it is the only meta-study that covers mobile robot failures.

## 2.2 Failure Analysis Approaches

This section covers the two distinct approaches to failure and reliability analysis found in the literature: characterization and formal validation. Characterization approaches (Section 2.2.1) group or classify documented failures based on a pre-defined set of categories, usually examining the set of failures as a whole and each group individually. Formal validation approaches (Section 2.2.2) create a model of the system to be studied and then examine that model to determine if it meets reliability criteria. Formal validation approaches are useful for analysis of a single specified task which can be explicitly modeled. For characterization approaches the generality of the categories is the only limit to the kinds of failures that can be examined in a single study. This meta-study deals with mobile robots used in a wide variety of environments for a wide variety of tasks, which is why this study employs a characterization approach.

### 2.2.1 Failure Characterization and Classification

This section presents existing classification schemes of failures which were developed for the dependability computing, robotics, and human-computer interaction (HCI) communities. In most failure analyses, like Starr *et al.*[52], the categories used for classification were developed through examination of the common attributes of the set of failures to be examined. These classification schemes tend to be limited to the scope of the set of failures, and the results of such analyses are difficult to apply to other applications or domains. Therefore this subsection only includes relevant failure classification schemes created for an entire class of failures, such as human-computer interaction failures, rather than those created for a specific failure analysis.

In 1984, Laprie [30] and his colleagues developed a set of concepts and definitions related to the dependability of computer-based systems. According to Laprie a fault is simply a cause, an error is a state, and a failure is an event. Specifically, a failure is defined as *a deviation from the specified service as seen by the client*. The client may be a human user or another component of the computer system that is trying to use the service. An error is *a state within the system which can lead to a failure*. A fault is *anything which could cause the system to enter an error state*. Laprie defines two major fault classes, namely *physical faults* and *human-made faults*. Human-made faults are further subdivided into *design faults* and *interaction faults*. [30] defines two levels for severity for failures. The consequences of *benign failures* are comparable to the benefits of the service they are preventing. *Malign* or *catastrophic* failures have a higher cost by one or more orders of magnitude than the service.

Laprie's dependability taxonomy is general enough that it can be applied to a large variety of systems and application domains. Unfortunately, it is not detailed enough for analyzing mobile robot reliability in the field. For example, a mobile robot can suffer from an infinite variety of physical faults. Laprie's levels of severity are also difficult to apply since the benefit of a service and the cost of a failure tend to vary widely based on the situation, that is a military training exercise versus a real engagement. Nevertheless, it provides a solid foundation, so the taxonomy used in this paper (see Section 3.2) draws a great deal from [30].

In [28] Kokkinaki and Valavanis present the error specification used in their reliability validation approach for computer-integrated manufacturing (CIM) systems. Their specification is interesting in that it is similar to Laprie's. Faults and errors have roughly the same definitions and [28] states that faults may be caused by a physical defect, the environment, or an operator though no explicit taxonomy of causes is created. Faults are classified temporally as *permanent* which exist until repaired, *transient* which disappear on their own, and *intermittent* which repeatedly appear. Errors are classified based on their scope of influence: *null-point errors* do not affect the system, *single-point errors* are localized to a single agent (task) within the system, and *multiple-point errors* affect more than one agent. A failure is defined as *an error that spans one or more agents in the current plan* (set of tasks the machine is currently executing). A failure is *recoverable* if the system can complete the plan in spite of the failure, *irrecoverable* if it cannot, and *catastrophic* if all agents are effected by the error.

In previous work by Carlson and Murphy [6] a classification scheme was used to examine failures encountered during day-to-day use of mobile robots in lab, office, and USAR environments. A *failure* was defined as *the inability of the robot or the equipment used with the robot to function normally*. Categories were defined to capture the source of the failure based on the common subsystems of a mobile robot: *effector* (a.k.a. actuator), *sensor, control system*, *power*, and *communications*. Two attributes were used to capture the severity of the failures in terms of repairability, *field-repairable* versus *non-field-repairable*, and its impact on the robot's mission, *terminal* versus *non-terminal*. This scheme was first verified through interviews with experienced robot operators and hardware specialists. The latter were graduate students with extensive experience maintaining and repairing robot platforms. The scheme was then validated through its application on a wide range of failures recorded over a two year period.

In [40] Norman draws from cognitive psychology, pointing out the weaknesses and strengths of the subconscious and conscious minds. In [40] he discusses the types and sources of human error, classifying them as *slips* (errors in execution of a selected action) and *mistakes* (errors in selection of the appropriate action). This classification scheme has been widely accepted by the HCI community.

### 2.2.2 Reliability Validation Methods

Formal validation methods have been developed for a wide variety of applications relevant to mobile robotics: software, industrial manipulators, computer-integrated manufacturing (CIM) systems, and autonomous systems in general. Some examples include the automata-based validation approach for CIM systems presented by Kokkinaki and Valavanis in [28]; and probability-based approaches presented by Sheldon, Mei, and Yang in [49] and Tchangani in [54].

Petri nets appear to be a preferred tool for validation. In [45] Ramaswamy and Valavanis present a hierarchical time-extended petri net designed to both analyze and provide fault identification and recovery capabilities for discrete event dynamic (DED) systems. González, Mediavilla, Fraile, Gayubo, Turiel, and García defined in [20] a petri net model of a multi-manipulator system in which three manipulators work together within the same area (cell) to cooperate on a task. The effect of soft and hard failures, and periodic maintenance are examined in terms of throughput of the system.

Simmons, Pecheur, and Srinivasan [50] present the use of Symbolic Model Checking to verify autonomous systems. The main goal of [50] was to create translators which accept source code for an autonomous system, and convert it to SMV (a specific Symbolic Model Checking system) specifications. Two target languages, and subsequently applications, were tested: the Model-based Processing Language (MPL) used to build Livingstone, the model-based fault diagnosis and recovery system used on Deep Space One (DS1); and the Task Description Language (TDL), an extension of C++ designed to implement the management layer (task decomposition, synchronization, monitoring, and exception handling) of autonomous mobile robot systems.

Tables 4 and 5 provide a summary of the failure and reliability analysis approaches presented in this section. Table 4 gives the target application of the analysis approach, the applicability (scope) of the results of an analysis which uses the approach, and the types of failures covered. Table 5 presents the strengths and weaknesses of each approach in the context of studying how mobile robots fail in the field. These tables show that no existing approach to failure analysis is suitable for this task. The classification schemes developed for dependability computing and HCI are complete for their respective areas, but are not sufficient for categorizing mobile robot failures in the field. Formal validation methods are restricted to systems and applications which can be described using their modeling technique (petri nets, Baysian networks, etc.), and can only be applied to a single system (e.g. robot model) and/or task at a time. A study of mobile robot reliability for USAR and MOUT applications in general simply cannot be completed using these methods. Therefore, the strategy taken in this meta-study, and described in detail in Chapter Three, is a characterization approach which defines its own novel taxonomy drawn from the classification schemes presented in Section 2.2.1.

Table 4. Comparison of Failure and Reliability Analysis Approaches. HCI refers to human-computer interaction. CIM refers to computer-integrated manufacturing systems. DED refers to discrete event dynamic systems.

| Approach | Application or Domain | Scope of Results | Failures Covered |
|---|---|---|---|
| Laprie [30] | Dependability Computing | General | System and Human |
| Carlson [6] | Mobile robots | General | Robot |
| Norman [40] | HCI | General | Human |
| Kokkinaki and Valavanis [28] | CIM | Specific to a system | System |
| Sheldon *et al.* [49] | Software | Specific to a system | Software |
| Tchangani [54] | General | Specific to a system | System |
| Ramaswamy and Valavanis [45] | DED | Specific to a system | System |
| González *et al.* [20] | Manipulators | Specific to a system | System |
| Simmons *et al.* [50] | Autonomous systems | Specific to a system | Software |

Table 5. Strengths and Weaknesses of Analysis Approaches.

| Approach | Strengths | Weaknesses |
|---|---|---|
| Laprie [30] | Completeness, widely accepted | Not detailed enough for mobile robot applications |
| Norman [40] | Completeness, widely accepted | Does not cover system failures |
| Kokkinaki and Valavanis [28] | Can validate a system's reliability | System-specific, Complete model required |
| Sheldon *et al.* [49] | Can validate a system's reliability | System-specific, Complete model required |
| Tchangani [54] | Can validate a system's reliability | System-specific, Complete model required |
| Ramaswamy and Valavanis [45] | Can validate a system's reliability | System-specific, Complete model required |
| González *et al.* [20] | Can validate a system's reliability | System-specific, Complete model required |
| Simmons *et al.* [50] | Can validate a system's reliability | System-specific, Few languages supported |

## 2.3 Fault-tolerance Systems

The majority of failure-related work encountered in the robotics literature is focused on creating fault-tolerance systems that can detect, isolate, and/or recover from failures. Fault-tolerance work is of interest to this meta-study for two reasons. First, each study that produces a fault-tolerance system for robots has assumed certain characteristics of robot failures to be true. For example, a method may require that all fault states be modeled, assuming that novel failures are scarce or uninteresting. It is of interest to see if the community as a whole agrees on these characteristics. Second, fault-tolerance researchers and developers are potential consumers of the results of this study. The community as a whole can benefit from knowledge of documented failures that would, for example, help them to determine if the majority of failures are easy or difficult to detect and diagnose, or could be handled by automatic recovery. This section provides a brief overview of the last six years of work in this area, grouped by approach. Purely model-based methods are covered in Section 2.3.1. Hybrid approaches are covered in Section 2.3.2. Fault-tolerance systems which use expert systems techniques for the Artificial Intelligence community are presented in Section 2.3.3. Data centric (processing and filtering) techniques for fault-tolerance are presented in Section 2.3.4. Finally, relevant work in the new field of *Autonomic Computing*, which is developing systems that are self-configuring, self-protecting, self-optimizing, and self-healing, is surveyed in Section 2.3.5.

### 2.3.1 Model-based Fault-tolerance Systems

The majority of fault-tolerance systems found in the literature are model-based. These methods use models of the target system to predict the correct values for input data. These predictions are compared to real data from the target system to detect and isolate potential faults. Failures are typically assumed to be caused by actuator or sensor faults, though technically the range of failures that can be diagnosed depends only on the constraints of the modeling method. Catastrophic failures are typically assumed to be either trivial to detect or impossible to recover from, so the majority of recent efforts are focused on minor failures which are difficult to detect and diagnose, as in slow degradations or intermittent failures. Model-based methods assume that novel failures are scarce and difficult to automatically recover from and are therefore of less interest than known failures. These methods also assume that everything that needs to be known to accurately detect and diagnose failures can be modeled.

Some examples of purely model-based fault-tolerance systems include Kawabata, Akamatsu, and Asama's [27] model-based diagnosis system for an autonomous mobile robot which breaks down a complete robot system into modules that can be modeled (expected output for a given input is known). In [61] Washington presents a preliminary attempt to create a fault detection system for rovers using a combination of Markov models and Kalman filters.

Three purely model-based methods were designed specifically for wheeled mobile robots. Dixon, Walker, and Dawson [17] developed a mathematical model of mobility faults to detect changes in the wheel's radius, and slipping or skidding faults. Goel, Dedeoglu, Roumeliotis, and Sukhatme in [19] use a Multiple Model Adaptive Estimation technique based on a set of eight Kalman filters, each with a model of expected values for normal and fault states (sensor and flat-tire failures), whose output is filtered through a neural network to decide the state of the robot. Meng, Zhen, Biswas, and Sarkar describe a fault-tolerance system in [26] where bond-graphs are used to model the robot system, and temporal casual graphs (TCG's) are used to detect and isolate faults in motors.

### 2.3.2 Hybrid Fault-tolerance Systems

Purely model-based methods fail when a novel failure is encountered or when the model is inaccurate. Hybrid fault-tolerance systems which use qualitative reasoning or learning methods along with models have been developed to help eliminate this weakness. These approaches tend to assume, like purely model-based approaches, that interesting failures are difficult to detect and diagnose. Unmodeled effects like the environment, and states like novel failures are assumed to be important. On the other hand, these approaches tend to assume that those effects will remain stable over time or will change slowly enough for training to compensate.

Deuker, Perrier, and Amy [16] present a neuro-symbolic hybrid system for diagnosis of faults in unmanned underwater vehicles. Combastel, Gentil, and Rognon in [12] present a fuzzy logic, model-based approach to fault isolation in electrical systems. Wang, Yamasaki, Yumoto, Ohkawa, Komoda, and Myasaka present in [60] a stochastic qualitative reasoning method which tracks the state of a real time system. In [29] Lamine and Kabanza describe a monitoring system based on temporal fuzzy logic for use with behavior-based robots.

Some approaches use training to mitigate the effects of inaccurate and incomplete models. Mackey, James, Park, and Zak present in [32] an overview of an extensive architecture for failure prediction, detection, and isolation for autonomous systems which uses both quantitative modeling, qualitative reasoning, and training methods. Other techniques work only at the symbolic level, using only casual or partial causal models of the target system. A multiple robot fault-tolerance system presented by Long and Murphy in [31] uses only partial casual models of the system combined with active diagnosis (probing) to isolate faults.

### 2.3.3 Expert System Based Fault-tolerance Systems

Expert system based fault-tolerance systems capture the diagnosis process used by human experts. Diagnosis techniques that take this approach are more common in medical diagnosis and have not, to date, been developed specifically for robotic systems. Nevertheless, they do have an advantage for challenging field domains like USAR and MOUT (where full-automation is not possible in the immediate future) in that they are easier for humans to interact with. Three fault-tolerance systems which use this approach are of particular interest because they have a promising feature for mobile robotics applications ([47] and [46]) or have been used in field environments [21]. In [47] Rymon presents a system for assisting physicians in the treatment of patients with multiple traumas. This approach is of interest because it is recovery-based in that it is not concerned with finding the source of the problem, but instead focuses on the steps required to return the subject (patient) to a normal state. Reed [46] presents a diagnosis method that correctly identifies multiple defects using a recognition-based reasoning module trained from an existing knowledge base. Multiple-simultaneous fault diagnosis is still considered to be a difficult problem in robot fault-tolerance systems. Helfman, Baur, Dumer, Hanratty, and Ingham [21] describe an expert diagnostic system which has actually been fielded by the US Army.

### 2.3.4 Data Centric Fault-tolerance Systems

Data centric fault-tolerance approaches are focused on using incoming data to detect and isolate anomalies. These fault-tolerance approaches assume that failure states present distinctly different data signatures from normal states and each other, and that all the data needed to find those signatures are present in the system. Hung and Zhao [23] present a diagnostic approach for systems with large amounts of data coming in from similar and/or distinct sets of sensors which uses a combination of existing signal processing and reasoning techniques. Madden and Nolan describe a learning algorithm called IFT in [33] which creates fault trees from classified raw sensor data. In [51] Soika presents a failure detection framework based on probabilistic analysis of correlation between redundant sensor readings.

#### 2.3.5 Fault-tolerance in Autonomic Computing

Another area of research concerned with the reliability of systems is *Autonomic Computing*. Researchers in this new field are interested in creating systems that are self-configuring, self-protecting, self-optimizing, and (most importantly for this paper) self-healing. It is the self-reflective nature of this approach that makes its eventual application to intelligent robotics likely. To date, work in the Autonomic Computing community on self-healing is preliminary in nature. It has not yet established the characteristics that will eventually set it apart from the broader fault-tolerance community, therefore its applicability to this meta-study is the same as that of the larger fault-tolerance community. This section provides a survey of current work in this area, for future reference.

Candea [5] has developed an application-generic Java-based fault detection and recovery system designed to enable web-based service providers to develop systems that are robust to transient software failures. In comparison to traditional fault-tolerance approaches, Candea's is a hybrid model-based system. In [18] Dong's model-based approach to self-healing uses software agents developed to handle a specific type of failure by detecting, analyzing, and recovering from those failures. Tohma [57] describes a data driven means of achieving fault tolerance in distributed Autonomic Computing environments where many duplicate service providers are available. The paper presents mechanisms which can be used to ensure that the system's registry only provides “healthy” alternatives to clients. A simple voting scheme among peers is used to identify (and subsequently exclude) faulty service providers.

Other research efforts in Autonomic Computing have provided high-level views of how to approach the problem of self-healing. Sterritt [53] discusses how the new field of Autonomic Computing can be used to achieve the goals of Dependable Computing. The paper strongly advocates grounding the new field on the concepts and definitions of key terms like dependability, failures, errors, faults, and tolerance (see Laprie’s work [30]) long established in the older field. Minsky [35] concludes that self-healing will be impossible without imposing some form of regularity in the system. Minsky’s solution is a system which provides that regularity via laws which are analogous to the basic laws of nature. The paper presents a system designed to enforce those laws.

Tables 6 and 7 summarize the general fault-tolerance approaches presented in this section as they relate to this study. Table 6 lists each approach’s assumptions about the failures they were designed to handle. Table 7 provides a synopsis of the benefits this study can provide to researchers and designers of each approach to fault-tolerance for mobile robots. As Table 6 shows, researchers in this area do not agree on the characteristics of failures a fault-tolerance system should be able to handle. None of the studies discussed in this section presented any evidence of having investigated the kinds of failures robots encounter. Therefore, it is likely that their approach was determined by their background (e.g. control theoretics for model-based and hybrid systems or AI for expert systems) instead of experience with robot failures. Table 7 shows that this is one of several reasons that the fault-tolerance community can benefit from this meta-study. All the approaches can benefit from knowledge of common failures for a target domain. Model-based and hybrid approaches in particular can use the frequency of failures and relative probability of failure for robot subsystems presented in Chapter Five as high-fidelity estimates for USAR and MOUT environments.

Table 6. Assumptions Made by Fault-tolerance Approaches About Mobile Robot Failures.

| Approach | Assumptions about failures |
|---|---|
| Model-based | All factors that affect failures can be modeled.<br>Detection and diagnosis of interesting failures is hard.<br>Novel failures are scarce and difficult to automatically recover from.<br>Actuator and sensor failures are common. |
| Hybrid | Novel failures are important.<br>Detection and diagnosis of interesting failures is hard.<br>Some factors that affect failures cannot be modeled accurately.<br>Factors that affect failures are stable or change slowly enough for training to compensate. |
| Expert system | Human intervention may be needed for successful diagnosis and recovery.<br>Limited knowledge of the target system is required for diagnosis and recovery. |
| Data centric | Failure states present distinctly different data signatures from normal states and each other.<br>All the data needed to find those signatures are present in the system. |

Table 7. How Fault-tolerance Approaches Can Benefit from this Study.

| Approach | How approach can benefit from this study |
|---|---|
| Model-based and Hybrid | Typically uses probabilistic methods which require the probability of the system entering a given failure state.<br>Needs to know common failures to check for when modeling a system. |
| Expert system | If failures cannot be handled automatically, additional work in this area is needed to create technician support and operator alerting systems.<br>Needs to know common failures to check for when creating a knowledge base. |
| Data centric | Needs to know common failures to determine the sensors and other data required for detection and diagnosis. |

## 2.4 Summary

This Chapter has provided a summary of related work including seven studies on robot reliability, nine failure and reliability analysis approaches, and 22 fault tolerant systems for mobile robots. It has established the uniqueness and potential benefits of this thesis, a detailed study on how mobile robots fail in field environments, within the larger robotics community.

Two studies were found in the literature that, like this meta-study, examined robot failures from multiple sources. Both covered industrial manipulators used primarily in the automotive industry. Beauchamp and Stobbe [1] examined documented human-robot system accidents from nine different studies. Starr, Wynne, and Kennedy [52] surveyed failure and maintenance reports from two large automotive plants. These meta-studies were found to be less complete, only human or robot failures were considered, though Starr *et al.*'s study examined more robots total (200 compared to the 28 considered here). Overall Section 2.1 established that this thesis is unique in three respects: it covers both human and robot failures, is focused on robot field failures in the USAR and MOUT domains, and is the only meta-study that covers mobile robot failures.

Section 2.2 examined existing failure classification schemes from the dependability computing [30], human-computer interaction (HCI) [40], and robotics [6] communities, as well as relevant reliability validation methods from the robotics and control theoretic literature. This section established that no existing approach to failure analysis is suitable for the task of examining mobile robot field failures. The classification schemes developed for dependability computing and HCI are not detailed and complete enough, respectively. Formal validation methods are restricted to applications which can be specified using their respective modeling technique, and can only be applied to a single system (e.g. robot model) and/or a single task at a time. Therefore, this meta-study uses a new characterization approach, and described in detail in Chapter Three, which defines its own novel taxonomy drawn from the classification schemes presented in this section.

Fault-tolerance work is of interest to this meta-study for two reasons. Each study which produces a fault-tolerance system for robots has assumed certain characteristics of robot failures. Fault-tolerance researchers and developers are potential consumers of the results of this study. Section 2.3 provides a brief overview of the last six years of work in this area, grouped by approach. Also included is a brief synopsis of recent work in the new field of Autonomic Computing on self-healing systems. It is concluded that researchers in this area do not agree on the characteristics of failures a fault-tolerance system should be able to handle, and that none of the studies presented evidence of having investigated the kinds of failures robots encounter. Therefore, all the fault-tolerant approaches can benefit from knowledge of common failures for a target domain. In particular, fault-tolerance approaches that use probabilities to detect and/or diagnose failure can use the frequency of failures and relative probability of failure for robot subsystems presented in Chapter Five as high-fidelity estimates for USAR and MOUT applications. Examples of these would be [25], [32], [51], [54], and [61]. In addition, approaches which use active probing, namely Long and Murphy [31], would also benefit from the incorporation of probability data to rank hypotheses, reducing the cost of diagnosis by ensuring that the most likely hypotheses are checked first.

# Chapter Three

## Taxonomy of Failures and Metrics

This chapter describes the approach taken in this thesis to examine mobile robot failures in the urban search and rescue (USAR) and military operations is urban terrain (MOUT) application domains. As discussed in Chapter Two, existing approaches for failure analysis in the dependability computing [30], human-computer interaction [40], and robotics [6] domains are not detailed or complete enough for the purposes of this meta-study. The past experience in each of these domains was applied to create the new approach.

This approach was developed iteratively as examples and results were gathered from the 13 studies that make up this meta-study. As a result, it is both a tool used to create the findings of this thesis, and a product of those findings. The fact that no approach for mobile robot failure analysis existed when the 13 studies were performed was a serious drawback to this work. Each study used its own approach, few of which were described in sufficient detail to allow conversion of the results into a common framework. This chapter endeavors to create a precisely defined and easily applied approach to mobile robot failure analysis which others can use in their particular application domain without similar difficulties.

Section 3.1 provides definitions of key terms like mobile robots, field environments, and failure used throughout the paper. Next, the novel taxonomy of mobile robot failures, one contribution of this thesis, drawn from the *robotics*, *human-computer interaction* and *dependability computing* communities will be presented in Section 3.2.

The taxonomy uses classes to capture the source of the failure which can be either physical (system or robot) or human. Two attributes are also included to describe the severity of the failure in terms of its repairability and impact. Finally, Section 3.3 describes the formulas used to convert the available raw failure and usage data into reliability metrics.

## 3.1 Terminology

This section will define a few of the key terms used throughout the rest of the thesis. For a complete list of definitions see Appendix A.

All of the platforms described in Section 4.1 can be considered to be mobile robots. A mobile robot is defined as *a mechanical device that can sense and interact with its environment*. It may possess any level of autonomy with respect to its human operator(s), from manual (where the human has complete control) to fully autonomous (where the robot can carry out assigned tasks on its own). All of the robots can also be called unmanned ground vehicles (UGV's) which are ground-based mobile robots. The majority of the robots considered in all 13 studies are teleoperated, or *manually controlled by an operator at a distance that is too great for the operator to see what the robot is doing* [36].

This paper is primarily concerned with mobile robots used in field environments. A field environment is defined as *an environment which has* not *been modified to ensure the safety of the robot or to enhance its performance*. Conditions a robot may encounter in USAR or MOUT field environments include: dirt, standing water, rain, intense heat, intense cold, confined spaces (see Figure 4), uneven surfaces (see Figure 5), the presence of obstacles with unpredictable movement, and hostile agents. Field robots used by the military and for USAR have to be packed and transported to remote locations. Robots designed for field environments are assumed to work outdoors, though generally not in

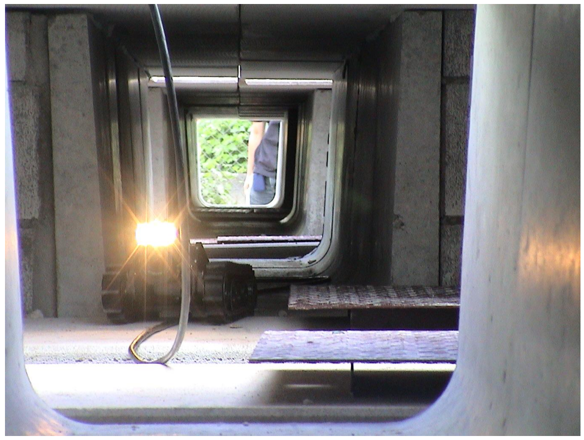

Figure 4. A Confined Space Training Maze.

Figure 5. A Rubble Pile Used for USAR Training.

rain or snow. They are expected to handle rough terrain, tolerate dirt and dust, and even multi-story falls.

Reliability metrics are susceptible to differences in the criteria used to determine if an event can be called a failure. Where standard criteria do not exist, reliability studies will necessarily select criteria based on the needs of the individual or group assessing the usefulness of the technology for a new task. In these cases, it is difficult to directly compare results across studies or to apply findings to new applications. This meta-study uses a general definition of failure so that the findings reported here can be readily applied and compared to results from similar studies.

For the purposes of this paper, a *failure* is defined as *the inability of the robot or its support equipment to function normally*. Both complete breakdowns and noticeable degradations are included. An example of a complete breakdown encountered in the MicroVGTV's is a failure of the control system where the robot becomes unresponsive, or freezes. An example of a noticeable degradation is a faulty camera cable causing signal loss from a camera mounted on a robot. The rest of the robot platform, including any additional cameras, would not be affected by this failure. Such degradations may or may not affect the robot's ability to complete a task. A task which requires stereo vision, for example, could not be performed with a single camera.

*Support equipment* is defined as *equipment that is not physically part of the robot and is required for the robot to complete its mission or task.* This includes traditional support equipment like tethers and operator control units (OCU's). Support equipment also includes maintenance equipment required to keep the robot operational, such as battery chargers and recording equipment. In most scientific, USAR, and MOUT scenarios there are often many stakeholders (individuals who are interested in and are influenced by the robot's actions). The varied information needed by each stakeholder (e.g. commanding officer, medical doctor, and human-robot interaction researcher) is rarely deliverable in real time; therefore recording equipment is often required for the robot's mission.

Rigorously applying specific criteria to a new domain or application area is a challenging task. For example, the reliability studies [6][7] relied on the judgment of experienced robot operators. The operators were asked to apply this definition of failure as they saw fit, based on their knowledge of the robot platform. In cases where the normal behavior of the robot can be described in measurable terms (e.g. rate of progress toward goal or the amount of information processed from incoming sensors), a more precise definition of failure can be enforced. For the field applications covered in this paper, this information is not available. Test and Evaluation Coordination Office's studies at Fort Leonard Wood [43] and the Center for Robot-Assisted Search and Rescue (CRASAR) [4], which provided the 13 studies examined in this thesis, have begun the process of identifying the characteristics of normal use of robots in the field domains of MOUT and USAR respectively, but their work is still in the preliminary stages.

## 3.2 Taxonomy of Failures

In order to gain insight from robot failures, individual failures cannot be treated as unique events. Meaningful common attributes must be found and used to categorize failures into well defined groups. To provide a foundation for such insights, this section defines a classification or taxonomy which can be meaningfully applied to any failure that a mobile robot used in the field might encounter. The taxonomy, shown in Figure 6, was created not only from experience within the *robotics* [6][7] community, but it also draws from the *human-computer interaction* [40] and *dependability computing* [30] communities as well. Though the taxonomy was designed to cover the range of field failures, it is expected to be sufficient for any application of mobile robots.

The taxonomy uses *classes* to capture the source of failure (or what Laprie [30] would call the *fault*), which is first divided into physical and human branches, following dependability computing practice. Physical failures are further subdivided based on common systems found in all mobile robot platforms, these being *effector, sensor, control system, power,* and *communications*. The following definitions were used to classify individual physical failures:

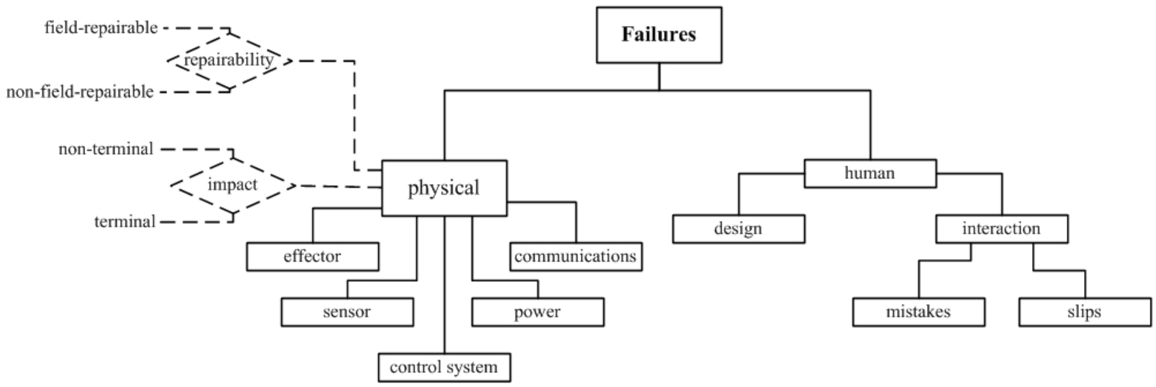


Figure 6. The Taxonomy of Mobile Robot Failures Used in this Analysis. Classes are shown with solid lines, and attributes with dashed lines.

1. *Effector.* Any devices that perform actuation and any connections related to those devices. Examples would be the motors, grippers, and treads or wheels.

2. *Control system.* Any devices or manufacturer-provided software that issue commands (at the symbolic or signal level) to other devices or software within the robot system and/or support operator interaction with the system. For example, an on-board computer, joystick, motor controller, or display unit.

3. *Sensor.* Any devices that sense the robot's state or the state of the environment and any connections related to those devices. Examples would be cameras and laser range finders.

4. *Power.* Any component that affects the power system of the robot. Examples would be the batteries, chargers, and various connections allowing the robot to be powered.

5. *Communications.* Any devices that provide communication between the robot and its OCU's. Examples would be tethers and wireless access points.

Using Laprie's categorization from dependability computing, human failures are subdivided into *design* and *interaction*. Design failures are caused by faults created during the design of a robot system, and are not covered in any of the studies this paper examines. Drawing from Norman's taxonomy [40], which is widely accepted in the human-computer interaction community, interaction is subdivided into mistakes and slips. *Mistakes* are caused by fallacies in conscious processing, such as misunderstanding the situation and doing the wrong thing. *Slips* are caused by fallacies in unconscious processing, where the operator attempted to do the right thing but was unsuccessful.

Each failure, physical or human, falls into exactly one of these classes. Physical failures also have two *attributes*, *repairability* and *impact*. The impact of the physical failure is evaluated based on its effect on the robot's assigned task or mission. A *terminal* robot failure is one that *terminates the robot's current mission*. A *non-terminal* failure *introduces some noticeable degradation of the robot's capability to perform its mission*. The repairability of the failure is described as *field-repairable* and *non-field-repairable*. A failure is considered to be field-repairable if it can be repaired under the following conditions:

1. *Only the equipment that commonly accompanies the robot into the field is available.* For example, if a small robot which is transported in a single backpack encounters a failure, that failure can only be labeled as field-repairable if the tools required for the repair are part of a small toolkit that fits in the backpack along with the robot and its support equipment.

2. *Favorable environmental conditions.* The environmental conditions are considered to be *favorable* if *all conditions, such as dampness (e.g. from rain) and light level, do not interfere with or prevent the repair*. Very few failures could be classified as field-repairable if they had to be repairable under the worst environmental conditions encountered in USAR and MOUT environments. Therefore, this constraint was included to keep the classification process simple, while ensuring

that a failure's repairability depends only on the difficulty of the repair process, not on the time and location of the repair.

3. *The only personnel available are trained operators.* This means that the expertise required to complete the repair has to be part of an operator's training for that type of robot.

It should be noted that packing procedures and operator training requirements were not standardized for robots in USAR and MOUT scenarios prior to this meta-study. Therefore, the field-repairable classification, as defined here, cannot be applied directly to the examples found in the 13 studies. Instead, the repairability results presented in Chapter Five were generated based on whether or not each failure was repaired in the field, termed *field-repaired* versus *non-field-repaired*. For now, this provides a deterministic estimator for each example failure's repairability.

This taxonomy is used in Chapter Five to classify and study mobile robot failures in the field. For CRASAR's reliability studies [6][7], CRASAR's field experiments with the Hillsborough County Fire Rescue Department (HCFRD) [10], and TECO's studies [42] it was used to place each failure reported into a single class (or leaf) from Figure 6. The classification of the data from CRASAR's World Trade Center (WTC) studies [34][8] was more difficult. Aside from four notable terminal failures, these studies recorded the operator's response to minor problems, rather than the failures themselves. Also, the data presented in the WTC studies only appears in terms of the categories defined in the WTC Engineering study [34]. The details needed to classify the more common failures themselves are missing. For this reason, the categories used in the WTC studies could fall into several classes within the taxonomy, depending on the circumstances surrounding each individual failure.

## 3.3 Calculations

This section will present the calculations used to transform raw failure and usage data into reliability metrics for mobile robots used in the field. These equations were originally and primarily used to analyze the data in the reliability studies [6][7] presented in detail in Section 4.6. They were also used to summarize any data provided by the HCFRD study [10], the WTC studies [34][8], and TECO's studies [42] (see Section 4.2).

All the formulas were taken from the IEEE standards presented in [24]. The mean time between failures or MTBF is calculated by equation (1). This metric provides a rough estimate of how long one can expect to use a robot without encountering failures. This formula was slightly modified, as defined in equation (2), for the follow-up reliability study [7] in order to perform statistical analysis on the results. All other MTBF statistics reported in this paper were calculated using equation (1). Another metric presented in this paper is the failure rate, which is simply the inverse of MTBF.

$$MTBF = \frac{\text{Number of Hours Robot Was in Use}}{\text{Number of Failures}} \tag{1}$$

$$MTBF = \frac{\sum_{i=2}^{n} \text{Hours Usage Between } F_i \text{ and } F_{i-1}}{\text{Number of Failures}}, \{F_1, F_2, \ldots, F_n\} \text{ are failures} \tag{2}$$

The projected availability of the robot is calculated by equation (4), where the mean time to repair, *MTTR* is defined by equation (3). Availability, also called reliability, should be interpreted as the probability that the robot will be free of failures at a particular point in time. Average downtime is the average amount of time between the occurrence of the failure and the completion of the repair that fixed it (see equation (5)).

$$MTTR = \frac{\text{Number of Hours Spent Repairing}}{\text{Number of Repairs}} \tag{3}$$

$$Availability = \frac{\text{MTBF}}{\text{MTBF + MTTR}} \cdot 100\% \tag{4}$$

$$AverageDowntime = \frac{\sum_{i=1}^{n} \text{Time Repair of } F_i \text{ Completed} - \text{Time } F_i \text{ Occurred}}{\text{Number of Repairs}} \tag{5}$$

Other values derived for this meta-study were calculated using standard formulas. For example, the probability that a failure was caused by a component from class (from the taxonomy, e.g. sensor, effector, slip, etc.) $c$ is simply (6).

$$P(c|failure) = \frac{\text{Number of Failures Caused by a component from c}}{\text{Total Number of Failures}} \tag{6}$$

## 3.4 Summary

This chapter describes the approach taken in this thesis to examine mobile robot failures in the field. The fact that no existing approach for mobile robot failure analysis was present at the time of the 13 studies was a serious drawback to this work. Each study used its own approach, few of which were described in sufficient detail to allow conversion of the results into a common framework. Therefore this approach was developed iteratively as examples and results were gathered from the 13 studies which make up this meta-study. As a result this taxonomy is both a tool used to create the findings of this thesis, and a product of those findings.

Section 3.1 provided definitions of key terms like mobile robots, field environments, and failure used throughout the paper. Failure is defined as *the inability of the robot or its support equipment to function normally*. Section 3.2 presented the novel taxonomy of mobile robot failures, one contribution of this thesis, drawing existing failure classification schemes from the *robotics*, *human-computer interaction* and *dependability computing* communities. The taxonomy uses classes to capture the source of the failure that can be either *physical* (system or robot) or *human*. Five subclasses, based on common subsystems found in all robot systems, fall within the physical branch. These are *effector, sensor, control system*, *power*, and *communications*. Human failures are divided into *design* and *interaction* subclasses, the latter of which is further subdivided into *mistakes* and *slips*. Two attributes are also included to describe the severity of a physical failure in terms of its *repairability* and *impact* on the robot's mission at the time of the failure. The values given to these attributes are *field-repairable* and *non-field-repairable*, and *terminal* and *non-terminal* respectively.

Section 3.3 describes the formulas used to convert the available raw failure and usage data into reliability metrics which were taken from the IEEE standards presented in [24]. One metric used was the mean time between failures (MTBF), which provides a rough estimate of how long one can expect to use a robot without encountering failures. Projected availability, also called reliability, was also used. This metric is reported as a percentage and should be interpreted as the probability that the robot will be free of failures at a particular point in time. The average downtime and probability that a failure was caused by a component from class $c$ were calculated using standard formulas.

# Chapter Four

# Source Studies

This chapter provides a detailed description of the information examined in this thesis. As this is a meta-study of mobile robot failures in the field, the information was gathered from 13 studies of mobile robot use in field environments. The chapter begins in Section 4.1 by describing the 28 ground-based mobile robots covered by this meta-study. Section 4.2 then provides an overview of the information available from each of the 13 studies. Finally, the goals, experimental approach, and relevant results and findings are presented for each study in Sections 4.3 through 4.6.

The studies come from two primary sources. The Center for Robot-Assisted Search and Rescue (CRASAR) at the University of South Florida, which studies the use of robot technology in urban search and rescue (USAR) applications and spends more than 200 hours a year in the field, provided five of the 13 studies. These include two studies of the robot-assisted response to the World Trade Center (WTC) disaster (covered in Section 4.3), two reliability studies of day-to-day use of mobile robots (Section 4.6), and a set of field experiments conducted with the Hillsborough County Fire Rescue Department (HCFRD) described in Section 4.5. The remaining eight (Section 4.4) were provided by the Test and Evaluation Coordination Office (TECO) at Fort Leonard Wood [42], which periodically conducts experiments to determine the suitability of a robotic platform for use in specified military operations (e.g. military operations in urban terrain or MOUT).

## 4.1 Robots Surveyed

This section describes the total of 28 robots considered in this paper. They represent 15 different models from seven manufacturers and range from small (less than 10 pounds) tracked vehicles capable of changing their geometry, to a modified M1 tank (over 60 tonnes). The list of robot models appears in Table 8 with the model name, manufacturer, total number of robots (over all studies), and the studies which analyzed the use of that model. CRASAR's reliability studies [6][7] are referred to as Reliability. CRASAR's WTC analyses [34][8] and HCFRD study [10] are denoted by WTC and HCFRD respectively. TECO's studies are collectively referred to as TECO. Table 9 presents basic information on each model including the size, weight, communication method, and traction method. The size of a robot is *man-packable*, *man-portable*, or *not man-portable* [34]. A man-packable robot can be safely carried by one or two people in backpacks. Man-portable robots are larger and cannot be easily carried into the field by a person. They can be transported in a HUMMV or personal car and one or more persons can safely lift them in and out of the vehicle. Robots which are *not* man-portable require additional (usually specialized) equipment for transport, e.g. a heavy truck or trailer.

The smallest robots examined are Inuktun's MicroTracs and MicroVGTV platforms (Figure 7) which are no larger than 15.5 by 30.5 cm. Both are tracked vehicles without onboard computers. Both have a microphone, speaker, a motor-driven manual-focus CCD camera, and a camera tilt unit with halogen lighting. MicroVGTV platforms also have the ability to adjust the shape of their chassis to raise or lower the camera tilt unit and change the track profile. MicroVGTV's are commercially available and were originally designed for chemical and nuclear inspection. The MicroTracs platform was an experimental design which attempted to meet Blitch's criteria [2] for USAR and MOUT scenarios. Both are built from experience; over ten years of

Table 8. The Robots Examined in this Meta-study. The column denoted by # contains the number of robots of that model included in this meta-study.

| Model | Manufacturer | # | Studies |
|---|---|---|---|
| MicroTracs | Inuktun | 1 | Reliability,HCFRD,WTC |
| MicroVGTV | Inuktun | 3 | Reliability,HCFRD,WTC |
| Urban | iRobot | 5 | Reliability,HCFRD,TECO |
| SOLEM | Foster-Miller | 2 | WTC,TECO |
| URBOT | Foster-Miller | 2 | TECO |
| Packbot | iRobot | 4 | Reliability |
| MATILDA | Mesa Assoc. | 1 | TECO |
| Talon | Foster-Miller | 1 | TECO |
| ATRV-Jr | iRobot | 1 | Reliability |
| ATRV | iRobot | 1 | Reliability |
| SARGE | Yamaha | 1 | TECO |
| ARTS | All Seasons Vehicles | 1 | TECO |
| DEUCE | Caterpillar | 2 | TECO |
| D-7G | Caterpillar | 1 | TECO |
| PANTHER | US Army | 2 | TECO |
| Summary | | 28 | |

Table 9. The Robots' Characteristics.

| Model | Size | Weight(lbs) | Comms | Traction |
|---|---|---|---|---|
| MicroTracs | man-packable | 8 | Tether | Track |
| MicroVGTV | man-packable | 8 | Tether | Track |
| SOLEM | man-packable | 33 | Both | Track |
| URBOT | man-packable | 33 | Both | Track |
| Urban | man-packable | 35 | Wireless | Track |
| Packbot | man-packable | 42 | Both | Track |
| MATILDA | man-packable | 50 | Wireless | Track |
| Talon | man-portable | 85 | Both | Track |
| ATRV-Jr | man-portable | 110 | Both | Wheel |
| ATRV | man-portable | 260 | Both | Wheel |
| SARGE | man-portable | 298 | Wireless | Wheel |
| ARTS | not man-portable | 5,800 | Wireless | Track |
| DEUCE | not man-portable | 35,000 | Wireless | Track |
| D-7G | not man-portable | 59,000 | Wireless | Track |
| PANTHER | not man-portable | 60,000 | Wireless | Track |

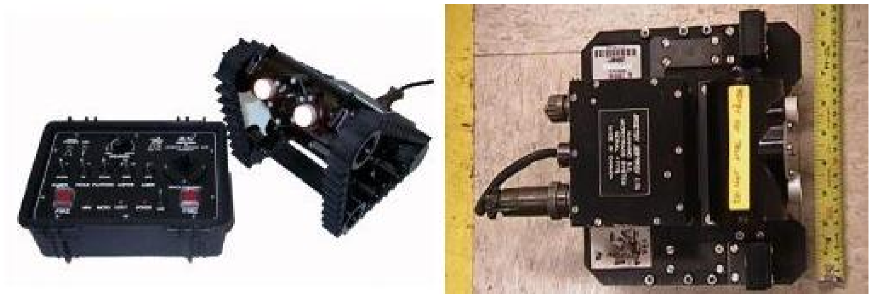

Figure 7. Inuktun MicroVGTV (left) and MicroTracs (right) Robots. MicroVGTV photo courtesy of Inuktun Services Ltd.

development work with similar platforms proceeded the design of these robots. Though they have limited sensing capabilities, both have been shown to be very useful in a variety of USAR scenarios (with roughly 400 hours of field usage logged to date by CRASAR). Their small size enables them to explore areas humans and dogs simply cannot fit inside. They are also the most portable. The robot and all support equipment that is needed can be packed into a single backpack and carried into the field.

The next size group includes the SOLEM and URBOT (Figure 8) from Foster-Miller Incorporated, the Urban and its successor the Packbot (Figure 9) from iRobot Corporation, and MATILDA (Figure 10) from Mesa Associates. All are tracked vehicles which carry one or more cameras and lighting. The Urbans also have a set of 13 sonar range sensors. All were developed between 1999 and 2001 for military operations, specifically MOUT, and continue to undergo modifications. These robots require two people to carry the robot and its support equipment into the field and therefore are at the limit of what can be considered man-packable. They typically use wireless communications to connect to the operator control unit (OCU). They carry their own batteries and a computer inside their chassis. An onboard computer and larger sensor payload capabilities, than Inuktun’s platforms, enable these robots to function with varied levels of autonomy. (The term autonomy applied to mobile robots is the level of

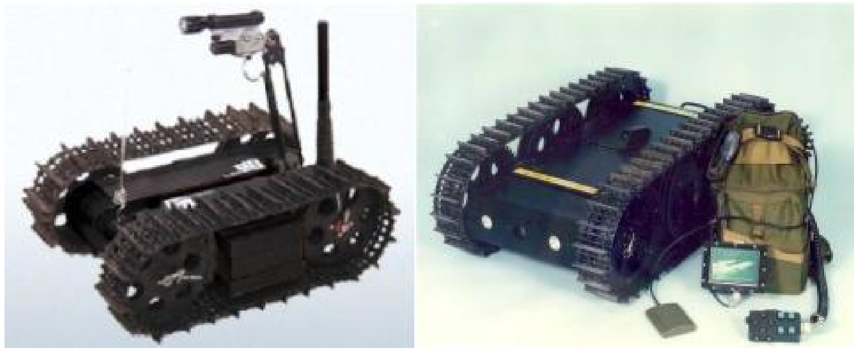

Figure 8. Foster-Miller Solem (left) and URBOT Built on a Solem Base (right). Solem photo courtesy of Foster-Miller. URBOT photo courtesy of US Unmanned Ground Vehicles / Systems Joint Project Office (UGV/S JPO).

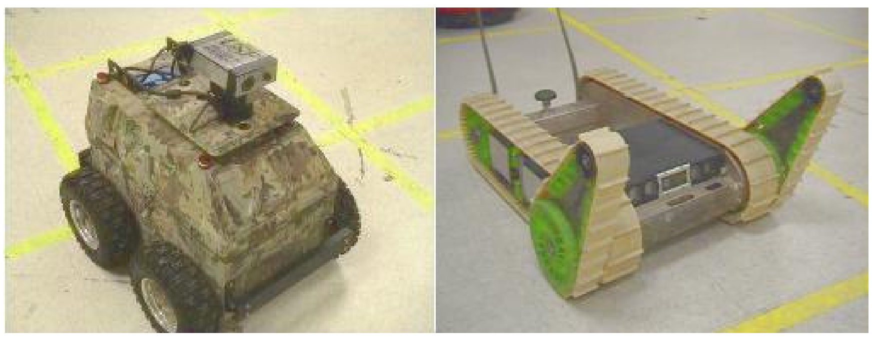

Figure 9. iRobot ATRV-Jr (left). iRobot Packbot (right) Exploring a Rubble Pile.

supervision required by humans.) Though high levels of autonomy (e.g. navigation and planning) are still largely experimental and therefore have rarely been used to date in the field, they can ease the workload of the operator and enable one operator to control groups of robots.

The Talon (Figure 10) from Foster-Miller, ATRV-Jr (Figure 9) and ATRV from iRobot, and SARGE (Figure 11) are man-portable. All the robots in this group carry onboard computers and one or more cameras. They have a wider range and increased flexibility compared to the man-packable robots due to their ability to carry more batteries, sensors, and effectors. Talon and the ATRV-Jr are small enough to be used for

Figure 10. Foster-Miller MATILDA (left) and Talon (right). MATILDA photo courtesy of UGV/S JPO. Talon photo courtesy of Foster-Miller.

both indoor and outdoor applications. The ATRV and SARGE are much larger platforms which can only operate in wide open areas but can be modified to carry smaller robots. These heterogeneous groups, usually referred to as *marsupial*, have the larger range of the “mother” robot as well as the maneuverability of the “baby” robots. The man-portable group varies in maturity from the Talon which was developed around 1999, to the ATRV’s which have been in production for about six years, to SARGE which is built on a mature recreational All Terrain Vehicle platform.

The largest group of robots is made up of the ARTS, DEUCE (Figure 12), D7-G, and PANTHER (Figure 13). All of these platforms have been adapted from commercially available heavy construction equipment or military platforms. They require special equipment to transport and weigh in excess of 5 tons. These platforms are too large for typical USAR or squad-level MOUT scenarios. TECO has equipped each of them with a standard teleoperation interface and tested them for demining and debris clearing tasks.

## 4.2 Information Available by Study

This section presents an overview of the information available from the 13 studies which have examined mobile robot use in the field. Table 10 outlines the data collection and

Figure 11. SARGE is Built on a Yamaha Breeze ATV Base. SARGE Photo courtesy of UGV/S JPO.

Figure 12. ARTS Built on a All Seasons Vehicles MD-70 Base (left) and Caterpillar DEUCE (right). ARTS photo taken from TECO's ARTS study [59]. DEUCE photo courtesy of Caterpillar.

Figure 13. Caterpillar D-7G and PANTHER Built on a US Army M1 Tank Base. Photos courtesy of UGV/S JPO.

Table 10. Overview of Data Collection Method Information Available from Each Study. Rel. refers to CRASAR's reliability studies.

| Study | Failure Defined | Failures Classified | Perspective | Granularity of Data Collection |
|---|---|---|---|---|
| Rel.[6][7] | Yes | Yes | Engineering | Hours |
| WTC[34][8] | Yes | Yes | Both | Seconds |
| HCFRD[10] | Yes | Yes | HRI | Hours |
| PANTHER[13] | No | Yes | Both | Unknown |
| DEUCE[14] | No | No | Both | Unknown |
| ARTS[59] | No | No | Both | Unknown |
| CBRNLOE[55] | No | No | Both | Unknown |
| D7[3] | No | No | Both | Unknown |
| SARGE[44] | No | No | Both | Unknown |
| UGVROP[62] | No | No | Both | Unknown |
| URBOT[43] | No | No | Both | Unknown |

analysis methods used in each study. For each study, whether or not a definition of failures was provided; whether or not the failures were classified; the perspective of the study as in engineering, human-robot interaction (HRI), or both; and the granularity of the data collection process are included. Table 11 provides an overview of the information that was available and examined for this meta-study. The availability of usage information, count and descriptions of failures, and the format of the results are included.

These tables show that key information is missing from most of TECO's studies [42] including: the definition of failure used, data collection methods, and numeric results. They also show that the reliability studies [6][7] and the WTC studies [34][8] differed in both data collection and result generation methods. For this reason, a true comparative study cannot be performed directly on this set of studies. A goal for this meta-study was to gather as much information as possible from the material available, and use that information to begin developing standard methods for collecting and analyzing mobile robot failure information. The taxonomy presented in Section 3.2 is the result of that effort.

Table 11. Overview of Data and Analysis Information Available from Each Study. Rel. refers to CRASAR's reliability studies.

| Study | Source Data Available | | | Results Presented As |
|---|---|---|---|---|
| | Usage | # Failures | Descriptions | |
| Rel. Original[6] | Yes | Yes | Yes | Standard reliability metrics |
| Rel. Follow-up[7] | Yes | Yes | Yes | Above and statistical analysis |
| WTC[34][8] | No | No | No | Frequency and percentages |
| HCFRD[10] | Yes | Yes | Some | List |
| PANTHER[13] | Yes | Yes | Yes | Summary |
| DEUCE[14] | Partial | Yes | No | Summary |
| ARTS[59] | No | No | No | Summary |
| CBRNLOE[55] | No | No | No | Summary |
| D7[3] | No | No | No | Summary |
| SARGE[44] | No | No | No | Summary |
| UGVROP[62] | No | No | No | Summary |
| URBOT[43] | No | No | No | Summary |

## 4.3 CRASAR WTC Studies

Two studies were generated from *post-hoc* analysis of data collected during CRASAR's robot-assisted search and rescue response at the WTC. A detailed analysis on the failures encountered by CRASAR while using robots was reported in the WTC Engineering study [34]. The WTC Human-Robot Interaction (HRI) study [8] examined the human-robot interaction and human-human interaction between the robots, their operators, and the other USAR professionals that worked with CRASAR during the rescue phase of the WTC response. The studies cover four robots from two manufacturers representing three different models. The data span a period of nine days between September 12th and 21st of 2001. The Engineering study contributed seven overall findings and a detailed taxonomy of the environmental and robot relationships. The HRI study provides seventeen findings and eleven recommendations for future work.

### 4.3.1 Approach

The WTC studies [34][8] both drew in varying amounts from three sources: video of the robots' camera view, field notes, and interviews of the robots' operators. Video of the robots' camera view was recorded each time a robot was deployed (used to search a hole in the rubble). This resulted in 5.5 hours of video available for analysis. Two sets of field notes were opportunistically maintained by CRASAR members. As this data were analyzed, the operators were interviewed for additional details or to clarify ambiguous cues in the recorded video and field notes.

The WTC HRI study [8] examined all the data in terms of the operating environment and conditions, agents and skills (human and robot), which of the traditional USAR tasks the robots were used to perform, overall workflow, and communications. The WTC Engineering study focused primarily on the video data, attempting to identify cues for minor to serious failures on the part of the robot or the robot's operator. For the Engineering analysis a failure was defined as *any event which hindered the progress of the robot in its search task*. Two levels of severity were defined: *catastrophic* and *significant*. A catastrophic failure *required that the robot be removed from the void it was searching* in order to be repaired [34]. A significant failure *introduced sub-optimal performance*[34] but did not keep the robot from continuing its mission. During the response, new techniques were developed for operating tethered robots. These allowed the person feeding the tether to assist the robot operator in overcoming problems. This individual was referred to as the *tether manager*.

Five categories were defined for the significant common failures encountered while using the small Inuktun robots. Two categories were provided for failures where the tether manager was required to assist the robot through the tether: *gravity assist* and *stuck* *assist*. The other three categories were *track slippage*, *occluded camera*, and *incorrect lighting*. They were defined in [34] as follows:

1. *Gravity assist.* Events that occur when the tether manager is required to provide support for the robot through the tether. Reported as the number of instances of these events.

2. *Stuck assist.* Events which occur when the tether manager must use the tether to free the robot from some obstacle or terrain that does not permit the robot to move. Reported as the number of instances of these events.

3. *Track slippage.* The amount of time that the track mechanisms do not have sufficient contact with the ground surface. Reported as a sum of the duration of each instance in minutes.

4. *Occluded camera.* Amount of time that the camera view is completely occluded by objects and debris. Reported as a sum of the duration of each instance in minutes.

5. *Incorrect lighting.* Amount of time that the lights were completely off or in a transition between intensities. Reported as a sum of the duration of each instance in minutes.

This taxonomy was defined for the MicroTracs and MicroVGTV as well as the fine-grained data collection methods used in the WTC video analysis. It therefore cannot be applied to the other 11 studies covered in this paper.

It should be noted that Inuktun's robots were not designed to perform USAR search tasks. Thus, the definition of failure used in the WTC Engineering study [34] is technically a broader definition of failure than the one used in this paper (see Section 3.1). For the purposes of this meta-study, the WTC Engineering study's definition of failure is accepted. This is done in the interests of eventually producing robots which *can* be expected to perform better under the extreme conditions encountered during the WTC rescue response.

### 4.3.2 Summary of Results

This section will report the overall results of the WTC Engineering study. In studying these results it is important to keep in mind that the robot and its operator were treated as one system in the WTC Engineering study. Not all of the minor problems referred to in Table 12 were the fault of the robot or the physical components that make up the robot. Some failures were the fault of the humans that interacted with it, and others could not be helped due to the extreme working conditions.

In the WTC Engineering study [34] the frequency and impact of failures was analyzed on a much smaller scale than the other 11 studies covered in this thesis. This analysis revealed that the robots often encountered minor problems (such as track slippage), 1.4 times per minute on average. Table 12 presents overall statistics from this analysis. The data is broken down by *attempt*. An attempt is an event in which a robot is inserted into a void in order to search that void. Only attempts for which there are recorded data are included. They are numbered sequentially for simplicity. See [34] for more details on the conditions under which each attempt occurred. The WTC Engineering study reported the duration (in seconds) of the track slippage, occluded camera, and lighting incorrect failure modes. The number of occurrences was not provided for these classes, though it was for gravity and stuck assists. Without access to the raw data, it is impossible to combine these two distinct measurements into a single statistic. Table 12 presents the best available summary of unclassified robot field failures from the robot-assisted response at the WTC. It includes the frequency per minute of gravity and

Table 12. Failures Encountered at WTC from [34].

| Model | Attempt | #/Min. | % of Time |
|---|---|---|---|
| MicroTrac | 1 | 1.8 | 0.7 |
| MicroTrac | 2 | 1.3 | 16.7 |
| MicroTrac | 3 | 1.3 | 4.0 |
| MicroTrac | 4 | 0.3 | 1.7 |
| MicroTrac | 5 | 4.7 | 21.3 |
| MicroTrac | 6 | 1.3 | 32.3 |
| MicroTrac | 7 | 0.0 | 13.3 |
| MicroVGTV | 8 | 0.1 | 0.7 |
| Overall Average | | 1.4 | 11.7 |

stuck assists; and the percentage of time spent in the track slippage, occluded camera, or lighting incorrect failure modes.

According to [34], assistance from the tether manager was needed an average of 2.8 times per minute. On average 11% of the search time was lost per attempt due to traction slippage, 18% due to camera occlusion, and 6% due to lighting adjustments.

An interesting attribute of the WTC Engineering study is that there were only four failures that would have been recorded without the detailed analysis that was performed on the video of the robots' camera view. The detailed video analysis uncovered 136 cases in which the tether manager had to assist the robot, and that 33% of the time was spent in failure modes (tracks slipping, camera occluded, etc.). These minor failures, not recorded by the other studies, had a significant impact on the robots' performance.

Several of the WTC HRI study [8] findings regarding the environment and conditions, robot skills, and communication are of interest in studying human failures in HRI. The environment was found to be benign as compared to most USAR environments. The only real environmental hazards encountered by CRASAR personnel were the dust, which could be managed with standard issue respirators, and the rubble itself. As for working conditions, CRASAR personnel were found to be cognitively fatigued mainly due to lack of sleep. It was also determined that none of the robots used at the WTC were designed or rated for use in USAR, and that key sensors that might have been needed could not be ported to the most suitable platforms for confined space operation. Considering these task analysis results, the performance of the robots as reported in the Engineering study are surprisingly good. Finally, the communication analysis revealed that two types of vital information were not getting from the robot to the operator: the state of the robot, and the state of the robot's environment.

The source for the data from the WTC studies [34][8] was not available. Therefore, statistics presented in Chapter Five are taken directly or derived from the information provided in the studies. Derived statistics were generated in the same manner as their counterparts in the reliability studies [6][7]. Chapter Three outlined the definitions, taxonomy, and calculations applied to derive the statistics.

### 4.4 TECO's Studies from Fort Leonard Wood

The results from eight studies conducted by the Test and Evaluation Coordination Office (TECO), part of the Maneuver Support Center at Fort Leonard Wood, have been posted to the Department of Defense Joint Robotics Program (JRP) library [42]. TECO provides operational test and evaluation expertise to the Chemical, Engineer and Military Police Schools and assists in the development and execution of Advanced Warfighting Experiments (AWE). The overall goal of their studies was to evaluate the feasibility of using the robotic platforms for their respective assigned tasks in the Future Combat System (FCS). The experiments focused on safety, maintenance, and possible tactics, techniques, and procedures (TTP's) for each platform.

These studies were performed on the following: an All-Purpose Remote Transport System (ARTS) for clearing and demining; integration of Chemical, Biological, Radiological, and Nuclear (CBRN) sensor modules on existing robot platforms (URBOT and MATILDA); the delivery of non-lethal munitions from an existing robot platform (SARGE); a UGV-based rapid obscuration system; a D-7G bulldozer, Deployable Universal Combat Earthmover (DEUCE), and an M1 tank (each equipped with a standardized teleoperation system); as well as a variety of smaller platforms (URBOT, Urban, SOLEM, and Talon). All of these studies were carried out in mock military operations which can be considered to be high-fidelity (close enough to a real scenario to produce similar results) field environments.

### 4.4.1 Approach

For all but the DEUCE study, experimental scenarios were developed and managed by TECO personnel and subject matter experts (where needed). Questionnaires and reports were developed and used to record: operator performance, operator feedback, platform and payload performance, and documentation of unanticipated events (e.g. equipment failure). These were used to develop the assessments and recommendations which appeared in each of the studies' Executive Summaries. Unfortunately, the raw data from these questionnaires and reports were not available. The documents stored in the JRP library [42] for each study consisted mainly of the Executive Summary, Pattern of Analysis (a detailed list of issues explored by the study), blank versions of any questionnaires or reports developed, and often pictures of the platform(s). Only the repositories for the CBRNLOE, DEUCE, and M1 PANTHER II studies included a complete Test Report. The following paragraphs provide a brief summary of each study.

*4.4.1.1 ARTS.* The All-Purpose Remote Transport System or ARTS platform was designed to conduct unmanned mine clearing and proofing (verifying that a given path is free of live mines), booby trap proofing, unmanned breaching of wire obstacles, and materials handling. The purpose of TECO's study [59] was to subject the unmanned platform to various terrain types and realistic missions over large distances. The study was also designed to determine which soil conditions and slopes the ARTS platform could handle.

*4.4.1.2 CBRNLOE.* In [55] TECO described a limited-objective experiment (LOE) on the integration of Chemical, Biological, Radiological, and Nuclear (CBRN) sensors on a ground-based mobile robot. The sensors were packaged as modules which could be easily added or removed from the robots' payload. Two small robot platforms were used: MATILDA and URBOT. The study was performed over a period of four days in a decommissioned coastal defense bunker in California. Two operators controlled the robots during the experiments. They were trained beforehand on the CBRN payload and robot teleoperation.

*4.4.1.3 D-7G.* The D-7G model bulldozer was modified for the purposes of remote mine clearing, rubble removal, and hazardous materials handling. TECO's study described in [3] was a follow-up on one that was completed a few months before. The purpose of the follow-up study was to evaluate the changes made to the optical system (recommended in the first study) and to explore night scenarios which were not conducted in the first study. In every other aspect the two studies were the same including the robot, operators, and scenarios designed to test the D-7's capabilities. Forward-looking infrared (FLIR) cameras were determined to be essential for night operations.

*4.4.1.4 DEUCE.* TECO's study of the Deployable Universal Combat Earthmover (DEUCE) platform [14] was exploratory in nature. It was designed to determine if DEUCE could support heavy forces in a combat environment while still meeting the weight requirements for transport and retain its top speed of 30mph (48 kph). Unlike the other studies the operator's tasks were not determined by TECO staff. A battalion from Fort Leonard Wood was using the platform during their National Testing Center (NTC) rotation, which lasts 28 days, at Fort Irwin. Aside from a one week period in which

TECO's staff was allowed to conduct formal experiments with the soldiers, they mainly served as observers. The soldiers were trained on the platform prior to this test period.

*4.4.1.5 PANTHER.* TECO's M1 PANTHER II study [13] examined the modified tank's utility for mine proofing in a potentially hazardous area. The experiments were conducted over a period of 32 days at TECO's test site at Fort Leonard Wood. Nine operators were trained and evaluated during the experiments. First, the soldiers' ability to control the vehicle and to handle payload operations was assessed in a benign environment. Then the PANTHER was operated in mine proofing scenarios in various terrain and weather conditions. The study focused on how well the integrated teleoperation system performed, the platform's limitations, how quickly it could be converted from manual to remote operation, and the capability of the installed cameras to assist in remote steering.

*4.4.1.6 SARGE.* In TECO's SARGE study [44] the objective was to evaluate the effectiveness of two non-lethal crowd control munitions delivered from a mobile robot platform. The munitions were the 40mm Crowd Dispersal Cartridge and the 37mm Grab Net. They were propelled from the remote vehicle of a SARGE system (consists of a two-man control vehicle, a HUMMV, and a smaller remote vehicle). The majority of problems reported in this study dealt with the recently developed non-lethal munitions rather than the robot platform itself.

*4.4.1.7 UGVROP.* The use of a robotic platform with added rapid obscuration, and obscurant generation capabilities was evaluated in TECO's Unmanned Ground Vehicle (UGV) Rapid Obscuration Platform (ROP) study [62]. The mobile robot platform was not specified, but the images included in the repository show a larger HUMMV vehicle delivering the obscurant and the control vehicle from the SARGE system. The study was conducted over a two week period at Fort Leonard Wood. As with the SARGE study, the majority of problems reported dealt with the obscurant firing and generation systems rather than the robot platform itself.

*4.4.1.8 Urban Robot.* Several smaller, man-packable platforms [34] were explored in TECO's Urban Robot study [43]. This study focused on the operational effectiveness of small robot usage for reconnaissance of bunkers and MOUT subterranean operations. Eight trained operators were asked to operate the robots over a course designed by TECO staff which included debris, inclines, and stairs. The robots used were: two Urbans, a SOLEM, an URBOT, and a Talon. The study lasted for four weeks. TECO's staff determined that the SOLEM and Urbans were not suited for such operations as they did not have the maneuverability needed to traverse the course in the target period of time. The Urbans were also deemed unfit due to their inability to keep mud, sand, and other small debris encountered in the test course from damaging the drive and manipulator systems.

### 4.4.2 Summary of Results

TECO has reported a mean time between failures (MTBF) of less than 20 hours, though their studies did not provide enough information (see Section 4.2) to validate that figure. Only the M1 PANTHER II study [13] provided details on each failure encountered. None provided sufficiently detailed usage information to calculate MTBF. During the 32 day period of the PANTHER experiments, a total of 35 failures were reported. Most (94%) of the failures were terminal. Experiments which relied on that robot stopped until the platform was repaired. Several sensor failures were non-terminal, but reduced the quality of feedback provided to the operators from the robot platform. The average downtime was 7.31 hours overall, or 7.75 hours excluding non-terminal failures. According to TECO 7.2 days were lost due to unscheduled vehicle maintenance occurring on both robots simultaneously.

The source for the data from TECO's M1 PANTHER II study [13] was not available. Therefore the statistics presented in Chapter Five are taken directly or derived from the documents provided in [42] for the study. Derived statistics were generated in the same manner as their counterparts in the reliability studies [6][7]. The method was described in detail in Chapter Three.

## 4.5 CRASAR HCFRD Field Experiments

In July of 2001 CRASAR performed a preliminary field study with Hillsborough County Fire Rescue Department (HCFRD). The purpose of the study was to simulate the use of robots with a real rescue team responding to an incident, and to collect human-robot interaction (HRI) data on the event. The study was conducted in a building scheduled for demolition in downtown Tampa. During the experimental scenarios, CRASAR members served as robot operators and collected data while HCFRD members directed the operators and assisted in completing the objectives of each scenario. The data collected during the field excursion included approximately 8 hours of video, two sets of field notes, and summaries of informal interviews with the fire professionals and post-excursion meetings. From this data, the study produced two new scripts (a set of actions which can be performed by a robot sequentially and/or in parallel) for USAR, determined a suitable human-to-robot ratio for teleoperated robots, and identified and categorized the failures encountered. For a complete discussion of this event see [10].

### 4.5.1 Approach

The tasks were selected by Clint Roberts, Incident Commander (the officer in charge at a search and rescue event) and HCFRD member, and Chief of Special Operations Rogers. Four tasks were devised: climb stairs and investigate the upper floors, search a dark and cluttered area for an unconscious fireman (simulated using a dummy), search the same area for an unconscious victim using a FLIR, and explore a floor by entering from a hole in the ceiling (vertical entry). Three tracked robots were used for data collection: an Urban, a MicroVGTV, and a MicroTracs. The Urban was run in two different configurations, with and without a Indigo Alpha forward-looking infrared camera (FLIR). The Incident Commander worked closely with the primary robot operator(s) during the four tasks, providing them with a secondary viewpoint of the information coming back from the robot.

The stair climbing task utilized the Urban to navigate up the stairs while assessing the environment for structural integrity and environmental indicators of hazards (e.g. smoke, vapor clouds). This task lasted 24 minutes during which 3.5 flights of stairs were traversed.

The downed fireman task was to teleoperate the Urban in a darkened and cluttered floor searching for a simulated downed fireman in a smoky building. The robot entered the floor from the stairway landing, found the fireman, and returned to the landing. The total execution time was 18 minutes. The operator and Incident Commander were located in a room on the far end of the floor, where they could not see (except through the robot's camera view) the area covered by the robot. The third task was identical with two exceptions: a live victim in civilian clothing was used in place of the dummy, and the FLIR was added to the Urban's sensor suite. The third task took 10 minutes and 40 seconds to complete.

The vertical entry task was to teleoperate the two Inuktun robots down a hallway, through a hole in a wall, into a room with a hole in the floor, enter the lower floor through the hole, and search it. The MicroVGTV (lead) robot was used to explore while the MicroTracs robot provided an external view of other robot's progress. The task took approximately 30 minutes.

The experimental method[1] includes a workflow analysis of the fire professionals utilizing robots in the specified USAR tasks, and informal interviews. The workflow was recorded using four synchronized cameras to record four different aspects of the tasks performed. The four viewpoints videotaped were: the operator and control unit, the robot, the fire rescue professionals within the vicinity of the operator, and an additional viewpoint which varied by task.

Field notes were used to record the start and end times, and any interesting events (e.g. failures) which occurred during the tasks. The estimated location, test environment status, and weather conditions were also recorded. Informal discussions took place with the participating fire professionals and operators after each task, and post-excursion meeting included the individuals who video taped and observed the events. Relevant comments and suggestions from both were recorded.

### 4.5.2 Summary of Results

The HCFRD study [10] found that the human to robot ratio for teleoperated robots was often 2:1 (two humans to one robot) and 3:2 at best. It was the first of several studies (see [4]) to find evidence of a heavy cognitive load associated with teleoperating a small robot, with limited sensing capabilities, in a USAR environment. In this study the robot operator drove by a live victim in plain view, while concentrating on navigating the robot through the environment. The fire rescue personnel served as a second pair of eyes, focused on the traditional search task including looking for structural hazards and victims, as well as keeping track of the area covered.

The most common errors were collisions, in which the robot collided with some obstacle, followed by communication failures with the wireless Urban platform. One

[1] Approved by the Internal Research Board (IRB) for human subjects.

navigation error during the stair climbing task was mentioned. In this case, the operator let the robot slip down one stair when he misinterpreted a cue in the camera view.

As with the WTC studies (see Section 4.3), the source for the data from the HCFRD study [10] was not available. Therefore the statistics presented in Chapter Five are taken directly or derived from the published study. Derived statistics were generated using the methods described in detail in Chapter Three.

## 4.6 CRASAR Reliability Studies

CRASAR currently has twenty-one robots from six manufacturers, and spends more than 200 hours per year in the field. In addition to the published studies already mentioned in Sections 4.3 and 4.5, CRASAR has also documented its experience using manual logging. Over the past three years this has produced a reasonable database of mobile robot physical failures and their characteristics. Two studies have been produced from this database. CRASAR's original reliability study [6] analyzed failure and usage data collected during the first two years, including information on 13 robots representing three manufacturers and seven models. The follow-up reliability study [7] expanded on the first with an additional year's worth of data, two more robots, and a statistical analysis of the results.

The studies were not limited to field environments, but included usage and failures which occurred in the lab as well. The failure data were analyzed using standard manufacturing measures for the reliability of a product, like *mean time between failures* and *availability*. The relative frequency of the physical classes were also determined. The original study's results showed an average mean time between failures (MTBF) of 8 hours (6 for field robots) and availability of less than 50% (64% for field robots). The follow-up study revealed that MTBF had improved by a factor of three (24 hours) but that availability remained low and the gulf between the reliability of indoor research (used only in the lab and similar office style environments) and field robots had widened. In the original study, the effectors were the most common sources of failures (42%) for field robots. The control system was the most frequent source of failures at 32% in the follow-up study. For the purposes of this meta-study only field (including both office and USAR domains) use and failures were considered.

### 4.6.1 Approach

User and failure logs served as the sources of data for this analysis. A total of 171 failures were recorded over a period of three years, specifically June 21, 2000 through January 10, 2003. Prior to February 2002 informal records were kept, including changes to the robots and information about ongoing repairs. Starting in February 2002 formal failure and user logs were kept. The user logs were entered by robot operators and the failure logs were recorded by the individual who performed the repair. Since then over 2100 hours of usage have been logged, including 500 hours of field work. The following information was gathered for quantitative analysis: which robot was involved, who repaired it, the date the failure was discovered, the date the failure was fixed, the total repair time, which component failed, where the failure occurred, and where the repair was performed. Chapter Three describes in detail how this information was analyzed. A brief synopsis is provided here.

The source of the failure was categorized as *effector, sensor, control system, power*, or *communications*. Human failures in the follow-up study are divided into *mistakes* and *slips*. A failure's *repairability* was considered to be *field-repairable* or *non-field-repairable*. Since the usage and failure logs covered both lab and field events, a distinction was made between data which came from the *lab* versus from the *field*. Lab usage and failures occurred in the lab. Field usage and failures occurred outside of the lab, usually during demos, outdoor testing, or training sessions.

Standard formulas taken from [24] were used to convert the raw data into common reliability metrics. The statistical analysis performed in the follow-up study consisted of calculating the confidence intervals for the mean-based and the probability-based results. The mean-based results were analyzed using the standard equation (7) for the 95% confidence interval where $m$ represents the sample mean. Confidence intervals for the probability-based results were similarly calculated using equation (8) where $s$ represents the sample probability.

$$m - 1.96\sqrt{\frac{\sum x - m}{n}} \leq \mu \leq m + 1.96\sqrt{\frac{\sum x - m}{n}} \tag{7}$$

$$s - 1.96\sqrt{\frac{s(1-s)}{n}} \leq \mu \leq s + 1.96\sqrt{\frac{s(1-s)}{n}} \tag{8}$$

#### 4.6.2 Summary of Results

Table 13 summarizes the general findings from the data collected for the reliability studies [6][7]. Here, we consider only the portion of data (usage and failure records) generated in each platform's target environment, grouped by manufacturer. For the Nomad indoor research robots (see Figure 14), only in-lab data was included. For the Inuktuns and iRobot models only field usage and failures were used. The platform type (field versus indoor research), percentage of usage in the target environment over all the recorded usage, and the mean time between failures (MTBF) are included to describe the overall frequency of failures. Availability and average downtime are included to show the impact of failures. Note that the MTBF does not include idle time (see Section 3.3).

Table 13 shows that MTBF by itself does not paint a complete picture. For example, the overall MTBF for Inuktun and iRobot in the original reliability study [6] were the same, but availability is quite different. The primary reason for this is that the

Table 13. Summary of Results from the CRASAR Reliability Studies [6][7]. Research refers to platforms suited for indoor research only.

| Manu. | Type | % of Usage | MTBF(hrs) | Availability | Ave. Downtime(hrs) |
|---|---|---|---|---|---|
| Inuktun | Field | 94% | 6.14 | 90% | 177 |
| iRobot | Field | 28% | 6.27 | 36% | 207 |
| Nomad | Research | 100% | 19.50 | 94% | 61 |
| Inuktun | Field | 80% | 10.27 | 27% | 39.65 |
| iRobot | Field | 24% | 4.57 | 88% | 0.66 |
| Nomad | Research | 94% | 149.08 | 99% | 0.3 |

Figure 14. A Nomad Research Robot Included in the CRASAR Reliability Studies. Platforms like these which are designed for indoor research only cannot handle field conditions and are therefore excluded from the results presented in Chapter Five.

Inuktun robots tended to suffer from minor failures in the first two years, which often took less than a minute to fix. The iRobot platforms were more likely to suffer from serious failures that took hours to repair. In the follow-up reliability study [7] the opposite was true. The iRobot models encountered failures more frequently in the field but had a much higher availability rate. This is due to the fact that the failures were easier to repair, based on an average downtime of 40 minutes compared to Inuktun's nearly 40 hour average downtime.

In comparison to the original study, the gulf between field and indoor robots increased dramatically in the follow-up study. This appears to be due to the innovative capabilities of these robots, and the inherent difficulty in constructing robots which can operate in unstructured, outdoor environments. Robots manufactured by iRobot in particular had a much lower MTBF in the field compared to their combined field and lab MTBF (almost 16 hours). The likely reason for this is that field environments are more challenging. Another reason is that the less reliable iRobot platforms were used more often in the field then the less fragile (but larger) platforms and that only 28% of iRobot usage was in the field. In the follow-up study, therefore, the more reliable platforms had a better chance of influencing the overall results.

The overall MTBF from the follow-up study improved by almost a factor of three from the original analysis results. Since only a year had passed, and the majority of robots were examined by both studies, it is unlikely that this resulted from an actual improvement in the reliability of the robots themselves. Instead, an additional year's worth of usage logs provided better records (and subsequently better estimates) of the robots' behavior. The statistical analysis showed that the time between failures, the time to repair, and the downtime vary widely therefore none of the differences between related means can be considered to be reliable predictors for future failures. Regardless, they do provide a good summary of the information found in the logs and a general assessment of robot reliability.

## 4.7 Summary

This Chapter has provided a detailed description of the information examined in this thesis. Thirteen studies from two primary sources, five from CRASAR and eight from TECO [42], were described in detail. These include the CRASAR's WTC [34][8], HCFRD [10], and reliability studies [6][7], as well as TECO's studies [59] [55] [3] [14] [13] [44] [62] [43].

The chapter began with a description of the total of 28 robots considered in this thesis. They represent 15 different models from seven manufacturers and range from small (less than 10 pounds) tracked vehicles capable of changing their geometry, to a modified M1 tank (over 60 tonnes). Then in Section 4.2, an overview of the information available from each study was provided. This section revealed that key information (the definition of failure used, data collection methods, and numeric results) is missing from most of TECO's studies [42]. It also showed that the reliability studies [6][7] and the WTC studies [34][8] differed in both data collection and result generation methods. Therefore, a true comparative study could not be performed directly on this set of studies. The goal for this meta-study was to gather as much information as it could from the material available, and use that information to develop a standard method for collecting and analyzing mobile robot failure information. The taxonomy presented in Section 3.2 is the result of that effort.

Section 4.3 covered the two studies generated from a *post-hoc* analysis of data collected during the robot-assisted search and rescue response at the WTC. A detailed analysis on the failures encountered while using robots was reported in the WTC Engineering study [34]. The WTC Human-Robot Interaction (HRI) study [8] examined the human-robot interaction and human-human interaction between the robots, their operators, and the other USAR professionals that worked with CRASAR at the WTC response. The data examined span a period of nine days between September 12th and 21st of 2001, and four robots from two manufacturers representing three different models. According to [34] *minor failures occurred 2.8 times per minute*. On average 11% of the search time was lost due to traction slippage, 18% due to camera occlusion, and 6% due to lighting adjustments. The WTC HRI study [8] found that CRASAR personnel were cognitively fatigued mainly due to lack of sleep. It was also determined that *none of the robots used at the WTC were designed or rated for use in USAR*, and that *two types of vital information were not getting from the robot to the operator*: *the state of the robot*, and *the state of the robot's environment*.

In Sec 4.4, TECO's eight studies were described. These studies were performed on a wide variety of platforms: small mobile platforms, several bulldozers, and a modified M1 tank. Experiments were carried out in mock military operations which can be considered to be high-fidelity field environments. TECO has reported a mean time between failures (MTBF) of less than 20 hours, though their studies did not provide enough information to validate that figure. During the 32 day period of the PANTHER [13] experiments, a total of 35 failures were reported. Most (94%) of the failures were terminal. The average downtime was 7.31 hours overall, or 7.75 hours excluding non-terminal failures.

Section 4.5 covers CRASAR's field study with the Hillsborough County Fire Rescue Department (HCFRD). The purpose of the study was to simulate the use of robots with a real rescue team responding to an incident, and to collect human-robot interaction (HRI) data. The data collected during the field excursion included approximately eight hours of video, two sets of field notes, and summaries of informal interviews with the fire professionals and post-excursion meetings. This study found that *the human to robot ratio for teleoperated robots was often 2:1 (two humans to one robot) and 3:2 at best*. *The most* *common errors were collisions*, in which the robot collided with some obstacle, followed by communication failures with the wireless Urban  platform.

The reliability studies [6][7] were described in Section 4.6. These studies examined CRASAR's database of manually logged usage and failure records over the past three years. The original reliability study [6] analyzed failure and usage data collected during the first two years, including information on 13 robots representing three manufacturers and seven models. The follow-up reliability study [7] expanded on the first with an additional year's worth of data, two more robots, and a statistical analysis of the results. The original study's findings showed an *average MTBF of 8 hours (6 for field robots)* and *availability of less than 50% (64% for field robots)*. In the follow-up study, the MTBF had improved to *24 hours* but that availability remained low and the gulf between the reliability of indoor research (used only in the lab and similar office style environments) and field robots had widened. In the original study, the *effectors were the most common sources of failures* (42%) for field robots. The control system was the most frequent source of failures at 32% in the follow-up study. For the purposes of this meta-study only field (including both office and USAR domains) use and failures were considered.

Though more source data and details were available for the reliability studies [6][7] than the others, and only three of the studies were focused on mobile robot failures; all have contributed valuable examples and insights into how mobile robots fail in the field. Their contributions have produced 44 representative examples (listed in Appendix B) of mobile robot field failures, and enabled the creation of the framework for future robot failure analyses presented in Chapter Three.

# Chapter Five

# Meta-Study Results

This chapter examines the mobile robot failures reported in 13 studies of field work in the application areas of urban search and rescue (USAR) and military operations in urban terrain (MOUT). Results and findings from these studies were not gathered under the same conditions (see Section 4.2) and for this reason cannot be synthesized into a single set of metrics which describe mobile robot failures in the field. This chapter therefore explores representative examples (44 total) which demonstrate how mobile robot failures can be classified using the taxonomy presented in Chapter Three, and the challenges associated with using robots in field environments, comparing numeric results whenever possible. For a complete description of every example included see Appendix B.

This chapter's organization follows the mobile robot failure taxonomy presented in Chapter Three exactly. This taxonomy uses *classes* to capture the source of the failure which can be either *physical* (system or robot) covered in Section 5.1, or *human* examined in Section 5.2. For each branch, the relative frequency of the classes under the branch and the examples which fall into each of those classes are included. This is true of all of the leaf classes in the taxonomy with the exception of the design failure class, which none of the 13 studies explored. The taxonomy also includes two attributes, examined in Section 5.1.7, to describe the severity of the failure in terms of its *repairability* and *impact* on the robot's mission at the time of the failure. Any information gathered from the source studies which relates to these attributes is included in this section.

## 5.1 Physical Failures

This section covers in detail the failures reported in the 13 studies this meta-study examines which do not directly involve a human (that is, physical failures). Taken as a whole, the vast majority of failures found in the studies fall under the physical branch. Since details on each individual failure encountered at the World Trade Center (WTC) was not available (see Section 4.2), the failures are presented by category as defined in the WTC Engineering study [34] performed by the Center for Robot-Assisted Search and Rescue (CRASAR). These were: *stuck assist*, *gravity assist*, *track slippage*, *occluded camera*, and *lighting incorrect*. Chapter Four provides detailed definitions of these categories. Each reported failure from CRASAR's reliability studies [6][7] and the studies performed by the Test and Evaluation Coordination Office (TECO) at Fort Leonard Wood [42] were individually classified. Both the CRASAR WTC HRI study [8] and CRASAR's field experiments with the Hillsborough County Fire Rescue Department (HCFRD) [10] were focused on human-robot interaction (HRI) issues, therefore their data are not covered in this section.

First the frequency of failures within the classes that fall under the physical failure branch of the taxonomy are presented in Section 5.1.1. In Sections 5.1.2 through 5.1.6, examples of failures which fall into each category are provided. Each of these sections will also include some discussion of general traits of that physical failure class.

### 5.1.1 Relative Frequency of Physical Classes

Table 14 presents data from the reliability analyses described in Section 4.6. It shows the relative frequency of each of the physical classes in the form of probabilities that a failure was caused by component(s) from each class. The reliability studies [6][7] covered day-to-day usage and failures in both lab and field environments. Therefore, it is

Table 14. Probability by Physical Class from the Reliability Studies [6][7]. Results from the original study appear above with the follow-up study's results below.

| Manufacturer | Effector | Control System | Power | Comms | Sensing |
|---|---|---|---|---|---|
| Inuktun | 0.50 | 0.34 | 0.03 | 0.00 | 0.13 |
| iRobot | 0.58 | 0.17 | 0.25 | 0.00 | 0.00 |
| Overall | 0.50 | 0.33 | 0.09 | 0.00 | 0.09 |
| Inuktun | 0.45 | 0.32 | 0.00 | 0.02 | 0.12 |
| iRobot | 0.22 | 0.30 | 0.15 | 0.22 | 0.11 |
| Overall | 0.36 | 0.31 | 0.06 | 0.10 | 0.12 |

important to note that this information was taken from the source data[1] for both the studies, rather than the studies themselves. All usage and failure events recorded in the lab were factored out of the statistics reported here. The failures are grouped by manufacturer with the overall probabilities for each class provided at the bottom of the table. Since sufficient descriptions of all the failures encountered in TECO's M1 PANTHER II study [13] was provided, a similar table, Table 15, was created for that study as well.

Figure 15 was generated from results from the follow-up reliability study [7] including the statistical analysis. As in the previous table the failures are grouped by manufacturer with overall probabilities for each category shown in the right-most set. The probabilities are shown as bars with the 95% confidence intervals from the statistical analysis indicated. The difference between effector and control system relative frequencies is significant only if a 50% or less confidence interval is used. Both are significantly more common than the other categories.

Table 14 shows that effectors are the most common source of physical failures, followed by the control system, sensors, communications, and power. Table 15 for the PANTHER shows very different results. In TECO's study the primary problem was a new teleoperation system installed on the modified tank. This resulted in a high percentage of control system failures. The sensors that came with the control system were second, with

[1] Database of usage and failure logs entered by the operator and repairer resp.

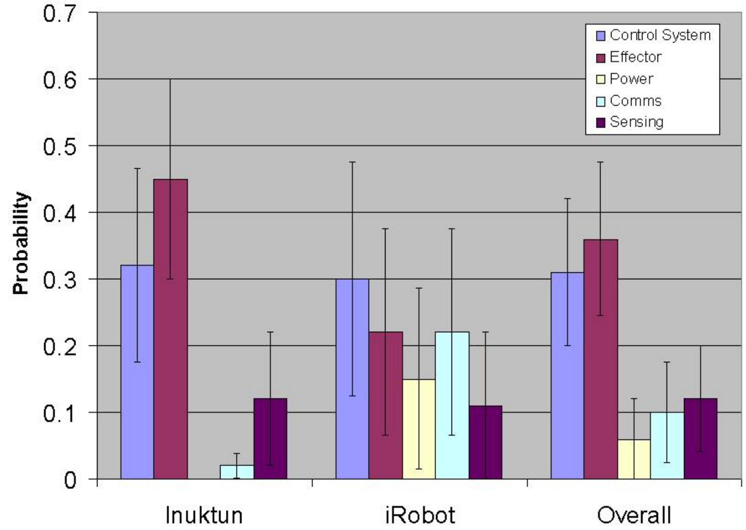


Figure 15. Probability by Physical Class from the Follow-up Reliability Study [7].

Table 15. Probability by Physical Class for M1 PANTHER [13].

| Model | Effector | Control System | Power | Comms | Sensing |
|---|---|---|---|---|---|
| PANTHER | 0.11 | 0.54 | 0.09 | 0.00 | 0.26 |

26% of the failures, followed by the effectors. Only power has a similar probability of causing failures across the three studies. The difference is probably due to the maturity of the M1 Tank platform, which has been used by the US Army for 20 years. In comparison, the platforms examined in the reliability studies were less than 10 years old.

### 5.1.2 Effector

The most common type of failure across the 11 studies which explored physical failures was failure of components that perform actuation and their connections, or *effector failures*. Common failure sources in the original reliability study [6] were the shear pin and pinion gear in the geometry shifting mechanism on the MicroVGTV. If the robot encounters resistance while shifting (low clearance in a confined space for example) the

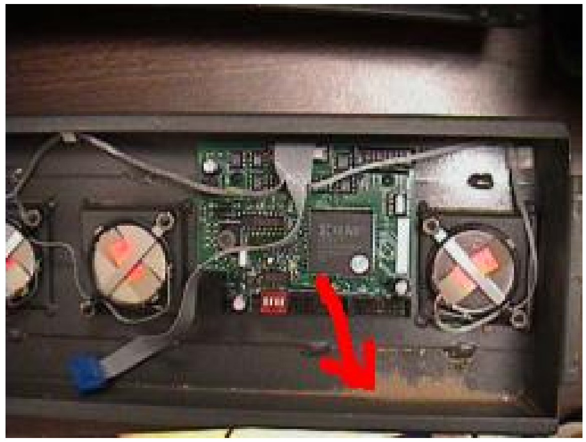

Figure 16. Dirt Found Near Sensitive Equipment Inside an iRobot Urban.

shear pin will break. The pinion gear is a problem because the area that houses it is open to the environment. Dirt and other debris get inside that area and cause premature wear. According to TECO, the Urban platform suffers from similar problems [43]. Open gearing for the articulating arms and drive motor collect debris which causes them to stop working. These examples illustrate a commonly found source of problems for field robots, namely dirt and other small debris. These particles have been shown to appear in every unsealed area inside a mobile robot (see Figure 16).

Results from the reliability studies [6][7] show that tracked vehicles were more prone to effector failure than wheeled platforms. In the original reliability study [6] 96% of the effector failures occurred on tracked rather than wheeled vehicles. 57% of the effector failures were the tracks working off their wheels (known as de-tracking), usually due to excessive friction with the ground surface. The Urban Robot study [43] described the same problem with the Urbans used in their field experiments. The study of the ARTS vehicle performed by TECO [59] mentioned two instances in which rocks became stuck in the track guides and sprockets (see Figure 17). The PANTHER also threw a track, a failure which took days to repair. Several of the studies, the WTC studies [34][8],

Figure 17. Rock Stuck in ARTS Track Mechanism. Photo taken from ARTS study. [59]

TECO's D-7G study [3], and TECO's DEUCE study [14], mentioned repeated problems with track slippage.

The track slippage category defined in the WTC Engineering study [34] was used to catalog the amount of time the tracks were spinning while the robot remained in place. The tracks were often slipping on piles of loose sand or paper, a problem which the effectors on a small tracked vehicle that weighs less than 10 pounds cannot easily overcome. Therefore only situations in which the tracks should have had enough friction with the ground surface under those conditions, would be considered to be an effector failure. The WTC Engineering study [34] do not provide sufficiently detailed descriptions of the failures themselves to determine what percentage of the track slippage time would meet this criteria. Two failures from the WTC do clearly fall into the effector category. In one documented case, the void a robot was exploring exceeded 122 degrees Fahrenheit and softened the track enough that it became loose and fell off. In another case, an aluminum rod became lodged into the track mechanism on a MicroTracs robot where the space tolerance between the track and the platform was less than one-eighth of an inch

Figure 18. Failure Encountered at the WTC.

(see Figure 18). These are classified as terminal failures, as the robots had to be pulled out of the void and repaired before being used again.

Effector failures include more than just mobility failures. For example, TECO's DEUCE study [14] mentioned problems with the ripper appendage mounted to the robot. The tool gets bogged down when used in particularly hard rock. TECO's M1 PANTHER II study [13] described problems with its hydraulic system which manifested as smoke issuing from the tank's turret.

### 5.1.3 Sensor

The sensor category covers failed sensors and problems with their connections. These failures tend to be less common than effector and control system failures, with only 9% of the failures analyzed in the original reliability study [6] and 11% of failures in TECO's M1 PANTHER II study [13]. At the WTC sensors were more of a problem. Due to incorrect lighting and occluded camera views, an average of 24% of search time was lost each time the robot was used to search a void [34]. By far the most common failed sensor in all of the studies was the camera. It was also the only sensor common to all of the robots' sensor suites.

Sensors were the most rare source of failures in the original reliability study [6], and tied with the Power class for least common in the follow-up reliability study [7]. The most common source of sensor failures in these studies was the sensor's connection to the control system. Note that this does not include problems in the smaller robots' tether or the larger robots' wireless connection, as those failures would fall under the communications class. Examples include faulty cabling and broken or loose connections at either end of the cabling. Statistical analysis in the follow-up reliability study [7] shows that these failures are equally uncommon across all the robot models examined in that study.

The WTC Engineering study [34] identified two categories of intermittent sensor failures: occluded camera and incorrect lighting. Occluded camera was defined as a state in which the entire camera view is blocked by obstacles. This failure was found to occur during 18%, on average, of the total time the robots spent searching a void. Note that this percentage is high despite the fact that 100% obstruction was required. The lighting incorrect category included states in which the lights were completely off (in which case the operator could not see) or were in transition between intensities. This failure was less common, occurring 6%, on average, of the total time the robots spent searching. Lighting problems were also mentioned in TECO's ARTS study [59]. The camera's automatic iris did not adjust enough for the operator to see to maneuver the robot.

TECO's M1 PANTHER II study [13] cited sensor problems which do not tend to occur under lab conditions. Bumpy terrain, sudden changes in lighting, and rainy weather caused problems for the on-board cameras. Since human operators rely heavily on camera views while teleoperating a robot [10] these minor failures made it difficult to control the robot from the remote operator control unit (OCU). The PANTHER study also mentions cases where camera lenses were covered in moisture, dirt, or mud.

### 5.1.4 Control System

The control system failure class includes any problems caused by the on-board computer, manufacturer provided software, and OCUs. They were the most common failures in TECO's M1 PANTHER II study [13] (54%), and the second most common field failures in both the reliability studies [6][7]. None were reported in the WTC Engineering study [34]. In TECO's M1 PANTHER II study [13] more than 6 days of the 32 available for testing were lost due to diagnosis and maintenance of the teleoperation system.

The most frequent control system failures in the original reliability study [6] were cases in which the robot was simply unresponsive (60% of field control system failures) and the solution was to cycle the power. Since rebooting the robot and/or OCU solved the problem, it was assumed that the problem was due to the control system. By the time of the follow-up reliability study [7], the control system failures had become more serious. The most common problem became an overload of the electrical system either on the robot or within the OCU which cycling power could not fix. In each case the robot or OCU had to be dismantled to replace either a fuse or a burnt component. These problems occur as frequently in the lab as they do in the field.

TECO's M1 PANTHER II study [13] reported a wider variety of control system failures. The steering system was the most frequent source of problems. Symptoms ranged from sluggishness to a complete loss of steering, sometimes manifesting in only one direction at a time. The emergency stop switch failed multiple times. The PANTHER's control system behavior was erratic and unstable in some cases. Reported failures include: uncontrolled acceleration, the RPMs shooting up to a critical level for no apparent reason, and a system shutdown when the operator tried to switch to teleoperation mode. TECO's UGVROP study [62] described similar problems with the same teleoperation system, but they appeared to be less frequent.

### 5.1.5 Power

Based on the results from the reliability studies [6][7] and TECO's M1 PANTHER II study [13], power failures do not produce many of the failures that occur in the field. The WTC Engineering study [34] revealed no failures due to batteries and their related connections during the two week rescue response. This was probably due to the fact that the robots were not used for an extended period of time. The longest period of time a robot was continuously used was a little over 24 minutes, therefore the batteries were not heavily taxed. Power may be more reliable than the other systems since it is the least affected by environmental hazards.

In the reliability studies [6][7] half of the power failures on the robots are due to the battery and its connections. The PANTHER platform suffered repeatedly from low batteries and low fuel. TECO had recurring failures during the DEUCE study [14]. One of the two DEUCE platforms suffered from clogged fuel filters, requiring a replacement roughly every six hours.

### 5.1.6 Communications

The majority of communications failures in the field were found and described by TECO, with the WTC Engineering study [34] providing one example (a robot was lost due to complete communications dropout). This is due in part to the fact that wireless communications is a known problem in field environments [34][10]. Wired robots are more commonly used (94% of Inuktun usage was in the field [6]) then the larger wireless robots (28% of usage in the field). CRASAR therefore encountered fewer communications failures in the field due to the use of relatively reliable wired communication. TECO did not have this luxury. Most of the robots they examined could only use wireless communications and none had a durable tether, like those used with the Inuktuns.

Experience with the wireless SOLEM platform at the WTC [34] provides a good example of why these robots are difficult to use remotely in field environments. The structural steel of the World Trade Center had a significant impact on the range of the 2 watt transmitter the platform was carrying. Instead of the usual mile or more, the robot lost communication with the OCU in under 20 feet. Even up to that point the signal was not very stable, 23.8% of the 7 minutes the robot spent searching the rubble pile resulted in completely useless video due to wireless dropout. The robot finally completely lost contact with the OCU. It was never recovered.

Similar problems may have been found with the PANTHER platform tested by TECO [13]. 14% of the failures encountered during that study were due to video dropout, a good indication of communications failures. TECO's D-7G study [3] concluded that the non-line-of-sight control requirement for the platform could not be met. This was because the teleoperation equipment could not transmit video through interposed materials or foliage. Video bandwidth and reliability limitations even impacted the performance of operators in line-of-sight scenarios. Occasional static was a problem for ARTS operators as well [59]. In the study conducted by TECO on the smaller mobile robot platforms (the Urban robot study), additional antennas were used in an attempt to improve the quality of the video signal. The analog signal was described as being adequate but was breaking-up often enough to distract the operators from the test scenario.

If communication technology improves, new problems are likely to emerge. For example, the problem of sharing limited bandwidth among many wireless robots in the same area. Limited bandwidth is already a problem for the military, where rules on allowed frequencies were found by TECO [59] to be a hindrance to improved signal strength and reliability. It is also a challenge to ensure that wireless transmitters adhere to

Table 16. Comparison of Terminal Versus Non-terminal Failures from the M1 Panther Study [13].

| Impact | # | Average Diagnosis Time(hrs) | Average Downtime(hrs) |
|---|---|---|---|
| Terminal | 33 | 0.33 | 7.75 |
| Non-terminal | 2 | 12.50 | 0 |
| Overall | 35 | 1.02 | 7.31 |

the established rules. The ARTS for example would bleed over to radio frequencies it was not allowed to use.

### 5.1.7 Attributes

In the taxonomy defined in Chapter Three two additional characteristics of physical failures were defined in addition to the cause (or fault) of the failure: the *repairability* of the failure and the *impact* of the failure. First the impact attribute is explored in Section 5.1.7.1, followed by the repairability attribute in Sec 5.1.7.2. Each section will discuss key traits of the attributes based on any data available from the 13 studies.

*5.1.7.1 Impact.* The impact of a failure is specified by the terms *terminal* and *non-terminal*. It is determined based on the effect the failure had on the robot's assigned task or mission at the time of the failure. Since information on the robot's mission was not consistently recorded for the reliability analyses [6][7], the largest source of documented failures in this meta-study could not be used to describe the traits of this attribute. Instead, TECO's M1 PANTHER II study [13] provided sufficient information to reliably distinguish between terminal and non-terminal failures. Table 16 shows the number of terminal versus non-terminal failures, and the average diagnosis time and downtime for each type. Overall results are provided at the bottom of the table.

Table 16 shows that terminal failures were far more common. The average diagnosis time shows that intermittent non-terminal failures tend to require more

Table 17. Comparison of Field-repaired vs. Not Field-repaired Failures. Results from the original study appear above with the follow-up study's results below.

| Repairability | % | MTBF(hrs) | Average Downtime(hrs) |
|---|---|---|---|
| Field-repaired | 65% | 9.5 | 0.14 |
| Non-field-repaired | 35% | 17.7 | 553 |
| Overall | | 6.17 | 185 |
| Field-repaired | 60% | 12.90 | 0.16 |
| Non-field-repaired | 40% | 32.06 | 50.91 |
| Overall | | 12.23 | 22.49 |

diagnosis time and additional technical knowledge of the robotic system. For example, an unresponsive control system may take less than a minute to diagnose and fix (power cycle). This is still considered to be a terminal failure as the robot cannot continue its mission until it is repaired. A non-terminal, but still significant steering problem may degrade the operators' performance and reduce the safety level of operation (especially for a vehicle as large as the PANTHER) for an extended period of time.

*5.1.7.2 Repairability.* Since this meta-study is concerned with field mobile robot failures, repairability is defined in terms of *field-repairability* (see Chapter Three). Table 17 compares the rates of physical failures that were field-repaired and those that were not using only only data collected in the field from the reliability studies [6][7]. The table presents the percentage of failures, MTBF's, and average downtime for field-repaired and non-field-repaired failures. Average downtime is the average amount of time between the occurrence of the failure and the completion of the repair that fixed it.

Based on Table 17, field failures are more likely to be repaired in the field than in the lab. This result has remained stable despite the increase in the MTBF and the drop in average downtime overall between the two studies. The average downtime for field repaired failures has also remained low compared to those that were not field repaired.

## 5.2 Human Failures

This section covers the human branch of the taxonomy presented in Chapter Three using human failures that emerged from the WTC studies [34][8], the HCFRD study [10], the reliability studies [6][7], and TECO's studies [42]. Design failures were not explored by any of the 13 studies, therefore this section is limited to interaction failures. As mentioned by Laprie in [30], all failures can eventually be traced to a human error at some level. This section covers only direct (or if not direct at least important) connections between human error and the failures that resulted from them. Section 5.2.1 explores the relative frequency of classes within and interaction branch and Section 5.2.2 provides examples of human-robot interaction failures.

This section will present results from a smaller set of recorded human failures as compared to the physical failures covered in Section 5.1. The reliability studies [6][7] and the WTC Engineering study [34] were focused on physical rather then human-robot interaction (HRI) failures. While an objective of TECO's studies was an assessment of the robotic system's usability, none of their studies included formal HRI experiments. Both the WTC HRI study [8] and the HCFRD study [10] were focused on HRI issues in USAR, not failures and therefore provide a more limited set of recorded examples.

### 5.2.1 Relative Frequency of Human Classes

Table 18 isolates the human failures described in the HCFRD study [10] and the WTC studies [34][8] and categorizes them based on the taxonomy presented in Chapter Three. The field event and the task the operator was asked to perform with the robot are included. Table 18 also includes the total duration of that task, total number of failures, mean time between failures (MTBF, see Chapter Three) in hours, percentage of mistakes, and

Table 18. Human Failure Analysis Results.

| Field Event | Task | Time(min) | # | MTBF(hrs) | Mistakes | Slips |
|---|---|---|---|---|---|---|
| HCFRD[10] | Climb Stairs | 24 | 3 | 0.13 | 33% | 67% |
| WTC[8][34] | Search Small Voids | 55 | 16+ | 0.06 | 38% | 63% |
| Overall | | 79 | 19 | 0.28 | 37% | 63% |

percentage of slips. The results are broken down by event with overall values provided at the bottom.

It is also important to note that, for 13 of the WTC failures reported here, the duration was recorded rather then the number of individual failures. More specifically, the six mistakes were from failures categorized as incorrect lighting (see Section 4.3), and seven of the slips were from the track slippage category. For the purposes of this meta-study, each duration value recorded was considered to be a single failure. Therefore, the number of failures reported here represents the minimum that actually occurred.

Table 18 shows that human failures occurred more often during the actual USAR response at the WTC as compared to the field experiments. This result is expected considering the difficulty of navigating a collapse site as extensive and compact as the WTC disaster (see Figure 19), compounded by fatigue and risk to personal safety. The ratio of mistakes to slips is similar despite these differences. More data is needed to determine if this is a universal attribute of HRI.

### 5.2.2 Interaction

The interaction category captures all of the failures caused at the human end of HRI. For mobile robots this means failures caused by the robot's operators, as well as any secondary and tertiary stakeholders who may be directing the operator's actions [10]. Both mistakes, or cognitive errors, covered in Section 5.2.2.1 and slips, or unconscious errors, described in Section 5.2.2.2 fall under this category.

Figure 19. Comparing WTC Working Conditions to that of the HCFRD Study. Image taken at the WTC disaster (left). A Microtracs and MicroVGTV cooperatively navigating a small pile of debris at the HCFRD study (right).

*5.2.2.1 Mistakes.* In the WTC Engineering study [34] many of the failures could be categorized as mistakes, where the operator was planning his actions based on incomplete knowledge. It is difficult for any human to maintain a cognitive model of the environment the robot is in with only a single color camera (with a limited field of view) and 2-way audio. An operator who is physically and cognitively fatigued (for instance due to perceived threats to personal safety) will have more problems. Gravity assists for example, may have occurred when the operator drove the robot into an area where the incline was too steep for it, because he could not judge the vertical orientation of the void.

Other examples would be stuck assists needed when the operator lost track of the obstacles around the robot, and occluded camera when he did not know which way to go to get around the obstacle blocking its view. Some of the time spent in the incorrect lighting failure mode was definitely due to mistakes on the operator's part. He was trying to improve the camera view of the void by adjusting the robot's halogen lights, but at the same time the camcorder was automatically adjusting to the new conditions. The operator knew about this feature of the camcorder, but did not immediately realize what was happening.

Figure 20. ARTS on its Side After a Fall. Photo taken from ARTS study. [59]

A sensor impoverished robot can lead to deficits in an awareness of the state of the robot, as well as the environment. In one example described by TECO the operators attempted to drive the ARTS up a 30% slope [59]. The platform became unstable and the operators could not recover in time to prevent the robot from rolling on its side (see Figure 20). TECO's SARGE study [44] noted navigation errors (positioning and driving) made by the operators due to the difficulty of judging distance and position. The study explicitly blamed these problems on the fact that the installed camera did not provide adequate peripheral vision or depth perception.

It is important to note here that the WTC studies [34][8] and TECO in three separate studies specifically cited the lack of depth perception as a problem encountered in the field. This appears to be an important feature lacking in current sensor suites. It occurs regardless of the payload capability or the location of the camera, as the ARTS vehicle is considerably larger than the robots used at the WTC. The difference in payload capabilities led TECO to recommend using additional cameras, whereas the WTC study recommended software and/or cognitive science-based solutions.

Undetected physical failures can also lead to human mistakes. TECO also had problems with the Urban platform [43] due to the fact that the operators did not recognize that the drive system was frozen, and would overtax the power system in a vain effort to get the robot to move. Even experienced operators who are not intimately familiar with the capabilities of a robotics platform may overestimate them, causing additional failures. An example of such a mistake from the reliability studies [6][7] was when an operator attempted to use an ATRV-Jr to push a heavy load up a hill. This resulted in a blown motor amplifier which immobilized the robot. A similar case with inexperienced operators was mentioned in TECO's DEUCE study [14]. The operator tried to steer the robot with the rippers embedded in rock, not realizing that this action would bend the tool.

*5.2.2.2 Slips.* The halogen lights failure [34] at the WTC was a good example of a slip. In this case the halogen lights failed due to an energy spike when the robot's tether was removed and then reconnected to the OCU. The operator who caused this failure knew the potential problems of plugging electrical components back together while one is still powered. He probably intended to turn off the OCU, just in case, but due to distractions and/or fatigue did not do so.

Minor slips can occur frequently when operators do not have enough experience with a particular robot system. Two examples from the reliability studies [6][7] would be a joystick that was dropped in sand; and a tether that was not properly connected to the OCU. In both cases the operators had learned enough about the platforms to understand how to use them properly, but did not have a lot of practice.

All of the slips mentioned so far are not unique to mobile robots used in field environments. These types of human error are common features of human-computer interaction (HCI) or even just man-machine interaction. Certain aspects of HRI, especially in field environments, lead to additional mistakes and slips not commonly found in other fields. For example, a distinct attribute of teleoperation (controlling the robot from a remote location) is that it removes the operator from the environment of the robot. In TECO's Urban Robot study [43] the operator would often drive the robot dangerously close to suspicious objects in order to determine if they were mines, grenades, or some other harmful device. If the soldiers had been there in place of the robot they probably would have acted more cautiously. Similar teleoperation slips from the HCFRD study [10] included two collisions with walls as the operator was trying to navigate a robot up a flight of stairs.

## 5.3 Summary

This chapter has reported example field failures and relevant findings from 13 studies of field work with mobile robots in the application areas of USAR and MOUT. The examples demonstrate how mobile robot failures can be classified using the novel mobile robot failure taxonomy presented in Chapter Three, and the challenges associated with using robots in field environments. Numeric results were compared whenever possible. The chapter's organization followed the taxonomy. Section 5.1 covered the physical failures, Section 5.2 explored the human-robot interaction (HRI) failures, and Section 5.1.7 presented data on the repairability and impact attributes.

Figure 21 provides a summary of the findings in terms of the taxonomy presented in Chapter Three. The probability that a given failure belongs to a given class is displayed beneath that class (leaf node) in the taxonomy tree. If multiple source studies provided data, the probability is shown as a range. Design failures (under human failures) were not explored by the 13 studies this meta-study drew from, and therefore no probability is included for this class. Ideally the probabilities of siblings should sum to 1.0 but since they are extracted from multiple sources, that is not always the case.

As seen in Figure 21, the *effectors and the control system are the most common sources of failures*, with at most half of the failures falling into one of these classes.

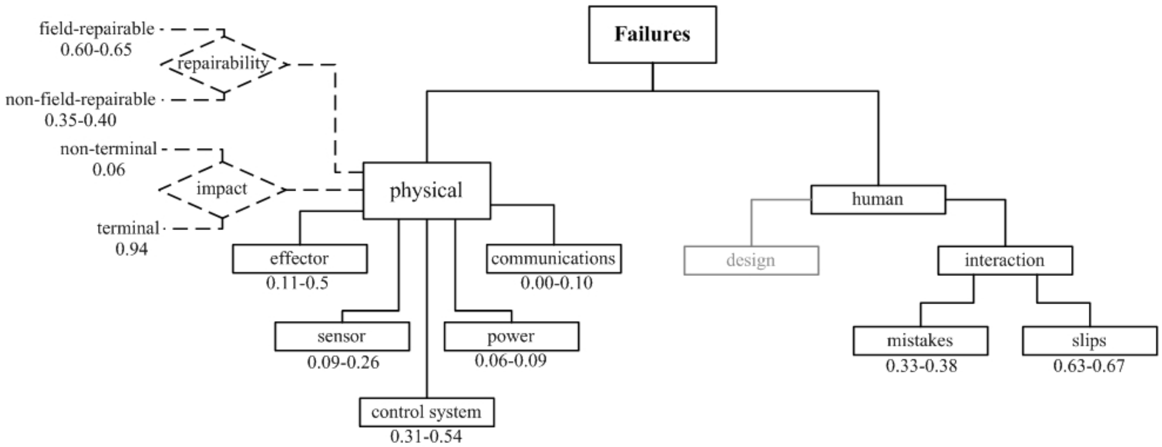


Figure 21. Summary of Classification Results Using the Failure Taxonomy. Includes probabilities for each leaf class and attribute value. For example, the probability that a failure was an effector failure is at least .11 and at most .5 (depending on the source) and the probability that the failure will be field repairable is between 0.60 and 0.65.

Sensor failures are less frequent with at most 26% of the failures, followed by power at 9%, and communications failures at 1%. Though communications failures appear to be the least frequent, it should be noted that several of TECO's studies, which did not provide enough details to derive relative frequencies, reported chronic communications problems. Within the human failures branch, *slips are more common with at most 67% of the failures* while mistakes contributed no more than 38% of the failures examined. Since the physical and human failure results came from different sources, the relative frequency of physical versus human failures cannot be determined from these studies. The reliability analyses show that *the MTBF for mobile robots in the field is between 6 and 12 hours*. TECO reported that the robots they examined failed within 20 hours of use [56], though their studies did not provide enough information (see Chapter Four) to validate that figure.

The attributes are similarly marked with the probability that a given failure will have that attribute value. *Field-repairable and terminal failures are more common* than their opposites, with up to 65% and 94% respectively of the failures covered in this meta-study. The studies did not provide sufficient data to calculate conditional probabilities between the classes and attributes, for example, the probability that a given effector failure will be terminal or field-repairable.

A detailed examination of the field failures described in the 13 studies uncovered the following common issues:

1. unstable control systems
2. chassis and effectors designed and tested for a narrow range of environmental conditions
3. limited wireless communication range in urban environments
4. insufficient wireless bandwidth for video-based feedback

# Chapter Six

# Conclusions

This thesis has explored the question of how ground-based mobile robots fail in the field. Two contributions were produced from this effort:

1. A novel taxonomy of mobile robot failures that reconciles failure classification schemes from the dependability computing [30], human-computer interaction (HCI) [40], and robotics [6] communities.

2. A meta-study including 44 representative examples of mobile robot field failures drawn from 13 studies in the urban search and rescue (USAR) and military operations in urban terrain (MOUT) domains.

The Center for Robot-Assisted Search and Rescue (CRASAR) at the University of South Florida provided five of the studies, and the remainder come from the US Army's Test and Evaluation Coordination Office (TECO) at Fort Leonard Wood. The failure examples drawn from these studies were used to demonstrate how mobile robot failures can be classified using the new taxonomy and the challenges associated with using robots in field environments.

A review of related work presented in Chapter Two established that this work was unique in three respects: it covers both human and robot failures, it is focused on robot field failures in the USAR and MOUT domains, and it is the only meta-study that covers mobile robot failures. It was also found that no existing approach to failure analysis is suitable for the task of mobile robot field failure analysis.

Chapter Three presented a new approach to mobile robot failure analysis used in this thesis, including a novel taxonomy built on existing work. Following Laprie[30], failures were divided into *physical* and *human* classes, with human subdivided into *design* and *interaction*. The human-computer interaction classes of *mistakes* and *slips* [40] fell under interaction failures. Physical failure classes were taken from Carlson and Murphy [6]. These are *effector, sensor, control system, power*, and *communications*. The new taxonomy was then used to explore, in Chapter Five, how mobile robots fail in the field based on 13 studies [3] [6] [7] [8] [10] [13] [14] [34] [43] [44] [55] [59] [62] (described in detail in Chapter Four) which examined mobile robot performance in the field. For each class of failure, examples were provided which illustrate the nature of mobile robot field failures which fall under that class. (Each example failure is described in detail in Appendix B.)

This chapter provides a summary of the findings of this meta-study in Section 6.1. This is followed by a discussion in Section 6.2 of the implications of those findings, as well as possible solutions to the problems encountered. Section 6.3 closes with a brief overview of future work.

## 6.1 Findings

*How do ground-based mobile robots fail in the field?* The nine overall findings listed below answer this question based on the information found in the 13 studies covered in this thesis. These findings cover studies from two field application domains: five in USAR, and eight in MOUT. 28 robots were examined which represent 15 different models from seven manufacturers, and range from small (less than 10 pounds) tracked vehicles, to a modified M1 tank (over 60 tons). Due to differences in data collection and reporting methods among the 13 studies, a precise quantitative summary of their experience in terms of reliability metrics was not possible. Therefore, the mean time between failures and relative frequency of the classified failures were presented as estimates only. Since these were the only studies found in the literature that describe mobile robot field failures, these numbers represent the best answer that can be made, at this time, to the question of how ground-based mobile robots fail in the field.

1. Robot reliability in field environments is low, mean time between failures (MTBF) is between 6 and 24 hours.
2. Common issues across the 13 studies are the following:
   (a) unstable control systems
   (b) chassis and effectors designed and tested for a narrow range of environmental conditions
   (c) limited wireless communication range in urban environments
   (d) insufficient wireless bandwidth for video-based feedback
3. Tracked vehicles are more prone to effector failures than their wheeled counterparts.
4. Effectors (11–50%) and the control system (31–54%) are the most common sources of physical failures.
5. Sensor failures make up between 9% and 26% of the failures.
6. Power (6–9%) and communications (0–10%) faults were the least frequent sources of failure.
7. Slips (63–67%) are more common than mistakes (33–38%).
8. Field-repairable failures make up two-thirds (60–65%) of the failures examined.
9. Terminal failures are more common than non-terminal with 94% of the failures reported in TECO's PANTHER study [13].

As the findings state, overall robot reliability in field environments is low, between 6 and 24 hours MTBF, depending on the criteria used to determine if a failure has occurred. Effectors and the control system are the most common sources of physical failures across the 11 studies which reported physical failures. This result was verified through statistical analysis in CRASAR's follow-up reliability study [7]. Though communications failures appear to be the least frequent, it should be noted that several of TECO's studies reported chronic communications problems but did not state the number of communications failures. Therefore, the quantitative results probably underestimate the frequency of communications failures for mobile robots used in the field. Within the human failures branch, slips are more common than mistakes. Human design failures were not covered in any of the 13 studies. Since the majority of physical and human failure results came from different sources (only CRASAR's World Trade Center (WTC) Engineering study [34] contributed both physical and human failures), the relative frequency of physical versus human failures cannot be determined. Field-repairable failures make up two-thirds of the failures examined. Terminal failures are also more common with 94% of the failures reported in the M1 PANTHER II study [13] performed by the TECO.

The results of this meta-study support the concept, theorized in the original reliability study [6], that maturity has a large impact on the reliability of a platform. The results from the original reliability study [6] indicated that mature platforms are more reliable, even in applications and environments that they were not designed for, than less mature platforms drafted for that application alone. In addition, it appears that the maturity of each subsystem within a robot platform also influences the overall system's reliability. For example, the new teleoperation system installed on the PANTHER failed far more frequently than the platform's effectors, which have been actively used for over 20 years as part of the US Army's M1 tank platform. Another example is the Inuktun platforms which fell from 90% to 27% availability between the original and follow-up reliability studies [6][7] due largely to upgrades in the control system, which did add valuable features to the platform, but also added to the complexity and reduced the reliability of that subsystem.

## 6.2 Discussion

Determining the underlying causes for the findings presented in Section 6.1 is beyond the scope and expertise of this thesis. The implications of these findings for potential users in field applications, mobile robot designers, and fault-tolerance researchers and developers are as follows:

1. A state of the art mobile robot cannot be expected to complete an entire shift without incident.
2. A 50% availability rate[6][7] implies that additional backup equipment must be available for field applications.
3. The most common sources of failure in modern robotic systems are custom-built by hand and increasingly complex (control and effector systems).
4. The most reliable components in modern robot systems are simple (power) and/or mass-produced (sensors).
5. Most failures will interrupt the robot's mission but require relatively minor repairs.

Potential users in field domains such as USAR and MOUT should be aware that a state of the art mobile robot cannot be expected to complete an entire shift (12 hours for USAR or 20 hours for the Department of Defense) without incident and robots are expected to have a 50% availability rate [6][7]. This implies that additional backup equipment must be available for field applications, doubling the resources and logistics needed to get a single robot in the field. In effect this raises the bar for mobile robot field applications, making it more difficult for a robotic system to prove that it is in fact useful enough to offset these costs.

Robot manufacturers should be cognizant of the fact that mobile robot technology is suffering from the same creeping increase in complexity identified by Norman in the computer industry [39]. To exacerbate this problem, the control and drive systems are usually custom designed for a specific robot model, and are built by hand (this is the case for the 15 models covered in this thesis). Quality control for a complex, custom-built system is difficult to manage even with sufficient resources. Ultimately, manufacturers must accept that their robots will suffer from failures in the field, and must design for maintainability. Regular maintenance tasks should be made as painless as possible for the end-user and any custom parts should be readily available in the event that serious failures occur.

Based on the common issues for all the robot platforms, limited mobility [2][9] and unreliable wireless communications are problems which need to be addressed. This will require the attention of robot designers in both industry and research domains. Some researchers [22] have spent years developing robot platforms with advanced mobility capabilities like wall climbing. These solutions need to be explored and hardened as part of a complete robot system, with sufficient payload capabilities to carry the materials the robots need to complete their assigned task. Alternative solutions to the wireless communication problem (for example, the use of a combination of wired and wireless communication or repeaters to boost signal strength) have also been explored [38][11] and need to be developed further for field applications.

Fault-tolerance systems similar to [17] and [19], which handle effector failures in wheeled robots, need to be developed for tracked vehicles, which are more prone to this class of failure. Researchers in fault-tolerance should also note that complex components are more likely to fail than simple ones. This favors model-based methods which are better at handling this level of complexity. On the other hand, the same components are usually custom built by hand, which means that a sufficiently precise model is likely to apply to exactly one robot. Based on the findings of this thesis, hybrid fault-tolerance systems which use learning [32], qualitative reasoning [60], or active probing (gathering additional information from other sensors or robots) [31] to augment less precise models appear to hold the most promise for field robotics applications.

## 6.3 Future Work

This thesis was the first of its kind, and has laid the groundwork for future studies characterizing how mobile robots fail in field environments. This section discusses three key avenues for such work: improved data collection methods, human-robot interaction failures, and new methods for applying results of studies like this one to improve existing fault-tolerance approaches.

Automated black box data collection methods, like those used on modern airplanes, are needed for mobile robots to automatically record both usage and failure data for future study. Due to limited communications bandwidth, operator control units often cannot receive all of the information generated by the robot's sensors and control system at a given time. Therefore loggers are needed that reside in a robot's onboard computer and have access to vital information which a robot operator cannot readily access. As computing resources on mobile robots are often limited, loggers need to have a minimal computational overhead. Further, constraints on communications bandwidth and storage require compact representations of information, and that this information be filtered for relevance to the operator and other consumers of usage and failure data (i.e. online fault detection and offline failure analysis modules).

On-going research in human-robot interaction [4][63] is likely to demonstrate that there are significant differences between it and the human-computer interaction field. More studies are needed to explore human failures with mobile robots as part of this effort. Reliable data collection methods which can be used for extended periods of time, like those in place for physical failures, need to be developed and implemented. The human branch of the failure taxonomy used in this thesis was sufficient for the limited number (less than 20) of human failures examined here. Studies of more extensive records of human-robot interaction failures are likely to lead to refinement of the human failure branch, just as similar studies of physical failures [6] lead to a more detailed classification scheme for that class of failures.

The incorporation of probability estimates, like those given in Section 6.1, is often straightforward in fault-tolerance approaches that use probability models to detect and/or diagnose failures (such as [25], [32], [51], and [61]). For other approaches to fault-tolerance which do not model the state of the system explicitly and use active diagnosis (probing for additional information from sensors and/or other robots), like [31] and [15], the incorporation of probability data is possible but more problematic. Systems are needed which can reliably rank failure hypothesis based on any information about the current state of the system (gathered during the detection phase) and the likelihood of that failure (based on the estimated probability). Such systems would reduce the cost of the diagnosis process (which can be quite high if other robots are recruited as in [31] to assist in hypothesis testing) by ensuring that the most likely hypotheses are checked first.

References


[1] Y. Beauchamp and T.J. Stobbe. A review of experimental studies on human-robot system situations and their design implications. *International Journal of Human Factors in Manufacturing*, 5:283–302, 1995.

[2] John G. Blitch. Adaptive mobility for rescue robots. In *Proceedings of SPIE. Sensors, and Command, Control, Communications, and Intelligence (C3I) Technologies for Homeland Defense and Law Enforcement II*, volume 5071, pages 315–321, 2003.

[3] Glenn Boxley. Teleoperational d–7 dozer concept evaluation program (cep) executive summary. Concept experimentation program (cep) report and executive summary, US Army, Test and Evaluation Coordination Office (TECO), Ft. Leonard Wood, 1999. From archives at www.jointrobotics.com.

[4] Jennifer L. Burke, Robin R. Murphy, and Michael D. Coovert. Moonlight in miami: An ethnographic study of human-robot interaction in the context of an urban search and rescue disaster response training exercise. *To appear in Human-Computer Interaction*.

[5] G. Candea, E. Kiciman, S. Zhang, P. Keyani, and A. Fox. Jagr: An autonomous self-recovering application server. In *Fifth Annual International Workshop on Active Middleware Services. Proceedings of the Autonomic Computing Workshop.*, pages 169–178, 2003.

[6] J. Carlson and R. Murphy. Reliability analysis of mobile robots. In *Proceedings of the IEEE International Conference on Robotics and Automation*, 2003.

[7] Jennifer Carlson, Robin R. Murphy, and Andrew Nelson. Follow–up analysis of mobile robot failures. To appear at IEEE International Conference on Robotics and Automation, 2004.

[8] J. Casper and R. Murphy. Human-robot interactions during the robot-assisted urban search and rescue response at the world trade center. *IEEE Transactions on Systems, Man, and Cybernetics Part B*, 33:367–385, June 2003.

[9] Jennifer Casper, Mark Micire, and Robin Murphy. Issues in intelligent robots for search and rescue. In *SPIE Ground Vehicle Technology II*, volume 4, pages 41–46, 2000.

[10] Jennifer Casper and Robin Murphy. Workflow study on human-robot interaction in usar. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, 2002.

[11] A. Cerpa and D. Estrin. Ascent: Adaptive self-configuring sensor network topologies. In *Proceedings IEEE Twenty-First Annual Joint Conference of the IEEE Computer and Communication Societies (INFOCOM 2002)*, volume 3, pages 1278–1287, 2002.

[12] C. Combastel, S. Gentil, and J.-P. Rognon. A symbolic reasoning approach to fault detection and isolation applied to electrical machines. In *Proceedings of the IEEE International Conference on Control Applications*, volume 1, pages 475–479, September 1998.

[13] F.W. Cook. Test report for the panther ii. Test report, US Army, Test and Evaluation Coordination Office (TECO), Ft. Leonard Wood, 1997. From archives at www.jointrobotics.com.

[14] F.W. Cook. Limited objective experimentation report for the deployable universal combat earthmover (deuce). Executive summary, US Army, Test and Evaluation Coordination Office (TECO), Ft. Leonard Wood, 2000. From archives at www.jointrobotics.com.

[15] J. de Kleer and O. Raiman. Trading off the costs of inference vs. probing in diagnosis. In *Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence*, pages 1736–1741, 1995.

[16] B. Deuker, M. Perrier, and B. Amy. Fault-diagnosis of subsea robots using neuro-symbolic hybrid systems. In *IEEE Oceanic Engineering Society. OCEANS'98. Conference Proceedings*, pages 830–834, 1998.

[17] W.E. Dixon, I.D. Walker, and D.M. Dawson. Fault detection for wheeled mobile robots with parametric uncertainty. In *Proceedings of IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, volume 2, pages 1245–1250, 2001.

[18] X. Dong, S. Hariri, L. Xue, H. Chen, M. Zhang, S. Pavuluri, and S. Rao. Autonomia: An autonomic computing environment. In *Proceedings of the IEEE International Performance, Computing, and Communications Conference*, pages 61–68. IEEE, 2003.

[19] P. Goel, G. Dedeoglu, S.I. Roumeliotis, and G.S. Sukhatme. Fault detection and identification in a mobile robot using multiple model estimation and neural network. In *Proceedings of IEEE International Conference on Robotics and Automation*, volume 3, pages 2302–2309, 2000.

[20] J. L. Gonzalez, M. Mediavilla, J.C. Fraile, F. Gayubo, J.P. Turiel, and F.J. Garcia. Influences of robot maintenance and failures in the performance of a multirobot system. In *Proceedings 2002 IEEE/RSJ International Conference on Intelligent Robots and Systems*, volume 3, pages 2801–2806, 2002.

[21] R. Helfman, E. Baur, J. Dumer, T. Hanratty, and H. Ingham. Turbine engine diagnostics (ted): An expert diagnostic system for the m1 abrams turbine engine. In *Proceedings of the Fifteenth National Conference on Artificial Intelligence*, pages 1032–1038, 1998.

[22] S. Hirose and H. Arikawa. Coupled and decoupled actuation of robotic mechanisms. In *Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation.*, volume 1, pages 33–39, 2000.

[23] E. Hung and F. Zhao. Diagnostic information processing for sensor-rich distributed systems. In *Proceedings of the 2nd International Conference on Information Fusion (Fusion 99)*, 1999.

[24] Institute of Electrical and Electronics Engineers, Inc. Ieee recommended practice for the design of reliable industrial and commercial power systems. IEEE Std 493-1997, 1998.

[25] E. Jackson. Real-time model-based fault detection and diagnosis for automated systems. In *Dynamic Modeling Control Applications for Industry Workshop, IEEE Industry Applications Society*, pages 26–28, 1997.

[26] Meng Ji, Zhen Zhang, G. Biswas, and N. Sarkar. Hybrid fault adaptive control of a wheeled mobile robot. *IEEE/ASME Transactions on Mechatronics*, 8:226–233, 2003.

[27] K. Kawabata, T. Akamatsu, and H. Asama. A study of self-diagnosis system of an autonomous mobile robot: expansion of state sensory systems. In *Proceedings IEEE/RSJ International Conference on Intelligent Robots and Systems (Cat. No.02CH37332C)*, volume 2, pages 1802–1807, 2002.

[28] A.I. Kokkinaki and Kimon Valavanis. Error specification, monitoring, and recovery in computer-integrated manufacturing: An analytic approach. In *IEEE Control Theory and Applications*, volume 143, pages 499–508, November 1996.

[29] K.B. Lamine and F. Kabanza. History checking of temporal fuzzy logic formulas for monitoring behavior-based mobile robots. In *Proceedings 12th IEEE Internationals Conference on Tools with Artificial Intelligence*, pages 312–319, 2000.

[30] J-C. Laprie. Dependable computing and fault-tolerance: Concepts and terminology. In *Twenty-Fifth International Symposium on Fault-Tolerant Computing*, pages 27–30, 1995. Reprint, originally published in 1985.

[31] Matt Long and Robin R. Murphy. Distributed multi-agent diagnosis and recovery from sensor failures. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, volume 3, pages 2506–2513, October 2003.

[32] R. Mackey, M. James, Han Park, and M. Zak. Beam: Technology for autonomous self-analysis. In *2001 IEEE Aerospace Conference Proceedings*, pages 2989–3001, 2001.

[33] M.G.M. Madden and P.J. Nolan. Monitoring and diagnosis of multiple incipient faults using fault tree induction. In *IEE Proceedings-Control Theory and Applications*, volume 146, pages 204–212, 1999.

[34] Mark Micire. Analysis of the robotic-assisted search and rescue response to the world trade center disaster. Master's thesis, University of South Florida, July 2002.

[35] N.H. Minsky. On conditions for seal-healing in distributed software systems. In *Fifth Annual International Workshop on Active Middleware Services. Proceedings of the Autonomic Computing Workshop*, pages 91–97, 2003.

[36] Robin R. Murphy. *Introduction to AI Robotics*. The MIT Press, 2000.

[37] Robin R. Murphy, Jennifer Casper, Jeffery Hyams, Mark Micire, and Brian Minten. Mobility and sensing demands in usar. In *IEEE International Conference on Industrial Electronics, Control and Instrumentation*, October 2000.

[38] H.G. Nguyen, H.R. Everett, N. Manouk, and A. Verma. Autonomous mobile communication relays. In *Proceedings of the SPIE - The International Society for Optical Engineering*, volume 4715, pages 50–57, April 2002.

[39] Donald A. Norman. *The Invisible Computer*. The MIT Press, 1999.

[40] Donald A. Norman. *The Design of Everyday Things*, chapter To Err Is Human, pages 105–140. The MIT Press, 2002.

[41] Illah R. Nourbakhsh. The mobot museum robot installations. In *Proceedings of the IEEE/RSJ IROS 2002 Workshop on Robots in Exhibitions*, pages 14–19, 2002.

[42] Department of Defense. Department of defense joint robotics program. http://www.jointrobotics.com.

[43] G. Piskulic. Military police/engineer urban robot (urbot) concept experimentation program (cep) report, engineer module. Concept experimentation program (cep) report, US Army, Test and Evaluation Coordination Office (TECO), Ft. Leonard Wood, 2000. From archives at www.jointrobotics.com.

[44] G. Piskulic. Military police cep for small robots in support of dismounted troops utilizing non-lethal weapons. Concept experimentation program (cep) report, US Army, Test and Evaluation Coordination Office (TECO), Ft. Leonard Wood, 2001. From archives at www.jointrobotics.com.

[45] S. Ramaswamy and Kimon Valavanis. Hierarchical time-extended petri nets (h-epns) based error identification and recovery for multilevel systems. In *IEEE Transactions on Systems, Man and Cybernetics, Part B*, volume 26, pages 164–175, February 1996.

[46] N.E. Reed. Constructing the correct diagnosis when symptoms disappear. In *Proceedings Fifteenth National Conference on Artificial Intelligence AAAI-98*, pages 151–156, 1998.

[47] R. Rymon. Goal-directed diagnosis-diagnostic reasoning in exploratory-corrective domains. In *Proceedings of the Thirteenth International Joint Conference on Artificial Intelligence*, pages 1488–1493, 1993.

[48] C. Sary, C. Peterson, J. Rowe, T. Ames, K. Mueller, W. Truszkowski, and N. Ziyad. Trend analysis for spacecraft systems using multimodal reasoning. In *Multimodal Reasoning. Papers from the 1998 AAAI Symposium*, pages 157–162, 1998.

[49] F.T. Sheldon, H. Mei, and S.-M. Yang. Reliability prediction of distributed embedded fault-tolerant systems. In *Fourth International Symposium on Software Reliability Engineering Proceedings*, pages 92–102, 1993.

[50] R. Simmons, C. Pecheur, and G. Srinivasan. Towards automatic verification of autonomous systems. In *Proceedings of IEEE International Conference on Intelligent Robots and Systems*, volume 2, pages 1410–1415, 2000.

[51] M. Soika. A sensor failure detection framework for autonomous mobile robots. In *Proceedings of the 1997 IEEE/RSJ International Conference on Intelligent Robots and Systems. Innovative Robotics for Real-World Applications*, pages 1735–1740, 1997.

[52] A.G. Starr, R.J. Wynne, and I. Kennedy. Failure analysis of mature robots in automated production. In *Proceedings of the Institution of Mechanical Engineers, Part B (Journal of Engineering Manufacture)*, volume 213, pages 813–824, 1999.

[53] R. Sterritt and D. Bustard. Autonomic computing — a means of achieving dependability. In *Proceedings IEEE International Conference and Workshop on the Engineering of Computer-Based Systems*, pages 247–251, 2003.

[54] A.P. Tchangani. Reliability analysis using bayesian networks. *Studies in Informatics and Control*, 10, 2001.

[55] Test and Evaluation Coordination Office (TECO). Final report for the chemical biological radiological nuclear (cbrn) sensor module with robotic platform limited objective experiment (loe). Final report, US Army, Test and Evaluation Coordination Office (TECO), Ft. Leonard Wood, 2003. From archives at www.jointrobotics.com.

[56] Roxana Tiron. Lack of autonomy hampering progress of battlefield robots. *National Defense*, May 2003.

[57] Y. Tohma. Fault tolerance in autonomic computing environment. In *Proceedings Pacific Rim International Symposium on Dependable Computing*, pages 3–6, December 2002.

[58] N. Tomatis, G. Terrien, R. Piguet, D. Burnier, S. Bouabdallah, and R. Siegwart. Design and system integration for the expo.02 robot. In *Proceedings of the IEEE/RSJ IROS 2002 Workshop on Robots in Exhibitions*, pages 67–72, 2002.

[59] R.R. Walker and M.R. Scarlett. Test report for the all-purpose remote transport system (arts) executive summary. Executive summary, US Army, Test and Evaluation Coordination Office (TECO), Ft. Leonard Wood, 1999. From archives at www.jointrobotics.com.

[60] P. Wang, T. Yamasaki, M. Yumoto, T. Ohkawa, N. Komoda, and F. Miyasaka. An efficient stochastic qualitative reasoning method for real time fault diagnosis of building air conditioning system. In *Proceedings of IEEE International Conference on Systems, Man, and Cybernetics*, volume 5, pages 854–859, 1999.

[61] R. Washington. On-board real-time state and fault identification for rovers. In *Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings*, pages 1175–1181, 2000.

[62] R. Weiss. Final test report for the unmanned ground vehicle rapid obscurant platform (ugvrop) chemical corps concept exploration program (ugvrop -cep). Concept experimentation program (cep) report, US Army, Test and Evaluation Coordination Office (TECO), Ft. Leonard Wood, 2001. From archives at www.jointrobotics.com.

[63] Holly A. Yanco and Jill L. Drury. A taxonomy for human-robot interaction. In *AAAI Fall Symposium of Human-Robot Interaction*, pages 111–119, November 2002. University of Massachusetts Lowell.

**Appendices**

## Appendix A
## Definitions of Reliability Related Terms

The following list of definitions covers the terminology used in this paper and is provided as a reference.

1. *availability*. Probability that a system will be error free at some given point in time. See (9).

$$Availability = \frac{\text{MTBF}}{\text{MTBF + MTTR}} \cdot 100\% \tag{9}$$

2. *autonomy*. Level of supervision required by humans. A continuum from no autonomy (teleoperated) to full-autonomy in which no supervision is needed.

3. *control system*. A robot subsystem that includes the onboard computer, manufacturer provided software, and any remote operator control units (OCU).

4. *effector*. Any device that performs actuation and any connections related to those components.

5. *error*. A state within the system which can lead to a failure.

6. *failure*. The inability of the robot or its support equipment to function normally.

7. *fault*. Anything which could cause the system to enter an error state.

8. *favorable environmental conditions*. Environmental conditions are considered to be favorable if all conditions, such as dampness and light level, do not interfere with or prevent a given repair procedure.

9. *field environment*. An environment which has *not* been modified to ensure the safety of the robot or to enhance its performance.

10. *field-repairable failure*. A failure is considered to be field-repairable if it can be repaired under the following conditions: only the equipment that commonly accompanies the robot into the field is available, environmental conditions are favorable, and the only personnel available are trained operators.

11. *mistakes*. Human failures caused by fallacies in conscious processing.

12. *MTBF*. Mean Time Between Failures. See (10).

$$MTBF = \frac{\text{Number of Hours Robot Was in Use}}{\text{Number of Failures}} \tag{10}$$

13. *MTTR*. Mean Time to Repair. See (11).

$$MTTR = \frac{\text{Number of Hours Spent Repairing}}{\text{Number of Repairs}} \tag{11}$$

14. *mobile robot*. A mechanical device that can sense and interact with its environment.

15. *non-field-repairable failure*. A failure that is not field-repairable.

16. *non-terminal failure*. A failure that introduces some noticeable degradation of the robot's capability to perform its mission.

17. *slips*. Human failures caused by fallacies in unconscious processing.

18. *support equipment*. Equipment that is not physically part of the robot and is required for the robot to complete its mission or task.

19. *teleoperated*. Manually controlled by an operator at a distance that is too great for the operator to see what the robot is doing.[36].

**Appendix A (Continued)**

20. *terminal failure*. A failure that terminates the robot's current mission.

21. *UGV*. Unmanned Ground Vehicle. A ground-based mechanical device that can sense and interact with its environment.

## Appendix B
## Example Field Failures with Classifications

This appendix provides descriptions and classifications of every example mobile robot field failure used in this paper. Note that the level of detail provided and the accuracy of this data is limited to the granularity and accuracy of the source material. For CRASAR's reliability studies [6][7] this was determined by the data collection method described in Section 4.6. For the rest this was limited to the information provided in the studies themselves.

For each example failure the following is provided: robot model name(s), the study or studies that reported the failure, classification, repairability, impact, cause, symptom, and a brief description with comments where needed. Some of the WTC Engineering failure categories were placed in multiple classes. Each additional appearance is presented below the first and contains only the classification, cause, and description.

**Artificial lighting failure**

| | |
|---|---|
| Robot(s) | MicroTracs |
| Study | WTC Engineering study [34] |
| Class | slip |
| Repairability | non-field-repaired |
| Impact | terminal when additional light is required |
| Cause | energy spike in electrical system |
| Symptom(s) | video became dark |
| Description | The operator reconnected the robot to the OCU while the latter was still powered. This is considered to be a slip because the operator was a hardware specialist with enough technical knowledge to know that this action was risky at best, but was heavily fatigued at the time. |

**Bent ripper appendage**

| | |
|---|---|
| Robot(s) | DEUCE |
| Study | TECO’s DEUCE study [14] |
| Class | mistake |
| Repairability | non-field-repaired |
| Impact | non-terminal unless ripper appendage is required |
| Cause | ripper is embedded in rock while robot is turning |
| Symptom(s) | unresponsive ripper appendage |
| Description | The operator tried to steer the robot with the rippers embedded in rock, not realizing that this action would bend the tool. |

**Blown motor amplifier**

| | |
|---|---|
| Robot(s) | ATRV-Jr |
| Study | Original CRASAR Reliability study [6] |
| Class | mistake |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | overtaxed the motor |
| Symptom(s) | motor unresponsive |
| Description | The operator attempted to use the robot push a heavy load up a hill. |

**Bogged down ripper appendage**

| | |
|---|---|
| Robot(s) | DEUCE |
| Study | TECO's DEUCE study [14] |
| Class | effector |
| Repairability | non-field-repaired |
| Impact | non-terminal unless ripper appendage is required |
| Cause | used in particularly hard rock |
| Symptom(s) | unresponsive ripper appendage |
| Description | The ripper appendage becomes bogged down and cannot move within the rock. |

**Cannot control robot remotely**

| | |
|---|---|
| Robot(s) | D-7G |
| Study | TECO's D-7G study [3] |
| Class | communications |
| Repairability | field-repaired if at all |
| Impact | terminal |
| Cause | cannot transmit through interposed materials |
| Symptom(s) | frequent loss of video, no signal from robot |
| Description | The study concluded that the non-line-of-sight requirement could be met because the equipment could not transmit through interposed materials. |

### Clogged fuel filter

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO's M1 PANTHER II study [13] |
| Class | power |
| Repairability | unspecified |
| Impact | terminal |
| Cause | unspecified |
| Symptom(s) | unspecified |
| Description | The fuel filter on one of the two tanks repeatedly clogged, requiring a replacement roughly every six hours. |

### Collision

| | |
|---|---|
| Robot(s) | Urban |
| Study | CRASAR HCFRD study [10] |
| Class | slip |
| Repairability | depends on damage from the collision |
| Impact | usually non-terminal, depends on damage from the collision |
| Cause | operators removed from robot's operating environment |
| Symptom(s) | usually visible through video |
| Description | Operator caused the robot to collide with the walls while trying to navigate up a flight of stairs. |

**Communications dropout**

| | |
|---|---|
| Robot(s) | All wireless platforms |
| Study | WTC Engineering study [34] |
| Class | communications |
| Repairability | field-repaired if at all |
| Impact | terminal |
| Cause | structural steel of the WTC interfered with the wireless signal |
| Symptom(s) | frequent loss of video, no signal from robot |
| Description | Instead of the usual mile (or more) range of the 2 watt transmitter the robot was carrying, communication was lost within 20 feet. The robot was never recovered. |

**De-tracking**

| | |
|---|---|
| Robot(s) | MicroVGTV, Urban |
| Study | Original CRASAR Reliability study [6], TECO's Urban Robot study [43] |
| Class | effector |
| Repairability | field-repaired |
| Impact | terminal |
| Cause | varies |
| Symptom(s) | significant decrease in mobility |
| Description | A track works its way off its wheels and/or guides. Common failure for tracked platforms. |

Appendix B (Continued)

**Emergency stop switch failure**

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO's M1 PANTHER II study [13] |
| Class | control system |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | unspecified |
| Symptom(s) | switch did not stop the robot |
| Description | Operators were taught to test the emergency switch and other key safety features before using the robots in field tests. It was noted each time these features did not work. |

**Failure of articulating arms or drive motor**

| | |
|---|---|
| Robot(s) | Urban |
| Study | TECO's Urban Robot study [43] |
| Class | effector |
| Repairability | non-field-repaired |
| Impact | usually terminal |
| Cause | dirt and other small debris get into effectors' housing |
| Symptom(s) | effector no longer responds |
| Description | Open gearing for the articulated arms and the drive motor collect debris until those components stop working. |

**Gravity assist (WTC Category)**

| | |
|---|---|
| Robot(s) | MicroVGTV, MicroTracs |
| Study | WTC Engineering study [34] |
| Class | mistake |
| Repairability | field-repaired |
| Impact | non-terminal |
| Cause | incline of ground surface was too steep for robot to keep itself from slipping |
| Symptom(s) | tension on tether required to keep robot from slipping |
| Description | This failure is a mistake when the operator mis-judged the vertical orientation of the void. |

**Heat induced track failure**

| | |
|---|---|
| Robot(s) | MicroVGTV |
| Study | WTC Engineering study [34] |
| Class | effector |
| Repairability | field-repaired |
| Impact | terminal |
| Cause | temperature exceeding 122 degrees Fahrenheit |
| Symptom(s) | significant decrease in mobility |
| Description | The track became hot enough to expand and soften until it fell off of its wheels. This failure could be field-repaired with a backup track. |

**Insufficient automatic adjustment to lighting conditions**

| | |
|---|---|
| Robot(s) | ARTS |
| Study | TECO's ARTS [59] study |
| Class | sensor |
| Repairability | non-field-repaired |
| Impact | depends on lighting conditions |
| Cause | camera's automatic iris did not adjust enough |
| Symptom(s) | dark, unclear camera view |
| Description | The iris did not adjust enough for the operator to see to maneuver the robot. |

**Jammed joystick**

| | |
|---|---|
| Robot(s) | Packbot |
| Study | Original CRASAR Reliability study [6] |
| Class | slip |
| Repairability | non-field-repaired |
| Impact | terminal if joystick is required |
| Cause | inexperienced operator |
| Symptom(s) | joystick unresponsive |
| Description | The joystick was dropped in the sand by a first-time operator. |

| **Lighting incorrect (WTC Category)** | |
|---|---|
| Robot(s) | MicroVGTV, MicroTracs |
| Study | WTC Engineering study [34] |
| Class | sensor |
| Repairability | field-repaired |
| Impact | terminal when a clear camera view is required |
| Cause | failure of artificial lighting |
| Symptom(s) | dark, unclear camera view |
| Description | State in which sufficient light is not present. |
| Class | mistake |
| Cause | automatic white-balance compensation for artificial lighting |
| Description | The operator attempted to improve the camera view by adjusting the artificial lighting, but the camcorder was automatically adjusting to compensate. |

**Low or un-powered**

| | |
|---|---|
| Robot(s) | All platforms |
| Study | Original CRASAR Reliability study [6], TECO's M1 PANTHER II study [13] |
| Class | power |
| Repairability | usually field-repaired, depends on cause and platform |
| Impact | terminal if un-powered, impact if low depends on the platform |
| Cause | low battery, fuel or loose battery connections |
| Symptom(s) | no power, loose connections can be detected if power loss corresponds with certain motions |
| Description | A low or failing battery can cause a wide variety of problems, depending on the characteristics of the electrical system. Dead batteries, or loose connections will leave the robot dead. Most common power failure. |

**Malfunction of track mechanism**

| | |
|---|---|
| Robot(s) | ARTS |
| Study | TECO's ARTS study [43] |
| Class | effector |
| Repairability | field-repaired |
| Impact | terminal |
| Cause | rocks kept track mechanism from functioning properly |
| Symptom(s) | significant decrease in mobility |
| Description | Rocks became stuck in track guides and sprockets. |

**Malfunctioning hydraulic system**

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO's M1 PANTHER II study [13] |
| Class | effector |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | unspecified |
| Symptom(s) | smoke issuing from the tank's modified turret |
| Description | TECO reported that the hydraulic system failed. When this occurred smoke was seen issuing from the tank. |

**Navigation errors**

| | |
|---|---|
| Robot(s) | SARGE |
| Study | TECO's SARGE study [44] |
| Class | mistake |
| Repairability | field-repaired |
| Impact | non-terminal |
| Cause | insufficient information from remote sensors |
| Symptom(s) | operator uncertain of the current position of the robot |
| Description | Position and driving errors due to difficulty judging distance and position through the teleoperation interface. |

### Obscured camera view

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO’s M1 PANTHER II study [13] |
| Class | sensor |
| Repairability | field-repaired |
| Impact | non-terminal where camera is not required |
| Cause | lenses covered in moisture, dirt, or mud |
| Symptom(s) | unclear or obscured camera image |
| Description | Camera lens becomes covered in moisture, dirt, or mud. A frequently encountered field failure, especially in wet or rainy environments. |

### Occasional static

| | |
|---|---|
| Robot(s) | ARTS, URBOT, Talon |
| Study | TECO’s ARTS [59], and Urban Robot studies [43] |
| Class | communications |
| Repairability | field-repaired |
| Impact | non-terminal |
| Cause | unstable wireless connection |
| Symptom(s) | static in video |
| Description | Occasional static disrupted the ARTS operators. In the Urban Robot study additional antennas were used to improve the quality of the signal, but this failure still occurred. |

**Appendix B (Continued)**

**Occluded camera (WTC Category)**

| | |
|---|---|
| Robot(s) | MicroVGTV, MicroTracs |
| Study | WTC Engineering study [34] |
| Class | sensor |
| Repairability | field-repaired |
| Impact | terminal |
| Cause | obstacle or debris in front of camera |
| Symptom(s) | occluded camera view |
| Description | State in which the camera view is completely occluded by obstacles |
| Class | mistake |
| Cause | robot placed (or left) in a position where the camera view is of no use |
| Description | The operator does not know how to navigate around (or away from) the obstacle or debris blocking the robot's camera view. This classification would be used to describe additional time spent in this state after the operator has detected the problem. |

### Overtaxed power system

| | |
|---|---|
| Robot(s) | Urban |
| Study | TECO's Urban Robot study [43] |
| Class | mistake |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | trying to use a frozen drive system |
| Symptom(s) | depends on the platform |
| Description | The operators did not realize that the drive system was frozen and would overtax the power system attempting to get the robot to move. |

### Pinion gear stripped

| | |
|---|---|
| Robot(s) | MicroVGTV |
| Study | Original CRASAR Reliability study [6] |
| Class | effector |
| Repairability | non-field-repaired |
| Impact | non-terminal where shape shifting is not required |
| Cause | dirt and other small debris get into gear's housing and cause premature wear |
| Symptom(s) | failure to shift though shift motor can be heard running |
| Description | Pinion gear inside the geometry shifting mechanism becomes stripped. A common failure for this model. |

**Punctured track mechanism**

| | |
|---|---|
| Robot(s) | MicroTracs |
| Study | WTC Engineering study [34] |
| Class | effector |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | aluminum rod lodged into the track mechanism |
| Symptom(s) | significant decrease in mobility |
| Description | The robot was resting on the rod until the operator tried to drive the robot. The track mechanism pulled the rod into the thin space between the track and the platform. |

**RPMs at critical level**

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO's M1 PANTHER II study [13] |
| Class | control system |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | unspecified |
| Symptom(s) | RPMs high while robot is stationary |
| Description | The RPMs shot up for no apparent reason. One of several problems encountered with the teleoperation system installed on the modified tank. |

**Robot placed in unsafe position**

| | |
|---|---|
| Robot(s) | URBOT, Talon |
| Study | TECO's Urban Robot study [43] |
| Class | slip |
| Repairability | field-repaired |
| Impact | non-terminal in training, potentially terminal in a real scenario |
| Cause | operators removed from robot's operating environment |
| Symptom(s) | robot casually placed in positions which the operator would not place themselves |
| Description | The operator would often drive the robot dangerously close to suspicious objects to determine if they were mines, grenades, or another harmful device. |

**Rolled on its side**

| | |
|---|---|
| Robot(s) | ARTS |
| Study | TECO's ARTS study [59] |
| Class | mistake |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | platform became unstable on 30% slope |
| Symptom(s) | visible through video |
| Description | The operator did not have a sense of the incline angle of the ground surface, and the robot's unstable state. |

### Shear pin broken

| | |
|---|---|
| Robot(s) | MicroVGTV |
| Study | Original CRASAR Reliability study [6] |
| Class | effector |
| Repairability | non-field-repaired |
| Impact | non-terminal where shape shifting is not required |
| Cause | robot encounters resistance while shifting |
| Symptom(s) | failure to shift though shift motor can be heard running |
| Description | Shear pin inside the geometry shifting mechanism breaks. A common failure which often occurs in confined spaces. |

### Spontaneous shutdown

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO's M1 PANTHER II study [13] |
| Class | control system |
| Repairability | field-repaired |
| Impact | terminal |
| Cause | unspecified |
| Symptom(s) | robot is shutdown |
| Description | Shutdown when the operator tried to switch from automatic to teleoperation mode on the controller. One of several problems encountered with the teleoperation system installed on the modified tank. |

**Steering lost**

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO’s M1 PANTHER II study [13] |
| Class | control system |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | unspecified |
| Symptom(s) | no response to steering command |
| Description | One of several problems encountered with the teleoperation system installed on the modified tank. Sometimes manifested in only one direction at a time. |

**Steering slow to respond**

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO’s M1 PANTHER II study [13] |
| Class | control system |
| Repairability | non-field-repaired |
| Impact | non-terminal |
| Cause | unspecified |
| Symptom(s) | delay in robot’s response to steering command |
| Description | One of several problems encountered with the teleoperation system installed on the modified tank. Sometimes manifested in only one direction at a time. |

| **Stuck assist (WTC Category)** | |
|---|---|
| Robot(s) | MicroVGTV, MicroTracs |
| Study | WTC Engineering study [34] |
| Class | mistake |
| Repairability | field-repaired |
| Impact | non-terminal |
| Cause | obstacles or piles of debris keep the robot from moving |
| Symptom(s) | tracks turning but the robot is not moving |
| Description | The failure is a mistake when the operator lost track of or did not see the obstacles. |

| **Thrown track** | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO’s M1 PANTHER II study [13] |
| Class | effector |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | unspecified |
| Symptom(s) | significant decrease in mobility |
| Description | TECO reported one case in which the modified tank threw a track. |

**Track slippage**

| | |
|---|---|
| Robot(s) | D-7G, DEUCE |
| Study | TECO's D-7 [3] and DEUCE [14] studies |
| Class | effector |
| Repairability | field-repaired |
| Impact | non-terminal |
| Cause | varies |
| Symptom(s) | treads rotating without a corresponding change in position |
| Description | Tracks cannot maintain sufficient friction with the ground surface. |

| **Track slippage (WTC category)** | |
|---|---|
| Robot(s) | MicroVGTV, MicroTracs |
| Study | WTC Engineering study [34] |
| Class | effector |
| Repairability | field-repaired |
| Impact | non-terminal |
| Cause | varies |
| Symptom(s) | treads rotating without a corresponding change in position |
| Description | Track slippage at the WTC would be an effector failure when there should have had sufficient traction in the environmental conditions the robot was experiencing at the time of the failure. The study did not provide enough information to determine if these conditions were ever met or not. |
| Class | slip |
| Cause | robot high centered or in a less than optimal configuration |
| Description | The operator is navigating through an area where the robot can become high-centered (treads cannot touch the ground due to uneven terrain or small obstacles) or has difficulty maintaining sufficient friction with the ground surface. During this task the operator errors and leaves the robot high-centered or uses the wrong configuration (see [34] for more details on the impact of a MicroVGTV's configuration on mobility). |

**Appendix B (Continued)**

**Transmitting over unauthorized frequencies**

| | |
|---|---|
| Robot(s) | ARTS |
| Study | TECO's ARTS study [59] |
| Class | communications |
| Repairability | non-field-repaired |
| Impact | non-terminal |
| Cause | imprecise transmitting equipment |
| Symptom(s) | signal detected in unauthorized frequency |
| Description | The transmitter would bleed over from authorized frequencies into unauthorized ones. |

**Uncontrolled acceleration**

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO's M1 PANTHER II study [13] |
| Class | control system |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | unspecified |
| Symptom(s) | still accelerating when operator is no longer trying to steer the robot |
| Description | One of several problems encountered with the teleoperation system installed on the modified tank. |

**Unresponsive (minor)**

| | |
|---|---|
| Robot(s) | MicroVGTV,Urban |
| Study | Original CRASAR Reliability study [6] |
| Class | control system |
| Repairability | field-repaired |
| Impact | terminal |
| Cause | unknown |
| Symptom(s) | cycling power fixes the problem |
| Description | The robot is unresponsive or frozen and there is no obvious source of the problem, like a dead battery or blown component. The robot begins responding again after one or two power cycles. |

**Unresponsive (serious)**

| | |
|---|---|
| Robot(s) | MicroVGTV |
| Study | Follow-up CRASAR Reliability study [7] |
| Class | control system |
| Repairability | non-field-repaired |
| Impact | terminal |
| Cause | overload in the electrical system on the robot or in the OCU |
| Symptom(s) | cycling power does not fix the problem and/or small amounts of smoke |
| Description | The robot consistently runs for a short period of time and then fails. |

**Unstable camera signal**

| | |
|---|---|
| Robot(s) | PANTHER |
| Study | TECO's M1 PANTHER II study [13] |
| Class | sensor |
| Repairability | depends on cause |
| Impact | non-terminal where camera is not required |
| Cause | bumpy terrain, sudden changes in lighting, rain |
| Symptom(s) | unclear, intermittent, or lost signal |
| Description | Intermittent, unclear, or lost signal from a camera. |

**Unstable sensor signal**

| | |
|---|---|
| Robot(s) | All platforms |
| Study | Original CRASAR Reliability study [6] |
| Class | sensor |
| Repairability | depends on cause and platform |
| Impact | non-terminal where the sensor is not required |
| Cause | faulty cabling, or broken or loose connections |
| Symptom(s) | unclear or intermittent signal, loose connections can be detected if signal dropout corresponds with certain motions |
| Description | Intermittent, unclear, or lost signal from a sensor where the sensor itself is functioning properly. Most common sensor failure. |

**Appendix B (Continued)**

| **Unstable teleoperation control** | |
|---|---|
| Robot(s) | MicroVGTV |
| Study | Original CRASAR Reliability study [6] |
| Class | slip |
| Repairability | field-repaired |
| Impact | terminal |
| Cause | tether was not properly connected to the OCU |
| Symptom(s) | lag in left turns and intermittent communications dropout |
| Description | The operator that setup the system did not properly connect the tether to the OCU. |