Evaluating Operator Performance in Aided Airborne Mine Detection

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ABSTRACT

In this paper we evaluate mine level detection performance of the human operator using high resolution mid-wave infrared (MWIR) imagery and compare it with the performance of automatic target recognition (ATR) like RX detector. Previous studies have shown that the anomaly detectors like the RX detector and even more sophisticated ATR techniques fall short of the performance achieved by human analyst for mine and minefield detection. There are three main objectives of the paper. First, we seek to establish performance bounds for mine detection using a single MWIR sensor under different conditions. Second, we evaluate the conditions under which the human visual system contributes significantly over and above RX anomaly detector. Third, we seek to qualitatively study the visual processes and mental models employed by the human operators to detect mines. A graphical user interface (HILgui) was developed using MATLAB to evaluate mine level detection performance for the operator. This interface is used to conduct a series of experiments examining performance for twenty subjects. The mine images varied systematically based on the time of day the images were collected, the type of terrain and type of mines. All the experiments were video-recorded and post-experiment interviews were conducted for qualitative analysis. Both qualitative and quantitative research techniques were used to gather and analyze the data. Results from different quantitative analysis including the accuracy of mine detection, propensity of false alarms and the time taken by the operator to mark individual targets are discussed. The mental models developed by the subjects for detection of mine targets are also discussed. Limitations of the current experiments and plans for future work are discussed. It is hoped that this systematic evaluation of a human operator in airborne mine detection will help in developing new and better ATR techniques and help identify critical features required in the operator interface for the warfighter-in-the-loop (WIL) minefield detection.

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

1. INTRODUCTION

Mine and minefield detection has become an increasingly important problem from both a military and humanitarian perspective. While the focus of mine detection systems is to locate individual mines for reclamation and humanitarian purposes, minefield detection is important in tactical military operations to identify avenues of approach. Mine and minefield detection systems have steadily grown from metal detectors and manual probes to highly sophisticated vehicle mounted and airborne systems. The increasing demand for real-time, accurate, semi-automated systems has directed the efforts of researchers around the world. One important desirable feature of mine and minefield detection systems is the “stand-off” operation. This type of system would allow a soldier or civilian deminer to detect mines from a location where they are not in the harms way. Many systems are currently being researched, which attempt to fill these system requirements. The focus of this paper is airborne minefield detection primarily concerned with tactical countermine and maneuver support operations.

Figure 1 shows the schematic of the airborne mine and minefield detection processing stream. The airborne data is collected in the form of partially overlapping sequence of images representing a footprint of the ground area. The processing takes place in 2 steps: mine detection, and minefield detection. Mine detection often uses an anomaly detector such as RX detector [1, 2] to detect possible mine locations. Mine detection block may also use a false
alarm mitigation process to reduce the false alarm rate [3, 4]. A set of consecutive image frames representing a contiguous ground area is registered to form a minefield segment. The likely mine targets detected in this minefield segment are analyzed for the patterns of potential minefields (which could be patterned or scattered) [5, 6]. Given the current state of the art, these two sequential processes will still not be enough to satisfy operational performance requirements using fully automatic minefield detection for different types of terrain, time of day and other factors. For this reason the operational system is conceived to employ a semi-automated aided ATR approach with a warfighter-in-the-loop to improve the minefield detection performance. A warfighter-in-the-loop is responsible for the final analysis with respect to the presence of minefield and subsequent decisions regarding a course of action.

The projected requirement for mine-level performance is a probability of detection at 0.4 at a false alarm rate of 0.001 FA/m² [7], which translated to an allowance of only 3 false alarms per seconds of flight at 90 knots. The ATR minefield detection requirement is to exceed a probability of detection of 0.9 with lesser than 0.5 false alarm per kilometer square, which translates to less than 5 false alarms per hour. The warfighter-in-the-loop is further expected to reduce the false alarm rate to less than 0.1 false alarms per kilometer square (1 false alarm per hour). These levels of performance requirement make the warfighter in the detection loop an integral and critical part of the overall airborne minefield detection system.

The warfighter has to reduce the minefield false alarm rate by a factor of 5. The processing load on the warfighter may be even higher if the ATR processing at mine level or minefield level is not able to meet their required performance level. In order to achieve such a significant false alarm reduction it is critical to evaluate and understand different aspects of warfighter-in-the-loop operations for airborne mine and minefield detection. Such analysis will help evaluate the level of performance that can be achieved, facilitate the development of an efficient warfighter-in-the-loop interface and help develop efficient and effective training techniques.

In order to answer some of the questions related to warfighter-in-the-loop operations, investigators at University of Missouri Rolla conducted a series of “warfighter-in-the-loop” experiments using a MATLAB-based graphical user interface application (HILgui [8] and HILMFgui [9]). This effort was initiated and supported by the US Army RDECOM CERDEC Night Vision and Electronic Sensors Directorate (NVESD), Countermine Division, Airborne Applications Branch. The aim of these experiments was to investigate how a person goes about detecting mines/minefields and how this knowledge can be used to assist in achieving the goals of an operational airborne minefield detection system. These experiments were conducted in two phases where the first set of experiments concentrated on the issue of individual mine detection while the second set of experiments was aimed at minefield detection and operational issues. In this and an accompanying paper [10], we report some of the finding of these investigations. In this paper we discuss the results for operators’ mine-level detection performance, while the accompanying paper [10] discusses the “mental models” and techniques that users developed for identifying minefields and how those models affected their performance.

In airborne operations, investigation of operator performance and techniques at the mine-level of detection is an over kill. Operationally, the ability to detect individual mines is clearly not as important as the ability to detect minefields. Although mine level performance is not very useful from an operational perspective there is still much...
that can be gained from such an investigation, including an examination of relevant parameters, human processes, performances and methodologies for evaluation. We had three broad objectives for this set of experiments:

1. **Evaluate sensor performance:** We seek to establish performance bounds for mine detection based on the available data from MWIR sensor under different conditions. This claim is based on the premise that human perception (given enough time and tools to evaluate the imagery) is the most effective detection system. Thus, the mean performance of human operators for imagery from a given sensor, for some operating conditions, can be used as a measure of the highest level of performance for the sensor under those conditions.

2. **Compare human performance with ATR:** We seek to evaluate and compare performance of the human operator with that of the current ATR method. This analysis will serve as an initial exploration of the conditions under which the human visual system contributes significantly more over and above the currently employed ATR technique (like RX anomaly detector). This is likely to point out major deficiencies with respect to different operating conditions that may exist in the ATR algorithm.

3. **Learn from human operators:** We seek to quantitatively and qualitatively study the mental processes and models employed by the human operators to detect mines. In a broader sense, the scope here is to determine the methods used by humans to detect mines, so that this knowledge may be used to help in the effort to improve ATR algorithms and techniques.

This remainder of the paper is organized as follows: the next section explains the user interface developed and used for the mine-level experiments in greater detail. Section 3 provides the details of the experiment. In particular the methods for data selection and procedure followed during the experiments are discussed. In section 4 the results of the experiment are discussed. Section 5 provides further discussion of results, including inferences that can be drawn from, and limitations of, the experiment. Section 6 concludes with some thoughts on potential applications and directions for future work.

### 2. USER INTERFACE

The aim of the warfighter-in-the-loop mine-level graphical user interface, called HILgui, is to facilitate evaluation of the operator performance for detection of mine targets in airborne data. This program allows for the display of a selected set of images sequentially to the operator. Figure 2 shows the graphical user interface the way the operator would see it, with the raw MWIR image on the left and the processed RX image on the right. The top ten targets in RX image obtained by non-max suppression [11] are shown overlaid on the RX image. The operator is required to analyze the image data and select the mine locations on the raw image using a mouse click. The user can skip to next image by pressing the **Next Image** button. It is possible to automatically advance the frame after a predetermined time but that option was not investigated in the current experiments. The program automatically records information for performance evaluation. In particular the location of the selected targets on each image, the time between selection of targets and the total time spent by the user analyzing the image are recorded.

This program was created for the purpose of collecting statistical data from multiple subjects. Data for each user is recorded separately and can be evaluated individually or as a group using the evaluation program. The program supports two distinct modes of operation, one for training and one for testing. The mode of operation is chosen when the test administrator sets-up the interface. In the training mode the program provides appropriate feedback to the operator in order to facilitate better training for detection of individual mines. More specifically, the user is allowed to view the ground truth location of the mine targets in the training mode. This feedback of ground truth locations is, however, not available in testing mode. The ground truth, when available, can be triggered on and off by pressing the **Show Mines** button. The data for evaluation is recorded only in the testing mode.

A separate evaluation program allows comparison of mine detection performance achieved by a human subject versus ATR performance. It allows the experiment administrator to view performance for a single user or selected multiple users. Performance is evaluated in terms of probability of detection for mines versus the false alarm rate. Note that while the ATR algorithm results in a complete receiver operating characteristics (ROC) curve, the human operator performance is just one point in this space. The ATR implemented for mine level detection is based on the RX algorithm. To analyze the time dependence of the operator performance, we draw comparison between the detection and false-alarm density as a function of time interval between selections. This comparison allows us to see when the operator has stopped making valid inferences on mine location and is now “guessing” for probable mine locations. The evaluation program further allows the experiment administrator to view user performance across
multiple variables or viewed as specific groupings of variables, such as results for selected mine type or selected background. Corresponding performance of the detection algorithm can be displayed for comparison. The raw data recorded during the tests along with the known ground truth is saved in a text table, which can easily be downloaded into other programs for statistical analysis.

![Figure 2](image.jpg)

**Figure 2.** User interface for the HILGui application developed for evaluation of mine-level detection performance of human operator.

### 3. METHOD AND EXPERIMENT SETUP

#### 3.1 Data Selection

We used airborne MWIR data collected as part of Lightweight Airborne Multispectral Minefield Detection (LAMD) program. Even though some buried mine data was available, for current experiments only surface laid mines are used. Two sets of data were used, one collected at a semi-arid test site in eastern region of the US in October 2002, and the other collected at a desert site in a western region of US in May 2003. Figures 3 and 4 show two representative images from the set of data available from each of these two sites. Each image is 512x640 at a ground resolution of about 1.1 inch, representing a ground area of approximately 250 square meters. The data collection in October 2002 (Figure 3), from the test site in the eastern US, represents mine targets embedded in high clutter backgrounds. No data for nighttime was available from this test site. The data collected in May 2003 (Figure 4), from the desert site, represents a relatively benign environment as far as MWIR clutter in airborne collection of surface laid mines is concerned. There is an extensive amount of data for both daytime and nighttime and for different MWIR filters, from multiple runs over the minefield collected for this test site. For the current analysis we selected a subset of data with solar band (band 2) selected for daytime data and thermal band (band 3) selected for nighttime data.

All data used for training and testing was selected based on two main criteria:

1. Selected equal number of frames with mines and those without mines. Half of these were from October 2002 collection and half from May 2003 collection. The October 2002 data was further equally divided between morning and afternoon data. The May 2003 data was equally divided between nighttime and daytime data. This selection meant that we had 25% data from nighttime and 75% data from daytime since October 2002 collection did not have nighttime data.

2. All frames with surface mines irrespective of ATR response or the type of mines were selected as candidates for selection under image frame with mines. For the case of image frame without mines, only frames triggered by RX detector as having high likelihood of containing mines were selected. This ensures
that the human operator is asked to analyze only image frames with actual mines or those which are likely to be triggered as false alarms by the ATR algorithm.

The data for testing and training was selected from 26 runs of available data from October 2002 and May 2003 data collections representing a total area of 1.34 square kilometer. Out of this, the RX detector flagged 0.23 square kilometer as having a high probability of containing mines (5 or more high contrast targets above minimum level of threshold). We used a total of 160 randomly selected frames representing about 0.04 square kilometer for the testing phase of the data (in two experiments with 80 frames each). Also, 40 randomly selected frames (excluding those selected for testing) were used for the training phase.

![Figure 3](image1.png)  
**Figure 3.** Representative MWIR image frames from semi-arid test site in eastern US collected in October 2002.

![Figure 4](image2.png)  
**Figure 4.** Representative MWIR image frames from desert test site in western US collected in May 2003.

### 3.2 Participants

A total of 20 participants participated in the mine-level experiments reported here. Table 1, provides demographic information about these 20 participants. We had fourteen male participants and six female participants. The participants were offered monetary compensation for their participation. The compensation was a flat fee for the participation in the experiments, and did not depend on the time spent or level of performance.

### 3.3 Procedure
The experiments were conducted at the Airborne Reconnaissance and Image Analysis (ARIA) Lab on the campus of the University of Missouri – Rolla. The experiment was broken up into 4 phases, all conducted over the course of about 2 hours (however there was no time constraint imposed on the participants). Subjects were given a break in between the 2 parts of the experiment and after the training phase if desired.

Phase 1: Introduction/instructions
Phase 2: Training session
Phase 3: Experiment (in 2 parts)
Phase 4: Post experiment interview

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Table 1. Demographics of experimental participants.

Each participant was given a consent form to sign before the experiment began. They were 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. 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. 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 mines and their impressions of the interface features. The test facilitator was available throughout the experiment, training and testing modes, to answer questions but he did not assist the user in detecting mines in any way. The mine detection interface was used in two modes: training and testing. In both modes subjects were shown the interface discussed in section 2. The main features of the two modes are described below:

**Training:** A mine 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 mines using the 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 the two different sites, and both daytime and nighttime images as discussed in section 3.1. The interface for test mode was identical to the one in training mode except that no feedback on detections was provided to the participant. They were required to click on locations on the MWIR image where a suspected mine was thought to exist. For each experiment, a specified number of images (80 for each test) 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.

Participants were given access to brightness and contrast controls so they could change the way the image displayed, to hopefully get a better perspective on the content of the image. Subjects were, however, discouraged from adjusting these controls during the actual tests so that this action would not alter the characteristics of the recorded time interval between selection of targets.

### 3.4 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.

4. RESULTS

Broad results for all 20 participants are presented and discussed here. Specific quantitative and qualitative results are discussed as part of analysis and discussion. In particular, quantitative performance across different participants, background and time of day, and qualitative mental models are discussed in section 5.

Figure 5 shows the performance of subjects and the performance of the RX processing across all frames. In the figure, the y-axis shows probability of detection and the x-axis shows false alarm rate in FA/m². Each participant is shown by a blue star. Mean performance across all users is shown using red star. ATR performance is also shown using magenta ROC curve for comparison. There are 2 features of note in this plot. Firstly, the subjects did significantly better than RX detector. The subjects were grouped between 0.5 and 0.9 PD in the $10^{-3}$ to $10^{-2}$ FAR range showing a significant performance increase over the RX processing for that same range. Secondly, the subjects were well grouped, showing that it was not a few subjects that did exceptionally better than others, but rather that human operators always did better when compared to RX, irrespective of experience, natural ability or disposition. The red dot showing the average human operator performance for all 20 participants is seen at a PD of 0.68 and a FAR of 0.0025 FA/m².

Figure 6 shows the performance of subjects across two different terrain types. The type of figure is the same as in figure 5, except that the results for different terrain are shown on different figures. The detection performance for semi-arid terrain (October 2002) is shown in Figure 6 (a) while the performance for desert terrain (May 2003) is shown in Figure 6 (b). There are many interesting features that can be seen from these plots. First, we may note that the participants performed generally better in the desert terrain as compared to the semi-arid terrain which was noted to be high clutter background. Second, the clustering of the subjects is much better with respect to the detection rate in the case of desert terrain as compared to the semi-arid terrain. This may indicate that in the case of semi-arid terrain natural ability, disposition or experience of the participants (mental models) played a bigger role in detection. Also the false alarm rates for the semi-arid terrain tended to be higher across all users (in the region of 0.01 FA/m²). The third point of interest is the RX curves for the 2 areas. In high clutter background of semi-arid terrain the RX performance is extremely poor (no detections even at a FAR of 0.01 FA/m²). The human operators, on an average, showed an approximately 0.3 increase in PD on both graphs.

Figure 7 shows the results of the analysis for the time (in seconds) taken by the users to make a selection of targets. The figure shows two plots. The blue curve shows the plot of the probability of selecting correct mine target as a function of time since last selection, while red curve shows the plot of probability of selecting false alarm as a function of time since last selection. This figure shows that the decisions made quickly had higher likelihood of being correct. As the time taken to make a decision increases, the likelihood of detecting correct mine target decreases while the likelihood of detecting false alarm increases. Decisions made between 0.5 second and 6 seconds were more likely to be correct mine targets while decisions made after 6 seconds were more likely to be false
alarms. The likely reason of this time-performance characteristics is that as the users spend more time pondering over the target to select they tend to second-guess themselves and are thus more likely to select false alarms. Also, we should note that the pool of mine targets in the given set of images was finite, so that in general, eventually there may be very few mine targets left to be detected. However in the current experiments, the mean probability of detection was approximately 0.68 so that there were still significant number of correct targets still undetected. Time analysis separated by the type of mines may be interesting. However, we had limited numbers of each type of mines and thus this level of analysis was not conducted on this data.

Figure 6. Detection performance (all 20 subjects) for image frames selected by terrain types (a) Semi-arid terrain (high clutter) (b) Desert terrain (low clutter).

Figure 7: Time response characteristics of the true detections and false alarms

5. ANALYSIS AND DISCUSSION

5.1 Quantitative Analysis
There quantitative analysis addressed two fundamental questions. First, can we identify different background conditions that impact human performance in identifying mines? And if so, how does this difference relate to ATR algorithm performance? Understanding these differences between ATR and human detection performance can impact further refinement of algorithm, taking into account the characteristics of the warfighter-in-the-loop. Figure 8 show the bar plots comparing human and ATR performance for different terrain and different time of day. Mean value and range of scores across different human subjects is shown. The Figure 8 (a) shows the plots for the probability of detection characteristics while Figure 8 (b) shows the comparison of false alarm rate. Analysis of the results reveals several interesting things. In particular we note that, in desert environments humans clearly are better able to identify individual mines and their false alarm rates are lower when compared to the ATR. The effect of the
time of the day is minimal. In terms of detections, human subjects clearly enhance the ATR in the low clutter dessert background, but not in high clutter background. On the other hand in the case of false alarms, human subjects add dramatically across all conditions, but particularly for high clutter background. This would suggest that the human subjects have better ability for false alarm reduction particularly in the high clutter environment where automatic detection system fails. We can draw two main implications from this for algorithm development; first we note that the type of background is an important performance driver for the airborne sensor. The detection performance at the semi-arid test site on the east coast is limited by the ability of the sensor to discriminate between the mine targets and the background and not so much by the ATR algorithm. Secondly, we note that there is a significant scope for false alarm reduction especially in high clutter background. This result is consistent with the earlier results reported using different false alarm mitigation techniques [12].

![Figure 8: Comparison of human and ATR performance for different terrain and time of the day (error bars represent the total range of scores).](image)

The second important question relates to the time response characteristics of the human subject in mine detection. In particular, does the time that a human subject takes to select a target relate to the accuracy (mine target being detected as mine) of the selection? If so, this could represent an indicator of certainty, and has implications for further research on interface and human factors in minefield level detection. Figure 9 shows the plot of average time taken by the human subjects for different terrain and different times of day. For each terrain and time of day, the bar chart shows the average time taken to select the mine target correctly to the left and average time taken when selecting false alarm to the right. From this chart, in particular we note that human subjects take significantly less time when correctly selecting a mine target as compared to a false alarm. Also, human subjects take significantly longer to make selections in high clutter background conditions where they are less certain of their selections. As in the case of the performance, time of day was not as big a driver for the time response characteristics as well. Implications of these findings could be that the warfighter-in-the-loop should be time constrained using some optimal time which may aid performance in mine and minefield detection.

![Figure 9: Average time taken by human subjects for different terrain and time of the day.](image)

5.2 Qualitative Analysis
The use of the interview, video recording of the subjects, and observation during the experiment, gave us some incite into how people thought about the mine detection problem. Participants had two types of mental models for identifying mines: object based and pattern based. First, they looked at the individual object characteristics. For instance, many participants stated that they would look for some type of shading within the object to distinguish the object from the surrounding terrain. If they saw the shading, they would identify the object as a mine. Conversely, they discounted or ignored objects that had almost constant dark gray value. The subjects found that these objects were not mines during their training and used this knowledge during the testing phase. The second type of mental model focused on patterns. Most of the participants recognized that if there was one mine then there would be other mines in the vicinity. So, if they identified a single mine, they would look for other mines around that mine. Because the layouts of the minefields were all horizontal, participants ignored any objects that were vertically aligned. They also ignored any individual objects that did not have other objects near them. Participants quickly learned the characteristics of individual mines and patterns that the mines were laid out in to create the mental models that they used in the training.

6. CONCLUSIONS

Performance of human subjects for mine detection in airborne data was evaluated using 20 subjects. The primary motivation was to learn how well the human subject could do in the mine detection task using the imagery provided by the airborne MWIR sensor. The quantitative evaluation of performance indicated that the value added by the human operator was most significant for complex, highly cluttered terrain. The operator performance was influenced significantly by the type of mines and was fairly consistent across different operators. The analysis of time interval between selections indicated the law of diminishing returns with the length of time, where the human operators tend to second guess themselves. The qualitative analysis indicated that subjects developed particular mental models at the object level (characteristic shape and shading of targets) as well their spatial distribution (linear patterns with regular spacing and similarity of targets) that they used when searching for mines.

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 a larger number of subjects and “real-world” technologies like the real time ground station. It is important to note that we do not have to necessarily depend on active-duty military personnel or likely warfighter in the ground station for this mine level evaluation. Our interest here is to explore basic issues associated with the general visual perception capabilities across human subjects. For the current analysis we have been concentrating on the detection and characteristics of the targets that human used to select them. An equally important need is to investigate false alarms. In particular, what are the characteristics of the false alarms that ATR selects but are consistently rejected by the human subject. This characterization will provide us with human mental models of false alarm mitigation which we may be able to implement in our ATR algorithms. It is hoped that this systematic evaluation of a human operator in airborne mine detection will help in developing new and better ATR techniques and help identify critical features required in the operator interface for the warfighter-in-the-loop (WIL) minefield detection.

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