Visual Inspection Simulator (VisInS): A Computer-based Inspection Simulation Tool for Off-Line Experimentation

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Abstract

Inspection literature has often emphasized the potential for human factors interventions to improve inspection performance. In order to define specific interventions, it is critical to conduct off-line experimentation on the efficacy of the various interventions to improve performance. To address this need a computer-based Visual Inspection Simulator (VisInS) was developed. The paper provides a detailed description of the simulator and the controlled experiments that were conducted using it. Plans for extending the simulator's function and other experiments currently in progress are also described.

Keywords

Inspection, advanced technology, simulation, search, decision-making

1. Introduction

The classic decomposition of the visual inspection task has revealed two fundamental components: visual search and decision making [1,2]. The search aspect involves locating a potential defect followed by decision making wherein the operator has to classify the item based on predefined criteria. Thus, the objective of any inspection process is to ensure that search and decision making are performed successfully. However, inspection tends to be less than 100% reliable using human inspectors [3,4]. To overcome this deficiency, many companies have resorted to automated inspection in an effort to eliminate error from the inspection process. Automated inspection systems [e.g., 5,6,7] automate various functions of the inspection task. Although, automation is considered to be a solution, each implementation tends to be a unique solution for a specific product type. Automated systems work well for tasks such as printed circuit board inspection because in this case the defect is highly discernible from the background.

The systems work well when the task's variability is low, the signal to noise ratio is high and the complexity of the decision-making is low. Automated systems are bound by these limitations and cannot achieve the inherent flexibility provided by human inspectors. Furthermore, we still lack generic automated inspection systems that can be applied to the inspection of a wide class of products. Thus, the robust adaptability of humans still holds a definite advantage for the majority of inspection processes [8,9]. Moreover, automated inspection systems do not surpass the superior decision-making abilities of the human inspector as evidenced by both laboratory and field studies of inspection [9,10]. Hence, humans are especially desirable for examination types of inspection tasks wherein the inspector has to search and then decide whether the item is to be accepted or rejected based on single or multiple attributes [11]. Since humans will continue to be part of the inspection process for the foreseeable feature, they need to be effective and efficient as inspectors.

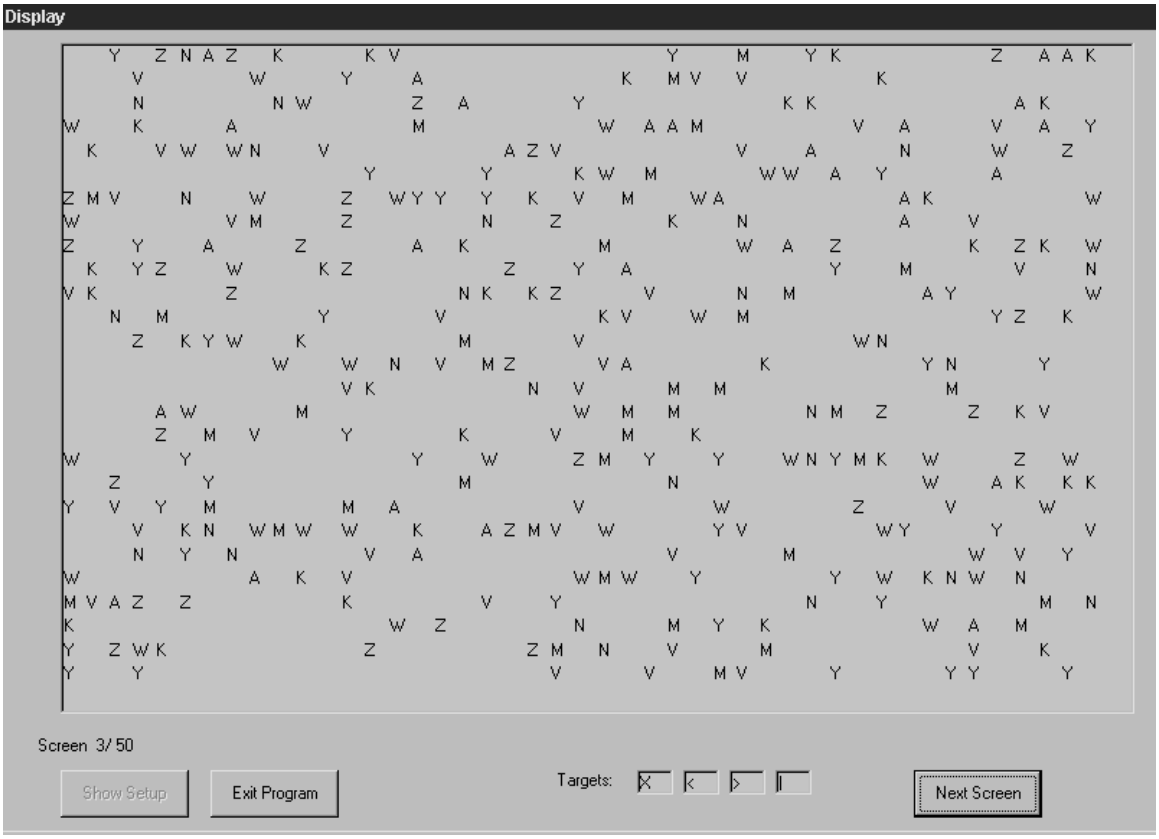
Human inspection is affected by various factors [see 12]. If we are to improve human performance in inspection it is critical that we understand the impact of these factors on inspection performance. It is only then that we will have a systematic body of knowledge which will enable us to design superior inspection systems. One way of achieving this is to study the impact of these factors through off-line experimentation using computer simulations of inspection tasks. However, the application of advanced technology and the use of simulation specifically for inspection, is the exception rather than the rule. On the other hand, as computer technology becomes less expensive, the future will bring an increased application of advanced technology to inspection. Over the past decade, the growth in computers has led to numerous technology based devices with the promise of improved efficiency and effectiveness. These devices are being used in a variety of applications. Examples of such technology include computer-based simulation [e.g., 13] interactive videodisks [14] and other derivatives of computer-based applications [15]. Compact disc read only memory (CD-ROM) and Digital Video Interactive (DVI) are two other technologies that will provide us with the "multi-media" systems of the future. Computer simulations have found use for a wide variety of applications such as computer-aided instruction [16], computer based multi-media training [17] and intelligent tutoring systems [18,19]. In the United States, the Department of Defense has taken a leadership role in applying advanced technology and in using simulations [20]. Examples of these applications currently used by the United States Air Force are [21]: the KG 194 Trouble Shooting Tutor, the F-15E Armament Maintenance Trainer, and the Undergraduate Navigator Training Tutor (all of which use the Intelligent Computer Aided Instruction approach to training).

In the domain of visual inspection, the application of advanced technology and use of simulators has only a short history. The earliest efforts to use computer simulation for off-line inspection controlled studies were reported by Latorella et al. [22] and Gramopadhye, Drury and Sharit [23]. These investigators used low fidelity inspection simulators using computer-generated images to develop off-line inspection training programs for airframe inspection tasks. More recently, Blackmon and Gramopadhye have reported the development of an inspection simulator using scanned images of airframe structures for aircraft inspection training [24]. Similarly, Drury and Chia-Fen studied human performance using a high fidelity computer simulation of a printed circuit board inspection [25]. Advanced technology has also been applied rather extensively to the study the process of inspecting X-rays in the medical field [e.g., 26].

If we are to make further progress in studying human performance in inspection we need simulations which will enable us to run controlled studies off-line. To this purpose, this paper describes the development of a Visual Inspection Simulator (VisInS) (see Figure 1.). VisInS is a computer simulation of a visual inspection task that simulates both the search and decision making components of the task. The software uses alphanumeric characters as targets and background to simulate the inspection task. A prototypical screen of the visual inspection tasks is shown in Figure 2.

Figure 1. Introductory Screen

Figure 2. Screen Prototype



2. VisInS -- Visual Inspection Simulator

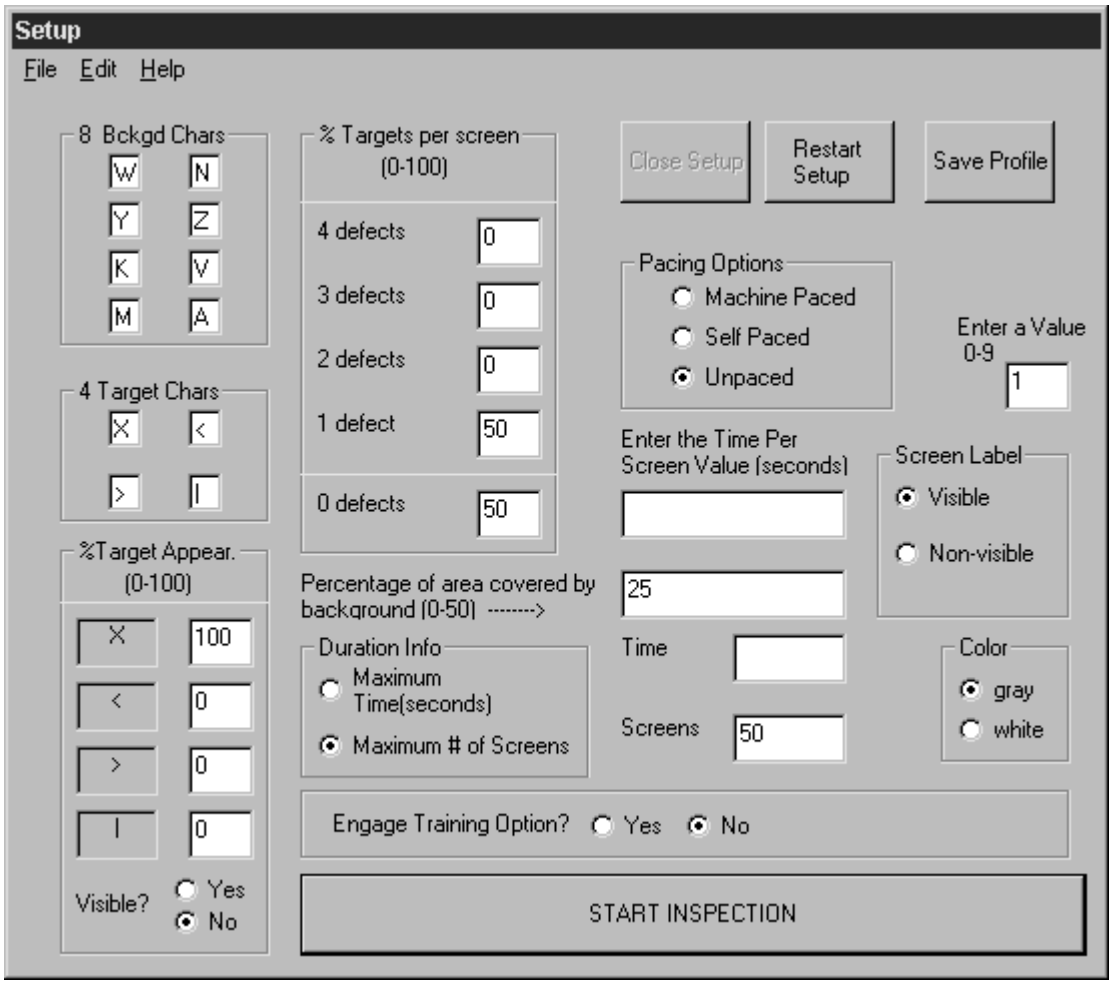
2.1 System Specifications

The simulator operates on a Pentium 150 Mhz platform running Microsoft Windows 95 operating system with 32 Mb RAM and a standard color monitor. Input devices are a standard keyboard and a two-button mouse. The tool was programmed in Visual Basic and the data reduction software was written using the C programming language.

2.2 Setup Screen

The setup screen allows the experimenter to set various inspection parameters. Selection of inspection parameters essentially enables the experimenter to manipulate the complexity of the inspection task (Figure 3.). Each of these parameters are described in turn.

Figure 3. Setup Screen



Background Options: The experimenter has the option to select up to 8 background characters.

Background density: This option allows the setting of the background density (0 - 100). Increased density obviously would imply increased difficulty in locating the targets, thus increasing the difficulty of the search component of the inspection task.

Target characters: The program allows for the selection of a maximum of four targets (or defects). The targets are defects that an inspector would look for when searching an area. Thus by varying the number of defects, the experimenter can simulate either a single-defect inspection task or a multiple defect inspection task. Regardless of whether it is a single or multiple defects task, the program allows the experimenter to define the number of search areas with defects (this specifies the probability of defective items). Furthermore, in the case of multiple defects, the experimenter can also specify the percentage occurrence of each defect and the combinations thereof.

Pacing options: The simulation can be operated in three different pacing modes. (1) Machine paced mode: In the machine paced mode the subject is given a fixed time (as defined by the experimenter) to inspect each search area. On reaching the pre-set time limit the simulation automatically advances to the next search area in the sequence. (2) Self paced mode: The self-paced mode is similar to machine paced however in this case, if the subjects completes the inspection before the maximum time has expired he/she can advance to the next area in sequence and (3) Unpaced mode: In the machine paced mode the subject has complete control over the inspection time and can advance to the next search area when desired.

Length of Inspection: The experimenter can end inspection by specifying the maximum number of search areas to be inspected or by defining the total inspection time for a session.

Target/Background Discriminability: The experiment can be operated in two modes of discriminability. The low discriminability condition uses black letters on gray background and high discriminability condition uses black letter on white backgrounds.

On-line Standards: This option allows the experimenter to provide on-line defect standards or none by selecting the training aids and target visibility options. Use of this option facilitates the study of the effects of providing on-line job standards as compared to relying on memory inspection while conducting inspection.

Random Number Selection: By using the random number selection the experimenter can generate a wide variety of search areas.

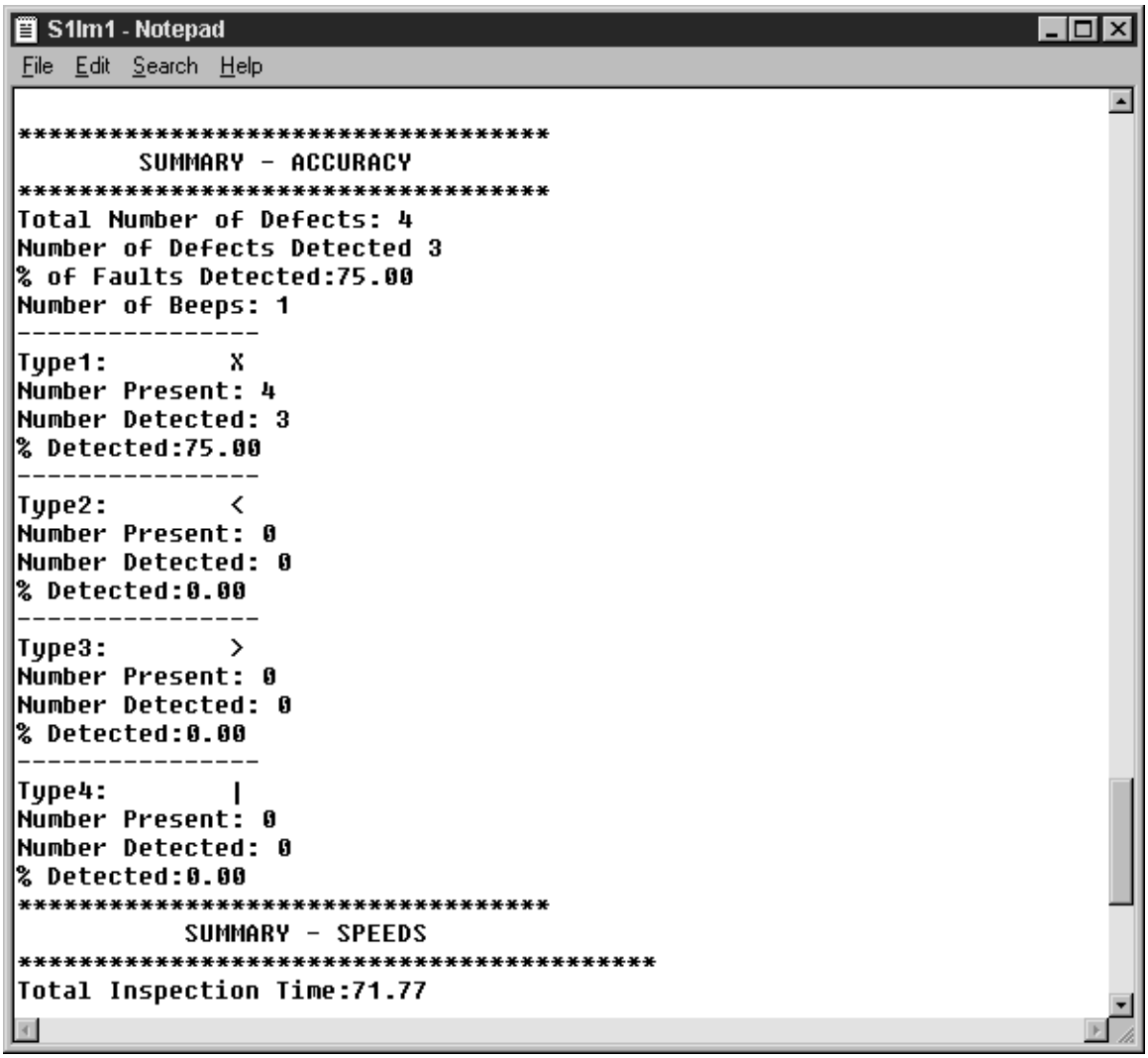
2.3 Visual Inspection

Once the parameters for inspection are specified, the simulation is ready for use. The inspection simulation consists of a series of search areas that may or may not contain any defects. The inspector has to visually look for defects and indicate the identification of a defect by clicking on the defect. Once all the defects are detected, or the subject is certain that the area does not contain any defects, he or she proceeds to inspect the next search area in sequence.

2.4 Data Collection Module

The software's built-in data collection module tracks the subjects' performance by collecting data on speed and accuracy measures. Data is collected on each individual screen and finally summarized for the entire session (see Figure 4.). Data is collected on the following -- (1) accuracy measures: percentage defects detected, percentage defects missed, hits, misses, false-alarms, correct accepts, and, (2) speed measures: search time - time to detect a defect, stopping time - time to stop search and inspection time - total time to inspect an area.

Figure 4. Output Screen



```
S1lm1 - Notepad
File  Edit  Search  Help

************************************
        SUMMARY - ACCURACY
************************************
Total Number of Defects: 4
Number of Defects Detected 3
% of Faults Detected:75.00
Number of Beeps: 1
----------------
Type1:        X
Number Present: 4
Number Detected: 3
% Detected:75.00
----------------
Type2:        <
Number Present: 0
Number Detected: 0
% Detected:0.00
----------------
Type3:        >
Number Present: 0
Number Detected: 0
% Detected:0.00
----------------
Type4:        |
Number Present: 0
Number Detected: 0
% Detected:0.00
************************************
           SUMMARY - SPEEDS
*****************************************
Total Inspection Time:71.77
```

3. Controlled Studies

The software has been used, thus far, to conduct two separate controlled studies to study human inspection performance. The first study looked at the effect of pacing on search performance. Specifically, the results of machine paced, self-paced and unpaced conditions were examined. The study also looked at the effects of varying levels of task complexity for the above-mentioned conditions. The second study evaluated the effect of noise on inspection performance. The specific objective of the study was to study the effect of quiet, continuous noise, and intermittent noise on visual inspection performance for various inspection task complexity conditions. The results of the above studies, when available it will lead to a better understanding of human performance in inspection. Furthermore, these results will lead to the identification of interventions that could involve changes to human, the process, or the environment to improve inspection performance and eventually inspection quality.

4. Conclusions

The research described the role of advanced technology and specifically that of a computer-based inspection simulation tool to facilitate the understanding of human performance in inspection. Research currently underway tries to extend it in two ways:
(1) simulation enhancements - this effort extends the functionality of the simulator by incorporating more complex decision making, use of heterogeneous search fields instead of homogeneous search fields and by using realistic images of actual inspection items, and
(2) conducting additional controlled studies which evaluate the effect of various task, subject, and environmental factors on inspection performance.

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