PETALS: Improving Learning of Expert Skill in Humanitarian Demining

Lahiru Jayatilaka
Red Lotus Technologies
lahiru@redlotustech.com

David M. Sengeh
IBM Research - Africa
DSengeh@ke.ibm.com

Charles Herrmann
Cornell University
cih5@cornell.edu

Luca Bertuccelli
Sensitech
lucab@alum.mit.edu

Dimitrios Antos
Verily Life Sciences
dimitrios.antos@gmail.com

Barbara J. Grosz
Harvard University
grosz@eecs.harvard.edu

Krzysztof Z. Gajos
Harvard University
kgajos@eecs.harvard.edu

ABSTRACT

To become proficient at landmine detection, novice deminers need to master several kinds of skills: the proper physical operation of the metal detector, the interpretation of the metal detector auditory feedback, and the abstract skill of constructing and interpreting mental representations of the "metallic signatures" produced by the buried objects. This last skill is particularly useful for safely dealing with mines laid out in cluster configurations, where their metallic signatures overlap and thus a danger exists that a deminer might either miss some of the mines or incorrectly assess their exact positions. However, some novice deminers find it challenging to learn how to properly reason about metallic signatures. We have developed PETALS, a system that explicitly visualizes a trainee's metal detector operation history on a training task as well as the edge points of the metallic signatures that the trainee collected. PETALS enables instructors to supervise multiple trainees at a time, to assess their performance at a glance, and to provide immediate and specific feedback both on the correctness of their final judgements about the number and positions of landmines, and on the *process* through which they arrived at their conclusions. The results of our field evaluations at the Humanitarian Demining Training Center showed that both the instructors and the trainees found the system a valuable addition to the training course. The results of a controlled study demonstrated that trainees who had access to PETALS during training made significantly fewer errors (6% error rate) on relevant tasks during the final exam (which was conducted without PETALS) than trainees who did not have access to PETALS during training (those participants had a 21% error rate).

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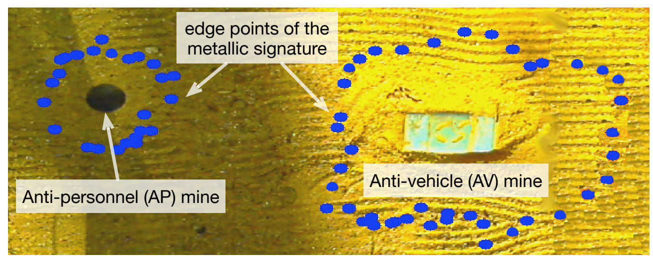

Figure 1: Edge points of metallic signatures of two landmines: an Anti-Personnel (AP) and an Anti-Vehicle (AV) mine. Edge points, shown in blue, are the points at which the metal detector goes from off to on. The AP mine has a small, round signature while the AV mine has a larger, roughly box-shaped signature.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**;

KEYWORDS

demining; explosives detection; training systems

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1 INTRODUCTION

Buried explosives have significant humanitarian, military and economic consequences. Post-conflict landmines and explosive remnants of war kill and injure civilians on a daily basis [26]. Even worse, just the presence or the mere *possibility* of presence of buried explosives causes agricultural, social and economic activities to grind to a halt in the affected areas [3].

While several advanced detection and neutralization technologies have been designed to increase safety and efficiency of landmine clearance (e.g., [7, 8, 11, 16]), these technologies have failed to be widely adopted due to their cost, complexity, low reliability, bulk, and high power requirements [13, 25, 43]. Instead, a human using a metal detector (a deminer) continues to be the primary approach for finding buried explosive threats [9, 12, 27]. Recently introduced dual sensor detectors, which combine a metal detector with a ground-penetrating radar (GPR), promise to be one technological intervention to find wide adoption as they are both versatile and genuinely useful. However, because of high cost, they are still largely inaccessible to humanitarian demining organizations.

There are two particularly complex challenges faced by deminers searching for buried explosives with hand-held detectors. First, with metal detectors, it is difficult to tell apart an explosive, like a landmine, from a harmless bullet shell or a wire. This is particularly frustrating given the ratio of harmless to harmful items: presently, deminers at the Landmine Relief Fund in Cambodia remove approximately a hundred pieces of harmless metal for every landmine that they find [31]. Second, it is also difficult to determine the exact number and locations of landmines when their *metallic signatures* (i.e., the areas, where the response of the metal detector is triggered, see Figure 1) overlap with each other. This typically occurs when mines are laid out in a *cluster configuration* (e.g., an anti-tank mine surrounded by several smaller anti-personnel mines). This, clearly, is a major safety concern.

Expert deminers have a technique for overcoming these challenges [39]: They systematically sweep the area near a potential threat to find points where the metal detector response (auditory beeps) starts and stops. By serially collecting these *edge points*, experts build a mental map of the buried object's metallic signature. This approach is illustrated in Figure 1. Given that an object's metallic signature is related in size and shape to the burial depth and to the size and shape of the metallic component of the object itself, experts reason about the geometry of these metallic signatures to decide whether the object under investigation is a threat, to determine whether the metallic signature corresponds to one object or several, and also to determine the object's position in the ground.

This technique, however, proves challenging for novice deminers to learn. Part of the reason for it is that the visuo-spatial skills required for representing and reasoning about abstract spatial patterns are complex in and of themselves, particularly for operators of dual sensor detectors [39]. Another reason is that during a typical demining training program novice deminers simultaneously learn the basics of the metal detector operation and the metallic signature technique. In other words, while on a practice lane, novice deminers must allocate their attention to several novel tasks simultaneously: controlling the height, trajectory and speed of the detector head, monitoring and interpreting the detector's auditory feedback, and collecting, memorizing and interpreting edge points of metallic signatures. Most trainees in the U.S. military eventually overcome these challenges, but teaching this technique in the humanitarian demining context is likely to be further hindered by the low literacy levels of most deminers in developing countries, where deminers are typically recruited from the local population [31]—prior research has demonstrated that limited exposure to formal education correlates with difficulties in learning abstract concepts [28].

In collaboration with the instructors at the Humanitarian Demining Training Center (HDTC) in Fort Leonard Wood, Missouri (where most of the humanitarian demining personnel—military and civilian—are trained in the United States), we developed Petals, a system that visualizes both the metal detector trajectories and the edgepoints of metallic signatures that instructors can use to evaluate the performance of multiple trainees simultaneously and to provide detailed and specific feedback to individual trainees immediately *after* they complete a training activity. Petals extends prior work that demonstrated that explicitly visualizing edge points of metallic signatures can ultimately help novice deminers make better decisions distinguishing buried landmines from harmless metallic clutter [22]. Petals, in contrast, uses visualizations to help trainees learn the skill faster so that they can apply it later in the field without the further aid from the technology.

To evaluate this approach, we conducted a controlled study with two HDTC instructors and 59 participants recruited from civilian population, who were put through the basic land mine detection course. Half of the participants had access to Petals during training and half did not. During the final exam, which all participants completed without Petals, we measured participants' error rates on the cluster tasks, where the metallic signatures technique was required for correct identification of the number and location of targets. Participants who used Petals during training made significantly fewer mistakes during the final exam compared to participants who trained without Petals (6% error rate with Petals, 21% without).

In this article, we make the following contributions:

- We designed, implemented and deployed Petals, a system that supports immediate and detailed feedback on trainee performance by visualizing metal detector movement trajectories and the edge points of metallic signatured collected by the trainee.
- We report on field observations of two demining courses at HDTC, in which Petals was used and iteratively redesigned.
- We conducted a controlled experiment with 59 trainees. The results show that trainees who used Petals during training were significantly more successful at applying the metallic signature technique during a subsequent test than trainees who did not have access to Petals during training.

2 BACKGROUND ON HUMANITARIAN DEMINING

Humanitarian mine clearance procedures require the identification and removal of all mine and other explosive hazards from a given area to a specified depth [13]. In practice, mine clearance takes place in environments as diverse as the deserts of Egypt, the mountains of Croatia and the tropical forests of Cambodia, with most programs operating on limited resources [26]. Given the procedural demands and the practical realities, mine clearance technology must be cheap, reliable and robust. Because of the difficulty of deploying technology within these constraints, a human with a metal detector has remained the primary method of mine clearance since the 1950s [9, 12, 27]. Even though safer methods such as machine [7, 17], robotic [30, 33] or animal clearance [6, 8, 29, 34] are available, their use is not widespread because machines are expensive to maintain and are constrained by terrain, while animals are difficult to train and are practically suited only for specific clearance scenarios [13, 17].

As of 2005, there were 48 manual mine clearance programs worldwide [9]. In the majority of these programs, deminers were recruited from local populations and trained over a two to four week period [10]. The deminers work according to strict operating procedures, which aim to preserve their safety and promote the efficacy of the mine clearance process [10, 13]. When using a metal detector, the primary tasks of a deminer are to carefully segment the ground in a marked lane with a meter-long stick, cut vegetation to clear the ground for detection, sweep with a detector, and investigate the ground carefully and methodically using a prodder or excavator [10, 25].

The metallic signature–based method for reasoning about type and location of buried objects was informed by research on expert deminer performance [39]. That work showed that expert deminers systematically sweep the area near a potential threat to find and remember *edge points* of the metallic signature. That is, they systematically find and remember points where the metal detector response starts and stops. These experts then refer to past experiences to draw inferences from the spatial pattern outlined by the edge points held in their "mind's eye". These behavioral findings have been incorporated into US military deminer training programs [4] and have been shown to improve novice performance not only with metal detectors but also with dual sensor detectors such as the PSS-14 described above [39]. With the PSS-14, inferences made from metallic signatures are used to guide investigation with the ground-penetrating radar.

While most trainees eventually succeed at learning the metallic signature method, some take a long time to do so and require disproportionate amount of attention from the instructors. In the next section, we identify possible reasons why this method is so challenging to learn.

3 RELATED RESEARCH

Prior training support technologies in deminer training have primarily focused on improving deminer skills related to sweep-search (exhaustive coverage of the ground surface for detector responses) and detector feedback interpretation. The Sweep Monitoring System[1] (SMS), for example, uses remotely mounted stereo cameras to visually track the detector head in a simulated minefield or outdoor training lane to provide real-time auditory and visual feedback. Audio warnings, like "too fast" or "too slow" are provided to the trainee deminer, while visualizations of area coverage, detector speed and detector height are presented to the instructor. SMS is currently in use at U.S. army training centers, deployed after formative laboratory evaluations that demonstrated that visual feedback on sweeping performance improved the performance of demining trainees [20]. Zhu et al.'s low-cost simulation system [46] provides similar feedback, but it is for indoor use and training on a specific type of detector, the AN/PSS14. To the best of our knowledge, there is no prior work in demining training technologies for supporting learning of the metallic signature method.

[1] https://www.ri.cmu.edu/robotics-area/sweep-monitoring/, Last accessed on February 15, 2018

There exist also several systems aimed at supporting deminers in interpreting detector feedback while in the field. Kruger and Ewald [24], for example, have developed a laboratory setup that uses an ultrasonic positioning system and detector-mounted palmtop computer to present detector feedback as 2D intensity-graded regions. Researchers at Tohoku University have developed and field-tested the Advanced Landmine Detection System (ALIS) which is an add-on system to a metal detector [36–38]. ALIS consists of a GPR sensing unit strapped to the operator's back, a palmtop computer (for computation and display) that is extended over the deminer's shoulder, and a camera attached to the detector handle for positioning. Metal detector feedback is presented as 2D intensity-graded regions, while the GPR signal is visualized as intensity fields for specific depths. Field evaluations have suggested that ALIS has potential for adoption. Another system performs a sensor fusion of metal detector and odor detector systems and visualizes the combined evidence to the operator to help them distinguish between mines and harmless metallic clutter [35]. These systems, however, are supporting trained deminers in the field rather than at helping deminers learn the skill in the first place.

The metallic signatures' edge points are typically visualized using other, non-electronic, approaches. In training, edge points are often marked with physical markers, such as poker chips. However, such marking is physically cumbersome and is time consuming for the operator, and thus necessitates the assistance of a trainer or training "buddy". This adds to training costs. Another possibility is to use spray paint to mark the edge points. A prototype of such a device has even been designed [42]. This approach requires a time-consuming and more permanent modification to the metal detector. It also lacks a mechanism to completely erase markings, which is a concern for training facilities. In contrast, another system uses computer vision to track the position of a metal detector head and a digital display to visualize the geometry of the metallic signature edge points collected by a deminer [22]. Laboratory studies demonstrated that this approach helps novice deminers make significantly more accurate decisions when discriminating between land mines and harmless clutter. However, a number of pragmatic considerations (feasibility of deploying overhead cameras, lack of robustness of the electronic equipment) make the actual field deployment of this technology unlikely. However, the evaluation of the approach demonstrated that novice deminers could use the visualizations produced by the system to make accurate threat assessments—even when the visualizations were based on edge points collected by another deminer—suggesting that these visualizations could augment or substitute for the mental models deminers should be creating when using the signature-based technique. Thus, we used this prior work as a starting point for our solution.

In analyzing the difficulties novice deminers experience learning the metallic signature technique, we relied on the Cognitive Load Theory (CLT) [41]. CLT posits that learning is a process of constructing and memorizing *schemas*. Computer scientists may think of schemas as abstractions or higher level representations of knowledge. Once a schema for a particular skill has been constructed and automated, the learner can perform a previously difficult task with less cognitive effort. For example, a child learning to read needs to process each letter individually and consciously combine them to form a word, while an experienced reader will effortlessly perceive entire words or phrases.

The core premise of the CLT is that to learn, a learner must dedicate some cognitive effort to the process of constructing and memorizing schemas. This cognitive effort is distinct from the effort the learner needs to allocate to the instructional activity (such as operating the metal detector) used to support learning. Instructional designs that demand that the learners allocate substantial cognitive resources to the activity itself risk exhausting learners' cognitive resources leaving little or no capacity for the actual learning [23, 40, 44]. Instructional designs based on the CLT aim to minimize cognitive load related to the learning activity (the *extraneous* load), while potentially increasing cognitive load related directly to learning (the *germane* load) [41].

In the current training programs for teaching the metallic signature technique, the instructional activity (searching for buried landmines with a metal detector) places substantial extraneous cognitive demands on the learners: they have to allocate cognitive resources to the proper operation of the metal detector and to the interpretation of the metal detector feedback. This leaves trainees with little (if any) cognitive capacity for learning concepts related to the metallic signature method. This problem is further exacerbated by the low literacy levels of most deminers in developing countries, where deminers are typically recruited from the local population [31]—prior research has demonstrated that limited exposure to formal education correlates with difficulties in learning abstract concepts [28].

Building on prior CLT-inspired research [21], our initial approach was to scaffold the learning activity by providing learners with a detector-mounted display that visualized in real time the edges of metallic signatures collected by the trainees. We expected that given the explicit visualization, the trainees would allocate fewer cognitive resources toward memorizing the locations of the edge points and creating mental images of the metallic signatures. Through a series of field deployments at the Humanitarian Demining Training Center, we learned that this approach was not effective: The trainees perceived tracking of the visualizations as an additional task rather than a means to simplify tracking of the edge points of metallic signatures.

Our final solution takes a different approach: There is a growing body of work in educational technology on learning systems that provide informative visualizations to the teachers so that they can quickly identify students who are having problems and diagnose common misconceptions. Such tools enable teachers to provide personalized assistance even in large classrooms ultimately boosting learning outcomes. For example, the student tracking tool [15, 32] in the MiGen project monitors students' activities with an exploratory learning environment for teaching algebra. The tracking tool visualizes landmarks, which occur when the system detects specific actions or repetitive patterns carried out by the student. OverCode and MistakeBrowser allow instructructions in large programming courses to identify common misconceptions among hundreds of student-generated solutions [14, 19] facilitating provision of personalized feedback at scale. A plan recognition and visualization system had been developed [1] to track students' progress on tasks performed in ChemCollective, a virtual chemistry lab. The visualizations produced by the system provide a static snapshot of the

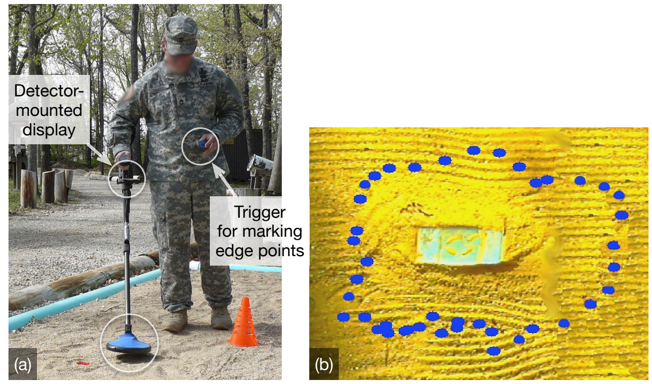


Figure 2: Initial design of Petals. (a) An overhead camera (not shown) tracked the position of a patch of color fabric attached to the metal detector head. Trainees used the trigger held in the non-dominant hand to record the positions of the edge points of metallic signatures. (b) A visualization showing the recorded edge points overlaid on top of a real-time image of the ground was presented in real time on a display affixed to the metal detector shaft.

activities performed by each student: these visualizations are used by the teachers to quickly assess success and to diagnose potential misconceptions. While our initial focus was on supporting learners, the final design of Petals supports instructors in monitoring performance of multiple students simultaneously and in providing immediate, specific and personalized feedback.

4 THE INITIAL DESIGN OF PETALS SYSTEM

At first, we designed Petals to support individual trainees in analyzing the geometry of the metallic signatures during hands-on landmine detection practice. This initial design, illustrated in Figure 2, was very similar to the system used in prior work to support novice deminers in the field [22]: an overhead camera (not shown in the photograph) tracked the position of a patch of color fabric attached to the metal detector head. Any time the trainee pressed a trigger button, the current position of the metal detector head was recorded and visualized on a screen and overlayed on top of a real-time image of the ground (Figure 2(b)). This allowed trainees to create visualizations of the edge points of the metallic signatures of buried objects and to reason about the actual locations of the inferred buried objects. The main difference from the previous work was that the visualization was now presented on a mobile device mounted onto the shaft of the metal detector instead of being presented on a desktop computer next to the practice lane.

We expected that this design would allow trainees to offload onto the system some of the cognitive effort associated with the memorization and analysis of the locations of the edge points. Consequently, we expected more cognitive resources to be available for learning resulting in improved learning outcomes.

5 FIELD DEPLOYMENTS

We brought Petals three times to the Humanitarian Demining Training Center (HDTC) in Fort Leonard Wood, MO. HDTC is the primary training center in the United States for both the military and civilian deminers engaged in humanitarian landmine clearance. During the first visit we demonstrated the initial prototype of PETALS to the instructors. During the two subsequent visits, revised versions of PETALS were incorporated into actual training. This project did not receive any funding from the military and the HDTC instructors were under no obligation to work with the authors—they chose to collaborate on the field deployments because they perceived an opportunity to improve the effectiveness of their training programs.

Metal detection training at HDTC. Metal detection training at HDTC involves a lecture component, hands-on practice sessions and a post-training evaluation exam. During the practice sessions, trainees apply techniques (metallic signatures, sweep search, etc.) taught during the lecture in order to find defused mines buried in sand practice lanes (like those in Figure 3). The instructors use these practice sessions to detect errors in trainee technique, to provide feedback on performance and also to provide additional coaching if required. The metal detection training component of an HDTC course ends with an assessment, during which trainees have to demonstrate that they can correctly detect and locate buried threats.

Because trainees who enroll in the program have some prior experience in both explosives disposals and handheld detection techniques, this segment of the course takes place in one day, whereas most metal detector-based demining training programs for novices take several. The training groups for the two field deployments of PETALS consisted of 12 (first visit) and 16 (second visit) U.S. Army personnel with military occupational skill of Explosive Ordnance Disposal.

The instructors incorporated PETALS into the hands-on practice sessions during both visits. They used four training lanes simultaneously, and they used PETALS to monitor parts of two of them. The target configurations in the four practice lanes consisted of a single Anti-Personnel (AP) mine, a single Anti-Vehicle (AV) mine, two side-by-side AP mines (AP+AP cluster task), and an AP mine bordering an AV mine (AV+AP cluster task). PETALS was used to monitor an AV + AP cluster task in both the practice lanes. The metallic signature technique is particularly important—and particularly difficult to apply correctly—for the cluster tasks because the metallic signature of the larger AV mine substantially overlaps with the metallic signature of the smaller AP mine.

5.1 Key Insights From the Field Deployments

Instructors needed better tools to monitor trainee performance. Even prior to the first field deployment, instructors reported that they were typically responsible for working with four trainees at a time, but that they could not monitor the performance of more than one at any given time. They requested a means to simultaneously observe multiple trainees. They also asked us to extend the visualization so that it would capture not just the process of constructing the metallic signatures, but also the trajectories of the metal detector heads so that they could identify problems in the trainees' sweep search technique.

Prior to the introduction of PETALS, instructors watched a trainee for a minute or two before offering feedback. With PETALS, instructors quickly fell into a pattern of occasionally coming up to the instructor console, glancing at the visualization and making quick assessments about how the trainees monitored by PETALS were doing. Trainers reported that a quick glance at the PETALS visualization provided them with a lot of the same information as actually watching a trainee perform the tasks:

> *"the main thing, like I said, is I can walk up here [to the instructor console] and within 2 seconds I can say, 'he doesn't need anymore help', 'he doesn't need anymore help' [pointing to trainees working on the two lanes monitored by the system] ... or [hypothetically] 'this guy might need help'."*

In particular, instructors determined that PETALS visualizations were effective for quickly spotting two common problems in sweep search technique: gapping (i.e., leaving too much space between successive sweeps creating a danger of missing a mine, Figure 5(a)) and target lock (a situation when trainee becomes so focused on investigating one target that they forget to sweep part of their lane, which also creates a danger of missing a mine; Figure 5(b)).

The scaffolding mechanism was not effective. In the initial design, trainees were provided with displays mounted on the shafts of the metal detectors that showed the locations of the edge points they collected overlayed on a real-time image of the ground. Most trainees turned off the displays and reported that the displays distracted them and made the task more difficult rather than easier.

Instructors adopted PETALS visualizations as a way to communicate specific feedback to trainees. When a trainee completed a practice lane monitored by the system, an instructor frequently beckoned the trainee to the instructor console to discuss his performance. If the trainee had done well, the instructor would use the visual feedback for positive reinforcement with comments such as: "good area coverage","nice tight loops", "nice pattern" and "tight sweeps". If the visual feedback indicated weaknesses in edge point collection or sweep search technique, the trainer discussed these mistakes by referring to the visual feedback using comments such as: "missing a spot over here", "going way out there with your loops", "you're gapping over there".

After providing feedback on performance, the trainer explained how improvements to the trainee's technique should modify the visual feedback. The trainer did this by referring to the trainee's own trace, by referring to a trace created by a peer or by retrieving a prototype trace created earlier by the trainer himself (as in Figure 4(a)). During this process, the trainer used the visual feedback to reinforce technical concepts related to edge point collection, sweep search and signature geometry as necessary. Finally, depending on the situation, the trainer physically enacted the ideal technique for dealing with the AV + AP cluster task at the practice lane itself and, on certain occasions, requested the trainee to repeat detection on the task after one-on-one coaching.

Overall, instructors spent significantly more time on the lanes monitored by PETALS than the ones that were not monitored. On certain rotations, instructors would not offer feedback to trainees

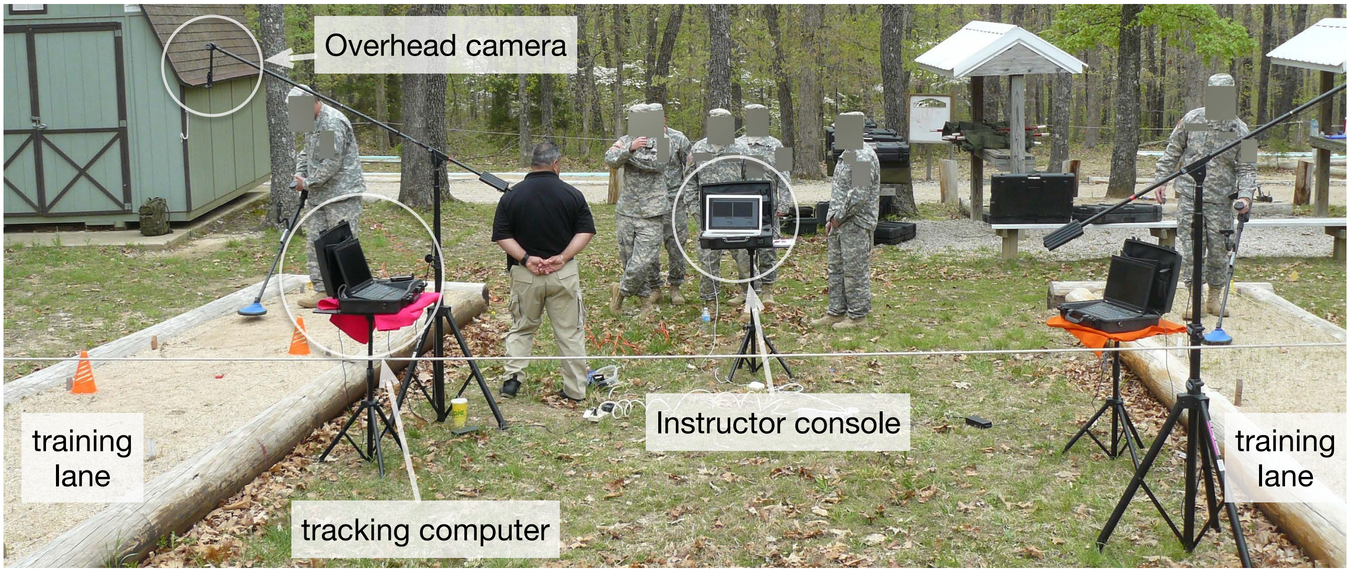


Figure 3: Deployment of PETALS at HDTC. Segments of two neighboring lanes are monitored by overhead cameras. A tracking computer is dedicated to each lane. A centrally-located instructor console displays real-time visualizations of trainee performance from both lanes.

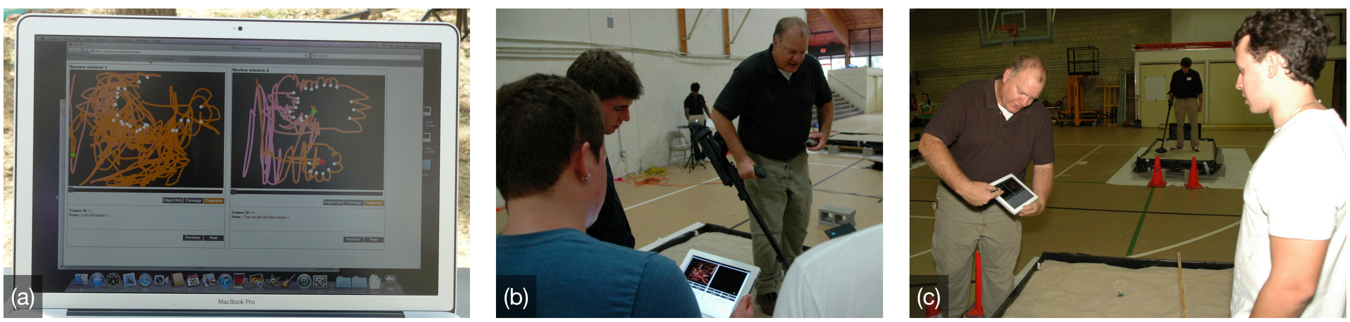


Figure 4: Final design of PETALS. (a) The display can be used to present multiple visualizations simultaneously. In this photograph, the left pane shows the trainee's actual performance while the right pane shows an expert's performance on the same task. By contrasting the actual and the desired performance, an instructor could explain what the trainee should do differently. (b) The instructors used portable tablets during the initial lecture to illustrate desired performance. (c) Instructors also used the portable tablet to provide feedback to trainees immediately after a trainee completed a training task.

on the non-PETALS lanes, waiting until these trainees rotated to the PETALS lanes in order to assess their skill levels and detect mistakes.

PETALS provided a way to identify problems in trainee performance that were not apparent before. After having monitored a handful of trainees using PETALS, one of the instructors realized that a common mistake was that trainees moved their detector head in large and irregular motions to sample edge points, which resulted in fuzzy signature shapes. By inspecting his own signatures and sweep trajectories using PETALS, the instructor realized that he was making "small and tight" loops to sample edge points.

> *"What I noticed is that I'm quite rapid when I do this [demonstrating building a footprint with dense and regular sampling motions].... and what the students would do is, that they would come-in and kind of creep in on it [the target] and then they'd overshoot and come back [demonstrating large and irregular motions]... they'd get confused and not figure out why they couldn't find the target."*

This resulted in a change in HDTC's training program: from that point on, including during our second field trial, during the lectures prior to metal detection practice, the instructors explicitly demonstrated to trainees that they needed to move their detector head in small and tight loops to find edge points.

6 THE FINAL DESIGN OF PETALS SYSTEM

The insights from the field studies caused us to adopt a different set of objectives and a different approach. The final design aimed 1) to support instructors in quickly assessing multiple trainees simultaneously on several aspects of metal detector operation; and 2)

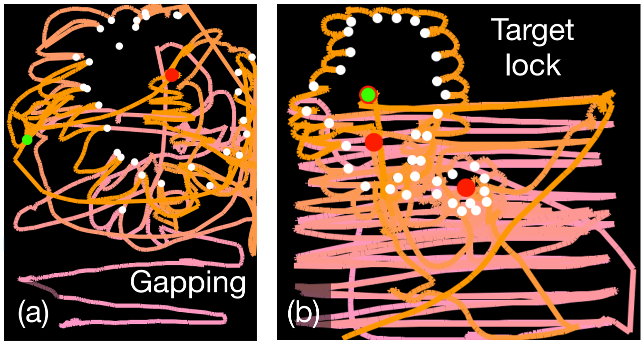


Figure 5: The final design of the visualization included edge points (white dots), current position of the detector head (green dot), declared positions of the buried explosives (red dots) and the trajectories of the metal detector head color coded such that the older traces were pink and newer orange. In addition to supporting feedback on metallic signature technique, this visualization allowed instructors to spot and communicate some common problems in metal detector operation: (a) gapping (leaving too much space between successive sweeps) and (b) target lock (failing to sweep part of the lane after attending to a potential target).

giving instructors a means to provide specific feedback to trainees immediately upon completion of a practice task. Providing immediate and specific feedback is a very effective pedagogical strategy, but one that is difficult to implement in demining training because trainees' visual and auditory channels are fully occupied by the operation of the metal detector so instructors cannot provide feedback without interrupting trainees' practice. Also, feedback that interrupts an activity may interfere with the development of fluency in the execution of this activity [18].

Consequently, in the final design, Petals can be used to track the progress of multiple trainees simultaneously (Figure 3) and instructors can monitor all of them either on a centrally-located instructor console (Figures 3 and 4(a)) or on a portable tablet (Figures 4(b) and (c)). The visualization (Figure 5) shows the trajectory of the metal detector head (color coded such that older movements are purple and newer are orange), the edge points recorded by the trainees (white dots), the locations of the mines as declared by the trainees (red dots) and the real time location of the detector head (green dot). The real-time view of the ground is no longer shown, however. The display allows multiple visualizations to be shown side by side. Instructors can either use this capability to follow several trainees simultaneously, or to bring up a previously stored visualization (e.g., one showing how an expert would perform a task) for a side-by-side comparison with a visualization showing a trainee's work (as in Figure 4(a)).

Prior to Petals, instructors could provide direct feedback on the correctness of trainees' final judgements by revealing the actual locations of the mines in relation to the poker chips dropped by the trainees. With Petals, instructors can provide feedback on the *process* by which trainees made their assessments. In most cases, process-related feedback is more effective at supporting deep learning than task-related feedback [2, 5, 45].

7 SUMMATIVE EVALUATION

We conducted a controlled study to test whether the presence of the Petals system during training improved learning outcomes on the metallic signature technique. We designed an indoor landmine detection training environment at one of our institution's indoor recreational facilitates. We co-designed this environment with the HDTC instructors to closely mirror HDTC's training facilities. Participants received standardized metal detection training from HDTC instructors either with or without Petals, and were subsequently tested on evaluation lanes. All participants completed the final test without access to Petals.

We hypothesized that compared to trainees taught with existing methods, trainees who had access to Petals during training would make fewer errors during a post-training evaluation exam on tasks requiring the metallic signature technique, that is on the AV + AP cluster tasks.

7.1 Participants

Trainees: 59 participants (36 male, 22 female, 1 unspecified) recruited from the local population (28 college students) volunteered for this experiment. Their ages ranged from 18 to 62 (M=29). Participants received a monetary reward of $30 for participation, and an additional $10 based on performance during evaluation.

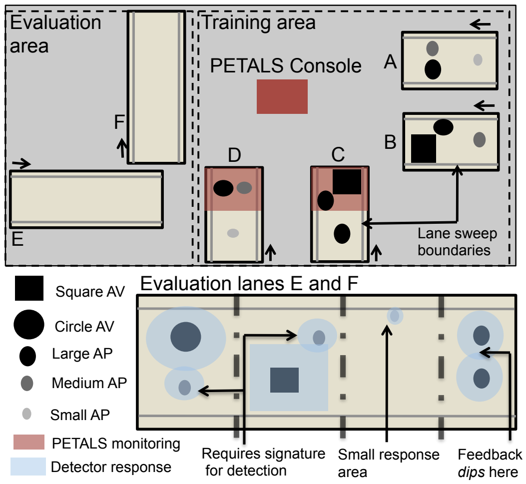
Instructors: Two HDTC instructors, who traveled to our institution to participate in this study, conducted training and assisted with evaluation. The instructors had previously used Petals at HDTC during our field deployments so they were already proficient users of the system. Both trainers had five or more years of experience in demining training. They were entirely in charge of how to conduct the training.

7.2 Indoor landmine detection training environment

The indoor training environment consisted of 4 training lanes and 2 evaluation lanes (Figure 6(a)). The training lanes *A,B,C* and *D* were each approximately 2.5 m long and 1.2 m wide and contained metal-free play sand that was 0.05 m deep. The evaluation lanes *E* and *F* were approximately 5 m long and 1.2 m wide and contained sand at a similar depth (Figure 6(b)). All the lanes were raised 0.2 m from the ground to avoid any interference from metal content present in the floor of the gymnasium. The visual feedback system used for the experiment was unchanged from the second field visit.

7.3 Training and evaluation task design

For training, we used three types of Anti-Personnel (*AP*) mine simulants: *large AP* (ovoid metallic signature $\approx 8in$ diameter), *medium AP* (ovoid signature $\approx 5in$ diameter) and the other one as *small AP* (ovoid signature $\approx 3in$ diameter). We also used an AV mine simulant, coded *square AV* (box-shaped signature $\approx 18in$ diagonal). As illustrated in Figure 6(a), the training lanes A, B, C and D contained two training tasks each: a single AP simulant in the first section and a dual-mine cluster configuration (AP + AP or AV + AP).



(a)

(b)

Figure 6: (a) Physical layout and target configurations for the training and evaluation areas for our controlled study. Cluster tasks on the two practice lanes C and D were monitored by the system. Each target configuration in the evaluation lane was specifically used to test certain components of trainee skill. The training area in this figure provides a good visual overview of the training area at HDTC and how the system was physically deployed during the field trials. (b) Evaluation component where trainees were evaluated in pairs without any visual feedback

For evaluation, we used the same targets as during training and one additional AV simulant, coded *circle AV* (ovoid signature $\approx 18in$ diameter). The evaluation lanes E and F, identically laid out, contained four tasks to test specific detection abilities (Figure 6(a)). But, only two tasks (AV + AP cluster tasks) specifically required the construction of metallic signatures and hence were the only tasks used for testing our hypothesis. The other two tasks in the evaluation lane were included for purposes of ecological validity: the trainers wanted an evaluation lane that mirrored practice and tested other aspects of trainee skill as well.

7.4 Procedure

Participants were trained and evaluated in groups of three or four. The training segment of the experiment lasted approximately 55 minutes. The two HDTC trainers were alternatively responsible for every two groups of trainees. Each trainer taught every other session with Petals and the remaining sessions without. One of the experimenters assumed the role of supporting trainer in order to ensure that trainees were inputting edge points and using the system correctly. The experiment concluded with an evaluation segment that lasted approximately 30 minutes on lanes E & F with trainees evaluated in pairs (Figure 6(b)). All participants conducted evaluation without access to Petals.

7.4.1 Demonstration-based lecture. The experiment started with a 15-minute demonstration-based lecture at Lane C and was similar in content to the pre-practice lectures at HDTC. The major differences between this lecture and a standard HDTC lecture was the omission of different detector models and an in-depth discussion about different types of mines. After teaching trainees how to switch-on and calibrate a MineLabs F3 metal detector, the instructor used a medium AP mine to familiarize trainees with the F3's auditory feedback tones. Next, the instructor demonstrated good sweep-search technique. The second-half of the lecture focused on the construction and interpretation of metallic signatures. First, using the medium AP, the instructor introduced the concept of signatures. Next, using the medium AP + circular AV task, the instructor demonstrated and discussed metallic signatures in the context of cluster configurations.

Trainees were also taught to verify location estimates using tone-based techniques. With an AP mine, trainees were taught to verify that the tone of the detector was constant over the estimated position from all angles of detector head approach. With an AV mine, they were taught the *airborne technique*. This technique involves spiraling the detector from chest level down towards the ground until feedback is heard. The point at which feedback is heard is approximately above the center of the AV mine.

Because our field trials suggested that our visual feedback system complements the instruction of technical concepts, together with the instructors we decided to include the system in the lecture component of this experiment. Trainees in the treatment condition could see in real-time (Figure 4(b)), as the instructor collected edge points and built a signature for the cluster task in Lane C. The instructor used the resulting visual pattern to i) show trainees the signature shapes for targets in the cluster, ii) to discuss *washout* (signature distortion), iii) to reinforce the need for using "small and tight" loops for edge point collection and iv) to explain how to geometrically reason about signatures in order to determine target positions.

7.4.2 Practice. Practice, which lasted 40-minutes, commenced with trainees randomly assigning themselves to one of the training lanes A, B, C or D. Trainees practiced on each lane for 10 minutes after which they rotated, in clockwise order, to practice on a neighboring lane. Four rotations were implemented to ensure that all trainees practiced exactly once on each training lane. This practice routine was a compressed version of HDTC’s standard training metal detection routine.

During practice, trainees detected and localized targets in the practice lanes using the techniques taught during the lecture. When their detectors responded to the presence of buried simulants, they constructed metallic signatures or used tone-based techniques to estimate target positions, and placed poker chips to record their estimates of the positions of the centers of the mines. Practice on a lane was completed only when a trainee had finished searching the entire lane.

During each practice rotation, the instructor stood at the center of the four practice lanes, and moved to individual lanes to assist with detector calibration, to alert trainees of mistakes related to sweep-search (sweep speed, detector height from ground etc.) and to answer questions. When the visual feedback system was available, the instructor used the Console to monitor trainee activity on the cluster tasks on Lane *C* and *D*. The instructor was also provided with the tablet that he could use when not at the central location.

Once a trainee had finished practicing on a lane, the instructor provided feedback on performance (Figure 4(c)). If the trainee had successfully detected all targets in the lane, the instructor explicitly acknowledged this success. When a trainee had failed to detect a target to the stipulated level of accuracy, the instructor provided feedback about how to achieve the desired accuracy. When a trainee had failed to detect the presence of a target in a cluster configuration, the instructor asked the trainee to recheck the area more carefully.

In addition to providing feedback on performance, the instructor sometimes conducted individual lessons to teach a trainee how to build and interpret signatures for cluster configurations or how to use tone-based techniques. The instructor would also revisit sweep-search concepts and signatures on individual mines, but this was much less common since most trainees had grasped these techniques during the lecture stage. For good measure, the instructor also frequently called out reminders to all the trainees to “check the entire lane" and to sweep with “small and tight loops" when building signatures.

When the visual feedback system was available, the instructor used the visual patterns constructed by the trainees i) to suggest improvements in signature construction technique, ii) to reinforce the relationship between the location of buried targets and signature geometry, iii) to detect when trainees were guilty of gapping and target lock. Occasionally, the instructor also used the visual traces constructed by a trainee’s peer on the neighboring lane to further supplement feedback and instruction. As we observed during our field trials, the instructor also used feedback from the visual feedback system to help decide on the allocation of individual attention between trainees.

7.4.3 Evaluation. Each training group was evaluated over a 30-minute time period after a short briefing period. Trainees were evaluated in pairs of two on Lanes E and F (Figure 6(b)). Trainees who were not being evaluated were moved to separate location to prevent them from overseeing the location of targets on the exam lanes. When an evaluation was in progress, instructors intervened only to assist with detector calibration. Instructors monitored trainee chip declaration to guard against chip abuse—a situation when a trainee scatters a lot of poker chips in the hope of “getting lucky”.

Each pair of trainees had 15 minutes to detect all buried targets, with auditory time warnings provided with 10, 5, 2, and 1 minutes remaining. In order to correctly detect an AP target a poker chip had to be placed within 3 inches (horizontally and vertically) from the AP target’s center, and in order to correctly detect an AV simulant a poker chip had to be placed over some part of the simulant. These thresholds are based on the target localization accuracy required to ensure safe neutralization when mines are discovered in the field. In order to receive the performance bonus of $10, trainees had to correctly detect all the targets buried in the evaluation lane (Figure 6(a)) in the allotted time. To ensure accurate scoring, exact x and y coordinates of each poker chip were recorded and compared to the known positions of the buried targets.

7.5 Data Analysis

The experiment was a between-subject design with *PETALS* {Provided , Not Provided} as the main factor. *Instructor* {Instructor 1, Instructor 2} was included in the analysis as a control variable to guard against possible differences in instructor style and skill.

Our primary measure was a *miss* on the two AV + AP tasks (Figure 6(a)). A miss was defined as either failing to declare the presence of either of the two mines in the cluster or as exceeding the allowed localization error threshold (see previous section). Because miss errors on a fixed number of tasks are best modeled using a binomial distribution, we used logistic regression (generalized linear model with binomial distribution) to analyze the results.

7.6 Results

7.6.1 Adjustment of Data. We discarded data for 11 participants in our analysis. Three participants were discarded as instructors believed that these trainees had not grasped basic detection skills during training. This exclusion was performed because HDTC training protocol would not allow these trainees to even attempt the final exam. Two participants were discarded due to cheating (poking in the sand to determine the true location of the targets). Finally, six participants had to be discarded because their training group size was smaller than 3 due to no-shows. Because instructors stated earlier that group size substantially impacted their ability to accurately diagnose problems in performance of trainees and to offer personalized feedback, we were concerned that participants who were trained in groups of two might be receiving substantially different instructions from those who were part of larger groups.

Of the 48 participants whose data were included in the analysis, 26 were trained with Petals. Participants completed $48 \times 4 = 192$ tasks in total during evaluation (96 on the AP + AV cluster tasks used in the main analysis).

After adjustment of data, Instructor 1 had trained 28 participants (15 with Petals, 13 without Petals), while Instructor 2 had trained 20 participants (11 with Petals, 9 without Petals).

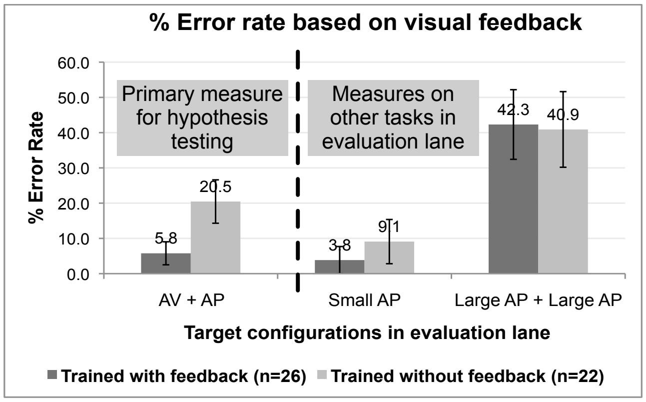


Figure 7: Error rates (misses) for our controlled study classified by type of evaluation task (Figure 6(a)) and based on whether participants had visual feedback provided during training. Only performance on the AV + AP cluster tasks was relevant for testing our hypothesis, because only these two tasks explicitly tested trainee ability to use metallic signatures. Error bars show standard errors.

7.6.2 Main Results. We observed a significant main effect of Petals on misses for the two AP + AV cluster tasks ($\chi^2_{(1,N=48)}$=4.88, $p = 0.027$): with Petals provided during training, participants' miss rate on these tasks was 5.8% compared to 20.5% without (Figure 7).

7.6.3 Additional Analyses. We did not observe a significant difference on misses for the AP + AV cluster tasks based on instructor: error rate for trainees trained by Instructor 1 was 18.5%, compared to 24.2% for those trained by Instructor 2.

Consistent with our expectations, we did not observe significant effects of Petals on target misses for the Small AP and Large AP + Large AP in the evaluation lane (Figure 7).

8 DISCUSSION AND CONCLUSION

Our initial design aimed to support individual trainees by scaffolding the complex task of learning how to use a metal detector to reason about metallic signatures of buried objects. The observations collected during the two field deployments indicated that trainees found the visualizations created by Petals to increase rather than decrease the cognitive demand placed on them by the learning activity. Based on those observations, we redesigned the system to support the instructors in the task of monitoring the performance of multiple trainees simultaneously and providing specific *process* feedback immediately upon completion of a training task by a trainee. Upon the completion of the redesign, we hypothesized that compared to trainees taught with existing methods, trainees who had access to Petals during training would make fewer errors during a post-training evaluation exam on tasks requiring the metallic signature technique, that is on the AV + AP cluster tasks.

The results of the controlled study support our hypothesis: participants who had access to Petals during training made significantly fewer mistakes during the post-training evaluation on the AV + AP cluster tasks, where the metallic signature technique could be used to identify and locate multiple threats, than participants who trained without access to Petals. It can be argued that these mistakes might have occurred because of incorrect application of other techniques such as the airborne technique discussed above. But, upon inspection of the data we found that more than 70% of the mistakes were because trainees did not correctly locate the position of the AP mine in the cluster. Because locating the AP is helped by mentally visualizing the bulge in the AV's signature, this suggests that trainees who were trained with the visual feedback system were more proficient with the metallic signature technique.

The lack of substantial differences between the two experimental groups on non-cluster tasks indicates that participants in both conditions learned the basic metal detector skills equally well. This provides additional evidence that the differences in performance on the cluster tasks were due to the Petals intervention rather than systematic differences in the aptitudes of the trainees between the two experimental conditions.

We went to great lengths to achieve a reasonable level of ecological validity for the controlled experiment. For instance, all simulant targets, except for the AV simulants, were acquired from HDTC's own training stock, and trainees used one of the most popular metal detectors in humanitarian demining, the MineLab F3. Furthermore, the two HDTC trainers in this experiment had conducted training in over 30 countries and had trained hundreds of deminers. We also worked closely with the trainers to design a training and evaluation routine that was as similar as possible to the routines used in real courses at HDTC. While the current evaluation of the system focussed on AV and AP signature detection, in the future, field tests and evaluation should include the addition of common harmless metallic clutter.

The major ecological shortcoming of this experiment was the training duration, trainee population and group size. Metal detection training at HDTC usually takes place over a day and trainees have about three times more practice time before evaluation. With respect to population differences, our participants had a higher average education level and much less exposure to explosive clearance when compared to the average HDTC training class. However, the trainers stated that in terms of learning ability and natural talent the participants were within the spectrum of students they had encountered over their careers.

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