Visualizing patterns: decision support for human-based demining

A Thesis presented

by

Lahiru G. Jayatilaka

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Thesis advisor

Krzysztof Gajos

Author

Lahiru G. Jayatilaka

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Abstract

Expert deminers using hand-held detectors construct outlines to make detection decisions. These outlines are constructed by finding a point near a potential target at which the metal detector goes from beeping to not beeping. This feedback transition point is known as an edge point. By finding numerous edge points systematically, these experts build outlines or patterns of the area in which detector feedback occurs. These patterns allow the expert operator to make decisions about the absence or presence of a mine, based on previous experience with patterns. That is, if a pattern currently encountered is similar to one belonging to a mine in the past, then the probability of mine presence is high. By incorporating such behavior into standard demining training programs, researchers have been able to improve performance of novices and also reduce performance differences amongst them. I propose that representing these outlines on a screen rather than relying on operator memory may result in further improvement. To test this, a simulated landmine detection experiment was designed where trained participants behaved like deminers trying on find dummy mines. These users constructed and used these outlines to confirm the presence or absence of a target. Some users adopted the present approach of remembering these outlines, while others were provided with a visual decision support tool. The visual decision support tool permitted operators to collect and store edge points, which were displayed on a simple interface, enabling them to "see" the outline. Users that had to remember these outlines could detect targets with a probability of 77%, while those with visual support detected targets with a probability of 95%. Furthermore, apart from being more correct, participants with visual support were 33% more accurate at locating target positions.

Contents

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Chapter 1

Introduction

1.1 The landmine problem

A landmine is a type of self-contained explosive device, which is placed on or in the ground to constitute a minefield, designed to destroy and damage equipment or personnel (see Figure 1.1) [18]. A landmine blast can be fatal or cause long-term debilitating injuries such as blindness, burns, damaged limbs, and shrapnel wounds.

Figure 1.1: A low metal anti-personnel mine [5]

States with 1,000 casualties or more from 1999–2008

State	Total 1999–2008
Afghanistan	12,069
Cambodia	7,300
Colombia	6,696
Iraq	5,184
India	2,931
Russia	2,795
Angola	2,664
Somalia	2,354
Myanmar	2,325
Lao PDR	2,295
Pakistan	1,969
Ethiopia	1,947
Sudan	1,748
Congo, Democratic Republic of (DRC)	1,696
Vietnam	1,545
Sri Lanka	1,272

Figure 1.2: Number of states with more than 1000 casualties 1999-2010 [4]

Landmines can be concealed in places where people carry out their daily activities and therefore indiscriminately target civilians and children many years after conflicts have ended. As of 2009, landmines were estimated to have affected nearly 70 states,[1] and during 2008 alone, were responsible for over 5000 casualties.[2] [4]

The landmine problem deserves attention on humanitarian grounds, primarily because these weapons harm thousands of innocent people every year without intent or cause. Between 1999-2008 73,576 causalities were reported of which 17,867 were fatal (see Figure 1.2) . During this period, in the most severely affected countries, approxi-

[1] The use of the words "states" indicates an individual country. This thesis uses this terminology to be consistent with humanitarian demining literature. See Ref. [4].

[2] All casualty statistics in this section are from landmines and explosive remnants of war. See Section 2.2 of thesis.

Figure 1.3: A landmine victim fitting artificial leg [47]

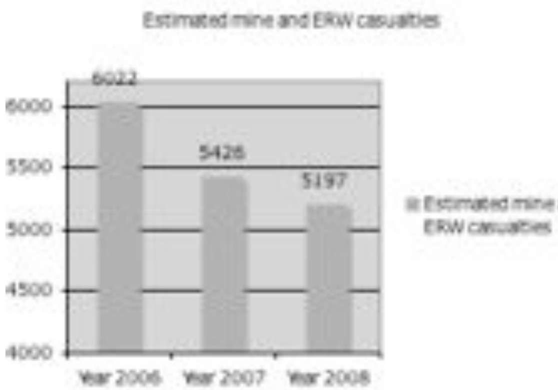
mately 71% of casualties were civilians and 32% children [4]. Sample data from 2008 shows that more than 1800 casualities during this period occurred while people engaged in activities such as traveling, playing, tending animals and collecting food/wood/water [4]. The number of such fatalities in 2008 is comparable to the size of Harvard College's graduating class of 2010.

Survivors of landmine incidents suffer from serious psychological and physical trauma, and face difficulty with reintegration [4]. The measured quality of life for victims is typically low because support systems are inadequate, and some survivors even face discrimination due to their disabilities [21, 26]. In many countries child survivors have to end their education prematurely due to the period of recovery needed and the accompanying financial burden of rehabilitation. Vietnam, one of the worst affected in this regard, has an estimated 100,000 survivors [28].

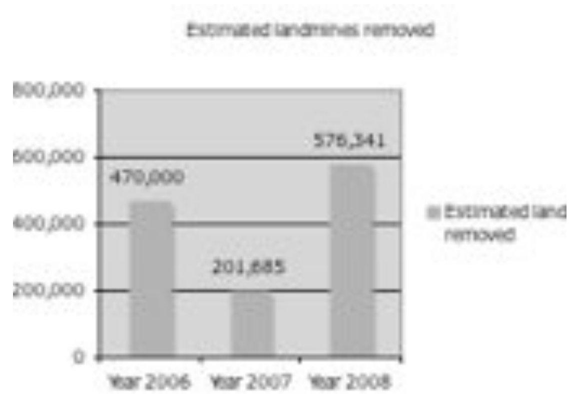
Figure 1.4: The extent of the displaced persons problem in Sri Lanka, in April 2009, during the height of the civil conflict [34]

Landmine effects extend beyond their immediate victims because these weapons instill fear and uncertainty in entire communities. While difficult to experience, it is still possible to imagine the fear associated with landmine threats on nearby footpaths and fields [31]. Accompanied by this fear is a restriction of movement which results in paralysis of community activity. This in turn hampers local economic activity, reduces welfare and inhibits progress. On the national level governments are forced to divert financial resources to national support programs for survivors. Governments must also spend money on local demining programs that potentially last for decades. For a primarily agrarian country, the loss in farmland due to landmine hazards is a significant strain on the national economy [4]. For example, Cambodia is estimated to have 672 km^2 of contaminated land, 13% of the country's total land mass [4].

Post-conflict landmines are also a significant barrier to the resettlement of internally displaced people. During the writing of this thesis thousands of displaced people in post-conflict Sri Lanka were unable to return to their communities due to landmine threats. Some of the displaced have been unable to return to their homes for decades due to the country's gruesome 30 year civil conflict. On the global scale, between 2006-2008, international donors spent over $1 billion on mine action funding [4].



(a) Estimated number of landmine and ERW casualties 2006-2008 [4]



(b) Estimated number of mines removed 2006-2008 [4]

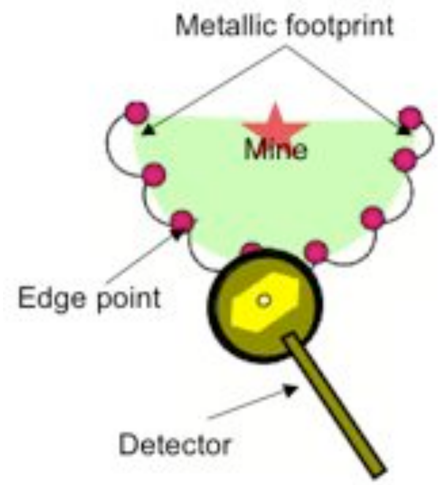
Figure 1.5: Trends in mine removals and casualties

1.2 Spatial models in human-based demining : an introduction

Humanitarian demining continues to be a major response mechanism to the landmine problem (See Figure 1.5) [4, 18, 33, 49, 16]. Presently, a human using a hand-held detector is the main method of threat detection (See Figure 1.6(a)) [4, 30]. This method of demining, however, is subject to serious shortcomings due to constraints related to safety, skill differences and other operational difficulties such as false alarms from metallic debris [18, 4, 41]. Efforts to overcome these difficulties have mainly focused on better detection technology, but progress has been difficult due to cost and robustness issues [18, 30]. Alternative efforts have tried to improve human performance with respect to existing detection technology. Human-centric improvements have focused on providing performance enhancing technology, improving training and engineering novel ways to use detector feedback [41, 19, 36].

In the context of human-centric improvements, the work of Staszewski and Davison has had noticeable impact [42]. This work has focused on improving deminer capabilities by incorporating expert techniques into standard demining training and practice. Extensive behavioral research on expert deminers suggests that successful detections with current hand-held detectors is related to recognition of visuo-spatial patterns created and held in memory [41, 44]. It is proposed that experts create "metallic footprints" by sequentially finding auditory on-off transition points (edge points) and "creating spa-

(a) Human with metal detector [41]



(b) Conceptual representation of metallic footprint construction [40]

tial patterns in [the] mind's eye by linking the contiguous edge marker locations" (See Figure 1.6(b)) [41]. If the patterns produced are sufficiently similar to those encountered previously with mines, a threat is signaled. By incorporating the concept of spatial patterns into demining training curriculum, researchers have witnessed both a significant improvement in detection performance and a reduction in skill differences amongst participants [41]. These findings have been evaluated, adopted, and implemented force-wide by the US Army [9].

1.3 Visual decision support: a hypothesis

Although the use of metallic footprints has been useful in augmenting performance, the representational modality of these patterns presents potential shortcomings. Retention and processing of these patterns is possibly dependent on spatial ability. This is documented to vary amongst individuals [23, 45]. Furthermore, retention is also affected by working memory limits and cognitive burdens of stress and distraction[22, 24, 8, 27, 39]. The possibility of circumventing these shortcomings through the use of visual decision support is the motivation behind this research endeavor. Hence, I propose spatially mapping these metallic footprints onto operator visual space as an alternative to the present mode of internal representation. I hypothesize that this visual mapping and representation, if correctly implemented, will circumvent psychological shortcomings and result in further improved performance.

1.4 Research Objectives

The primary objective of this research endeavor was two-fold. First, to verify that visual decision support could theoretically improve detection performance in the context of human-based demining, which employs the concept of metallic footprints. Secondly, to understand the extent to which visual decision support improves pattern resolution in relation to present representation modalities. The secondary objective of this work was to asses the usability of visual decision support for practical relevance.

In order to achieve these goals, an extensive human-based experiment was designed to assess user performance in simulated landmine detection tasks, with visual support used as the treatment condition. Experimentation and interpretation of results were guided by the following research questions:

- **Research Question # 1:** How does visual tracking and display of metallic footprints affect correct detections and correct rejections?
- **Research Question # 2:** How does visual tracking and display of metallic footprints affect target localization error?
- **Research Question # 3:** How does visual tracking and display of metallic footprints affect subjective measures of confidence and ease?

Chapter 2

Background

2.1 Summary of chapter

This chapter aims to provides insight into the importance of human-based demining, and the methods by which people have sought to improve it. After an overview of related work, a more detailed description of "metallic footprints" in human-based demining is provided. This chapter concludes with a proposal for visual decision support in the context of metallic footprints.

2.2 Landmines and Explosive Remnants of War

Landmines can detonate by the action of their target, the passage of time or by controlled means. Fusion activation mechanisms include pressure release, movement, and magnetic influence among others [18] . Landmines can be broadly classified into two categories, Anti-Personnel mines (AP) and Anti-Tank mines (AT). AP mines are specifically designed to injure people, while AT mines are designed to destroy vehicles and their occupants. Figure 2.1 shows some commonly used AP and AT mines.

AP mines are small, weigh about a few hundred grams and are of varying complexity. These mines are normally placed on the ground or buried a few centimeters from the surface. Typical detonation mechanisms involve pressure of a person's foot or using tripwires. AT mines are much larger and heavier. These mines are buried at a depth of about 30 cm below the surface. Modern AT mines use a magnetic influence trigger, which enables detonation even when tires or tracks do not touch it. Some AT mines are dual purpose and can be triggered by people, serving as a remote detonation weapon [18].

Under international legal definitions, explosive remnants of war (ERWs) refer to unexploded ordnances (UXOs) and abandoned explosive ordnances (AXOs). UXOs are wartime weapons that have failed to detonate as expected when deployed, but pose a similar threat as landmines given that they could be unstable. AXOs are unused explosive ordnance that have been left behind and are no longer under any party's control. Examples of ERWs include unexploded artillery shells, mortars, rockets, air-dropped bombs and cluster munitions [3].

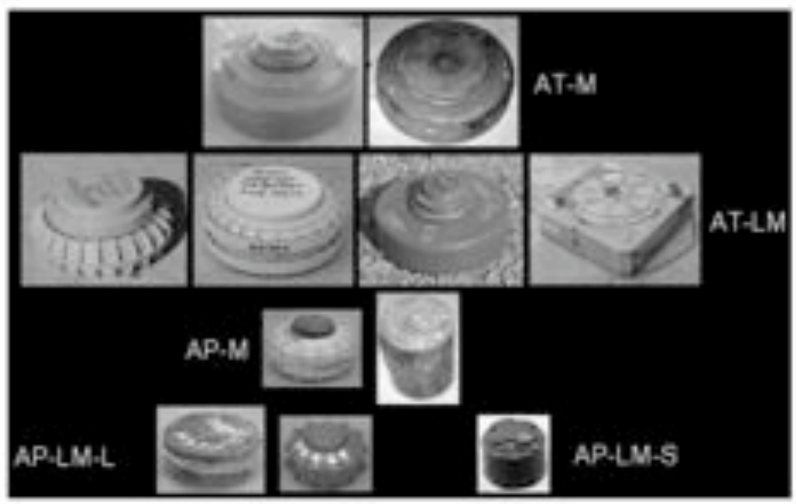


Figure 2.1: Row 1 shows metallic anti-tank (AT-M) mines. Row 2 shows newer anti-tank mines with plastic bodies and minimal metal content in their firing mechanisms (AT-LM). Row 3 shows anti-personnel mines containing substantial metal content compared to the low-metal anti-personnel mines (AP-LM)) shown in Row 4 [41]

2.3 Challenges for humanitarian demining

Humanitarian demining demands that all landmines and explosive remnants of war affecting civilian land use must be completely cleared [18]. Land that has been cleared in this sense must present no risk whatsoever to land users. Countries with humanitarian demining efforts range across the globe from Colombia to Egypt to Russia to Cambodia, with demining programs for each country varying in duration and scope.

Figure 2.2: Deminer prodding to investigate a detection signal [19]

Tunisia, which laid approximately 7,408 mines along its border in 1976 and 1980, completed full clearance as of May 2009 [29]. Cambodia, on the other hand, which contains mines from three decades of civil war and millions of ERWs from the US-Vietnam war in the 1970s, expects a further ten years until full clearance [29]. Humanitarian demining programs are mostly carried out by national armed forces during peace time, but international non-governmental organizations (INGOs) such as *The HALO Trust* run significant programs as well [49].

Humanitarian demining in its present state faces many challenges. Metal detectors, which are widely used, have high false alarm rates due to metallic clutter such as nails, barbed wire and shrapnel found on minefields [48, 30, 4]. The presence of clutter has been identified as the one of the biggest impediments against efficiency, since every time a signal is received, the deminer must stop and investigate through excavation [48, 4]. Operational difficulties also arise from the variability associated with target objects. Newer landmines are harder to detect because they are made mostly of plastic with miniscule amounts of metallic content (see Figure 2.1) [41]. The performance of presently available detection technology is also effected by environmental factors such as terrain and soil composition, burial depth and other climatic variables [18, 30, 15]

Humanitarian demining also faces serious economic and political challenges. A lack of demining resources is a significant problem for most mine-affected countries. For example, in 2009, Morocco claimed to have 10,000 deminers engaged in clearance effort, but only possessed 400 detectors and sets of personal protective equipment [4]. Disturbingly, many demining units around the world continue to excavate mines using

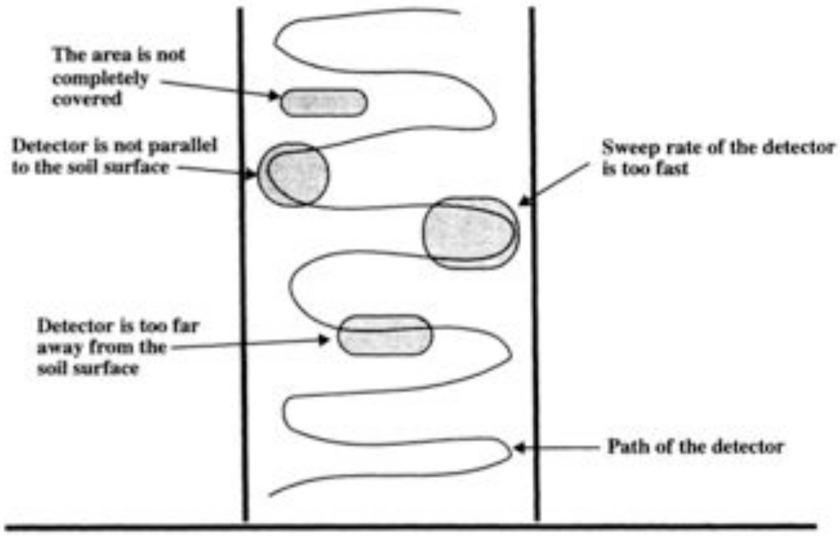


Figure 2.3: Some common mistakes in deminer sweeping [19]

hand tools such as bayonets and rakes (see Figure 2.2), while only select humanitarian demining programs have started use state-of-the-art GPR and metal based fusion detectors [38, 48, 41]. Speed is also sometimes an important factor in humanitarian demining as quick clearance of land is required to resettle displaced people. In this scenario, there is pressure on demining efforts from both the general public and international community. As an occupation, demining continues to be unsafe. In 2009, there were approximately 100 deminer casualties [4].

2.4 Challenges for human-based demining

The most widely used technique for demining, presently, is a human searching a minefield using a hand-held detector[1] [4] . This demining mechanism can be subdivided into three main phases, **Search**, **Investigation**, and **Detection** [45]. In each of these phases, limitations arise due to available detection technology and human involvement in the task activity.

In the search phase, sweeping the search area accurately and methodically is important to ensure that suspected areas are completely cleared. "Good sweeping" relies on sweeping at the correct speed, maintaining sensor head angle and covering all loca-

[1] For a consideration of non-human-based techniques see Conclusion chapter

tions (see Figure 2.3) [19]. In a typical setting the human must actively ensure that these goodness parameters are satisfied. However, due to boredom with the repetitive nature of the task or physical/mental fatigue, lack of task engagement may cause sensor sweeps to become inadequate [43].

Investigation involves acquiring more information about potential threats. This may involve close visual inspection or systematic feedback retrieval around the threat area. Issues with the investigation phase arise from different investigation strategies yielding different results. Work on expert operator behavior shows that investigation occurs systematically to find the spatial contours inside which feedback occurs. This has been identified as a contributing factor to the performance differences between experts and novices [41].

The detection phase is influenced by the quality of sensor feedback. Variations in burial depth, soil conditions and climatic variables cause variations in sensor output, which in turn influences the information resolution available for decision making [43, 41, 18].

It is also likely that influences such as work pressure and stress, given the task context, effect decision making at all three stages. With respect to certain spatially driven investigation strategies, it has already been argued that individual differences in operator spatial ability, working memory and stress levels may influence performance (See Section 1.3).

2.5 Improving the deminer: a survey of related work

Research and development efforts have occured to improve human performance in demining by circumventing the challenges described above. These efforts have mainly focused on better detection technology, while other efforts have tried to improve human performance with respect to existing detection technology. Human based improvements have focused on providing performance- enhancing technology, improving training and engineering novel ways to use detector feedback. Given the scope of this work, the consideration of related work will be mostly limited to efforts that have aimed to improve performance with respect to existing detection technology.

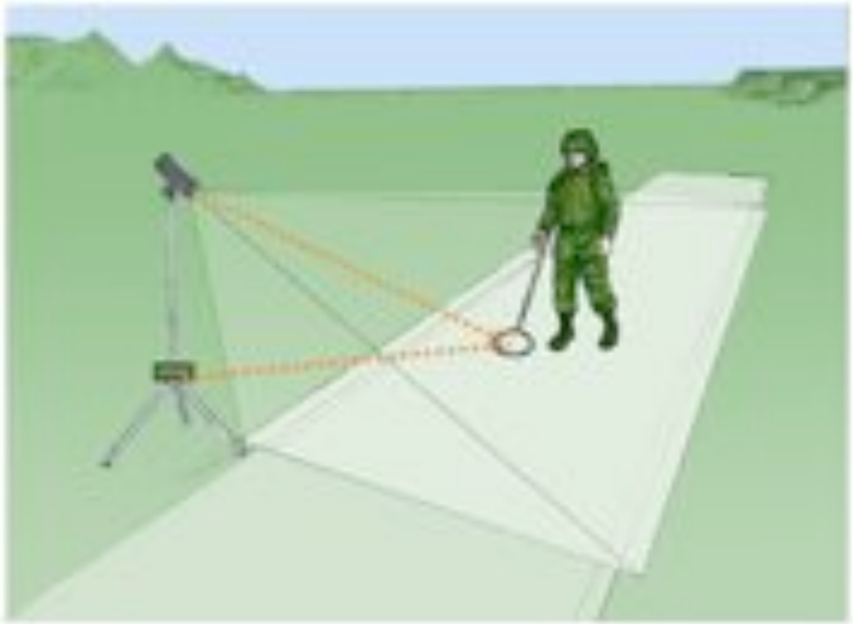


Figure 2.4: Representation of how Sweep Monitoring System records trainee activity [19]

Virtual Mine Lane

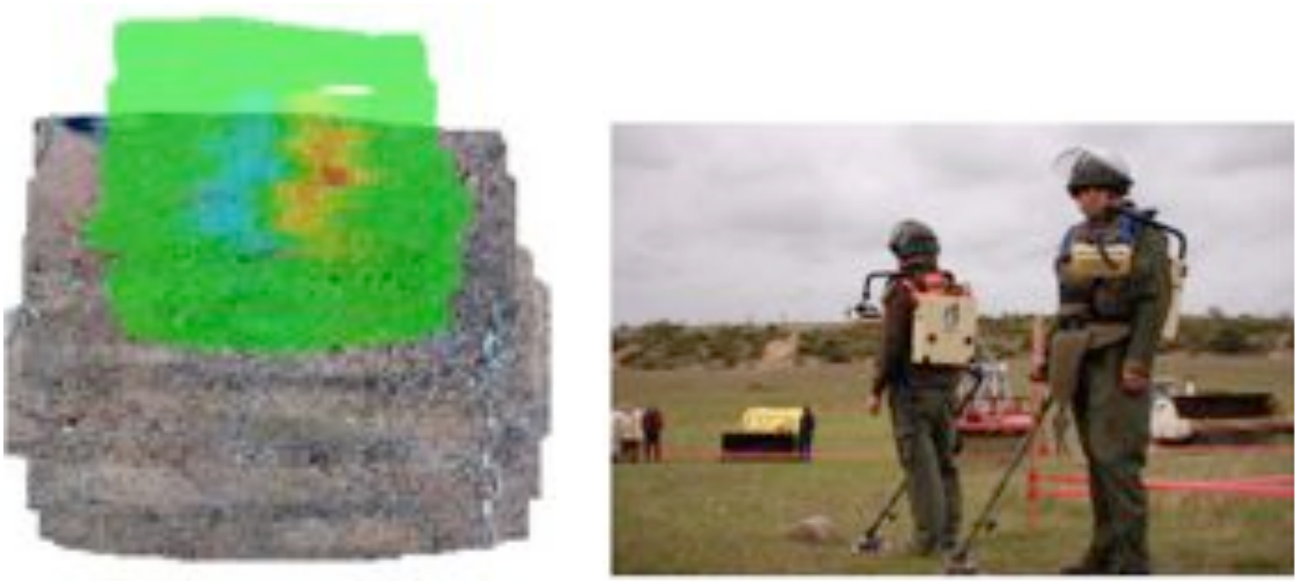
This was a tool designed to simulate real mine detection lanes. A video projector was used to display a surface texture on the ground, and provide visual feedback. This permitted operators to learn basic sweeping and target identification techniques in a highly controlled environment [20, 19] .

Enhanced operator interface

Based on virtual mine lane, this was an exploratory study carried out to explore the design of a real-time interactive audio and video operator interface to improve operator sweeping patterns. Initial studies showed that feedback not only improved sweeping performance but also reduced performance differences stemming from varying skill levels [19].

Sweep Monitoring System

The sweep monitoring system (SMS) stemming from *Enhanced operator interface* and *Virtual Mine Lane* , tracks the movement of a hand-held land mine detection wand and gives immediate feedback to both instructor and trainee on the trainee's progress (see Figure 2.4). It provides an objective measurement of a trainee's skill, improving the relia-



(a) Visualized metal detector data

(b) Pulse GPR based ALIS

Figure 2.5: The ALIS system [36]

bility, safety and accuracy of land mine detection [25].

ALIS

This is a high-end protoype hand-held land mine detector that records and can visually display GPR and metal detector signals. During operation, the sensor operator can observe the metal detector response image together with a picture of the ground surface displayed on a palmtop PC (see Figure 2.5(a)). Imaging is done using an overhead CCD camera (see Figure 2.5(b)). Field tests were carried out in Croatia in 2007-2008 and in Cambodia in 2009. The hope is that by providing 3-D GPR images, operators can better understand subsurface conditions [36].

Studying performance in a mine-detection-like task

An experimental study, motivated by models of detection of cryptic prey by foraging predators, was designed to study the perceptual and learning processes involved in landmine detection, . The study examined the effects on target detection and false-alarm rates with respect to intensity differences between target and distractor signals, the number of distractors and training order [6].

Mine detection based on expert skill

This work in the field of Cognitive Engineering, by Staszewski and Davison, has had significant impact on the training and performance of deminers [9]. A series of application based projects focused on studying expert deminer behavior with the aim of reverse engineering this behavior for training purposes. Experiments showed that incorporating certain expert behaviors into standard training routines both improved the performance of novice deminers and reduced skill differences. The expert behaviors in consideration were focused on the spatial reasoning of metallic footprints generated using metal detectors. The success of this study has led to the adoption of the experimental training program by the United States Army [45, 42, 44, 41].

2.6 Spatial models in human-based demining: a detailed overview

Extensive behavioral research on expert deminers suggests that successful detections with current hand-held detectors is related to recognition of visuo spatial patterns created and held in memory [41, 44]. It is proposed that experts create **"metallic footprints"** by sequentially finding auditory on-off transition points (edge points) and "creating spatial patterns in [the] mind's eye by linking the contiguous edge marker locations" (see Figure 1.6(b)) [41]. If the patterns produced are sufficiently similar to those encountered previously with mines, a threat is signaled. By incorporating the concept of spatial patterns into demining training curriculum, researchers have witnessed both a significant improvement in detection performance and a reduction in skill differences amongst participants [41]. These findings have been evaluated, adopted, and implemented force-wide by the US Army.

This work relies on the operational premise that typical landmines have roughly semi-circular metallic footprints, with the size and shape of these footprints vary according to mine type. For example, low metal mines result in edge points clustered within a foot or so of one another, while high metal mines result in footprints more than a meter in diameter (the length of the radii are positively correlated with the metallic content of the target) (see Figure 2.6). Furthermore, metallic footprints generated by non-target materials, clutter, are not as regular as the footprint signatures belonging to mines.

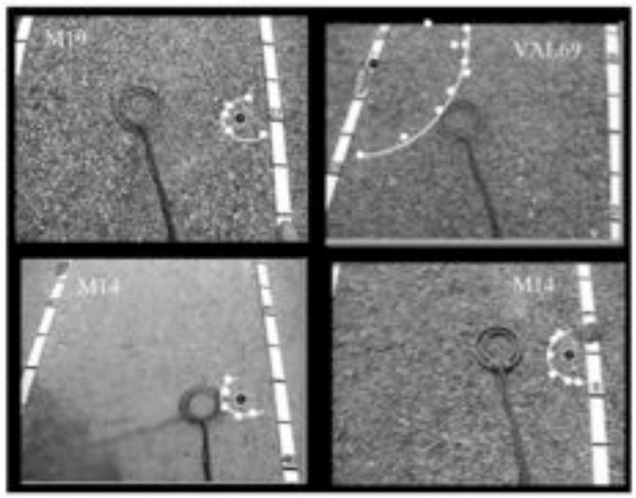


Figure 2.6: Spatial patterns derived in analyses of expert's successful detection of mines in performance testing. Crosshair marks indicate the approximate centers of the buried targets; solid white circles indicate the "edge" locations defined by either onset-offset or offset-onset of the auditory output signal. [41]

Given the nature of these footprints, and observed expert behavior, there is strong reason to believe that expert operators create spatial patterns in their "mind's eye" and compare these patterns against a knowledge base of previously detected mines. Incorporating the concept of metallic footprints into experimental training programs, researchers have witnessed significant improvements in correct detection rates and consistent performance amongst trainees who were taught this concept (see Figure 9.11 in [41]).

2.7 Metallic footprints and proposed visual decision support

Instead of representing metallic footprints internally in the "mind's eye", this thesis proposes a real time visual decision support system to track and display metallic signature patterns. This proposal is made to the extent that only permits for verification of the research hypothesis. That is, that visual representation of metallic footprints should, theoretically, further improve deminer performance. The proposed visual decision support system will permit operators to place edge points on a live video feed of the detection space. By recording a sufficient amount of edge points, the support system will permit the operator to visualize the metallic footprint and make decisions (see Figure 2.7).

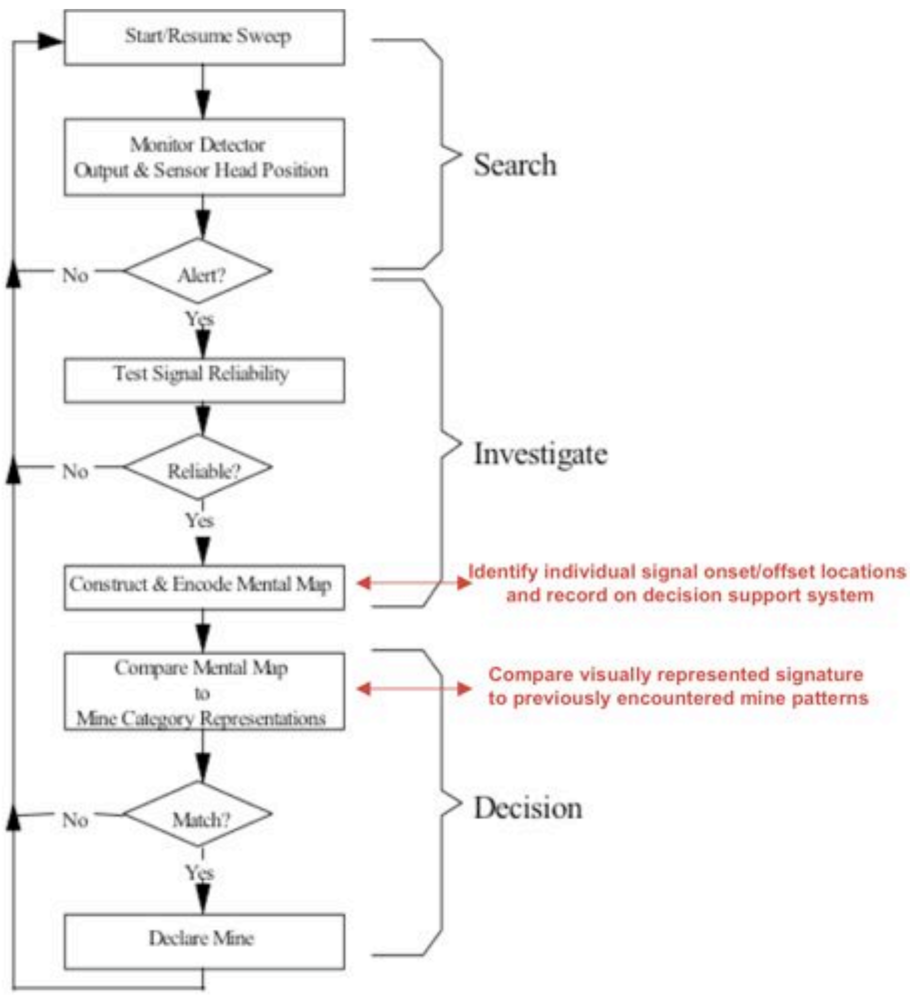


Figure 2.7: Envisioned workflow mapping in metallic footprint based mine detection between present model and visual decision support system (image adapted from Ref. [45])

Chapter 3

Method

3.1 Summary of Chapter

This chapter describes a simulated landmine detection experiment to investigate objective and subjective performance in this task. Ecological and confounding concerns with regards to experimentation are explicitly identified followed by a description of design choices made in order to respond to these challenges. A detailed overview of the experimental setup is provided, followed by a detailed identification of all measures collected during experimentation.

3.2 Experimental Procedure

In this experiment trained subjects discriminated and localized mine-like targets amid metallic clutter in a simulated detection environment with the use of a hobby metal detector. Detection tasks involved either a mine-like target amongst clutter or only a combination of clutter items.

Subjects completed a 1.5 hour long instructor guided interactive training program before passing onto testing. The training program consisted of the training phase and the training exercise phase. The training phase, approximately 40 minutes long, oriented subjects with metal detector use, sweeping styles, the distinction between targets and clutter, and footprint construction techniques. Subjects were taught how to identify and use footprints belonging to mine-like targets and how to distinguish them from those belonging to clutter-only items. This phase was reinforced through training videos, interactive demonstrations and hands-on practice.

Upon completion of the training phase, subjects proceeded onto the training exercise phase after a short briefing break. In the training exercise phase, approximately 60 minutes long, subjects performed discrimination and localization on a set of training detection tasks. These tasks were presented in randomized cycles. Subjects were given extensive correctness and performance feedback on each task and could only proceed to the testing phase if all tasks in the training set were correctly discriminated and localized in one cycle. For subjects who could not complete this phase in a reasonable amount of time, the experiment was aborted with compensation.

Upon completion of training, demographic information was collected and subjects were informed of the applied treatment condition. That is, whether they would be performing all tasks in the testing phase with or without visual assistance. Subjects were also informed that they would be performing all testing tasks under time pressure of 120 seconds and were reminded of the applied monetary reward penalty scheme. Rewards were provided for accurate target localizations (+$1) and weighted penalties were incurred for incorrect detections (-$1) and incorrect rejections (-$3).

Subjects had to perform six (6) detection tasks. For each detection task, subjects created a metallic footprint, and used the metallic footprint, either visually or through memory, to identify the presence or absence of mine-like target and localize if a mine was thought to be present. During each detection task, sensor head motion and other user input actions were recorded. Upon completion of a detection task, user assessments such as confidence, ease and perceived accuracy were collected with respect to the completed task.

Upon completion of all detection tasks, post experiment user data such as satisfaction with training scheme, overall performance assessments and suggestions for interface improvement were collected. Finally, subjects were informed of their performance on each testing task, debriefed about the experiment and compensated.

3.3 Participant Demographics

44 students, 30 male and 14 female, aged between 18-26, all right-handed, with normal/corrected to normal vision and previous computer experience participated in this experiment. Participants received monetary gratuity for taking part in the study.

3.4 Design considerations

The experimental design process presented complexity both in terms of ecologically valid simulation and in terms of teaching and testing subjects in the context of a simulated mine detection task. This section deals with ecological and confounding factors identified during the design process, followed by a mapping of design choices employed as response mechanisms.

3.4.1 Ecological considerations

During the design phase, particular attention was paid to ecological requirements and also to the tradeoff between ecological validity and experimental control [14, 38, 9, 12, 43]. Certain ecological factors were, of course, impossible to simulate to a realistic extent, while others were limited in scope due to practical and experimental constraints. The ecological factors considered were :

- Stress associated with task activity
- Physical tiredness
- Sensory distractors
- Environmental cues to assist in metallic footprint construction
- Fear inherent in task
- Specialized operational techniques required for safety during task activity
- Deminer operational protocol
- Physical form of typical threats and clutter items encountered on a minefield
- Consequences of a missed target
- Boredom associated with repetitive nature of task

3.4.2 Identification of confounding factors

Following is a list of all factors that were identified as potential confounds to the measured variables :

- **Cognitive differences**
  Differences in cognitive capabilities, especially spatial abilities, were highly relevant given the nature of the tasks at hand [41, 23, 51, 24, 8].

- **Task ordering bias**
  Given that the decision set was binary and the testing set small (6 tasks), it was hypothesized that the effect of subject bias based on prior tasks encounters in the testing sequence was problematic.

- **Behavioral trait differences**
  During pilot testing it was observed that meticulousness, patience, capacity to perform under stress and risk aversion affected performance levels [10, 22].(This confound was observationally confirmed during experimental testing as well)

- **Time based learning**
  The more time subjects spent constructing and dealing with footprints the better they could become at this general task. This was witnessed during pilot testing when some pilots were run without time pressure.

- **Type based learning**
  It was hypothesized that the more encounters subjects had with footprints of a certain type, the better they could become at operating on tasks of this type. Given the binary nature of the decision set (no target or have target), discrimination improvements on one task type, would automatically improve discrimination performance on the other task. For example, improvements in target task discrimination would automatically lead to improvements in clutter task discrimination.

- **Treatment based learning**
  Learning or concept formation rates in this context may be affected by the use of the treatment condition of visual support [7, 2].

- **Variability in task difficulty**
  Variations in difficulty between tasks could either have aided or slowed the learning process based on order of presentation [1].

3.4.3 Responses to ecological concerns and confounds

Summary of response mechanisms : Confounding factors

Table 3.1 documents the various design choices that were made in order to account for the confounding factors discussed above [43].

Table 3.1: Design choices to mitigate confounding factors

Response	
Confounding factor	**Design factor(s)**
Cognitive differences	• Large sample size • Counterbalancing and Randomization of tasks • Exit criterion on training (see Page 28) • Blocking on sex
Task Ordering bias	• Counterbalancing and Randomization of tasks • Blinding with respect to performance results
Time based learning	• Between subjects design with time pressure • Counterbalancing and Randomization of tasks • Blinding with respect to performance results
Type based learning	• Counterbalancing and Randomization of tasks • Blinding with respect to performance results • Symmetry in training program (see Page 28)
Treatment based learning	• Symmetry in training program (see Page 28) • Between subjects design
Variability in task difficulty	• Controlled task design (see Page 26) • Counterbalancing and Randomization of tasks
Behavioral trait differences	• Large sample size • Counterbalancing and Randomization of tasks

Summary of response mechanisms : Ecological Validity

Table 3.2 documents the various design choices made to achieve ecological validity to an acceptable degree [43].

Table 3.2: Design choices for ecological validity

Response	
Ecological factor	**Design factor(s)**
Stress	• Time pressure (see Page 28) • Duration of experiment
Physical fatigue	• Duration of experiment
Sensory distractors	• Time Pressure (see Page 28) • Detection floor background (see Page 33)
Environmental cues to assist in metallic footprint construction	• Detection floor background (see Page 33)
Fear inherent in task	• No feasible response
Specialized operational techniques required for safety during task activity	• Ecologically motivated training program (see Page 28)
Deminer operational protocol	• Ecologically motivated training program (see Page 28) • Reward-Penalty Scheme (see Page 27)
Physical form of typical threats and clutter items encountered on a minefield	• Ecological valid clutter items used from a training minefield (see Page 34)
Boredom due to repetitive nature of task	• No feasible response

(a) A clutter task

(b) A user generated pattern for a clutter task

Figure 3.1: Testing set clutter task

3.5 Design choices

3.5.1 Detection task design (Target with clutter and clutter tasks)

Detection tasks were of two types, clutter-only tasks and target with clutter tasks. The design of these detection tasks was guided by findings that showed that mines had semi-circular footprints while the footprints created by clutter items were more irregular[43, 41]. The guiding theme of design was to ensure that target tasks had clearly visible semi-circular footprints of similar size, while clutter-only tasks did not. The testing set contained 3 target with clutter tasks and 3 clutter-only tasks while the training set contained 2 target with clutter tasks and 2 clutter-only tasks. (See page 34 for details of ecologically valid clutter items used and mine-simulants).

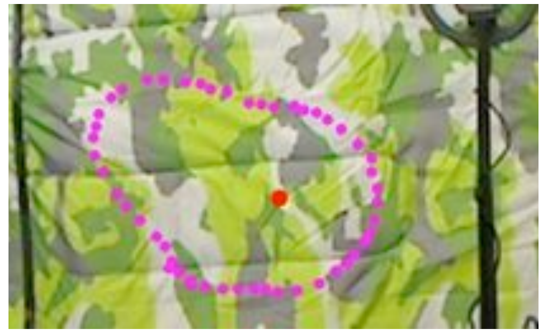
Clutter-only task design

The number of and curvature of arcs in these footprints was controlled. Arc curvature was controlled to ensure that arcs in these footprints were not of either shape or size which suggested that the arc could belong to a target footprint (see Figure 3.1).
(See Appendix Pgs 77 78 79 for target with clutter task construction and footprint patterns)

Target with clutter design

These tasks were designed with a standard mine-like simulants, with one source of distortion (clutter). The similarity in simulants ensured that target footprints were similar in size

(a) A target with clutter task



(b) A user generated pattern for a target with clutter task

Figure 3.2: Testing set target with clutter task

and shape. The distortion was such that it skewed a portion of this circular footprint. The amount of skew was relatively similar across all tasks of this type (see Figure 3.2). (See Appendix Pgs 74 75 76 for target with clutter task construction and footprint patterns)

3.5.2 Reward-Penalty Scheme

To simulate the relative importance of identifying the presence of threat (correct detection) as opposed to its absence (correct rejection), a weighted penalty scheme was used. To simulate the important need to localize a present threat accurately, a reward scheme was used. All subjects started off with a lump sum of $27 dollars. Gains or losses were applied to this starting sum on a per task basis as shown in Table 3.3 . Subjects were informed of their performance and results divulged after completion of the entire testing set.

Subjects received a minimum compensation of $15 in the worst case scenario, while they received $30 in the best case scenario. Apart from crudely reflecting the consequences of a missed mine and providing motivation to accurately localize targets, the monetary reward system was also aimed to provoke active engagement and interest in the detection tasks [43, 46].

Table 3.3: Reward penalty scheme information

Reward Penalty Scheme	
Condition	**Incentive**
False negative	- $3
False positive	- $1
Localization error for correctly identified target task$\leq$ 6 inches	+ $1

Table 3.4: Time pressure information

Time Pressure	
Time of auditory notification (s)	**Notification**
30	"30 seconds"
60	"60 seconds"
90	"90 seconds"
100	"20 seconds remaining"
110	"10 seconds remaining"
115	"5 seconds remaining"
120	"Time is up"

3.5.3 Time pressure

The time limit was intended to apply cognitive stress, and was ecologically valid given that deminers do operate under efficiency demands [14, 38, 9, 12, 43]. A time limit of 120 seconds was placed on all tasks upon observing typical times taken by pilot subjects to construct footprints. In order to minimize confounds on the visual treatment channel, and further increase stress, time pressure was externally exerted through forceful auditory notification, see Table 3.4.

3.5.4 Training program

The overall goals of the training program were to prepare subjects for the testing phase, strive for uniformity in skill level across subjects, and instill typical deminer protocol and behavior in subject's task based behavior [14, 38, 9, 12, 43, 40]. The training program was divided into the training phase and the training exercise phase.

Phase 1: Training phase

Following is an brief chronological overview of the standard training routine that subjects were passed through in this phase.

1: **Orientation**
Subjects were briefed on overall logistics of the experimental procedure and informed of the reward penalty scheme.

2: **Sweeping technique**
Subjects were taught accepted detector sweeping principles through the use of diagrams and video demonstrations. Sweeping technique was practiced and repeated based on experimenter feedback.

3: **Calibrating and using the metal detector**
Subjects were taught how to calibrate and use the metal detector.

4: **Understanding and building metallic footprints without visual support**
Subjects were taught about the concept of metallic footprints and were taught how to create footprints through diagrams and video demonstrations. They built footprints for a training target and a piece of wire using the detector (see Figure 3.3).

5: **Using the visual interface**
Subjects were taught how to use the controller and display screen to create footprints through the use of video demonstrations and practice exercises.

6: **Understanding and building metallic footprints with visual support**
Subjects used the interface to build and visualize footprints for a training target and a piece of wire using the detector (see Figure 3.3).

7: **Interpreting and using metallic footprints**
Subjects were taught how to use footprints to identify and to localize targets. This was taught using diagrams and a practice task both with and without the visual support. During this stage, it was strongly stressed that the targets used for this experiment had relatively circular footprints of similar size and shape (see Figure 3.3).

(a) Training Clutter Item

(b) Training Target Item

(c) Training task on user interface

(d) Training task design

Figure 3.3: Training and clutter items

Phase 2: Training exercise phase

Subjects performed discrimination and localization exercises on four detection tasks from the training set, 2 target with clutter and 2 clutter-only (see Section 3.5.1). Task cycles were repeated until the subject classified and localized with reasonable accuracy all tasks in a given cycle. This condition acted as an exit criterion required to move onto the testing phase. The display was used for every other cycle to satisfy the objective of training symmetry. In designing the training schedule for this exercise, the following design principles were adopted (see treatment based learning, type based learning and bias on page 22):

- Counterbalanced and randomized tasks orderings per cycle
- Randomized cycle schedules across subjects

To ensure that subjects could readily and successfully apply the concepts learned during training to the testing phase, the tasks used in the training exercise phase were similar to testing set tasks in terms of difficulty (See Section 3.5.1). Various concept induction measures were also employed. Subjects verified circularity of target footprints and estimated diameter. Subjects reasoned out aloud both during and post-task activity about the various parts of the pattern they were seeing and what such observations implied. If an incorrect decision was made, subjects were helped to reason out why their choice was wrong. Reasoning and teaching in this phase was carried out with respect to observed pattern contours, stressing on the fact that the targets used for this experiment had circular footprints of a certain shape and size. See Section 3.5.1.

To ensure that the subject pool was of comparable skill level, all participants were subject to the same training program irrespective of treatment condition (visual support or no visual support). The training program mirrored exposure to both conditions in terms of footprint construction and interpretation, and also in terms of target with clutter task and clutter-only task exposure. Furthermore, the strict exit criterion was intended to act as a measure of concept grasp [43].

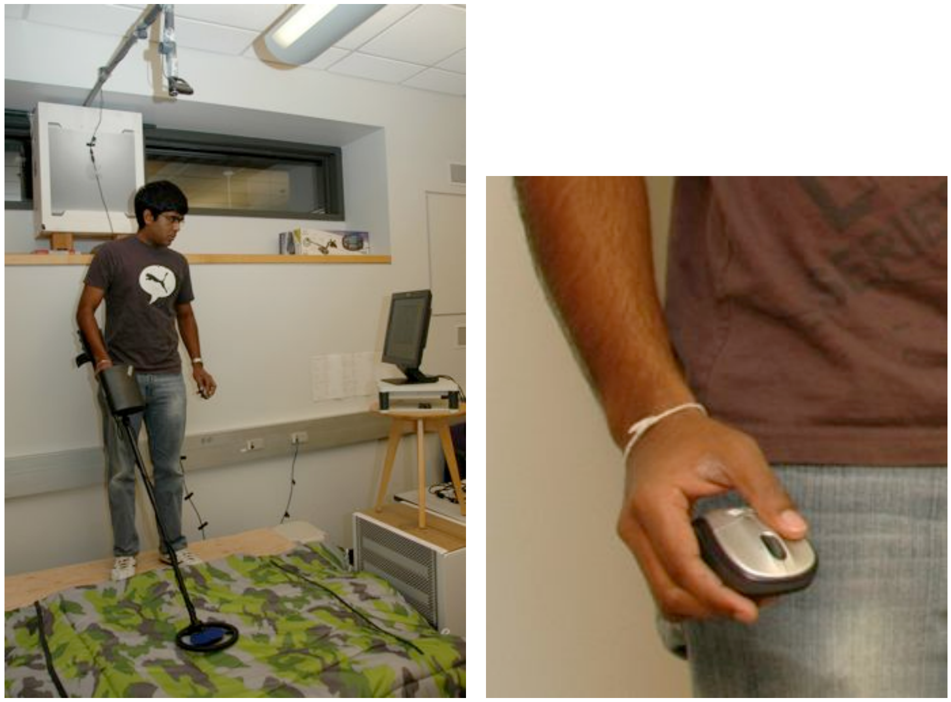
3.5.5 User interface

The user interface consisted of two components, the controller and the visual interface.

Controller

A three button controller was used in both conditions. In the visual support condition, the controller was used to record edge points belonging to a footprint, erase previously selected edge points and declare a target location. In the no visual support condition, it was used to signal instances when an edge point was discovered and to declare target location. The device was held in the subject's free (non-dominant) hand, and during training it was recommended that the subject only operate the device with one finger.

Two sources of inaccuracy were identified with the use of this controller. Firstly, the delay associated between finding an edge point (detector transitioning from no feedback to feedback) and clicking. That is, the delay associated with receiving an auditory



(a) User with controller and display on left hand side

(b) Typical controller posture

Figure 3.4: User with controller and controller posture

cue, processing the auditory cue and physically acting upon the cue. Secondly, the additional reaction time due to placement of the selection module in the subject's non-dominant hand. Using manual control theory and approximates about expected subject demographics a conservative delay of 200 ms was estimated [50]. To respond to this problem, specific footprint construction techniques were embedded into the training program. Namely, enforcing that the sensor head motion was close to stationary before an edge point was recorded [43]. See Figure 3.4(b).

(a) User referring to visual interface

(b) User Interface in Action

Figure 3.5: Using the visual interface

Visual interface

A visual display unit displayed a real time high resolution color video feed of the detection area. The video feed was captured from a close range bird's eye view perspective. The center of the sensor head appeared as a colored cricle and served as a pointer on the screen. When the user recorded an edge point, a small colored circle (edge point), was placed at the location of the pointer. When the user wished to remove an edge point, the pointer was placed over the edge point on the screen and the remove button was clicked. When the user wished to declare a target location, the pointer was placed over the suspected location and the target button was clicked. This visual interface, the *Experimental Mine Footprint Builder©*, was coded using Open CV 2.0 in Visual C++ 2008. See Figure 3.5 and Section 3.7.

3.5.6 Physical setup

The physical setup consisted of a detection area, under which detection tasks were concealed, a display screen at standing face level (for a person of average height), a standing bench, and an overhead camera. The detection area was a 1.5m by 1.2m flat board raised 0.5m of the ground that was covered with a cammo background. The cammo background was chosen in order to provide visual cues and distractors of a form similar to actual demining environments. The detection area was raised 0.5m from the ground in order to account for metallic interference from the indoor concrete floor. This height was

Figure 3.6: Physical Setup

chosen because it permitted for calibration of the detector such that metal in the floor was ignored while metallic items placed on the raised detection area were picked up sufficiently. The overhead camera was suspended 1.85m from the raised detection area, and was oriented such that the optical axis was approximately perpendicular to the plane of the detection surface. The display screen was placed on the left side of the user, based on the assumptions that the display would be less intrusive if placed on the non-detector side and that the most users would be right handed. See Figure 3.6.

3.6 Experimental Apparatus

Following is a list of major apparatus used for this experiment :

- Bounty Hunter Pioneer 505 Metal detector
- Logitech Quickcam Pro 9000 Web camera
- Logitech V450 Laser Cordless Mouse
- Portable plastic drawers as detection trays (see Figure 3.7)

(a) Clutter task tray (b) Target with clutter detection tray

Figure 3.7: Detection trays

(a) Mine Simulants (b) Clutter items

Figure 3.8: Clutter and target items

- 6203, 6202, 6202 ball bearings as mine simulants (see Figure 3.8(a))
- Barb wire, Nails, Screwdrivers, Scrap metal, Stainless steel wire and empty M-16 and M-14 bullet shells as clutter items (see Figure 3.8(b))
- 17′ IBM ThinkVision Monitors
- Quad-core Mac Pro operating Windows XP

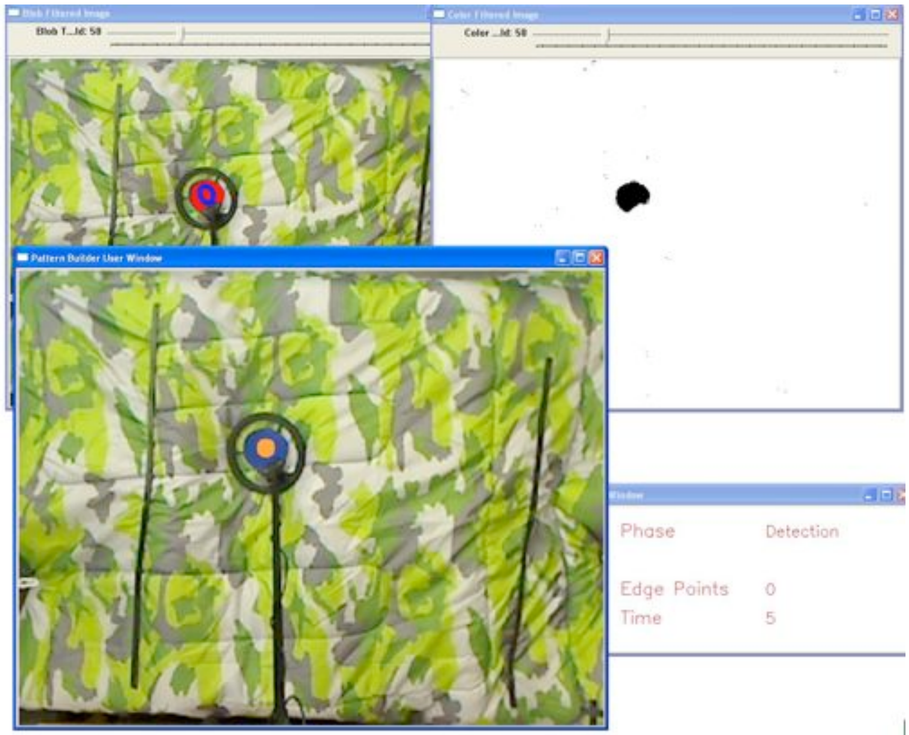


Figure 3.9: Screenshot of EMPB in operation

3.7 Experimental Mine Pattern Builder

Experimental Mine Pattern Builder, EMPB, was a custom built software program for use in this experiment (see Figure 3.9). The software was developed in Visual Studio 2008 using the Open CV 2.0 real time computer vision development platform. EMPB used Open CV 2.0 library routines to locate the colored detector head in input images frames. Tracking was done realtime using a combination of color filtering and blob detection techniques. Based on user controller input, EMPB used the sensor head position to either add/remove a edge/target point from images in the video feed (see Figure 3.10). The software was also designed to log experimental data such as sensor head position, time taken for a detection tasks, number of edge points added etc.

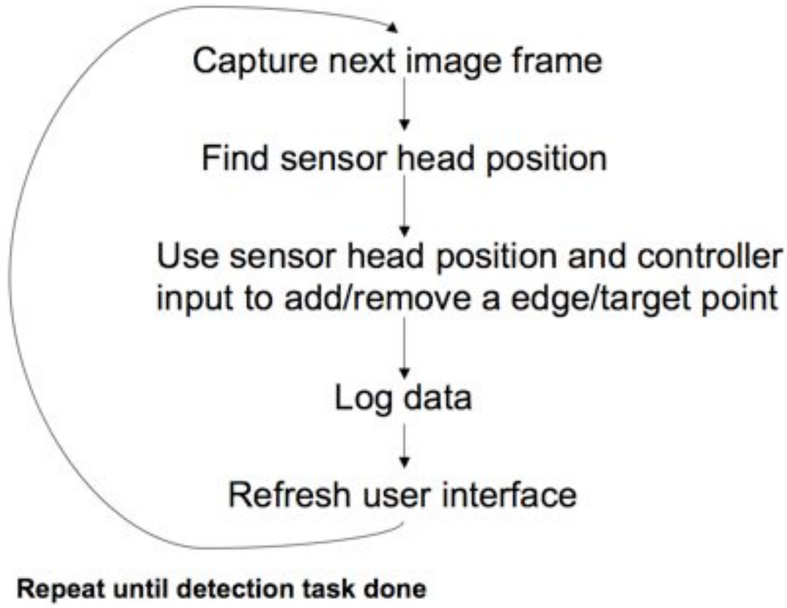


Figure 3.10: High level description of EMPB

3.8 Experimental structure and measurements

The study was designed as a mixed 2 x 2 x 2 factorial design study with visual support, either provided or not, gender as a between-subjects factors, and task type, clutter-only or target with clutter, as a within-subjects factor. Table 7.1 on page 62 describes the primary measures, while Table 7.2 on page 63 describes secondary measures. Table 7.3 on page 64 describes demographic data that was collected in order to account for subject based confounds.

3.8.1 Description of primary measures

- Correctness (binary) - 1 if correct detection or correct rejection. 0 if not.
- Localization error (pixel units, if target present) - Straight line distance from pre-defined target position to user selected target position.
- Time to complete task - Time taken for user to make final decision
- Confidence in mine presence/absence - Acquired in post task questionnaire using

statement : "I am confident about my decision about the absence/presence of a mine" (see Appendix Pg 69)

- Confidence of localization (if target thought to be present) - Acquired in post task questionnaire using statement : " I am confident about the mine location I indicated" (see Appendix Pg 69)
- Ease in determining mine presence/absence - Acquired in post task questionnaire using statement : "It was easy to decide whether there was a mine in this task" (see Appendix 69)
- Ease of localizing target (if target thought to be present) - Acquired in post task questionnaire using statement : "It was easy to establish the location of the mine" (see Appendix Pg 69)
- Ease in building and interpreting patterns - Acquired in post task questionnaire using statement : "It was easy for me to construct and interpret the edge pattern in this task" (see Appendix 69)
- Noticed good circular/elliptical symmetry - Acquired in post task questionnaire using statement : "I noticed good circular/elliptical (partial) symmetry in the constructed pattern " (see Appendix Pg 69)
- Overall confidence about finding all targets - Acquired in post task questionnaire using statement : "I am confident that I found all targets" (see Appendix Pg 70)
- Overall confidence about separating clutter tasks from targets tasks correctly - Acquired in post task questionnaire using statement : "I am confident that I seperated targets from clutter " (see Appendix 70)
- Overall confidence about localization - Acquired in post task questionnaire using statement : "I am confident about my overall target localization accuracy" (see Appendix Pg 70)

Chapter 4

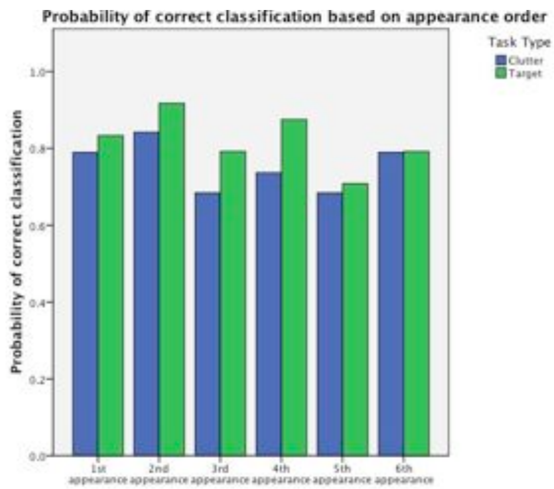
Analysis

4.1 Summary of Chapter

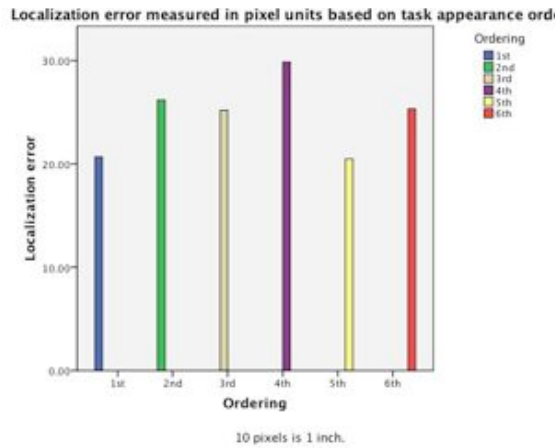
This chapter reports the results of statistical analysis performed on the experimental data. Statistical methods and techniques are described, followed by descriptions of tests used to verify experimental assumptions of no order-based learning and uniform task difficulty. Effects of gender and visual support on primary quantitative and qualitative measures are reported. In addition to analysis of the effects of visual support on target and clutter only tasks.

4.2 Statistical methods

The non-parametric Wilcoxon's Rank Sums test was used to test for statistical significance on primary measures such as task correctness, localization error and user subjective measures. This non-parametric test was chosen for the sake of conservatism as it deals with non normally distributed data. An alpha level of $\alpha = 0.05$ was used for all statistical tests. Primary subjective measures were graded on a 5-point Likert Scale. (1 = Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree). To account for multiple hypotheses being tested simultaneously, the Bonferroni Correction was applied when doing a per question analysis [37]. The notation "ns" is used to report not significant tests.



(a) Possible classification learning over time



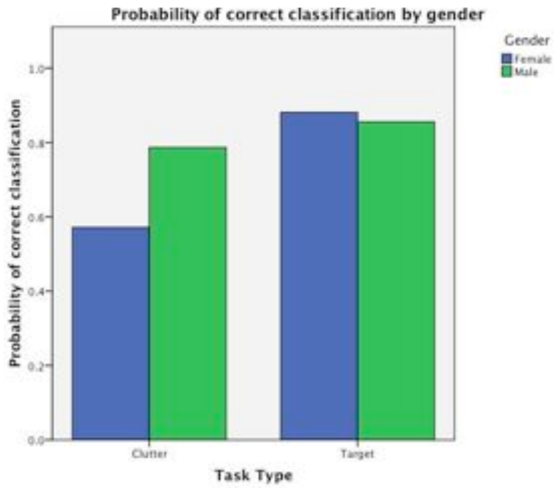
(b) Learning with respect to accurate localization

Figure 4.1: Learning effects graphs

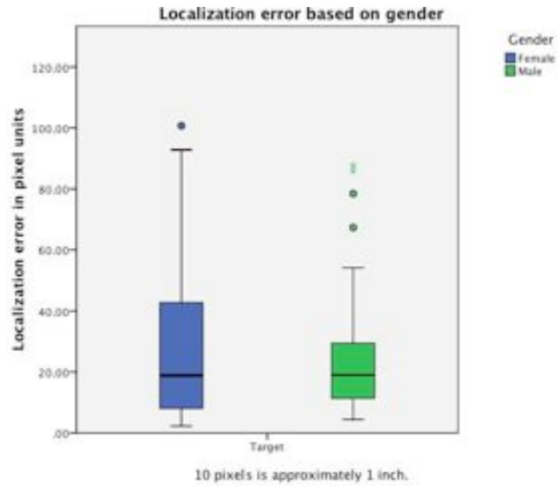
4.3 Verifying experimental assumptions

The Wilcoxon signed rank and Friedman test were used to verify two experimental assumptions of i) no order based learning and ii) uniform task difficulty. Based on the Friedman test, there was no significant difference in the detection rates between the three different target with clutter tasks ($\chi^2(2) = 1.286$, $p < .0526$) (see Section 3.5.1 for different target with clutter task designs). Based on the Friedman test, there was also no significant difference in the detection rates between the three different clutter tasks ($\chi^2(2) = 0.963$, $p < 0.618$).

A carefully planned contrast analysis was carried out to test for learning effects over time, for both detection rates and localization errors (see Figure 4.1(a)). This was done by comparing performance on the first task appearance against averages across the rest of the 5 task appearances using a Wilcoxon signed rank test, and repeating by shifting one order up if there was significance. No learning effects were observed based on detection rates ($Z = -1.183$ $p < 0.237$). No learning effects were observed for localization accuracy ($Z = -1.720$, $p < 0.85$) (see Figure 4.1(b)).



(a) Correct classification by gender



(b) Localization error by gender

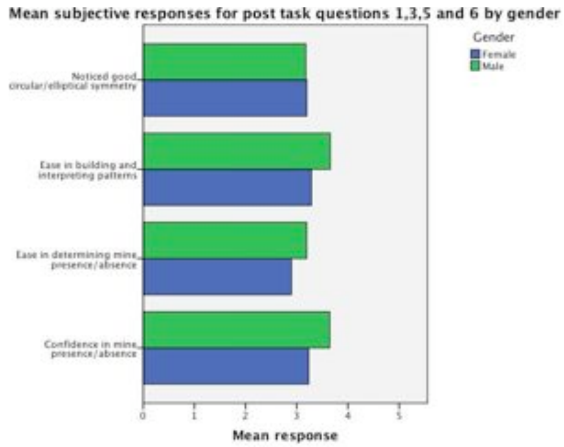
Figure 4.2: Detection rates and localization error by gender

4.4 Gender based effects

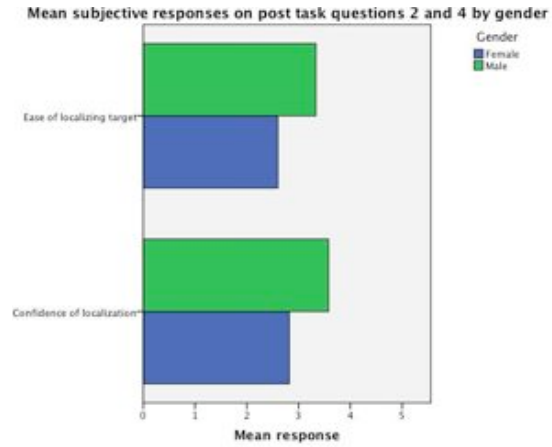
Given the potential influence of spatial abilities on task performance and reported gender differences in this regard, gender was considered as a between-subjects blocking factor [23]. With respect to correct classifications over all tasks, women (Mean = 0.726) and men (Mean = 0.821) did not differ significantly (W_s = 10373.5, ns) (see Figure 4.2(a)). With respect to time to task completion, men (Mean = 106.12, Median = 112.7) and women (Mean = 104.79, Median =111.1) did not differ significantly (W_s = 11187.5, ns). Localization error difference, measured in pixel units, between women (Mean = 28.73, Median = 18.867) and men (Mean = 23.07, Median=19.0263) also showed no statistical significance (W_s = 2122.5, ns) (see Figure 4.2(b)).

However, a significant main effect of gender on the overall subjective responses was observed (W_s = 8714.5, $p < 0.001$), with men (Mean = 3.40) having a higher mean response than women (Mean = 3.02). Based on this main effect, an additional post hoc analysis (with Bonferroni Correction) was carried out to determine the effect of gender on the individual subjective measures.

Men (Mean = 3.64) were significantly more confident about their decision concerning the absence/presence of a mine when compared to women (Mean = 3.21), (W_s = 9167, $p < 0.0094$). Men (Mean = 3.57) were also significantly more confident about their



(a) Gender based response for post task questions 1,3,5



(b) Gender based response for post questions 2 and 4

Figure 4.3: Post task questionnaire responses by gender

localization accuracy than women (Mean = 2.81), (W_s = 3277.5, p < 0.0004). There was no significant difference between men (Mean = 3.20) and women (Mean = 2.87) with respect to the ease associated with declaring the absence/presence of target (W_s = 8814.5, ns by Bonferroni). Men (Mean = 3.31) found it significantly easier to localize targets when compared to women (Mean = 2.6), (W_s = 3333, p < 0.0007). Men (Mean = 3.66) also found it significantly easier to construct and interpret edge patterns when compared to women (Mean = 3.27), (W_s = 8558.5, p < 0.0051). There was no significant difference between men (Mean = 3.17) and women (Mean = 3.21) with respect to the circular/elliptical symmetry noticed across tasks (W_s = 9837.5, p < 0.9852) (see Figures 4.3(a) and 4.3(b)).

With respect to primary subjective measures collected **post testing** , no significance emerged. Males (Mean=2.80) did not feel significantly more confident about finding all possible targets compared to females (Mean = 2.50), (W_s = 284, ns). Males (Mean = 3.00) were not significantly more confident about separating target tasks from clutter tasks compared to females (Mean =2.5) , (W_s = 268.5, ns). Males (Mean = 3.50) also were not significantly more confident about their localization accuracy compared to females (Mean = 2.69), (W_s = 220.5, ns).

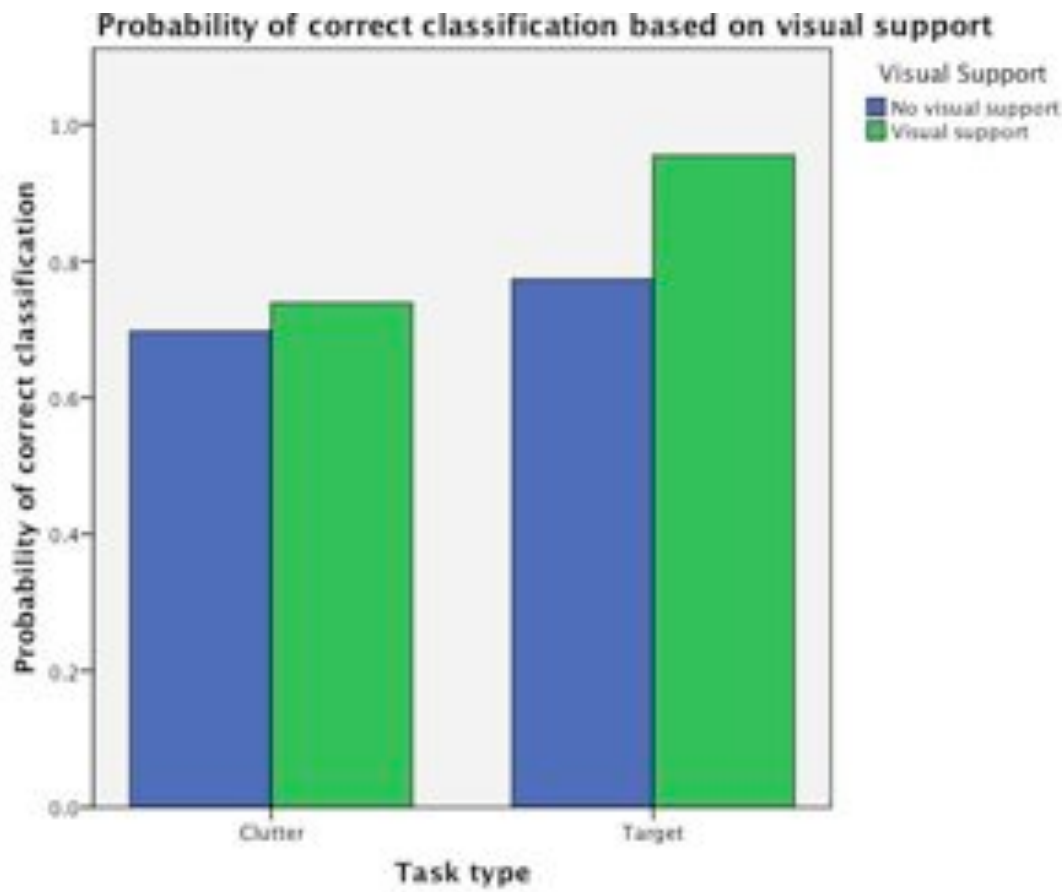
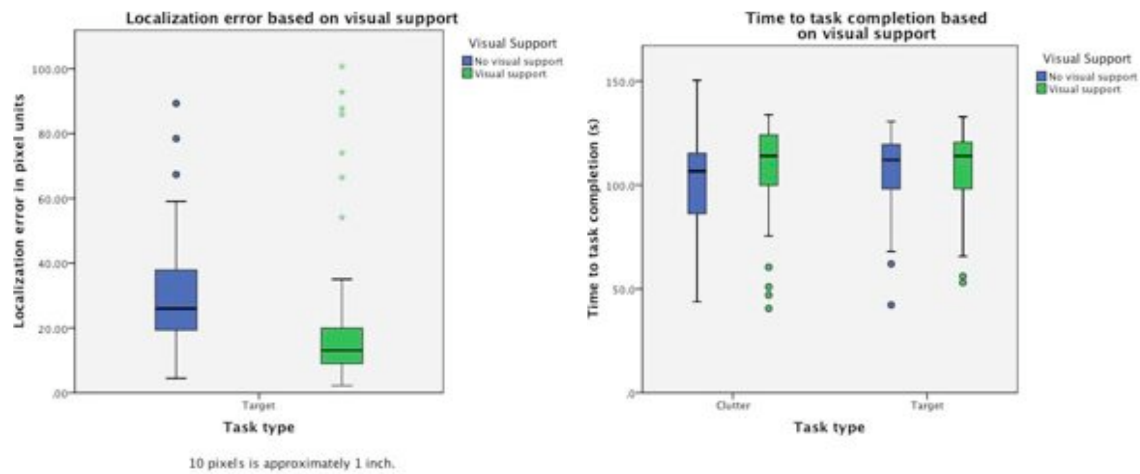


Figure 4.4: Classifications based on visual support

4.5 Visual support effects

With respect to correct classifications over all tasks, subjects with visual support (Mean = 0.847) were significantly better than subjects without visual support (Mean = 0.734), (W_s = 18264.5, p < 0.0252) (see Figure 4.4). Subjects without visual support (Mean = 103.196, Median = 110.6) took significantly less time (measured in seconds) than those with visual support (Mean = 108.22, Median = 114), (W_s = 18720.5, p < 0.0081) (see Figure 4.5(b)). In terms of pixel units, subjects with visual support (Mean = 20.76, Median = 13.04) were significantly more accurate than those without visual support (Mean = 30.04, Median = 26) in localizing targets (W_s = 3678.5, p < 0.0001)(see Figure 4.5(a)).

A significant main effect of visual support on the overall subjective responses was observed: subjects with visual support (Mean = 3.48) hada higher mean response



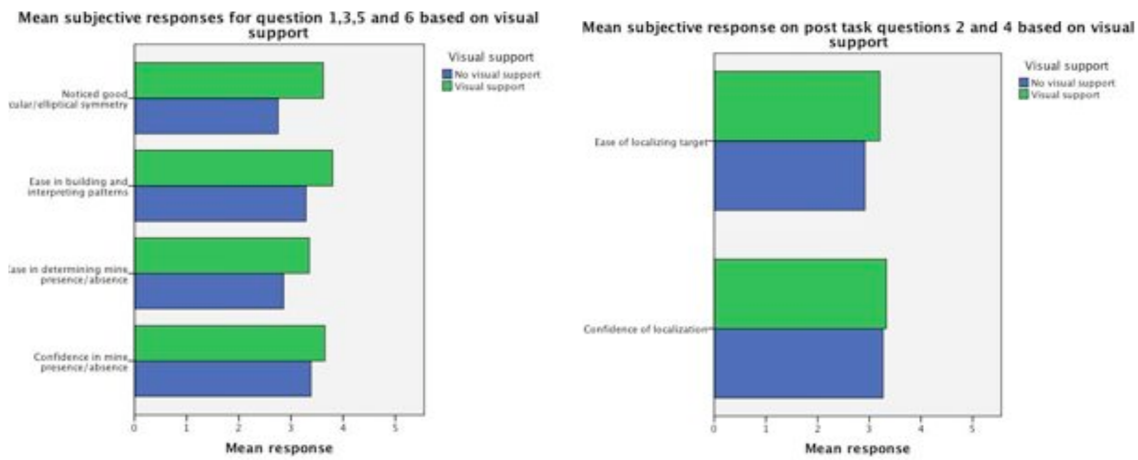
(a) Localization error based on visual support (b) Time to task completion based on visual support

Figure 4.5: Localization error and time based on visual support

than subjects without visual support (Mean = 3.07), (W_s = 18613.5, p < 0.0001). Based on this main effect, an additional post hoc analysis (with Bonferroni Correction) was carried out to determine the effect of visual support on the individual subjective measures.

There was no significant difference in confidence about the absence/presence of a mine between subjects with visual support (Mean = 3.63) and those without visual support (Mean = 3.37), (W_s = 17571, ns). There was also no significant difference in confidence about localization accuracy between subjects with visual support (Mean = 3.32) and subjects without visual support (Mean = 3.26), (W_s = 5286.5, p < 0.7747). Subjects with visual support (Mean = 3.35) found it significantly easier to determine the absence/presence of a mine when compared to subjects without the visual support (Mean = 2.84), (W_s = 17587.5, p < 0.0004). However, subjects with visual support (Mean = 3.17) did not find it significantly easier to localize targets when compared to subjects without the visual support (Mean = 2.91), (W_s = 5058, p < 0.1941). Subjects with visual support (Mean = 3.80) found it significantly easier to construct and interpret edge patterns when compared to subjects without visual support (Mean = 3.27), (W_s = 18107, p < 0.0001). Subjects with visual support (Mean = 3.60) also noticed significantly more circular/elliptical symmetry in constructed edge patterns when compared to those without visual support (Mean = 2.77), (W_s = 18382, p < 0.0001) (see Figure 4.6(a) and 4.6(b)).

With respect to primary subjective measures collected post testing, no signifi-

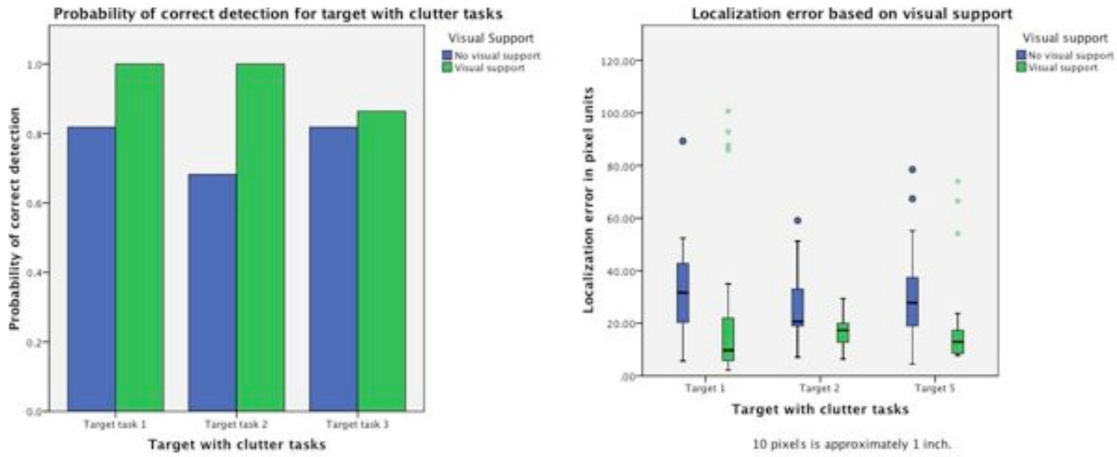


(a) Post task questions 1,3,5 according to visual support

(b) Post task questions 2 and4 according to visual support

Figure 4.6: Post task questionnaire responses by visual support

cance emerged. Subjects using the visual support (Mean=2.77) did not feel significantly more confident about finding all possible targets compared to subjects without the visual support (Mean = 2.63), (W_s = 512.5, ns) . Subjects using the visual support (Mean = 3.04) were not significantly more confident about separating target tasks from clutter tasks compared to those without the visual support (Mean = 2.59), (W_s = 551.5, ns). Subjects using visual support (Mean = 3.36) also were not significantly more confident about their localization accuracy compared to subjects without the visual support (Mean = 3.14), (W_s = 436.5, ns).



(a) Probability of correct detection according to target with clutter tasks

(b) Localization error by task basis

Figure 4.7: Correct detections and localization error for target with clutter tasks

4.6 Visual support effects on target with clutter (correct detections)

Additional analysis of the effects of visual support on tasks containing a target and those containing only clutter was carried out. This and the following section presents the results. With respect to **correct detections** over target with clutter tasks, subjects with visual support (Mean = 0.955) were significantly better than subjects without visual support (Mean = 0.772), (W_s = 4785, p < 0.0025) (see Figure 4.7(a)). The difference in time taken to complete these tasks between subjects with visual support (Mean = 107.94, Median = 113.95) and subjects without visual support (Mean = 105.92, Median = 112.05) was not statistically significant (W_s = 4752, p < 0.4062). For analysis of localization error for these tasks see Section 4.5, and for a visualization of localization error based on different types of target with clutter tasks see Figure 4.7(b).

A significant main effect of visual support on the overall subjective responses was observed, with subjects with visual support (Mean = 3.81) having a higher mean response than subjects without visual support (Mean = 3.13), (W_s = 3326.5, p < 0.0001). Based on this main effect, an additional post hoc analysis (with Bonferroni Correction) was carried out to determine the effect of visual support on the individual subjective mea-

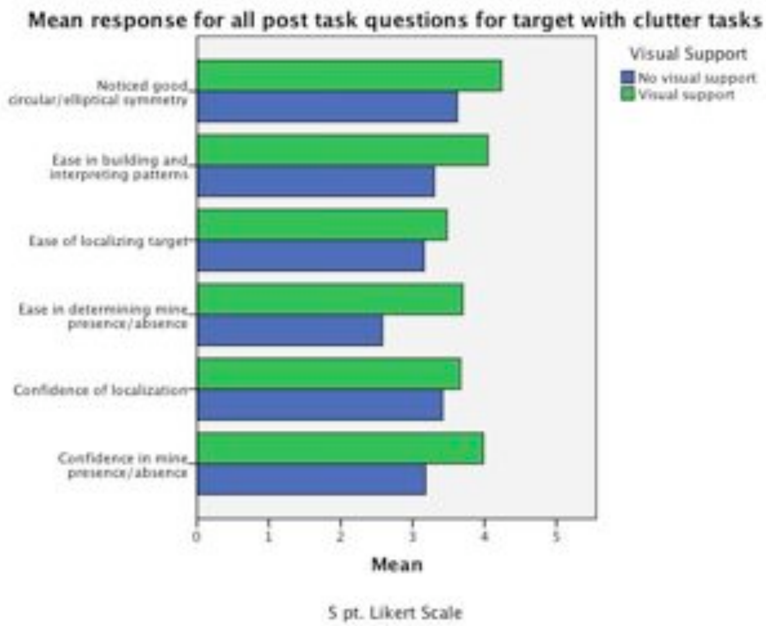
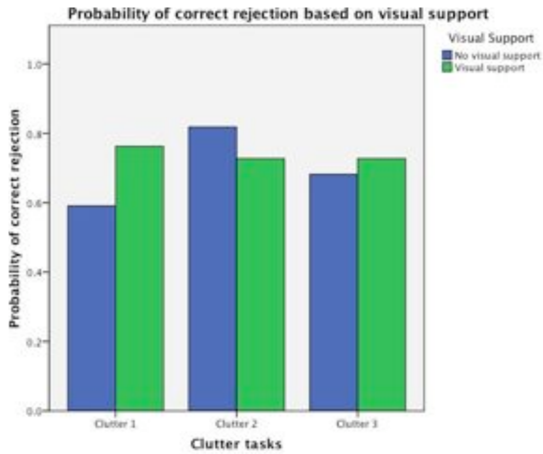


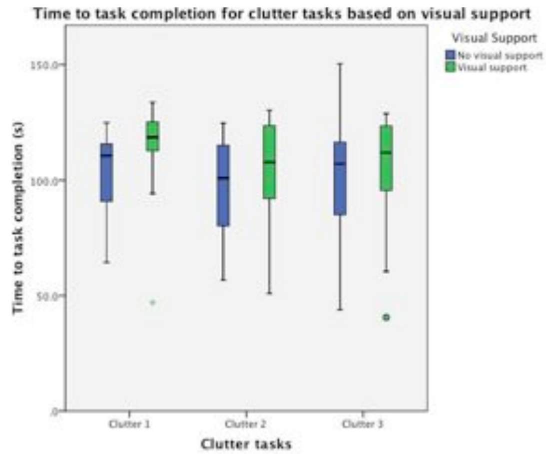
Figure 4.8: Post task subjective responses for target with clutter tasks

sures.

Subjects with visual support (Mean = 3.92) were significantly more confident about their decision concerning the absence/presence of a mine when compared to subjects with no visual support (Mean = 3.22), (W_s = 3416, p < 0.0001). There was no significant difference in confidence about localization accuracy between subjects with visual support (Mean = 3.67) and subjects without visual support (Mean = 3.43), (W_s = 2757.5, p < 0.2977). Subjects with the visual support (Mean=3.62) found it significantly easier to determine the absence/presence of a mine when compared to subjects without the visual support (Mean = 2.65), (W_s = 3206.5, p < 0.0001). However, subjects with the visual support (Mean = 3.47) did not find it significantly easier to localize targets when compared to subjects without the visual support (Mean = 3.18), (W_s = 2672.5, p < 0.1241). Subjects with visual support (Mean = 4.015) found it significantly easier to construct and interpret edge patterns when compared to subjects without visual support (Mean = 3.30), (W_s = 3217, p < 0.0001). Subjects with visual support (Mean =4.212) also noticed significantly more circular/elliptical symmetry in constructed edge patterns when compared to those without visual support (Mean=3.27), (W_s = 3113, p < 0.0001) (see Figure 4.8) .



(a) Probability of correct rejections for clutter tasks



(b) Task completion time according to clutter tasks

Figure 4.9: Correct rejections and time for clutter tasks

4.7 Visual support effects for clutter (correct rejections)

With respect to **correct rejections** over clutter tasks, there was no significant difference for subjects with visual support (Mean = 0.74) and subjects without visual support (Mean = 0.70), (W_s = 4379, p < 0.6014) (see Figure 4.9(a)). Subjects without visual support (Mean = 100.47,Median = 106.65) took significantly less time (measured in seconds) than those with visual support (Mean = 108.50, Median = 114), (W_s = 4820.5, p <0.0045) (see Figure 4.9(b)).

A significant main effect of visual support on the overall subjective responses was not observed for subjects with visual support (Mean = 3.02) and subjects without visual support (Mean = 3.13), (W_s = 4098.5, p < 0.2049). For further analysis purposes, a per question analysis was carried out. There was no significant difference in confidence about the absence/presence of a mine between subjects with visual support (Mean = 3.32) and those without visual support (Mean = 3.53), (W_s = 3664.5ns). There was no significant difference in the ease associated with determining the absence/presence of a mine between subjects with visual support (Mean = 3.05) and those without visual support (Mean = 3.03), (W_s = 3566,ns). There was no significant difference in the ease associated with constructing and interpreting patterns between subjects with visual support (Mean = 3.55) and those without visual support (Mean = 3.25), (W_s = 3946.5,ns). However, there was a

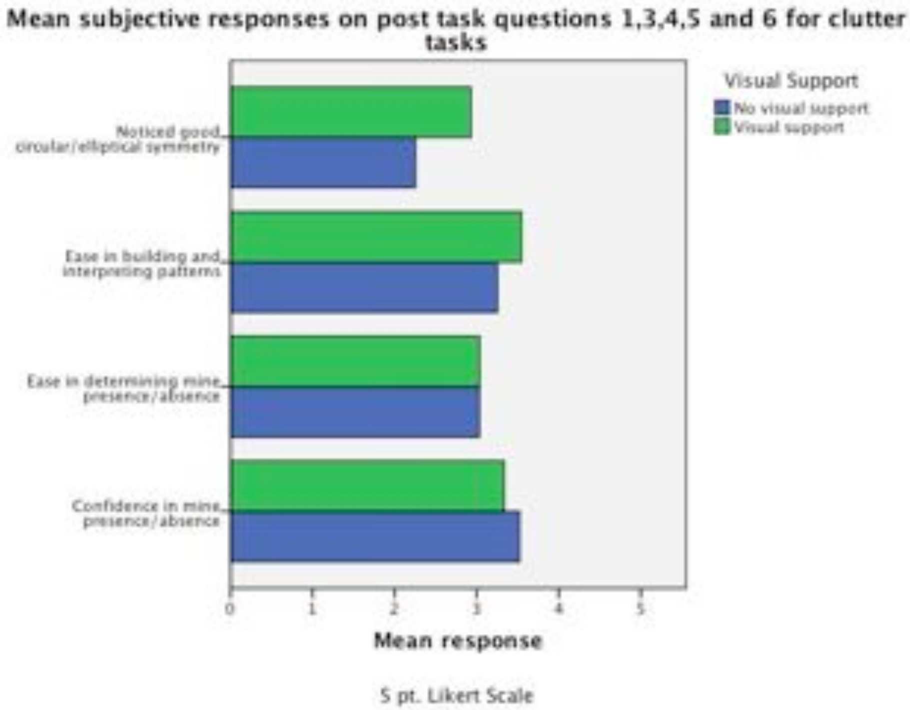


Figure 4.10: Post task subjective responses for clutter tasks

significant difference in the noticed circular/elliptical symmetry in the constructed edge patterns between subjects with visual support (Mean = 2.897) and without visual support (Mean = 2.28) (see Figure 4.10).

Chapter 5

Discussion

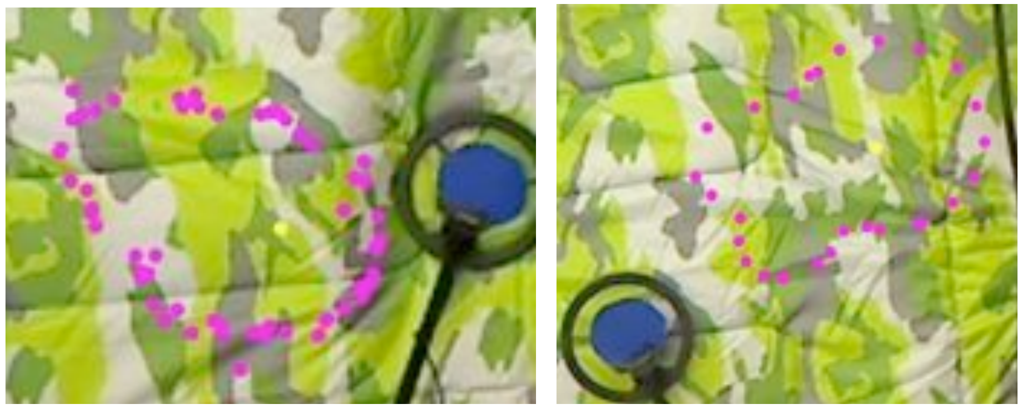
5.1 Summary of Chapter

This chapter engages in a critical interpretation of the results obtained in the Analysis section, and relates quantitative and qualitative findings where possible. Subject detection patters are used to demonstrate experimental findings. For the sake of experimental validity and ecological relevance, the effectiveness of the training program is discussed at the end of this chapter.

5.2 Impact of visual support on detection performance

This thesis hypothesized that visualization of metallic footprints, through a visual decision support system, could improve detection performance in relation to the present approach of internal representation (see Section 1.4). Experimental results support this hypothesis. The difference in overall detection rates was significantly in favor of subjects that were provided visual support (see Section 4.5). Subjective feedback investigations show that subjects who were provided with visual support *found it easier to construct and interpret edge patterns* (see Section 4.5). This may be one reason as to why visual support improves detection performance. The implications of this finding need to be confirmed through future work.

Visual feedback significantly improved correct detection rates for **target with clutter tasks** was highly significant (see Section 3.5.1). **Subjects with visual support had a 95% correct detection rate, while those without visual support had only a 77%**

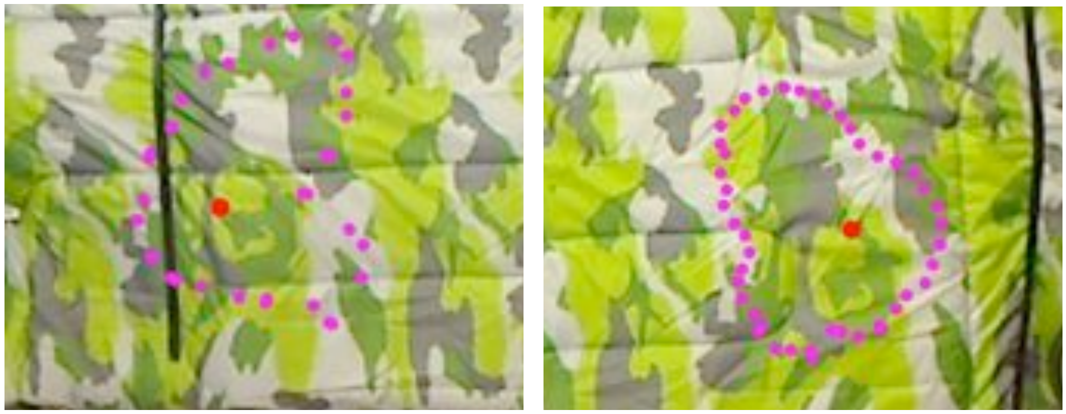


(a) (b)

Figure 5.1: Missed targets by participants without visual support. Yellow is actual target position. Red is subject's target position

correct detection rate for these tasks. On 2 of the 3 target with clutter tasks, subjects with visual support had 100% accuracy (see Figure 4.4) The task design phase ensured that these tasks clearly signaled the presence of a target by ensuring that a sub component of the pattern represented a partial circle (**marker**). (see Section 3.5.1) The inclusion of markers was motivated on ecological grounds, which stated that mines created relatively circular footprints of consistent shape and size [41]. Interestingly, subjective feedback investigations showed that subjects who were provided with visual support *notice more circular and elliptical symmetry* (markers) on these tasks. It is likely that visual decision support makes these markers easier to notice, a hypothesis that will need to be investigated further (see Figure 5.1).

However, performance differences for **clutter-only** tasks was not significant. **Both groups had correction rejection rates of around 70%.** Task design ensured that these tasks did not contain markers to indicate the presence of a target (see Section 3.5.1). While arcs were included in these tasks to create difficulty, the fact that correct rejection rates are sufficiently high suggests that correctness could have been achieved through ecological concept application. (see Figure 4.9(a), and Section 3.5.4). Subjective feedback investigations showed that subjects who were provided with visual feedback **continued to notice more circular and elliptical symmetry (makers) on clutter-only tasks** . It is possible that visual support hindered confident rejections given the



(a) (b)

Figure 5.2: Incorrect target declarations for clutter tasks by subjects with visual support. Red is subject's target position

pronounced visibility of these markers (see Figure 5.2). This coupled with conservative behavior may provide a starting point for understanding the lack of improvement in performance in clutter-only tasks.

5.3 Impact of visual support on localization performance (pattern resolution)

This thesis aimed to quantify the extent to which visualization of metallic footprints improved pattern resolution. Subjects localizing targets was a mechanism by which to perform this quantification, given that localization involved finding the centroid of a (circular) footprint belonging to a target [41]. This measurement mechanism was motivated by the intuition that the clearer the circular pattern, the easier it was to geo-locate its center. The goal, as stated, was achieved, given that the difference in localization error rates was highly significant. Physically, average localization error improved by 1 inch. While the ecological relevance of this figure is unclear, it is theoretically significant. **Localization error was reduced by 33% from 3 to 2 inches, when visual support was provided.** Intuitively, it is natural to posit that people with visual support can improve localization accuracy given higher pattern resolution (see Figure 5.3). Interestingly, this does not map directly to subjective confidence in localization as will be explained in the next sections.

(a) (b)

Figure 5.3: Localization by participants with display. Yellow is actual target position and Red is subject's target position

5.4 Impact of gender on performance

The experiment was designed as a 2x2x2 factorial study, with gender considered as a factor. This structural choice was motivated based on spatial skills being important for task activity success, and findings in psychology which suggest spatial skills are influenced by gender [41, 23]. **Interestingly, no significant differences in detection or localization performance were noticed.** This finding raises interesting points worthy of further inquiry. The most immediate is the extent to which effective use of metallic footprints depends on spatial ability skills . This line of inquiry is further motivated by experimental observations where some subjects without visual support referred to muscle memory or patterns feeling too large/small as descriptions of methods employed during task activity. Conversely, this experiment may offer both qualitative and quantitative insight into the extent of spatial differences based on gender, at least with respect to spatial pattern matching tasks.

5.5 Visual decision support and user perceptions

An objective of this research effort was to understand how visual decision support would affect end-users in this task context. This aspect of the study, surprisingly, yielded equally interesting results as well. After completing all tasks, subjects with visual support did not feel significantly more confident about correctly detecting present targets, correctly discriminating clutter tasks or accurately localizing present targets. A similar result was obtained when aggregating subjective responses across post task questionnaires, except that subjects with visual support felt it was easier to discriminate targets from clutter.

A more detailed look at target with clutter tasks and clutter tasks, on a post task questionnaire basis, also yielded interesting results. For targets with clutter, subjects with visual support were significantly more confident in their correct detections and also found it significantly easier to carry out these tasks when compared to those without visual support. This appears consistent given the variation in correct detection performance (see Section 5.2). Interestingly, there was no significant difference in confidence or ease associated with localization, which was contrary to **significant localization performance** differences (see Section 5.3). With respect to clutter-only tasks, there was no significant difference in confidence or ease associated with task activity between either group. This appears consistent given similar performance over these tasks.

While the visual decision support system in question was engineered solely to study the effects of visualizing metallic footprints, there was automatic bias amongst all participants that it was "easier" and "better" during training (recall that all subjects trained both with and without visual support). Given the performance based incentive structure, subjects assumed they could do better if given visual support. This reaction was intuited during experimental design as well. However, the fact that there was no difference in overall subjective measures with regards to confidence or ease, post testing, raises concerns (see Section 5.2). Whether the lack of improvement in confidence and ease associated with task activity stems from shortcomings in the interface or the inherent nature of the task activity (finding concealed targets in a highly pressured and difficult environment) is unclear at this point and requires extensive exploration. See Table 5.1 for some user feedback on the visual decision support system.

Table 5.1: Some user suggestions for visual decision support

User suggestions	
Positive feedback	**Negative feedback**
I believe that the visual interface was just fine the way that it was. Its position was very good because it was out of my peripheral vision when I focused solely on the "mine field" yet when I looked up it was right there.	It's hard to look over at the screen, so maybe have the screen in front, or have a way to actually see the dots you are placing in the field
I think it is [visual interface] very clear and simple the way that it is.	A tool that could connect the adjacent dots with a line to allow better visualization of the edges, and a tool that would allow determination of distance between two points.
The only thing I can think of is that the middle button is a little difficult to use - it would be best to have something with 3 identical buttons	A clicker on the sensor would be ideal. Using a mouse requires telling the other hand to click which takes longer and gets you out of your train of thought with the pattern
This was actually a good size. It was small enough so that you noticed the difference in scale, but big enough that everything was as visible as it should be.	Maybe a little larger (I have terrible terrible vision)
I cannot see a better way to position the interface so as to optimize performance or learning capabilities. I think that it in a good position so that one may ignore it while outlining edge patterns and be able to look up at it to determine your pattern	The only place that would be a better position would be in a place that is actually on the detector. That way the interface could be viewed without looking away from the ground.

5.6 Training effectiveness

Experimental testing was based on the assumption that subjects had a good understanding of how to build and use metallic footprint for detection and localization purposes. Subjects were given a time span of one hour to correctly detect and localize all the training tasks in one cycle. Further qualitative checks such as asking participants to explain their decisions and forced reconfirmation of correct answers before a final declaration were instituted as well (see Section 3.5.4).

With respect to subjective assessment of the training program, 98% of participants either agreed or strongly agreed that the training helped with target localization, all participants either agreed or strongly agreed that the training helped with clutter vs target discrimination. All participants also agreed that training helped them to understand the concept of edge patterns.

Statistical tests carried out to detect the presence of learning effects were not significant. This result provides empirical validity for the effectiveness of the training program (see Section 4.3).

Chapter 6

Conclusions

6.1 Research outcomes

This thesis was motivated by the possibility of improving human performance, in the realm of human-based demining, through the provision of a visual decision support system. To this end, three explicit goals were defined. Understanding the influence of visual support on detection performance, quantifying the increase in footprint resolution and understanding user attitudes towards a decision support system in this task context. An extensive experiment was designed in order to realize these goals, and the results obtained provided meaningful, though not necessarily obvious, insight with respect to the stated research objectives.

The results showed that visual support improved detection accuracy. However, improvement was not uniform between correct detection rates and correct rejection rates. Visual support significantly reduced the number of missed targets but did not significantly effect the rejection of clutter-only items. Measures of target localization error indicated a pattern resolution improvement by 33%. Visual support, as provided, did not improve post testing subjective assessments of confidence and ease associated with task activity. Aggregating across post task questionnaires yielded similar results, except that subjects with visual support did find it easier to discriminate between clutter and targets.

Results with respect to correct rejections and subjective assessments were contrary to research expectations. As mentioned before, the problem of clutter (correct rejections) is one of the biggest challenges for humanitarian demining (See Section 2.3). The expectation was that by circumventing psychological challenges associated with present practice, decision support would permit for improved detection performance across the board. However, this was not the case for clutter-only items. In reducing the cognitive workload by substituting for operator memory, it was intuited that visual decision support would improve user comfort at task activity. Based on the experimental visual decision support system used, this was not strongly evident.

6.2 Research challenges and recommendations

6.2.1 User perceptions

Improving user ease and confidence associated with task activity through the provision of decision support is potentially challenging for two reasons. The inherent nature of the task may place limits on confidence gains that can be achieved through technology. That is, the cost of making a mistake is so severe that, within the scope of this task, there may be a low ceiling for confidence in detection decisions. Secondly, with current technology, there are ecological constraints on how much information can be provided to improve ease of task activity. Thus, understanding how to realistically overcome this problem lies at the intersection of user interface design, psychology and technology: providing the right tools required for the deminer mindset.

6.2.2 Correct rejections

While any endeavor to make demining safer is useful, research on human-based demining must also account for efficiency concerns (See Section 2.3). That is, technology should make it easier to reject distractors. As this controlled experiment has shown, this is not an easy or obvious task. Even with relatively minor penalties associated with missing a target in this controlled setting, subjects with visual support exhibited conservative behavior. Understanding how to provide decision support to overcome conservative tendencies is extremely challenging, Not only is it difficult to deduce the right support required for confident rejections, but such support must not simultaneously result in overcompensation (missing present targets).

6.2.3 Experimental simulation

Studying how to improve human-based demining is ecologically challenging. Simulating fear, pressure, strain and operational variability associated with demining work is especially difficult in a controlled setting. While this experiment employed extensive measures for the sake of ecological validity, there remains room for improvement. Following is a list of possible areas of improvement garnered through experience with this experiment and expert advice [43]:

- Enforcing more realistic penalties for missed targets
  It was difficult to ascertain whether the enforced reward-penalty scheme was achieving the intended effect (See Section 3.5.2). Whether this effect can be achieved through a monetary reward penalty scheme is debatable. An alternative penalty method, derived from psychology, such as electrical shock treatment may provide a more feasible simulation [17].

- Incorporating searching and sweeping
  In this experiment, subjects were presented with a small detection area that they searched by standing in one position. Simulation would be more realistic if subjects were forced to move around an area trying to find threats through sweeping motions, as done in the real world [20].

- Adding more variability to detection
  In this experiment, standard mine-like stimulants were positioned such that detector response was uniform. An experiment that could create variability in this regard by changing target 'burial depth and angle' would come closer to simulating feedback variability encountered in the real world [32].

6.3 Relevance of work to demining : dedication to cause

This experiment is unique in its effort to create an ecologically reasonable simulation of human-based demining in a controlled indoor setting. It is also one of the few present research efforts that have aimed to systematically pursue the problem of clutter (correct rejections). However, given the present seriousness of the landmine problem identified previously, it is important to question the practical relevance of this work.

This work was motivated through practical challenges encountered in humanitarian demining, pertaining to operational and resource constraints (See Section 2.3). Given the proposed method of redress, the direct impact of decision support technology is moot if more complex detectors or alternative methods such as animal-based detection and mechanical clearance come to the fore. This work was pursued, however, after careful consideration of these possibilities. Presently, human-based demining remains significant because of the difficulty associated with training and trusting animals, and accessibility and environmental issues faced with heavy mechanical clearance [13, 11, 12, 35]. Furthermore, even with the introduction of more complex dual fusion detection technology, metallic footprints remain useful [41]. While the possibility of completely removing the human from the task environment through robotic substitution is conceivable, this is an area of research where much progress is required in the context of demining [18]. Finally, even if such alternatives are proven to be helpful the issue of whether poor countries can afford such technology becomes pertinent. If nothing else, it should be telling that most countries around the world have been using metal detection technology that has been used since the 1940s, with human-based demining still the most prominent technique [48].

The disconnect between research efforts and real world needs has been tragic in this area. The scientific community has been unimpressive in contributing cheap, robust and simple technology to mitigate this global man-made problem [48]. This endeavor represents an effort to create effective solutions that are operationally robust in tough conditions and also economically affordable. A portable and cheap visual decision support system, if carefully engineered, can meet this criteria given the usefulness of metallic footprints. This research effort represents the first step towards this goal: careful scientific understanding of the problem domain and identification of the main challenges for an in situ decision support system.

6.4 Future work

Results of this experiment may be sufficient to promote end-product development of a visual decision support tool. This approach is justified given the immediacy of the landmine problem and the perceived usefulness of such a decision support system in the short run. Alternatively, more scientific research work can be devoted to understanding human behavior in relation to decision support technology within this task context. The utility of these two approaches will depend on the rate of alternative technological progress for humanitarian demining along with the capacity for demining programs to afford such technology. I propose an integrated approach. An approach that not only seeks to understand the human technology paradigm in this task context, but also seeks to push support technology closer to the realm of real world application. This approach while complex and difficult, if pursued immediately, will result in a scientifically valid technological contribution to the problem of humanitarian demining. To this end, I define very specific goals for the immediate future of this research project. Further extensive analysis must be carried out on collected data to gain insight into performance trends associated with visual support in this experiment. Why did visual support improve correct detection rates but not affect correct rejection rates? Based on these findings and experimental observations, I propose augmenting the present visual decision support system, and repeating a similar experiment. Continued success should be met with a similar iterative strategy until an applicable decision support system has been generated. Along the way, I foresee significant contributions from the fields of psychology, human computer interaction, human factors and artificial intelligence to achieve this goal.

Chapter 7

Appendix

Table 7.1: Identification of primary dependent variables

Primary dependent measures		
Variable	**Type**	**Stage of collection**
• Correctness (binary) • Localization error (pixel units, if target present) • Time to complete task	Quantitative	Recorded by software module during each detection task
• Confidence in mine presence/absence • Confidence of localization (if target thought to be present) • Ease in determining mine presence/absence • Ease of localizing target (if target thought to be present) • Ease in building and interpreting patterns • Noticed good circular/elliptical symmetry • Overall confidence about finding all targets • Overall confidence about separating clutter from targets accurately • Overall confidence about localization	Qualitative	User supplied after each detection task through post task questionnaire (measured according to 5pt. Likert Scale)

Table 7.2: Identification of secondary dependent variables

Primary dependent measures		
Variable	**Type**	**Stage of collection**
• Selected edge points • Number of edge point insertions and deletions • Sensor head position as a function of time	Quantitative	Recorded by software module during each detection task
• Total experimental time • Total time to complete training exercise • Number of cycles to complete training exercise	Quantitative	Experimental data logged by experimenter at the end of each trial

• The usefulness of the experimental training program in:
  – Interface operation
  – Developing understanding of footprint and associated concepts
  – Developing understanding of footprint based localization
  – Developing understanding of footprint based discrimination
• Assessment on display size
• Assessment on display position
• Assessment about controller
• Suggestions for improving interface
	Qualitative	User supplied after all detection tasks completed at the end of experiment questionnaire (See Appendeix Pgs 69-70)

Table 7.3: Collection of independent subject based confounds

Response		
Variable	**Stage of collection**	
• Gender • Age • Height • Occupation • History of previous military service • Present enrollment in military training • Prior experience with metal detection • Sports activity • Color blindness (ability to distinguish interface colors) • Left or right handed • Normal or corrected to normal vision • Computer use • Video game use • Prior participation in similar experiments	Qualitative and Quantitative	User supplied through demographic questionnaire (See Appendix Pg 65)

Poll Tool

Poll Home **Poll Response Form**

EFFECTS OF METALLIC FOOTPRINT VISUALIZATION

Hello, Lahiru Jayatilaka

This poll's results will not be available to respondents online.

Thank you for volunteering.

QUESTION 1:

Please indicate your sex

- Male
- Female

QUESTION 2:

Please indicate your age

Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

QUESTION 3:

Please enter your height in METERS?

Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

Please request for assistance if you want help with unit conversion.

QUESTION 4:

Please indicate your occupation

QUESTION 5:

Are you currently or have you ever served in the armed forces of any country?

- Yes
- No

QUESTION 6:

If YES to Question 5, please specify the country of service

QUESTION 7:

If YES to Question 5, please specify the nature of your service. You may select more than one option.

- Army
- Navy
- Air Force
- Marine Corps

QUESTION 8:

If YES to Question 5, please specify your duration of service

Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

QUESTION 9:

Are you currently involved with ROTC or similar program?

- Yes
- No

QUESTION 10:

If YES to Question 9, please specify the program

QUESTION 11:

Are you a varsity athlete?

- Yes
- No

QUESTION 12:

If YES to Question 11, please specify sport

QUESTION 13:

Do you have any experience with metal detection?

- Yes
- No

QUESTION 14:

If YES to Question 13, please specify the detector model you are most familiar with

QUESTION 15:

If YES to Question 13, please state approximate number of hours of experience

Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

QUESTION 16:

If YES to Question 13, please provide a brief description application. (example : humanitarian demining, military demining, hobby etc.)

Text Limit: 100 characters (approximately 2 lines)

QUESTION 17:

Have you previously participated in controlled experiments based on demining technology?

- Yes
- No

QUESTION 18:

Can you distinguish red and yellow from both green and gray colors?

- Yes
- No

QUESTION 19:

Are you left or right handed?

- Left
- Right

QUESTION 20:

Do you have normal / corrected to normal vision?

- Yes
- No

QUESTION 21:

Do you use a computer at either home or work?

- Yes
- No

QUESTION 22:

How much experience do you have playing video games? (enter hours per week - on average)

Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

QUESTION 23:

Post Task Questionnaire 1

	N/A	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am confident about my decision about the absence/presence of a mine						
I am confident about the mine location I indicated *						
It was easy to decide whether there was a mine in this task						
It was easy to establish the location of the mine*						
It was easy for me to construct and interpret the edge pattern in this task						
I noticed good circular/elliptical (partial) symmetry in the constructed pattern						

(*) Answer N/A to these questions if you thought there was NO MINE in this task

QUESTION 24:

Post Task Questionnaire 2

	N/A	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am confident about my decision about the absence/presence of a mine						
I am confident about the mine location I indicated *						
It was easy to decide whether there was a mine in this task						
It was easy to establish the location of the mine*						
It was easy for me to construct and interpret the edge pattern in this task						
I noticed good circular/elliptical (partial) symmetry in the constructed pattern						

(*) Answer N/A to these questions if you thought there was NO MINE in this task

QUESTION 25:

Post Task Questionnaire 3

	N/A	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am confident about my decision about the absence/presence of a mine	○	○	○	○	○	○
I am confident about the mine location I indicated *	○	○	○	○	○	○
It was easy to decide whether there was a mine in this task	○	○	○	○	○	○
It was easy to establish the location of the mine*	○	○	○	○	○	○
It was easy for me to construct and interpret the edge pattern in this task	○	○	○	○	○	○
I noticed good circular/elliptical (partial) symmetry in the constructed pattern	○	○	○	○	○	○

(*) Answer N/A to these questions if you thought there was NO MINE in this task

QUESTION 26:

Post Task Questionnaire 4

	N/A	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am confident about my decision about the absence/presence of a mine	○	○	○	○	○	○
I am confident about the mine location I indicated *	○	○	○	○	○	○
It was easy to decide whether there was a mine in this task	○	○	○	○	○	○
It was easy to establish the location of the mine*	○	○	○	○	○	○
It was easy for me to construct and interpret the edge pattern in this task	○	○	○	○	○	○
I noticed good circular/elliptical (partial) symmetry in the constructed pattern	○	○	○	○	○	○

(*) Answer N/A to these questions if you thought there was NO MINE in this task

QUESTION 27:

Post Task Questionnaire 5

N/A	Strongly Disa	Disagree	Neutral	Agree	Strongly Agree

I am confident about my decision about the absence/presence of a mine	○	○	○	○	○	○
I am confident about the mine location I indicated *	○	○	○	○	○	○
It was easy to decide whether there was a mine in this task	○	○	○	○	○	○
It was easy to establish the location of the mine*	○	○	○	○	○	○
It was easy for me to construct and interpret the edge pattern in this task	○	○	○	○	○	○
I noticed good circular/elliptical (partial) symmetry in the constructed pattern	○	○	○	○	○	○

(*) Answer N/A to these questions if you thought there was NO MINE in this task

QUESTION 28:

Post Task Questionnaire 6

	N/A	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am confident about my decision about the absence/presence of a mine	○	○	○	○	○	○
I am confident about the mine location I indicated *	○	○	○	○	○	○
It was easy to decide whether there was a mine in this task	○	○	○	○	○	○
It was easy to establish the location of the mine*	○	○	○	○	○	○
It was easy for me to construct and interpret the edge pattern in this task	○	○	○	○	○	○
I noticed good circular/elliptical (partial) symmetry in the constructed pattern	○	○	○	○	○	○

(*) Answer N/A to these questions if you thought there was NO MINE in this task

QUESTION 29:

What do you think about your overall performance?

	Strongy Disagree	Disagree	Neutral	Agree	Strongly Agree
I am confident that I found all targets	○	○	○	○	○
I am confident that I seperated targets from clutter	○	○	○	○	○
I am confident about my overall target localization accuracy	○	○	○	○	○

QUESTION 30:

What are your thoughts on our training program?

	N/A	Strongy Disagree	Disagree	Neutral	Agree	Strongly Agree
The training helped me to use the interface effectively	○	○	○	○	○	○
The training helped me to understand the concept of edge patterns	○	○	○	○	○	○
The training helped me to understand how to use edge patterns to detect presence/absence of targets	○	○	○	○	○	○
The training helped me to understand how to localize targets using edge patterns	○	○	○	○	○	○

QUESTION 31:

Do you think the interface could be better positioned, if so , please describe briefly?

Text Limit: 250 characters (approximately 5 lines)

QUESTION 32:

Do you think the interface should be of a different size, if so , please describe briefly?

Text Limit: 250 characters (approximately 5 lines)

QUESTION 33:

Do you think the mouse controller could be improved, if so , please describe briefly?

Text Limit: 250 characters (approximately 5 lines)

QUESTION 34:

What suggestions do you have for improving the visual interface? Would additional information or a certain display format be more useful?

Text Limit: 250 characters (approximately 5 lines)

* TASK ID 1 (for experimenter use only):
Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

* TASK ID 2 (experimenter use only) :
Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

* TASK ID 3 (experimenter use only) :
Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

* TASK ID 4 (experimenter use only) :
Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

* TASK ID 5 (experimenter use only) :
Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

* TASK ID 6 (experimenter use only) :
Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

* Subject ID (experimenter use only):
Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.
This will be entered by the experimenter

*** QUESTION 42:**

Visual assistance provided during tasks? Select one:

*** QUESTION 43:**

Reward amount
Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

*** QUESTION 44:**

Total experimental time (s)

Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

QUESTION 45:

Total training time (s)

Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

QUESTION 46:

Total training exercise time (s)

Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

QUESTION 47:

Total number of cycles for training exercise

Numeric answer required, use numbers only, with a decimal point and/or minus if necessary.

Thank you!

* *Indicates an answer to the question is required.*

Figure 7.1: Target with Clutter task 1

Figure 7.2: User generated pattern for Target with Clutter task 1

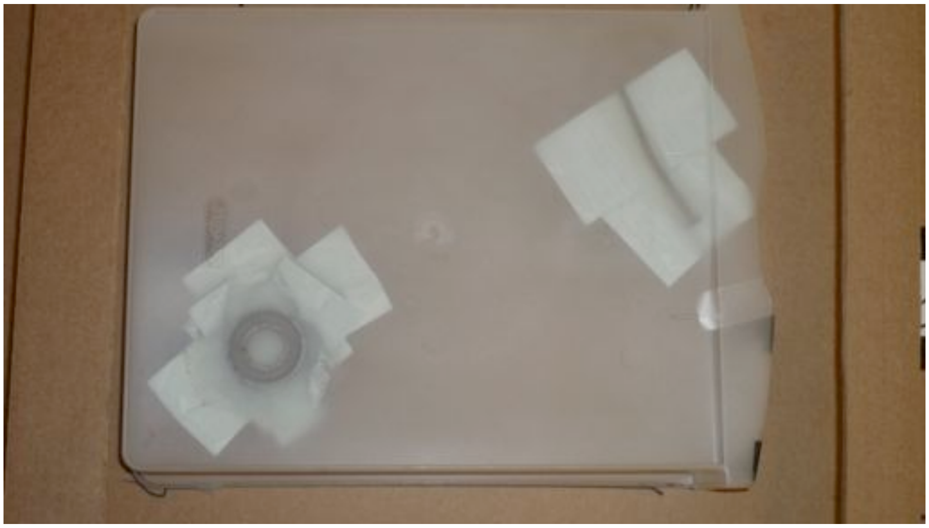


Figure 7.3: Target with Clutter task 2

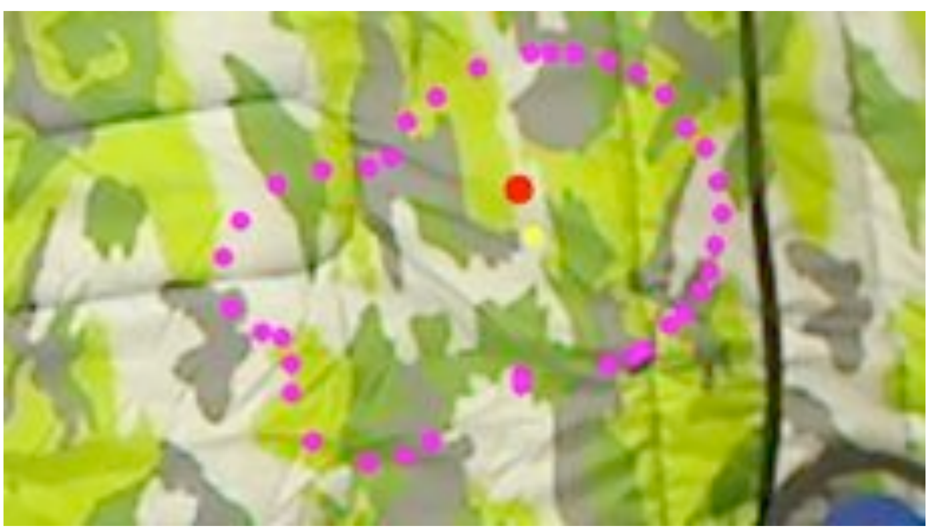


Figure 7.4: User generated pattern for Target with Clutter task 2

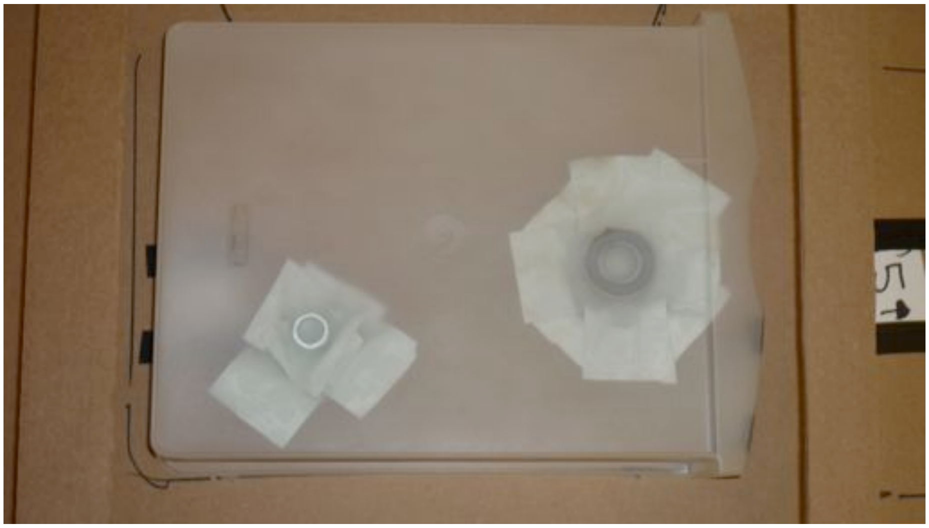


Figure 7.5: Target with Clutter task 3

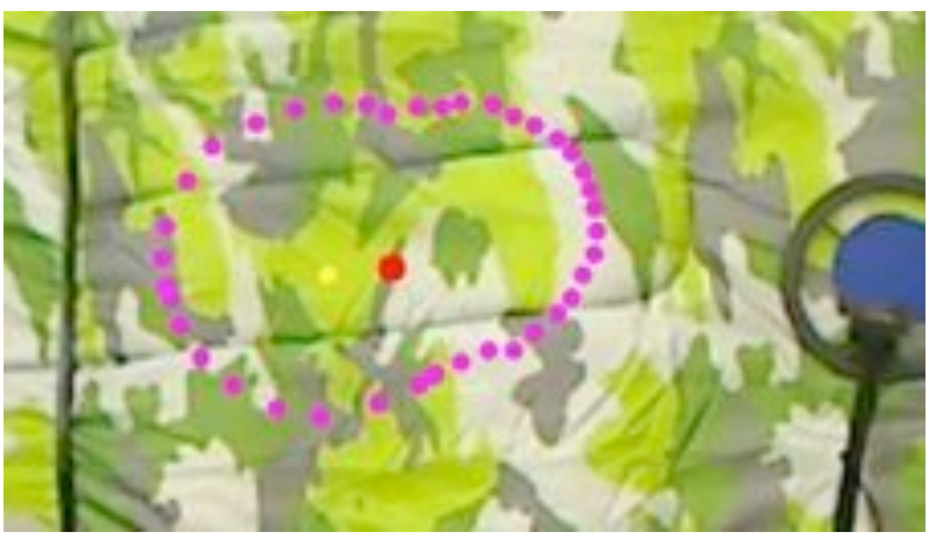


Figure 7.6: User generated pattern for Target with Clutter task 3

Figure 7.7: Clutter task 1

Figure 7.8: User generated pattern for Clutter task 1

Figure 7.9: Clutter task 2

Figure 7.10: User generated pattern for Clutter task 2

Figure 7.11: Clutter task 3

Figure 7.12: User generated pattern for Clutter task 3

Figure 7.13: Training exercise Target task 1

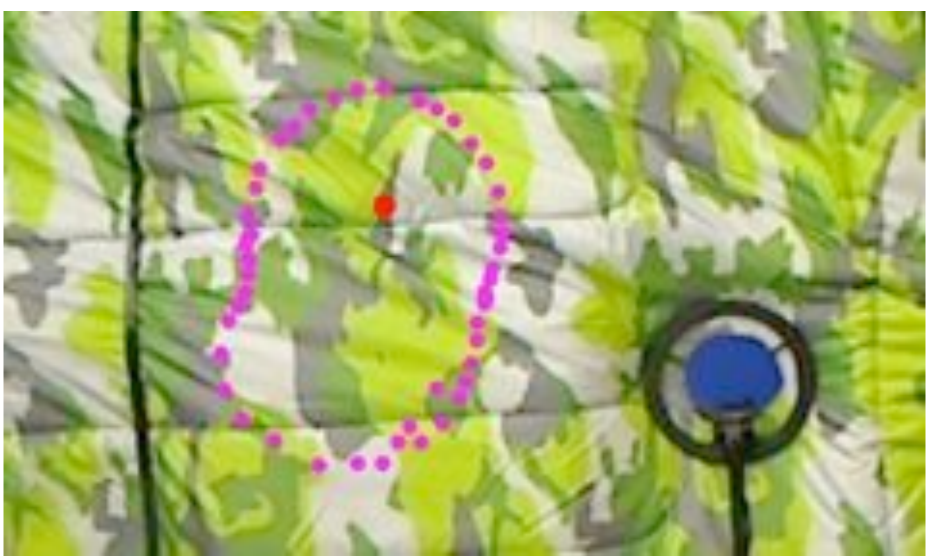


Figure 7.14: User generated pattern for training exercise Target task 1

Figure 7.15: Training exercise Target task 2

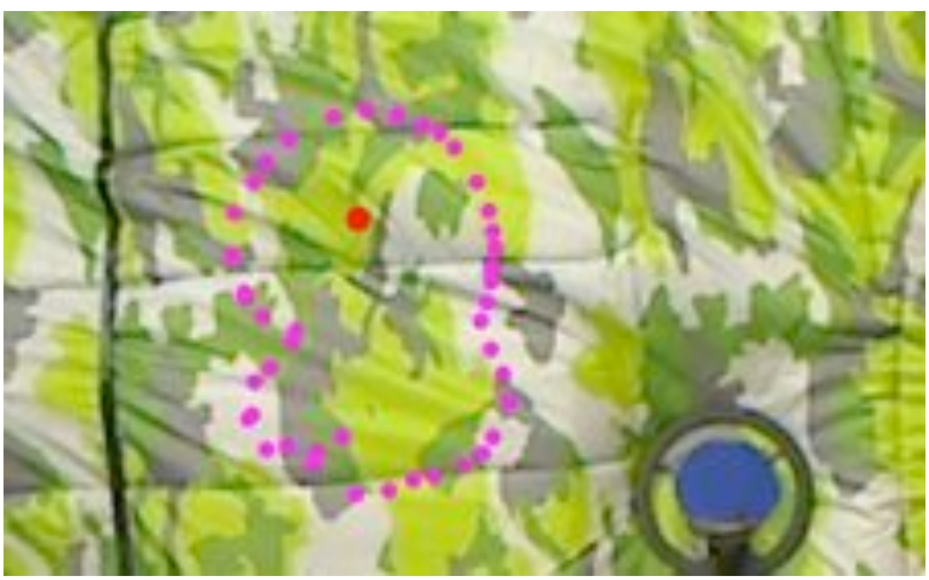


Figure 7.16: User generated pattern for training exercise Target task 2

Figure 7.17: Training exercise Clutter task 1

Figure 7.18: User generated pattern for training exercise Clutter task 1

Figure 7.19: Training exercise Clutter task 2

Figure 7.20: User generated pattern for training exercise Clutter task 2

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