# Use of Eye Movements as Feedforward Training for a Synthetic Aircraft Inspection Task

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### ABSTRACT
Aircraft inspection is a vital element in assuring safety and reliability of the air transportation system. The human inspector performing visual inspection of an aircraft is the backbone of this process and training is an effective strategy for improving their inspection performance. Previous studies have shown offline feedback training to be effective in improving subsequent visual inspection performance. Because experienced inspectors are known to adopt a better inspection strategy than novices, providing visualization of experts' cognitive processes a priori can accelerate novices' adoption of the experts' strategy. Using eye tracking equipment, we record the point of regard of an expert inspector performing an inspection task in a virtual reality simulator. Analysis of their eye movements leads to a visualization of their scanpaths and allows us to display the inspector's visual search (hence cognitive) strategy. We show how providing this type of scanpath-based feedforward training of novices leads to improved accuracy performance in the simulator coupled with an observed speed-accuracy tradeoff. We contend that the tradeoff results from trained novices adopting a slower paced strategy through increased fixation durations, suggesting trained novices learn a more deliberate target search/discrimination strategy that requires more time to execute.

### ACM Classification:
H5.1; H1.2. Information interfaces and presentation (e.g., HCI): Multimedia information systems; Models and principles: User/machine systems (human factors).

### Keywords:
Virtual Reality; Visual Search; Eye Tracking

### INTRODUCTION
Visual inspection has been used extensively for the detection and classification of defects in a variety of industrial processes such as printed circuit board inspection. In the air transportation industry, safety is of utmost importance. Inspection and maintenance are vital in assuring safety of an aircraft. The two main types of aircraft inspection are visual inspection and non-destructive inspection. Approximately ninety percent of all aviation maintenance inspection is visual [5].

In an aircraft inspection process, the human inspector performing visual inspection plays a critical role. Training has been found to be a very effective means of improving an inspector's performance [11]. There are various forms of training systems that are used in industrial inspection, including instructional training, on-the-job training, and offline training methods using multimedia-based technologies. Previous studies have identified offline training within a virtual environment to be effective in improving aircraft inspection performance [15, 31, 21]. One element of a training program is the provision of feedforward information. Feedforward training provides prior information, such as information on the defects present, specific locations of defects, and special strategies.

Visual search e.g., for nonconformities of an item, is a key aspect of a visual inspection task. Visual search is viewed as either being driven bottom-up by features in the visual field or by top-down cognitive processes involving *intent* or *expectation*. The bottom-up model of visual search describes the process in terms of basic visual features that tend to attract visual attention such as color, size, orientation, and/or direction of motion [4, 33]. Edges, corners, or blinking/flashing lights are common examples of such attractors. The bottom-up model effectively describes low-level, involuntary attention and eye movements and forms a powerful basis for computational models. Several such models have been developed successfully in recent years [14, 22].

A bottom-up model of visual search, however, does not adequately describe higher-level cognitive functions involved in human vision that drive voluntary eye movements. Classic eye tracking research has demonstrated that eye movement sequences, or *scanpaths*, differ with the observer's strategy (expectations or goals) when viewing a scene [34]. Since this early work, sequential eye movements have led to the sequential model of visual attention (and visual search) described as a three-stage process: first, information is processed during a fixation; second, attention is shifted covertly (without an eye movement) to a parafoveal/peripheral scene


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region (an area outside of the current fixation); third, an eye movement is programmed and executed to the newly selected location [13]. During visual search, where the eyes (and detailed foveal vision) are moved depends on the saliency of parafoveal/peripheral information [24]. Furthermore, scanpath characteristics, such as their order of progression, are task-dependent. Attributes such as fixation durations and length of saccades (the fast, brief eye movements from one fixation to the next) vary considerably as a function of the particular search task. It is generally agreed that fixation durations reflect the acquisition and processing of information in the visual scene. Visual search studies show that fixation durations increase with: (i) the difficulty of discriminating the target from surrounding distractors, (ii) the expectation of a target among distractors, (iii) the viewer's use of information conveyed by distractors about the relative location of a target, and (iv) hindrance to the opportunity to preview an object before it is fixated [1, 12].

In practical models of visual inspection, visual search strategy has been categorized as either random or purely systematic [19]. A random strategy is a memoryless process where fixations can occur anywhere in the search field. A purely systematic strategy is one where perfect memory guarantees that no two fixations will occur at the same location. Generally, human search strategy falls in between these two extremes. Inspection performance increases when the search strategy tends toward a systematic approach as the inspection coverage is then exhaustive with no overlap between successive fixations. It has been observed that eye movements of experienced inspectors are far from random. In radiology, an expert radiologist's scanpath is neither random nor resembling that of a novice; experienced radiologists use a more systematic strategy while inspecting chest radiographs than untrained viewers [16]. In chip inspection, trained inspectors adopt a better inspection strategy than novice inspectors [27]. It has also been shown that search strategy can be taught and search behavior improves with training [32, 3].

The improvement in inspection performance of novice inspectors over time may be accelerated if novices are trained to adopt an expert inspector's inspection strategy. Using eye tracking equipment, the point of regard data of an expert inspector can be recorded while performing an inspection task. The analysis of this data allows the characterization of the expert inspector's visual search strategy. The expert's search strategy can then be shown to novices as feedforward training to accelerate their adoption of a more effective search strategy.

Scanpaths have successfully been used for feedback training ("you looked here") of resident radiologists as well as for guidance of automated image processing algorithms [17, 20]. Graphical cognitive feedback of search strategy has also been shown to enhance visual inspection performance [6]. Real-time gaze over shared workspaces has also benefited resolution of ambiguous deictic references [29, 30, 9]. However, to our knowledge, feedforward display of search strategy ("you should look here") via static depiction of recorded scanpaths has not been investigated for its training potential.

This study deals with the development of a training medium to provide the search strategy of an expert inspector to novice inspectors. The effect of this *a priori* training on novice inspectors' visual search process and performance is experimentally evaluated. An initial study was performed to examine display techniques that may be used to effectively present feedforward information [26]. The present study deals with the evaluation of the previously developed display technique and also with the evaluation of the effectiveness of search strategy training.

## RESEARCH HYPOTHESIS

This study explores the effect of providing feedforward search strategy training to novices, based on an expert inspector's recorded visual search scanpath. Performance (speed, accuracy) and process (eye movement) measures of participants on a visual inspection task are analyzed for improvement in inspection accuracy and efficiency as a result of feedforward training.

The research hypothesis predicts that participants receiving feedforward search strategy training will show greater improvement in visual search performance than the participants not receiving training. That is, we expect a positive effect on performance imparted by feedforward training.

The research hypothesis concerning eye movement process measures predicts increased fixation durations following feedforward training. This expectation stems from research showing that, in a visual search task, prior knowledge of the stimulus leads to longer fixation durations provided parafoveal preview is insufficient (e.g., search in an area with sparsely distributed distractors) [Greene, personal communication]. In knowledge-driven (top-down) visual search, fixation durations are thought to be modulated by the availability of parafoveal/peripheral preview (the so-called *pre-attentive* or *preview* benefit [23, 13]). In contrast, fixation durations in image-driven (bottom-up) visual search are thought to be preset based on the viewer's prior experience with the search task, and hence, for the most part, invariant. Because the visual inspection task in our case is performed in a room-like virtual reality environment with an effectively large field of view and sparsely distributed targets, the context of our search area offers little preview benefit. We thus expect longer fixation durations following training, if, after training, viewers adopt a knowledge-driven search strategy.

## METHODOLOGY

### Subjects

A sample population of 16 college students participated in the study. The age of the participants (10 male and 6 female) ranged from 19 to 33 years. Participants were screened for visual acuity (20/20 natural or corrected with contact lenses), color vision, and our ability to calibrate an eye tracker with the participants' eye movements. It has been demonstrated that student subjects can be used in lieu of industrial inspectors [10].

**Figure 1. Head Mounted Display (HMD).**

**Figure 2. Cargo bay of L1011 aircraft.**

Due to loss of eye tracking data of 3 subjects when the simulator failed to record the point of regard of the participant (e.g., due to calibration error or the eye tracker's dropping of the data), process (eye movement) measures were available only for 6 subjects in the treatment group and for 7 in the control group. For analysis purposes, process data for one randomly selected subject in the control group was dropped and analysis was performed with a sample size of 6 subjects per group. Performance (speed and accuracy) data were recorded independently of eye movements for all 16 subjects. For analysis purposes, performance measures include data from all 16 subjects, 8 subjects per group.

### Stimulus Materials and Equipment

A virtual reality aircraft inspection simulator developed previously was used to carry out the experiment [8, 7].

The principal hardware component is a Head Mounted Display (HMD) integrated with a binocular eye tracker (Figure 1), jointly built by Virtual Research and ISCAN. An Ascension Technology Corporation's Flock of Birds (FOB) tracking system is used for rendering the virtual environment with respect to the participant's position and orientation. For the purpose of selection and pointing in the virtual environment, a hand held mouse with 6 degrees of freedom (6DOF) is used. The simulator executes on a 1.5GHz dual Pentium 4 processor Dell personal computer with an NVidia GeForce4 FX5950U graphics card, running the Red Hat Linux 8 operating system.

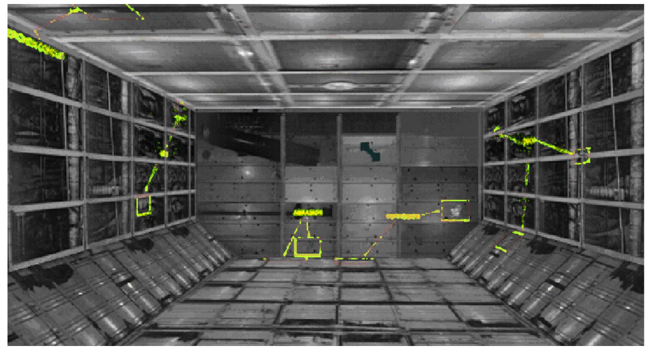


**Figure 3. Familiarization scenario with highlighted defects.** *(Image artificially enhanced for greyscale reproduction.)*

The software component of this simulator consists of two programs, `Inspector` and `Vspec`. The `Inspector` program displays the virtual reality scenario to the participants and at the same time records the participants' eye movements, while `Vspec` is used to analyze the data collected by `Inspector`.

The task scenarios used in this study were variations of a virtual reality model of an aircraft cargo bay texture mapped with images taken of a real cargo bay of a Lockheed L1011 aircraft (Figure 2). Target defects were representations of defects typically found in the aircraft cargo bay, namely crack, corrosion, broken electrical conduit, abrasion, and hole.

Five variants of the cargo bay scenario were used for this study. The first was a familiarization scenario (Scenario A) with the different types of defects highlighted (Figure 3). The purpose of this scenario was to familiarize participants with virtual reality and to allow them to become accustomed to the cargo bay environment. This scenario also presents highlighted examples of the five different defect types.

Participants performed the inspection task using two additional multiple defect inspection scenarios (Scenarios B and C). These scenarios (Figure 4) were constructed to be equivalent in task difficulty (identical distribution of defect types and similar locations) and contain twenty-two defects of the five defect types listed above.

The fourth scenario (Scenario D) was the feedforward training scenario (Figure 5). This scenario displays the search strategy information collected from an expert inspector. The fifth scenario (Scenario E), the practice scenario, was identical to Scenario D, except that there was no display of the search strategy information of the expert inspector.

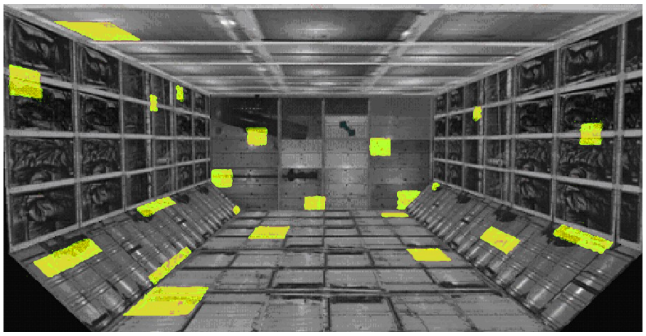


**Figure 4. Inspection task scenario with 22 defect locations (not shown during testing).** *(Image artificially enhanced for greyscale reproduction.)*

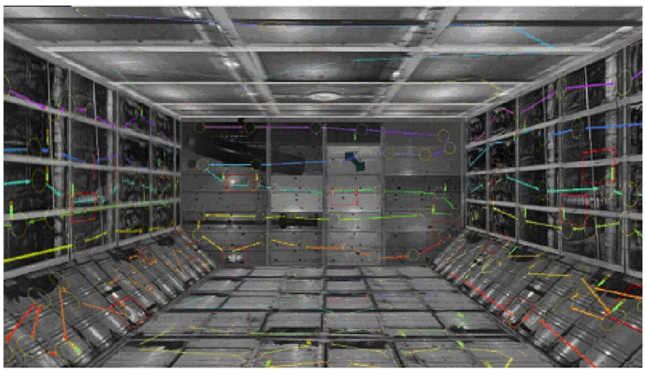


**Figure 5. Feedforward training scenario showing expert's search strategy.**

### Feedforward Training Scenario Development

The feedforward training scenario displays an expert inspector's search strategy. An expert inspector's eye tracking data (Figure 6) was recorded while performing the inspection task in the multiple defect inspection scenario. The expert inspector had extensive prior experience with the simulator, training in the theoretical concepts of search strategy and a high level of performance on the task.

The expert inspector's raw eye tracking data was then analyzed and processed. The data was classified into three categories:

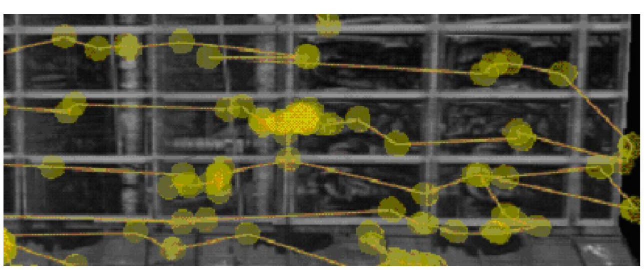


**Figure 6. Eye tracking data of expert inspector.**

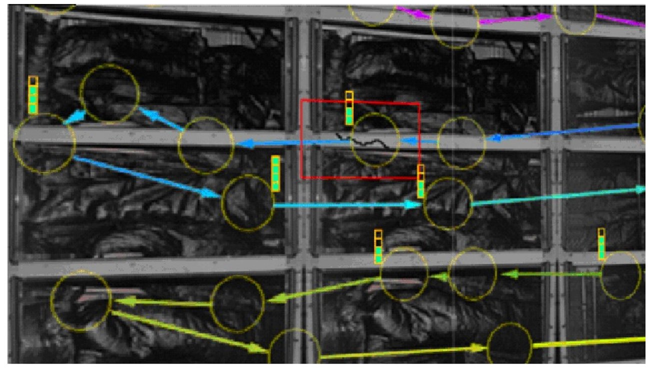


**Figure 7. Final display for feedforward training.**

1. Area of interest: Where the inspector was looking. This was achieved by grouping neighboring fixation points to determine an area of fixation.

2. Sequence of fixations: The path of the inspector's eye movement from one area of interest to the next. These were determined by the isolation of saccades, identified by the analysis of the inspector's raw eye movement data.

3. Time spent at each area of interest: How long the inspector spent looking at each area of interest. This data was quantized into four relative durations of time. The time spent at each area of interest ranged from 151 milliseconds to 777 milliseconds (see below).

The final feedforward display (Figure 7) was developed by combining the preferred characteristics of two display techniques evaluated in an earlier study [26]. Area of interest was represented by yellow circles. The sequence of the eye movements on each wall was represented by arrows from one area of interest to the next using a color gradient ranging from violet (start) to red (end) through the colors of the rainbow. The relative time spent at each area of interest was represented by yellow vertical bars filled with green placed next to the area of interest. The level to which the bars were filled denotes the amount of time spent at that area of interest. The levels were as follows: 1/4 filled denotes the lowest level (151ms to 307ms); 1/2 filled denotes the second level (308ms to 464ms); 3/4 filled denotes the third level (465ms to 620ms); when completely filled, the bar denotes the highest level of time (621ms to 777ms). To reduce clutter, the bar denoting the lowest level was considered the default and not displayed. Thus, no time bar next to a particular area of interest meant that the expert spent time classified at the lowest level at that area of interest. Defects in the scenario were highlighted with a red rectangular outline around them.

### Experimental Design

A Pretest-Posttest Control Group design was used for this experiment [2] with one independent variable, the treatment condition, at two levels: training (treatment group) and no training (control group). Study participants were randomly assigned to each group (Table 1).

| Stage | Familiarization | Pre-test | Treatment | Post-test |
|---|---|---|---|---|
| Treatment Group (randomly assigned) | Familiarization | Inspection Task (O1) | Feedforward Training + Practice | Inspection Task (O2) |
| Control Group (randomly assigned) | Familiarization | Inspection Task (O3) | Practice | Inspection Task (O4) |

**Table 1. Experimental design.**

Only the treatment group received feedforward training. The feedforward training scenario consists of the search strategy information presented in the cargo bay scenario. This potentially also provides a participant in the treatment group more exposure to the cargo bay environment than a participant in the control group. To isolate the effect of feedforward training, the effect of exposure was blocked. This was achieved by exposing the participants in the control group to a scenario identical to the training scenario with the defects highlighted, but without the feedforward information.

### Procedure

Participants were first asked to complete a consent form and a demographic questionnaire, and given instructions to ensure their understanding of the experiment. All the participants were then immersed in the familiarization scenario to familiarize them with virtual reality, the cargo bay environment, and the different types of defects.

They were then asked to perform an inspection task in a multiple defect environment. The task was an unpaced task: the participants were instructed to terminate the task when they wished. One of two multiple defect inspection scenarios was presented for this task. The two multiple defect inspection scenarios were counter balanced to assure that both groups received the same number of orderings of the two scenarios. The task involved the participants searching for defects in the virtual inspection scenario. Once they found a defect, they marked it in the scenario by pointing and clicking using the 6DOF mouse. If the selection was correct, the defect was then highlighted in red.

The eye movements of the participants and the selections they made by clicking the 6DOF mouse were recorded. The participants in the control group were then immersed in the exposure scenario. They were allowed to spend as much time as they wished in this scenario.

The participants in the treatment group were immersed in the feedforward training scenario. The feedforward display was briefly explained to them and they were allowed to spend as much time as they wished in this scenario.

All the participants were then asked to perform a second inspection task in a multiple defect environment. The task was again unpaced and the participants could terminate the task when they wished. The participants were immersed in the multiple defect inspection scenario that they had not been exposed to in the first inspection task. The eye movements of the participants and the selections they made by clicking the 6DOF mouse were recorded. The participants were not given feedback on their performance for this task.

A subjective questionnaire was administered to the participants after this stage.

### Measures

Performance measures and process measures were collected for each inspection task. Performance measures obtained relating to speed and accuracy consisted of:

1. Number of defects detected (hits).
2. Total time taken from presentation until the participant considered the search task complete.

Process measures expressed by eye movements consisted of:

1. Total number of fixations.
2. Total number of fixation groups.
3. Mean fixation duration.

Subjective measures garnered from a questionnaire were used to evaluate participants' perceptions of training effectiveness.

## RESULTS

Collected performance, process, and subjective measures were analyzed using SAS (v8.2) and Microsoft Excel 2002. Results measured the effect of training provided to novice inspectors in terms of performance and the visual search process. Performance measures report accuracy (the number of defects detected) and efficiency (speed; time taken for the task in seconds). Process measures were obtained by analyzing the raw point of regard data of the participants, recorded by the eye tracking equipment [7].

Process measures are reported in terms of the number of fixation points, the number of fixation groups (fixation point clusters) and the mean fixation duration in milliseconds. Fixation points are identified by isolating fixations from saccades using a velocity filter with a threshold value set at 130 degrees of visual angle/second. Fixation grouping is performed by condensing a string of consecutive fixation points to a single fixation by finding the centroid of the group and verifying that each fixation group's duration is greater than or equal to the minimum theoretical fixation duration of 150ms.

Subjective measures were collected on nine questions using a five point Likert scale where 1 was strongly disagree, 3 was neutral and 5 was strongly agree.

| Measures | Relative difference (%) | | t | p |
|---|---|---|---|---|
| | Control | Treatment | | |
| | Mean (SD) | Mean (SD) | | |
| No. of defects detected | 13.77 (17.59) | 42.27 (37.15) | 1.96 | 0.035 |
| Time taken for the task | -18.36 (31.65) | 73.03 (45.74) | 4.64 | 0.0001 |
| No. of fixation points | 3.05 (41.74) | 54.67 (72.01) | 1.51 | 0.079 |
| No. of fixation groups | -3.69 (36.61) | 53.38 (75.84) | 1.65 | 0.064 |
| Mean fixation duration | -23.63 (27.45) | 35.41 (66.99) | 1.99 | 0.037 |

**Table 2. Performance and process measures.**

For the control group, the difference between the post-test and the pre-test represents the effect of practice while, for the treatment group, the difference represents the effect of the training coupled with the effect of practice. The effect of training can be isolated by comparing the post-test - pre-test difference for the treatment group with the difference for the control group. The inherent ability of the participants to perform the search task varies. Hence the absolute difference between the post-test and pre-test measures is not comparable across individuals. This variability is accounted for by transforming the absolute difference to a relative difference. The relative difference was calculated by representing the difference (post-test - pre-test) as a percentage of the pre-test score for each participant, thus focusing on the improvement of the participant's abilities relative to his or her initial ability.

An independent-means t-test was used to analyze the performance and process data. For subjective data, we use a non-parametric Wilcoxon signed rank test.

### Performance Measures

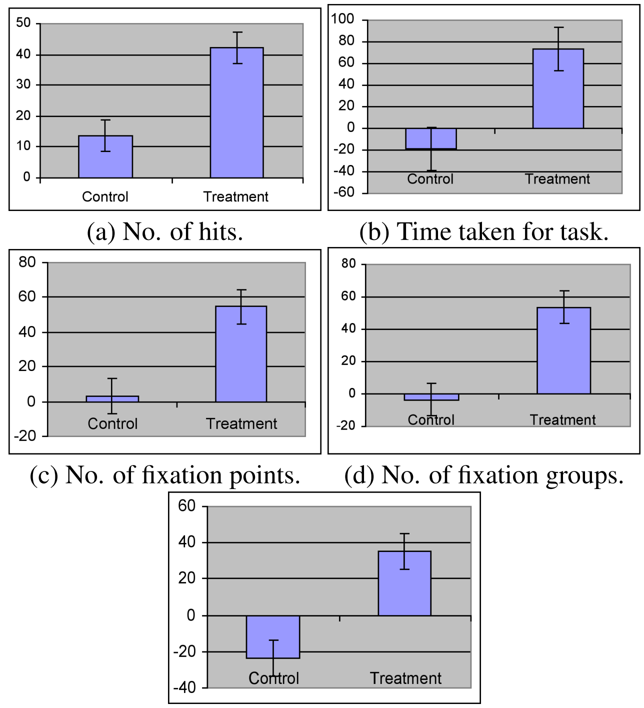
Table 2 presents the objective performance and process measures. The t-test of the relative difference in accuracy shows that the improvement for participants who received training was significantly higher than that of the participants in the control group ($p < 0.05$). Figure 8(a) presents this result graphically.

The t-test of the relative difference in time taken to complete the inspection task was significant ($p < 0.001$). The time taken to complete the inspection task by participants who received training increased, while the time taken by participants in the control group decreased. This result is shown graphically in Figure 8(b).

### Process Measures

The effect of training on the relative difference in the number of fixation points was not significant ($p = 0.079$). This result is shown graphically in Figure 8(c). The effect of training on the relative difference in the number of fixation groups was also not significant ($p = 0.064$). This result is shown in Figure 8(d).

The t-test of the relative difference in the mean fixation duration was significant ($p < 0.05$). The mean fixation duration for participants who received training increased, while the




(a) No. of hits. (b) Time taken for task.

(c) No. of fixation points. (d) No. of fixation groups.

(e) Mean fixation duration.

**Figure 8. Performance and process measures: relative difference (%).**

mean fixation time for participants in the control group decreased. This is graphically represented in Figure 8(e).

### Subjective Measures

The results of the analysis of subjective measures are summarized in Table 3. Subjective measures were collected only from the treatment group and were analyzed using a Wilcoxon signed rank test with an anchor point of 3. For questions 1,2,3,4,7,8, and 9, the Wilcoxon test showed that the responses were significantly greater than the anchor point of 3. The results for questions 5 and 6 were not significant.

## DISCUSSION

The objective of this study was to determine whether search strategy can be taught using a feedforward training display that represents the eye tracking information gathered from an expert inspector performing an inspection task. Training

| | Question | Mean rating (SD) | Wilcoxon test p |
|---|---|---|---|
| 1 | The information presented in the training display was understandable. | 4.375 (0.517) | 0.0078 |
| 2 | The training display provided a helpful representation of the different types of defects. | 4.125 (0.641) | 0.0156 |
| 3 | The training display provided a helpful representation of the areas of interest. | 3.875 (0.641) | 0.0313 |
| 4 | The training display provided a helpful representation of the sequence of an expert inspector's eye movements. | 4.5 (0.756) | 0.0156 |
| 5 | The training display provided a helpful representation of the relative time an expert inspector spent at each area of interest. | 3.875 (0.991) | 0.0938 (ns) |
| 6 | The colors used on the training display were helpful. | 3.875 (1.356) | 0.1719 (ns) |
| 7 | Overall, the training provided useful information on search strategy. | 4.25 (0.463) | 0.0078 |
| 8 | The training session helped me to adopt the expert's search strategy. | 4.625 (0.517) | 0.0078 |
| 9 | The training session helped me to perform the search task more efficiently. | 4.5 (0.756) | 0.0156 |

**Table 3. Analysis of subjective measures (5-point Likert scale where 1 = strongly disagree, 3 = neutral and 5 = strongly agree) with significance measured with respect to an anchor point of 3.**

effectiveness was evaluated by comparing the performance of a group of participants exposed to the training against the performance of a group of participants who did not receive the training. Process measures were analyzed to understand how the training affected the participants' search strategy.

### Performance Measures

The results show that feedforward search strategy training was effective in improving the accuracy of novice inspectors in detecting defects. At the same time, improved accuracy was accompanied by a significant increase in the time taken to complete the search task. Thus, a speed-accuracy tradeoff was observed.

### Process Measures

Process measures show that participants who received feedforward training appear to have executed a larger number of fixations after training, although the result is marginally significant for both comparisons of fixation points and the clustered fixation groups ($p > 0.05$ in both cases). Participants who received feedforward training significantly increased their mean fixation duration following training. A slower paced inspection strategy adopted by the participants in the treatment group would explain the increase in time taken for the task. It was observed that the participants who received the search strategy training appeared to adopt a search process that was similar to the search strategy of the expert inspector. It was also observed that the search strategy of the participants in the treatment group tended towards a more systematic (memoryless in the statistical sense) search strategy after training, relative to the search strategy they adopted before training (more random and repetitive in nature). Recall, a perfectly systematic search strategy is a sequential inspection process that covers the inspection area without overlap.

### Eye Movements, Speed, and Accuracy

Collecting eye tracking data during an inspection task in a virtual reality simulator provided us with useful additional information beyond performance measures that gave us insight into participants' cognitive processes during inspection.

The training scenarios that we have developed are based on an explicit representation of an expert's cognitive processes and thus lead to knowledge-driven (top-down cognitive) visual search vs. image-driven (bottom-up) search performed by the control group. Along with bottom-line performance data showing better accuracy of trained novices, the observed increase in fixation durations is significant, since it is evidence of trained novices devoting more cognitive processing to the target discrimination task. This is, in our view, a poignant interpretation of the speed-accuracy tradeoff in light of previous psychological findings (e.g., [12]): trained novices were thoughtfully looking for defects in the simulator vs. naively "hunting and pecking" for them. We contend that this is the reason for increased time in the simulator and an indicator of training effect: novices learned a more deliberate target search/discrimination strategy that required more time to execute; they did not merely spend more time in the simulator. Spending more time should not have led to higher accuracy unless subjects in the treatment group adopted a more systematic search strategy.

### Subjective Measures

The information gathered from the subjective questionnaire helped evaluate the usefulness of scanpath-based training from the participants' perspectives. It also allowed us to evaluate the effectiveness of the representation of various types of categorical information.

The analysis of the subjective data (Table 3) suggests that the participants found the feedforward information on search strategy understandable. Perceived understandability of feedforward information, coupled with the improvement in performance, suggests that offline training provided in the form of a static representation of the expert's search strategy is effective. Our results therefore support the use of offline training, which can be conducted in controlled circumstances as an adjunct to on-the-job training, currently the primary training methodology available for aircraft inspectors.

Questions 2 through 5 were used to evaluate the representation of different categories of information. The analysis indicates that participants found the representation of the defects, the areas of interest, and the sequence of the expert's eye movements helpful, but not the representation of relative time spent at each area of interest. Participants also did not find the colors used in the display very helpful and, therefore, the color gradient used to represent the timeline associated with the scanpath (hence substantiating Tufte's derision of rainbow encoding [28]).

Participants felt that the training provided useful information on search strategy. They also felt that the training allowed them to adopt the expert inspector's search strategy and helped them perform the inspection task more efficiently. Most of the participants who received the training commented that they found the training very useful for the task.

Participants' impressions of improved search efficiency, following feedforward training, at first appears to contradict the resulting increase in the time taken to complete the inspection task. This could be a result of participants' appreciation of the expert's search strategy as more systematic in nature, ensuring that search time is not wasted in repeatedly inspecting previously covered areas, which would be the case in a more random search strategy.

## CONCLUSION

From the results of this study, it can be concluded that subjects can be trained to adopt a search strategy tending toward a more systematic approach and away from a purely random effort. Feedforward search strategy training is effective in improving inspection performance. With an increase in performance, an increase in time taken to complete the task was observed. Thus, a speed-accuracy tradeoff was found in the application of this training. It has also been shown that eye tracking information can help elicit the cognitive processes of an expert inspector while performing a search task. The sequential nature of scanpaths reveals locations where the expert devoted greater processing time during visual search, and, perhaps more importantly in this case, the expert's chosen sequential progression during search. The display technique developed for search strategy training was found to be effective in representing this information.

Future applications of scanpath-based feedforward training are potentially numerous, generally related to comparison of expert/novice performance. Eye movements of experts have been compared to those of novices during various inspection tasks ranging from poultry, meat, and fish inspection, to drug inspection, to medical X-ray inspection, to production line inspection, to photo interpretation, to name a few [27, 16]. These studies were conducted largely in an effort to understand experts' cognitive processes. As our work shows, scanpaths have the potential for feedforward training in these and many other visual inspection applications.

Scanpath-based training may also be applicable to a broader range of human activities involving skilled performance. Examples of past skilled performance studies, aimed at enhancing our understanding of human expertise, include chess play and laparoscopic surgery [25, 18]. When deciding if the king is checked, eye tracking has shown that chess masters made fewer fixations and had a greater proportion of fixations between individual pieces, rather than on pieces. In a laparoscopic surgery simulator, comparison of eye movement strategies between expert and novice surgeons showed that experts tended to fixate the target while manipulating the laparoscope, while novices tended to vary more in their behavior (e.g., tracking laparoscope movement). Other dynamic situations where eye movements have been examined for insight into experts' cognitive strategies include driving, basketball foul shooting, golf putting, table tennis, baseball, gymnastics, walking in uneven terrain, mental rotation, and interaction with computers [24].

For future training purposes, our work demonstrates the potential for skilled performance training via feedforward (*a priori*) display of an expert's cognitive strategy through visualization of their recorded scanpaths. Simple playback of recorded expert scanpaths may lead to quicker skill acquisition in skilled tasks.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