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# Warfighter-In-The-Loop: Mental Models in Airborne Minefield Detection

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**ABSTRACT**

The warfighter analyst in the data processing ground control station plays an integral role in airborne minefield detection system. This warfighter-in-the-loop (WIL) is expected to reduce the minefield false alarm rate by a factor of 5. In order to achieve such a significant false alarm reduction and to facilitate the development of an efficient WIL interface, it is critical to evaluate different aspects of WIL operations for airborne minefield detection. Recently, researchers at the University of Missouri – Rolla have developed a graphical user interface (HILMFgui) application using MATLAB to evaluate minefield detection performance for the operator. We conducted a series of controlled experiments with HILMFgui using ten participants. In these experiments, we video-recorded all the experiments and conducted post-experiment interviews to learn more about the usability of the interface and the cognitive processes involved in minefield detection. The effect of various factors including the availability of automatic target recognition (ATR), availability of zoom and time constraints were considered to evaluate their influence on operator performance. Qualitative results of the factors affecting the warfighter performance in the minefield detection loop are discussed. Through the qualitative data analysis, we observed two different types of participants (classified here as aggressive and cautious). We also identified three primary types of mental models: mine centric, mine-field centric, and logical placement. Those who used a primarily mine focus had a substantially higher false alarm rate than those whose mental models were more consistent with a mine-field centric or logical placement perspective.

**Keywords**: airborne minefield detection, target detection, warfighter-in-the-loop, qualitative evaluation, human factors, mental models.

## 1. INTRODUCTION

Minefield detection is evolving from a completely manual process to a semi-automated one. In the past, minefield detection techniques have ranged from specially built bull dozers used to explode mines to soldiers probing with hand-held mine detectors [1]. The traditional minefield detection techniques have two distinct disadvantages. First, these techniques place soldiers at greater risk of exposure to enemy forces and to undetected mines. In these circumstances, soldiers must activate the mines or observe them visually. Either activity places soldiers at greater risk of injury. Second, the traditional detection methods do not generally provide adequate advanced warnings of up-coming minefields. Thus, decision-makers often do not have enough time to make tactical decisions about maneuvering with respect to a particular minefield. Therefore, although the traditional techniques are still widely used, there is growing emphasis on providing detection information using more automated and "stand-off" methods. In particular, there is a great deal of attention being paid to airborne minefield detection [2].

Airborne detection has the advantage of being safer and potentially more efficient than traditional minefield methods. In airborne detection, manned and unmanned aircraft mounting a wide variety of sensors attempt to identify minefields. The use of airborne techniques provides a number of advantages to traditional techniques. First, it is safer than requiring soldiers to physically locate and identify minefields using techniques such as handheld mine detectors. Furthermore, the use of unmanned drones can further reduce the risk by eliminating the need for pilots to fly over hostile territory. Second, a wide variety of sensors can be mounted on the aircraft to detect potential mines. These sensors use different

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methods such as near infra-red (NIR) and mid-wave infra-red (MWIR) to identify mines [3, 4]. Therefore, the chance of detecting mines increases with the use of a wider range of sensors. Finally, airborne detection can provide battlefield commanders with enough advanced warning about minefield locations that they can then make decision about how they want to handle the situation. Although the use of airborne detection has the potential for increasing both the detection and handling of minefields, there are still a number of challenges to overcome. For instance, the data collected by the aircraft sensors may first be automatically analyzed by some detection algorithm but at some point a “warfighter” in a ground station must interpret the data and verify the decision made by the algorithm. Therefore, even in airborne detection, the warfighter remains an essential part of the minefield detection process.

The warfighter plays an extremely important role in airborne detection. He must make rapid decisions about the existence of minefields under sometimes highly stressful conditions. However, we have little understanding of how warfighters will perform in minefield detection, what techniques they use to identify the presence or absence of a minefield, and what interface features best support their detection capabilities. To begin to answer these questions, we conducted a series of “warfighter-in-the-loop” experiments using a MATLAB-based graphical user interface application (HILMFgui) [5]. The application used airborne data collected at two different test sites of the US Army. Both military and non-military personnel were used in the experiments. In this paper, we focus on the “mental models” that users developed for identifying minefields and how those models affected their performance. An accompanying paper [12] in the same conference discusses the results for operator’s detection performance at mine-level.

The paper is organized as follows: in the next section, we provide a discussion of mental models and general techniques for landmine detection. In section three, we discuss the HILMFgui in more detail. Section four describes the participants, setting, and procedures for this experiment. In section five, we present the results of our analysis. Section six discusses the mental models that we identified and their implications for the “warfighter-in-the-loop”. We also discuss the limitations of these experiments and analysis in section six. Finally, we conclude with some thoughts about the experiment and future work.

## 2. BACKGROUND

### 2.1. Mental Models

The term 'mental model' is defined as internal cognitive representations of external activities and objects [6]. These mental models consist of the knowledge people bring to a given task or acquire as they perform the task. This knowledge comes in the form of predefined perceptions that they use to guide them in their approaches to accomplishing tasks. For instance, as pointed out by authors in one paper, “people import their everyday uncertain reasoning strategies into the laboratory.” [7] The authors point out that even in controlled environments, people bring their prior experience and knowledge to the task. Their mental models help individuals understand the unfamiliar. For instance, when faced with a situation such as using an unfamiliar computer program, users fall back on what they already know to guide them in understanding what is unfamiliar. In this case, a user’s mental model of how a similar program works can help him use the unfamiliar one. In essence, people use mental models to help them make accurate deductions about how they should carry out tasks [8, 9]. In addition to the mental models users bring into a task, they also develop mental models during the performance of the task. These mental models arise from “work-based learning” [10]. They are often beneficial to the task performance. However, in some cases if not properly guided or trained, a user can develop an inefficient mental model based upon erroneous assumptions during the performance of the task.

The variety of the theories and uses of the mental model concept illustrate the importance of likely users early in the design process. An understanding of the mental models that users bring to the task due to their pre-disposition and those they are likely to develop during the performance of a task, can be used to enhance user training and system design.

### 2.2. Airborne Landmine Detection

Currently a number of approaches are being explored for the purpose of detecting landmines and minefields from an airborne platform such as predator drones, blimps, and maritime patrol aircraft. These platforms employ a variety of sensors such as Infrared Imagery, Synthetic Aperture Radar, and Laser Detection and Ranging.

Surface landmine and minefield detection from airborne imagery is a difficult problem [4]. Mid-wave infrared (MWIR) imagery is used to help improve the likelihood of making an accurate detection and identification of minefields. The data collected from a sensor mounted on an unmanned aerial vehicle is downloaded, processed through an automatic detection algorithm, and displayed to a human operator for analysis. Passive infrared is also being used to detect the imaging signature of buried mines under different soil surface conditions. This method takes advantage of the three-dimensional (3-D) nature of the mine using short- and long-wavelength radiation. In addition, the convective heat transfer is incorporated in this analysis and the temporal development of the temperature distribution over a diurnal cycle is presented for different surface conditions [11].

There are many current programs in development for the purpose of detecting landmines and minefields from airborne platforms. Surface landmine and minefield detection is a difficult problem because of weak target signals and tremendous clutter problem [4]. Signal processing and false alarm mitigation have been applied to airborne data for clutter rejection. However, clutter rejection alone is not adequate because mine signatures vary with environments and time of day. Therefore, the involvement of the warfighter-in-the-loop is necessary to improve minefield detection.

## 3. SYSTEM DESCRIPTION

The aim of the graphical user interface application (HILMFgui) (figure 1) is to facilitate evaluation of the warfighter-in-the-loop performance for airborne minefield detection. This GUI allows the experimenter to evaluate minefield detection performance achieved by a human operator. An extended patch of minefield data is generated by registering consecutive frames from a given run of the Lightweight Airborne Multispectral Minefield Detection (LAMD) data. Both the raw MWIR image data and associated automatic target detector (RX detector, [13]), output is displayed for operator to evaluate. The operator is required to make a minefield or no-minefield decision based on this data. Evaluation of minefield detection performance is done in terms of probability of correct identification of minefield frame (frame with mines in it) versus probability of false alarm at the frame level (incorrect flagging of a frame as minefield frame when it does not contain any mine).

The HILMFgui supports two distinct modes of operation one for training and one for testing. In the training mode the HILMFgui provides feedback to the operator in order to facilitate better training for detection of individual mines and well as minefields. In particular the user is allowed to view the ground truth location of the mine targets and minefield area in the training mode. This feedback is not available in testing mode.

As figure 1 highlights, the operator has various functions to choose from including zoom, brightness and contrast controls, and an automatic detection overlay toggle. The zoom function allows the user to zoom the image (down to the pixel level) by using the left mouse button while positioned over the image. The zoomed imaged allows the participant to take a closer look at the images to determine the nature of objects on the images. Brightness and contrast controls allow the user to change the appearance of the image to eliminate background clutter and better identify minefields. The ATR toggle button allows the user to place and remove an overlay of the ATR selected targets on top of the unprocessed infrared image.

## 4. METHODS

### 4.1. Participants

Table 1 provides demographic information about the 10 participants that participated in this experiment. We had eight male participants and two female participants. The participants were offered monetary compensation for their participation.

### 4.2. Materials and Procedure

The experiments where conducted on the campus of the University of Missouri – Rolla in its Airborne Reconnaissance and Image Analysis (ARIA) Lab. Each participant was given a consent form to sign before the experiment began. They where then given an instruction sheet that provided background information and interface instructions. The instructions provided information on how to use the interface function (i.e. brightness and contrast controls). However, it did not contain information regarding the type, number, or appearance of the mines and minefields.

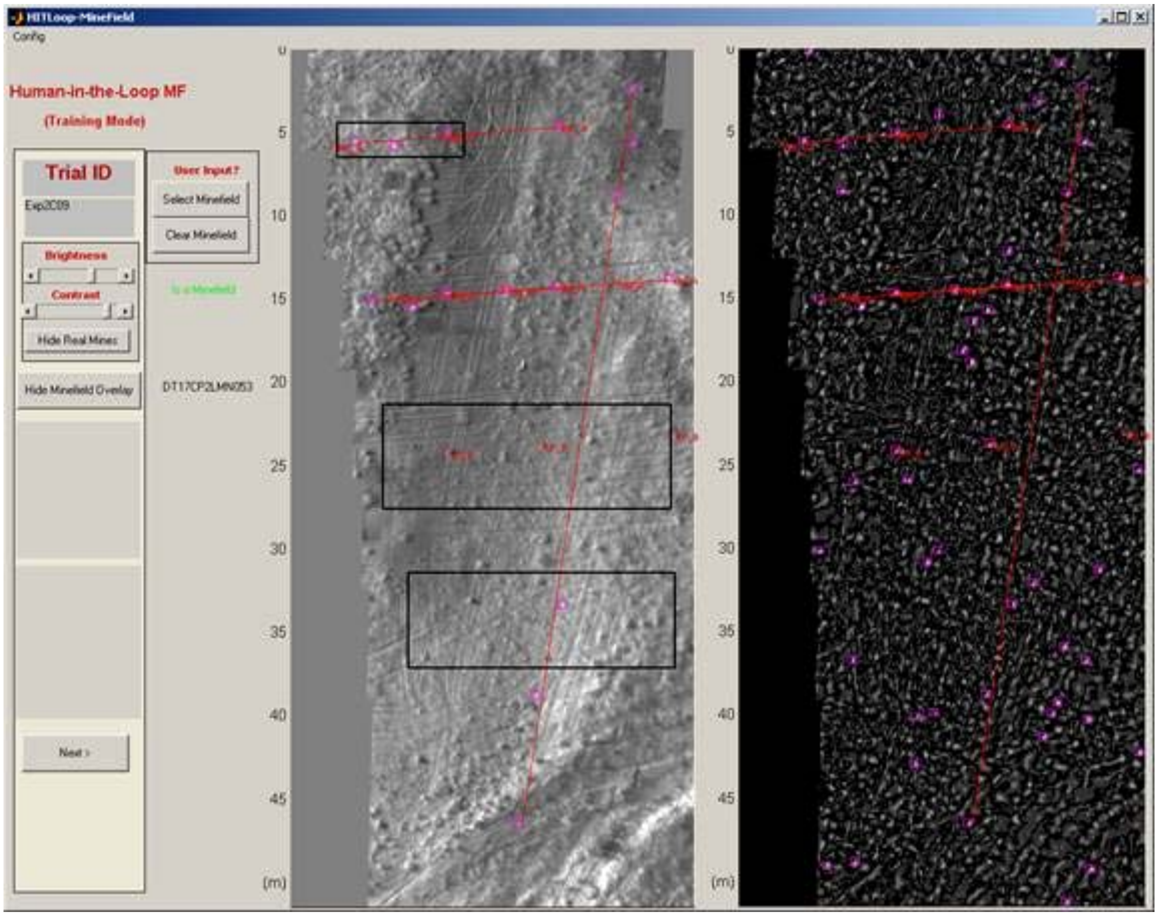


**Figure 1**: *User Interface for the HILMFGui application developed for the warfighter-in-the-loop evaluation for minefield detection.*

| Participant | Age | Sex | Military Experience |
|---|---|---|---|
| 1 | 21 | Male | No |
| 2 | 21 | Male | No |
| 3 | 21 | Female | No |
| 4 | 20 | Male | No |
| 5 | 20 | Male | No |
| 6 | 23 | Male | No |
| 7 | 22 | Female | Yes |
| 8 | 23 | Male | Yes |
| 9 | 20 | Male | Yes |
| 10 | 41 | Male | Yes |

**Table 1**. Demographics of experimental participants

The facilitator then sat next to the participants and showed them the features of the interface. They were also told what to expect in terms of experiment length and what questions they could and could not ask the facilitator. For example, the participants were told it was acceptable to ask about how to select a minefield or skip a frame but they could not ask what a minefield should look like. The participants worked through the training phase and then moved to the testing phase. Finally, they participated in a post-experiment survey and interview to identify the methods they used to locate minefields and their impressions of the interface features.

***Training:*** A minefield detection training module was created for the participants. The module was example/experience based, as opposed to principle based, in that participants were presented with many examples of imagery where the users could identify the presence/absence of a minefield using ground truth interface. The participants were required to carry out a series of identification tasks, with feedback provided for their detection. The premise of such a system was that it would encourage users to develop their own principles for detection, in a bottom-up fashion. The interface provided on-line feedback to the user on the correct location of the mine targets and the errors made in selection. The time spent by individuals on training with different sets of data was tracked and recorded.

***Testing:*** The HILgui interface in test mode was used to display a series of images from a selected database. Images were shown to the users in a random order and consisted of data from two different sites (one from eastern US and other from western US), and both daytime and nighttime images. The interface for test mode was identical to the one in training mode except that no feedback on detections was provided to the participant. For each experiment, a specified number of images (approximately 120) were used. In half of the images, mines were present and in half they were not (this ratio was not known to the participants). The order of the images was random but was identical for each participant.

### 4.3. Data Collection and Analysis

All the experiments were video-recorded to capture expressions and comments that the participants made during the experiments. An observer (e.g., facilitator) also noted any actions and comments made by the participants. After the experiment, participants were asked a series of questions concerning such issues as what approaches did they take to identify mines, what problems did they face in using the interface, and what would they do to improve the interface. The data from the observations and interviews were then systematically analyzed to identify patterns of behavior.

## 5. RESULTS

In this section, we describe results from our qualitative analysis of the experiments. We found that the participants were either aggressive or cautious and that they had different types of selection and rejection techniques.

### 5.1. Types of Users

As we analyzed the data, one of the striking features was how the participants approached the problem of detecting minefields. There were two distinct approaches used by the participants.

On one end of the continuum were "aggressive" users. We identified three participants (2, 6, 8) as aggressive. These users typically made quick decisions about whether an image did or did not contain a minefield. They also spent very little time second-guessing themselves; once they made a decision, they went to the next image. They also had the interesting characteristic of choosing to select a minefield when in doubt about whether an image contains a minefield. The following observational excerpt highlights the behavior of an aggressive user.

> *During the training phase, participant 8 made very few selections, instead focusing on ground-truth overlay to learn what the mines and minefields looked like on the different terrains. During testing, he quickly and without hesitation selected a minefield when he thought he saw one. The participant did very little second guessing. When asked how he thinks he did, he answered, "100% of what I thought was there."*

Participant 8 was typical of the aggressive users. He was sure of his choices and confidently made his selections. However, there were more users that were "cautious". These users (1, 3, 4, 5, 10) took almost the exact opposite actions to the aggressive users. The cautious users did not make quick decisions about whether an image contained a minefield. They spent a great deal of time examining all aspects of the image before they made a decision about an image. They also second-guessed themselves more than aggressive users. Cautious users would often change their minds about the contents of the image. Finally, unlike the aggressive users, cautious users often did not select a potential minefield if they had any doubts about the image as highlighted in the following excerpt.

> *Participant 5 seemed to be very cautious when looking for minefields on an image. He would take his time and when in doubt would not select a potential minefield if he had any doubts. When asked about his selection choices, he stated that "he would rather not select a target than make an incorrect selection."*

Participant 5 typified the cautious users who were concerned about making incorrect selections. Although most of the participants were cautious or aggressive, we did find some interesting shifts in their practices. In particular, some of the users who were cautious at the beginning became more aggressive as they became more familiar with the images and the interface. Aggressive users, for the most part, stayed aggressive throughout the entire experiment. We also found that some users (in particular 7, 9) shifted back and fourth between aggressive and cautious depending on the image and other constraints.

### 5.2. Selection and Rejection Techniques

During their attempts to determine whether an image contained a minefield, participants utilized different minefield selection and rejection techniques. We noted three major techniques: mine level, minefield level, and topography.

One technique that participants used to select or reject potential minefields was to view the minefield from a mine level perspective. Many of the participants had prior experience with detecting individual mines [12]. Therefore, even at the minefield level, they were most comfortable looking for individual mines. One participant noted that he was *"looking for bright spots"* and *"leaning toward obvious mines."* The behavior of this participant was characteristic of those who focused on the individual mines. If they identified any single mines, they quickly selected those mines. Similarly, these participants would reject minefields based on the shape of the individual objects. For instance, if the object was not circular or natural looking, participants determined that the object was not a mine. One participant noted that he was not "*sure about dark spots because mines are perfect white circles."* (We should however add that this was true for only a small fraction of mines in the data). Therefore, participants using a mine level approach for selection or rejection focused on the characteristics of the individual mines and ignored features such as the shape or location of the entire minefield.

A second group of participants tried to select or reject minefields based on the characteristics of the minefield instead of the individual mines. These users did not focus on individual objects but instead looked for particular patterns. If they identified a pattern, they then selected the area as containing a minefield. In particular, participants used three patterns when trying to identify minefields. They were (1) similar objects in a row (2) equal spacing between objects and (3) same number of objects in rows. One participant noted that "*I would be in trouble without patterns."* On the other hand, participants also rejected potential minefields based on its appearance. If the objects were not laid out in linear patterns and evenly spaced, the participants did not select the area as containing a minefield. As one participant stated, "*non-parallel lines of mines seem unusual."* This participant and others that focused on the minefield were quick to note that mines in the minefield were laid out in parallel lines. Therefore, non-parallel lines indicated to them that this was not a minefield. Participants also rejected potential minefields if they saw only two objects in a row because they perceived that minefields contained rows of multiple mines (e.g. more than 2 mines). Participants using minefield level techniques did not attempt to examine the individual mines but instead focused their attention on the entire minefield.

A third category of participants focused on the geographic location of the minefield instead of the particular mine or minefield level characteristics. These participants looked at the surrounding topography to help them determine if there was a likelihood of minefield. For example, they would note whether the "suspected" minefield was located on or near a road. If it was on a road then, in their opinion, there was a higher likelihood that it contained a minefield. One participant explicitly noted this in her comments to the observer. She stated, *"military experience tells me that mines would be close to road."* The topography technique was used by participants who had military experience to help guide their thinking about minefield placement. These participants also rejected potential minefields based on the topography. For instance, participants rejected potential minefields if they saw them on hilltops or under trees. Participant 10 stated that he could not imagine why anyone would lay a minefield on a hilltop. The topographical technique, allowed participants to focus their attention on the environment surrounding the minefield and not just the characteristics of either the individual mines or the minefield.

## 6. DISCUSSION

In the following section, we will discuss the three mental models that emerged from our analysis. We will also address in greater detail the usefulness of the various features present in the interface. Finally, we will discuss some limitations that we faced in this study.

### 6.1. Mental Models

#### 6.1.1. Types

The different selection and rejection techniques lead us to identify three major mental models (figure 2) of how users approached the problem of minefield detection. Not surprisingly, these mental models are mine level, minefield level, and logical placement.

The mine level mental model was the simplest model. Three participants (3, 6, 7) had both selection and rejection techniques that focused on the individual mines in the minefield. Interestingly, these three participants had participated in a previous experiment [12] that evaluated mine level detection. Therefore, they may have already developed a model of detecting mines from the previous experiment. Hence, in this experiment, these participants could not focus on the more abstract concept of the minefield and instead focused on the individual mines. They had trouble expanding their vision to encompass the entire minefield. Instead, they would constantly select one or two mines at a time. If they were lucky, they would be able to select enough of the individual mines to cover the entire minefield. However, more often, they would miss significant aspects of the minefield because of their selection choices. The mine level mental model focused too much on the details of the individual mines at the expense of contextual information provided by the minefield or surrounding topography.

The minefield mental model provided a more abstract view than the mine level. Five participants (1, 2, 4, 8, 9) had both selection and rejection techniques that focused on the characteristics of the entire minefield. This did not mean that they completely ignored the individual mines; however, these participants integrated the mine level techniques into their focus on the entire minefield. As stated in the results section, participants looking at the entire minefield tried to identify patterns and other characteristics that would help them *identify* multiple mines. Participants focusing on the minefield were less likely to be bothered by little inconstancies that may appear in the individual mines. They were also more likely to accurately select the entire minefield than participants with a mine level mental model.

Finally, we identified a third mental model, logical placement that we had not anticipated that participants would use for identifying minefields. Two participants (5,10) had this mental model. In many ways, this was the most interesting mental model that we observed because the focus was not initially on the mines or minefield, as it was with the other two. The participants who had this mental model had prior or current military experience. In fact, participant 10 is an active duty member with background in armor. These two subjects constantly thought of the minefield in terms of logical placement. This helped them determine the existence of the minefield. For instance, neither subject thought that anyone would place a minefield on top of hill, so they immediately rejected objects located on top of a hill. The logical placement model points to the importance of the environment surrounding the minefield. While the first two mental models focused on the internal characteristics of the minefield, this model focused on the external characteristics surrounding the minefield. This type of information is the type a warfighter is likely to rely on when making decisions.

Clearly, participants did not always take just one perspective of the image. Sometimes, participants combined elements of the selection and rejection techniques to help them make a decision. For instance, one participant looked at both the shape of the individual mine and the regularity of the mine patterns in the minefield to help him make a decision about what's contained in the image. However, the majority of the time, participants use one dominant mental model in their tasks. These mental models provide us with an understanding of how participants approached the problem of detecting the minefield. From our observations and analysis, the best approach seemed to be the logical placement model followed by the minefield level model.

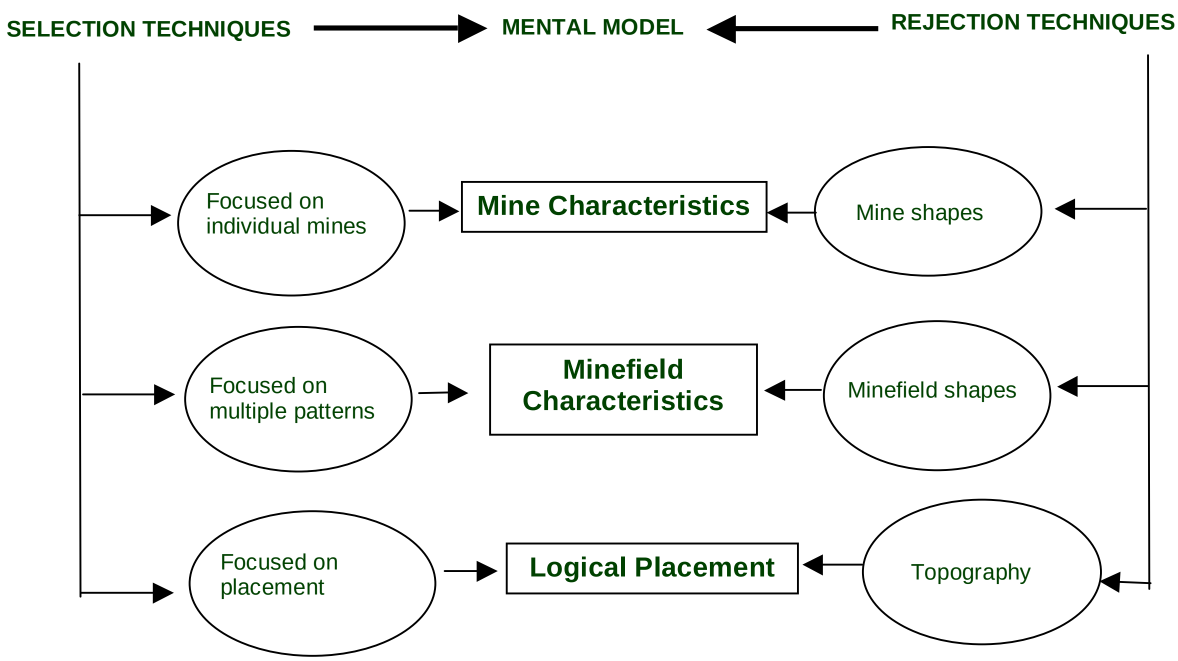


**Figure 2**. The three major mental models.

### 6.1.2. Relationship of Mental Models to Performance

In order to examine the relationship between mental models and performance, the participants were divided into three groups, based on mental models, as described above. The mean false alarm rate for each group was then calculated.

Although the sample size was too small to make any inferences with regard to statistical significance a clear pattern emerged with those who had a mine focus having substantially higher false alarm rates than those who had a minefield or logical focus. As indicated in Table 2, the high mean false alarm rate for those in the mine level group was strongly influenced by participant 3 who had a dramatically high rate. However, it's also important to note that the other two participants who were classified with a mine level orientation, had higher false alarm rates than any other participants.

| Mental Model | Participant | False Alarm Rate | Group Mean |
|---|---|---|---|
| **Minefield** | | | **.05** |
| | **1** | **.05** | |
| | **2** | **.07** | |
| | **4** | **.07** | |
| | **8** | **.00** | |
| | **9** | **.07** | |
| **Mine** | | | **.33** |
| | **3** | **.77** | |
| | **6** | **.08** | |
| | **7** | **.13** | |
| **Topographic** | | | **.03** |
| | **5** | **.06** | |
| | **10** | **.00** | |

**Table 2.** Probability of Detection for All Participants by Mental Model Group

### 6.2. Supporting Interface Features

The warfighter making the decision about potential minefields needs an interface that will provide him the necessary features to help make informed decisions. Therefore, we evaluated the effectiveness of three major interface functions.

One feature used by participants was the automatic targeting recognition algorithm (ATR/RX) overlay. As stated in section 3, participants had the ability to toggle on/off the ATR/RX overlay. Most of the participants used this function continuously throughout the experiment to help them quickly identify individual mines. The overlay also provided connecting lines between "mines" identified by the ATR/RX. The participants used these lines as a guide for their eyes. Participants would look at the ATR/RX overlay then quickly look at the unprocessed image. They would use the lines to direct their eyes to same location on the unprocessed image to see if they could spot any mines. However, none of the participants made their decisions solely based on the ATR/RX. Its primarily served to help their identification process.

A second function that played a critical role in the interface was the brightness and contrast feature. Participants used this feature to help them identify mines in rough topography. The participants manipulated the brightness and contrast to highlight the artificial characteristics of the mine. This was valuable because it allowed them to take advantage of the differences between the mines and surrounding topography. As one participant stated, *"It was very useful when I was looking for differences between the mines and surrounding areas."* The brightness and contrast was also used a great deal in conjunction with the third major feature, zoom.

Of the three major functions, zoom may have played the most important role as a mechanism for allowing participants to double check their decisions and verify that they have made the correct decision. We did observe that participants would use the zoom function to get a closer view of a particular region when trying to make a decision about the existence of a minefield. Yet, more often, we noticed that participants would make a selection then zoom in to take a closer look at the selected area. When asked why he did that, one participant stated, *"It helps find out if I made the right choice."* Zoom played an important role in re-assuring the participants about their decisions.

The available interface features supported the participants' decision-making abilities. Participants utilized these features both singularly and in combination throughout the experiments.

### *6.3.* Study Limitations

Although the minefield experiment provided some interesting results about participants' mental models and the interface features, these results should be considered within the context of methodological constraints. More specifically, we faced five major constraints. First, due to time and budget requirements, our sample size was small. Therefore, it was not possible to carry out any meaningful inferential statistics. Second, the majority of our participants did not have any military training or background in minefield detection. Although we did provide training as part of the experiment, it cannot replicate "real-world" experience. Third, a MATLAB-based interface could not simulate the real-world processing of images that would occur in a battlefield environment. More realistic processing and display of images may well have created a more realistic environment for participants, which may well have affected their processing strategies and performance. Fourth, in the current experiments we did not have geographic image data corresponding to the airborne MWIR data being displayed to the operator. Given that more experienced subjects with military background tended to relay on contextual information in their decision making, that may have been the most important piece of raw data that was missing from these experiments. Finally, we were limited by the amount of data we could present the participants. We had access to a limited number of images with a very limited number of distinct minefield layout. We attempted to mitigate this by combining different images together to provide new images. However, participants did have a certain amount of predictability about what they viewed which may have affected their performance.

## 7. CONCLUSIONS

Minefield detection is a non-trivial activity. Equipment to identify potential minefields has been growing in sophistication. However, the warfighter must still play an important role in the process. In these experiments, we have focused on trying to understand participants' mental models when making decisions about potential minefields. By understanding their mental models, we can begin to develop better technical and organizational support for the "warfighter-in-the-loop".

In this study, we identified three main types of mental models – mine level, minefield level, and logical placement. These mental models begin to give us insight into the cognitive processes of the participants. Depending on their mental model, participants used different minefield selection and rejection techniques. Although the sample size is too small to make any conclusive remarks, we identified that the logical placement and minefield level mental models were the most effective in reducing the failure rate. These findings have implications for the training of warfighters who are involved in minefield detection. The wrong mental model could greatly increase error rates.

We also observed that the functions provided by the HILMFgui interface allowed the participants greater flexibility in identifying minefields. The ATR/RX overlay, brightness and contrast, and zoom played an important role in participants' performances. One thing that often gets overlooked when developing interfaces is the need to provide the *appropriate* functionality to the users. The appropriateness of the functions depends on the tasks. In this case, participants needed ways to allow them to closely examine an object and distinguish it from other objects. The features on the interface supported those functions.

These experiments provided us with interesting preliminary results. However, more research is needed to confirm these initial findings. We plan on continuing these experiments using larger sample sizes, active-duty military personnel, and "real-world" technologies. The warfighter plays an essential role in minefield detection and our goal is to provide him the appropriate training, support, and tools to do his job.

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