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The Role of Visual Inspection in the 21st Century

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Visual inspection research has a long history spanning the 20th century and continuing to the present day. Current efforts in multiple venues demonstrate that visual inspection continues to have a vital role for many different types of tasks in the 21st century. The nature of this role spans the range from traditional human visual inspection to fully automated detection of defects. Consequently, today's practitioners must not only successfully identify and apply lessons learned from the past, but also explore new areas of research in order to derive solutions for modern day issues such as those presented by introducing automation during inspection. A key lesson from past research indicates that the factors that can degrade performance will persist today, unless care is taken to design the inspection process appropriately.

INTRODUCTION

Lessons learned from past research. Visual inspection is commonly used in both manufacturing tasks and non-production environments. In manufacturing tasks, the purpose is to verify that a product is free of defects before installation in the next level of assembly or final distribution to the customer. In non-production environments, the objective is to determine whether the features indicative of a "target" are present and prevent potential negative impacts. Many fields in which visual inspection is used are considered high consequence due to the potentially high costs of inspection errors—injury, fatality, loss of expensive equipment, scrapped items, rework, or failure to procure repeat business. Such high-consequence fields include nuclear weapons, nuclear power, airport baggage screening, aircraft maintenance, food industry, and medicine.

Visual inspection has been extensively researched since the early 20th century to understand the factors that impact performance (See, 2012; See, 2015). The most frequent and consistent observation is the imperfection of human inspectors. The minimum error rate of 10^{-3} applies primarily to very simple accept/reject inspection tasks (Swain & Guttmann, 1983). Most inspection tasks are much more complex and typically exhibit error rates of 20% to 30% (Drury & Fox, 1975). Inspection errors may occur for many reasons, but can be traced to task, environmental, individual, organizational, and social factors (See, 2012) (Table 1). Although they cannot be eliminated entirely, inspection errors can be reduced with appropriate interventions. Namely, the quality of an inspection process can be enhanced by proper attention to three primary factors—training, inspection procedures, and apparatus (See, 2012).

Challenges of visual inspection in the 21st century. The premise of this discussion panel is that human visual inspection continues to have a vital role in the 21st century. In some cases, the nature of this role remains virtually unchanged as compared to traditional 20th century processes. In other cases, the nature of this role has evolved, in large part due to recent advances in the use of automated techniques for visual inspection. Consequently, practitioners in the 21st century face multiple challenges. On the one hand, they must successfully identify and apply the lessons learned from the past that continue to impact visual inspection processes in the 21st century. On the other hand, they must pursue new avenues of research in order to derive solutions for modern day issues, such as those introduced by automation.

Table 1: Factors Impacting Inspection Performance

Task	Individual
• Defect Rate	• Gender
• Defect Type	• Age
• Defect Salience	• Visual Acuity
• Defect Location	• Intelligence
• Complexity	• Aptitude
• Standards	• Personality
• Pacing	• Time in Job
• Multiple Inspections	• Experience
• Overlays	• Visual Lobe
• Automation	• Scanning Strategy
	• Biases
Environmental	**Organizational**
• Lighting	• Management Support
• Noise	• Training
• Temperature	• Retraining
• Shift Duration	• Instructions
• Time of Day	• Feedforward Information
• Vigilance	• Feedback
• Workplace Design	• Incentives
	• Job Rotation
Social	
• Pressure	• Isolation
• Consultation	• Communications

Successful application of lessons learned from past research is a challenge for all visual inspection processes, regardless of whether automated techniques are used. All too frequently, the engineers who design the product also develop the associated inspection procedures. Operating under the faulty assumption that visual inspection will be performed with 100% accuracy, the engineers may or may not consult the human factors practitioners who can apply principles from previous research to optimize inspection training, standard operating procedures/concepts of operation, and apparatus. This problem can be especially detrimental for processes that rely entirely on human visual inspection without automated aids. For example, in small production runs characterized by low throughputs, it may not be cost effective to use automated inspection due to required investments in equipment, training materials, and time.

Introducing some form of automation into the process presents different types of challenges. Automation does not replace humans in the system; it merely transforms the nature of their role. For instance, if machine detection is used to search for and identify defective parts, an active visual inspection task may become a passive supervisory task. The result is that vigilance effects may become more pronounced—the human monitors the system for continued functionality and perhaps performs spot checks on accuracy, but is not an active participant in the process. In tasks such as baggage screening wherein automation may augment the error-prone search phase, humans function as the final decision makers in the system, judging whether an item meets criteria for rejection. When the human role during search is supplemented or replaced, any human issues associated with the decision-making phase become even more prominent.

Finally, despite nearly a century of research, gaps exist that continue to present challenges for visual inspection in the 21st century. For example, while many individual factors have been investigated to identify traits of the "perfect" inspector, an approach that adequately explains variance in the data has yet to be discovered (Drury & Wang, 1986; See, 2012). Additional research to address such gaps will benefit visual inspection in general, regardless of whether automated techniques are incorporated.

Panelist contributions. The contributions from each panelist in the remainder of this paper highlight various aspects of these challenges confronting human visual inspection in the 21st century. Colin Drury describes the changing nature of visual inspection and identifies new applications that can benefit from past research. Ann Speed discusses visual search and inspection during baggage screening, highlighting continued efforts to discover which individual differences best explain observed differences in performance. Allison Williams and Negar Khalandi describe the enduring role of traditional forms of visual inspection in processes characterized by low throughput. Ms. Khalandi further discusses attempts to use virtual and augmented reality techniques to provide training or to assist inspectors during visual inspection.

CONTRIBUTIONS

Is visual inspection shrinking or merely changing?

Colin G. Drury

The study of human factors in visual inspection began with mass production in manufacturing. However; with improved techniques in sensing, measurement, and computing power in many fields; the human visual inspection function is frequently being replaced by automation (Friedman, 2016). The obvious place to replace human visual inspection involves repetitive measurement of physical variables of industrial-scale mass production, given that machines are more rapid and accurate than humans. In fact, in tightly-coupled production systems with defect rates of 10^{-6} being expected and achieved, human detection of defects becomes ineffective. Instead, we look for necessary precursors to error rather than error itself. If we know the mean of a process has shifted by a given amount, then we can deduce that defects will be more common, even if we find no defects. This principle of in-process Statistical Process Control is widely used, but often misused, in manufacturing (Kelly & Drury, 2002). In addition to "variables" inspection, the industrial quality control function, there has traditionally been "attributes" inspection to detect and remove items with discrete blemishes or defects from the production stream. Here, the human, who may be aided by rather simple visual tools, is used as the detector and decision maker (e.g., Kleiner & Drury, 1992, for jet engine roller bearings). Drury and Sinclair (1983) studied this same task to test an automated system for detecting visual defects, finding that neither unaided humans nor total automation was effective.

However, the capabilities of automation are constantly improving, so that the study of hybrid systems, potentially combining the best aspects of human visual inspection and automation, is appropriate. Hou, Lin, and Drury (1993) found that the combined attributes of humans, sensors, and computers typically yield better performance than any single "component." Perhaps visual inspection as a human task, even in mass production, is changing rather than disappearing.

With the rise of human factors/ergonomics (HFE) came the study of not just how well people can perform visual inspection tasks, but how their roles in the system could be modeled to predict performance during systems design. Studies of industrial inspection were undertaken for a variety of products, combining detailed observations and interviews with measurements of defect detection performance, a tradition that continues today (See, 2015). The two theories most widely used in inspection are visual search theory and signal detection theory. The insights from these theories proved beneficial as they combined aspects of speed and accuracy (or productivity and reliability) into a single model (Drury, 1975). This combined search-plus-decision model, which focuses on the two most complex steps in the inspection process (Figure 1), was found to be a powerful predictor of overall performance, even in later applications to airport baggage screening (Drury, Ghylin, & Scwanninger, 2007). Across 11 data sets, the model fit for both hits and false alarms was greater than $r = 0.8$ in all but one case.

Does this mean human visual inspection need no longer be studied? Perhaps not. Industrial production is not the only use of inspection, and it may be limited to special tasks such as surface finish on automobiles (Lloyd, Boyce, Ferzacca, Eklund, & He, 2000). Modern imaging systems allow visual inspection using non-visual wavelengths, and even ultrasound images, as in nondestructive inspection of composite structures in aircraft. Not only can we use novel energy sensing, but we can transmit images remotely and rapidly to allow for physical decoupling of the inspector from the item inspected. This approach applies to medical images, security images, and the problem of continuing in-service inspection of a variety of systems such as aircraft. All require HFE input if the best use is to be made of the unique capabilities of the human as inspector. Specifically, the human search process must often be aided with visual image processing, as search is the component of inspection least likely to achieve high levels of success. Finally, as Drury (2009) has noted, the whole field of auditing is merely inspection applied to systems. HFE continues to have a vital role in visual inspection and must remain involved.

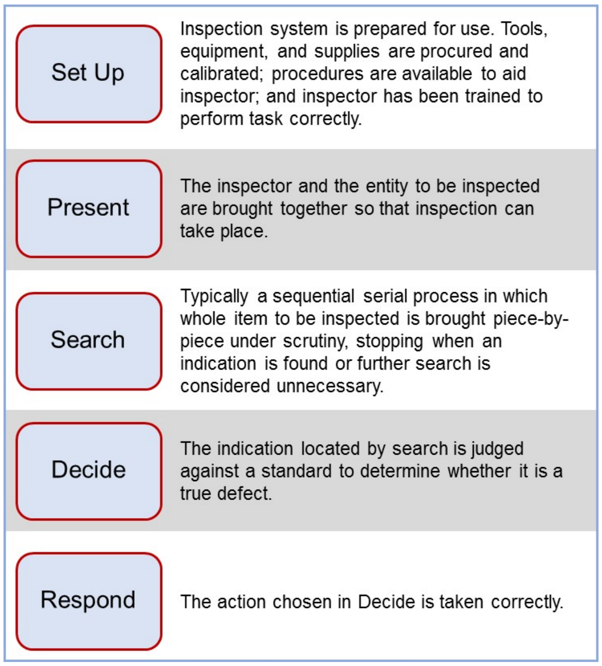

Figure 1. Inspection process. Search and decide are the most complex steps in the process.

Visual search in airport baggage screening
Ann Speed

Since 2009, my team and I have conducted experiments for the Transportation Security Administration (TSA) to understand the impact of different factors on Transportation Security Officer (TSO) decision making, primarily at the X-Ray duty station. Over the course of seven studies focused on X-Ray baggage screening, we have collected data from more than 1000 TSOs at 10 different airports (see Speed et al., 2015). We also conducted a detailed review of several decades of empirical work on X-Ray decision making led by the Federal Aviation Administration (FAA), Department of Homeland Security (DHS), and the TSA.

One theme that has emerged from this work is the importance of closely mirroring live checkpoint conditions in our experiments, an approach I call a "near operational" environment. This approach requires considerable effort, but is important for two reasons. First, we want to understand the checkpoint environment and avoid assuming that certain characteristics of the checkpoint (e.g., the noise) do or do not influence TSO threat detection without actually testing, or controlling for, those factors. Second, we want to ensure that study results are not summarily dismissed due to poor face validity. Many TSA decision makers came from TSO checkpoint positions; thus, they have an intuition for factors that impact their decisions. We honor those intuitions by attending to constraints in the operational environment and including such characteristics in our designs as best we can. As a result, the TSA is more willing to believe results that may counter their intuitions.

As an example of this approach, in later studies, we created custom software that emulates the look, feel, and functionality of the checkpoint X-Ray system. We locate computers with this emulator at checkpoints in order to capture the effects of checkpoint noise and chaos. This software uses X-Ray images of mock passenger bags, created for us by the TSA to mimic the "stream of commerce"—the composition and numbers of bags, contents, and threat items.

Another theme that has emerged from our work is the large contribution of individual differences to variability in TSO threat detection, which often far overshadows the effects from any manipulated variables. As a result, we have looked for proxy tasks in open peer-reviewed literature to identify people who may excel at the X-Ray task (Matzen, Haass, McNamara, Stevens-Adams, & McMichael, 2015). Proxy tasks include standards from the visual attention/visual search world such as the "TL" and "OQ" visual search tasks, spatial reasoning tasks such as mental rotation and the Group Embedded Figures Test (Witkin, Oltman, Raskin, & Karp, 1971), measures of general intelligence (a variant of Raven's Progressive Matrices) (Matzen et al., 2010), and even visual acuity tests such as the Early Treatment Diabetic Retinopathy Study (ETDRS) test. We have also explored numerous standard demographic variables such as age and gender. To date, we have not found a test or group of tests that explains more than 4% of the variance in accuracy for baggage search tasks in any reasonable sample size.

Visual inspection in high-consequence production
Allison Williams

Nondestructive testing (NDT) methods in low-throughput high-consequence production operations such as nuclear weapons assembly and disassembly rely heavily on human visual inspection. Upon receipt from the manufacturer; cables, critical components, tools, and equipment used in these operations undergo some level of visual inspection before each use to verify quality and functionality. Additionally, NDT methods such as radiography, magnetic particle, and liquid penetrant testing rely on human-led visual inspection. Liquid penetrant testing involves visual observation and interpretation of surface defects. At the Pantex Plant, penetrant testing is used to inspect weapon components, high explosives, tooling used to machine high explosives, hooks used on facility hoists, and other maintenance equipment. Penetrant testing is one of the most sensitive methods used to detect surface discontinuities in a wide variety of materials and can be performed quickly with relatively inexpensive equipment (Moore, 2016). However, recent studies show relatively poor detections around 50% (Stephens, 2000).

HFE has a key role in the reliability of liquid penetrant testing. Visual acuity, external work environment factors, and training are important during interpretation of test results. Visual acuity, defined as the ability to recognize a certain object, depends on five factors: contrast of the luminance between the object and its background, adaptation of the eye to lighting changes, object dimension, object presentation time, and probability of recognizing the object (Stadthaus, 1997). Visual acuity and various eye conditions can affect inspector performance (Stadthaus, Michalski, & Kaiser, 1976). Although most conditions can be corrected with lenses, changes in the eye at the age of 55 cannot likely be corrected to the extent of supporting adequate visual inspection (Stadthaus, Michalski, & Kaiser, 1976).

External work environment factors are also important in visual inspection. As previously stated, object presentation time is one factor affecting visual acuity and, therefore, visual inspection. Time pressure and excessive time on shift decrease the quality of visual inspection (Bainbridge, 2002); however, there is a tradeoff associated with inspection time. Too little time for inspection leads to missed defects, while too much time leads to false alarms (See, 2015). For continuous visual inspection, a limit of two hours is recommended to prevent degradations due to vigilance effects (Bainbridge, 2002). Unrealistic inspection criteria can negatively impact inspector motivation and attitude (Larson, 2002). Therefore, inspection specifications should provide clear accept/reject criteria.

Finally, training and familiarity with the parts for inspection enhance quality. NDT training focuses on the methods for applying and interpreting the test. In liquid penetrant testing, inspectors must be trained to recognize a particular defect in order to increase detections and decrease false alarms (Larson, 2002). In highly specialized high-consequence operations, impacts of defects on part functionality should also be trained to decrease the probability of false alarms (Moore, 2016).

Incorporating automation into visual inspection tasks in low-throughput operations such as those at the Pantex Plant would be ideal; however, with current capabilities, that goal is not yet practical. For example, digital radiography is becoming increasingly popular to inspect internal defects using software tools that enhance image contrast. Human-led traditional film radiography is still the current method for large components because the equipment cannot withstand the higher energies used in radiography. Semi-automated processes for liquid penetrant testing have been patented for some high-throughput operations (Mendoza, 1973; Vetterlein, Wagener, Rongen, & Sampson, 2006); however, the human still has a role in visual inspection for this NDT method. Some fully automated methods for liquid penetrant inspection have been proposed but have not yet been implemented (Popescu, Anania, Cotet, & Amza, 2013). Thus, the human continues to have a vital role in visual inspection for low-throughput high-consequence operations such as those at the Pantex Plant.

Technological aids for visual inspection
Negar Khalandi

For the purposes of our work at the Kansas City National Security Campus (KCNSC), visual inspection is used to detect defects and verify quality in four primary areas:

1. Dimensional quality
2. Surface quality
3. Correct assembly
4. Accuracy or correct operation

As demonstrated in previous research, visual inspection errors typically range from 20% to 30% (Drury & Fox, 1975). Some of the imperfections can be attributed to human error (Chi & Drury, 2001; Drury & Sheehan, 1969; George, 1963), while others are due to space limitations (Mozrall, Drury, Sharit, & Cerny, 2000). Errors can be reduced through training and practice (Koller, Drury, & Schwaninger, 2009), but cannot be eliminated entirely. Visual inspection errors in manufacturing take one of two forms—missing an existing defect or incorrectly identifying a defect that does not exist (false alarm). Misses tend to occur much more frequently than false alarms (See, 2012). Misses can lead to quality escapes, whereas false alarms can increase production costs and waste.

Given inherent human limitations during visual search and inspection, there is an opportunity to supplement inspectors with technological advances to improve overall results. Automated Optical Inspection (AOI) instruments reduce variation in inspection processes, but do not entirely eliminate error (Jalili, Dehgan, & Nourani, 2013; Lee, Ko, & Lee, 2016). Further, not all applications lend themselves well to the use of AOI. At the KCNSC, improvements in inspection of two-dimensional components and two-dimensional surfaces of three-dimensional components have occurred with AOI. However, additional maturation is needed before AOI can be confidently applied in three-dimensional applications.

Technologies such as virtual reality and augmented reality have shown promise to enhance visual inspection. Virtual reality replaces the real world with an interactive simulated world. Virtual reality and computer-aided systems have been used for many years for inspector training in large industries characterized by high throughputs, particularly aircraft inspection and airport baggage screening (See, 2012). In a simple form, eye tracking techniques are useful to support inspector training and improve subsequent performance by linking failure modes to visual search activity (e.g., the problem of “looking but not seeing”) (Muczynski & Gucma, 2013). Virtual reality training scenarios emulating aircraft inspection have led to improved search and detection performance by permitting novices to observe expert inspectors’ scanning patterns in real time (Mehta, Sadasivan, Greenstein, Gramopadhye, & Duchowski, 2005).

Augmented reality provides a real-time view of the actual physical environment and augments it with computer-generated inputs such as sound or graphics. The most popular form of augmented reality uses wearable digital eyewear such as Google Glass and Microsoft HoloLens, which frees the user’s hands for important tasks. Other modes of augmented reality include smart tablets, gloves, and work surface projection. When visual inspection is still a necessity, augmented reality can help overcome human limitations contributing to error. For example, given that human inspectors tend to perform relatively more poorly during the search portion of the visual inspection task, augmented reality can be leveraged to improve the search component and essentially eliminate it. Human inspectors can then focus more heavily on the decision-making portion of the task. Augmented reality can also be leveraged pre-inspection during assembly. For instance, augmented reality can provide haptic, visual, or audio feedback during manual assembly to communicate inaccurate assembly. In this application, object detection is used to visually verify the current assembly before continuing to the next step, providing user feedback real-time and offering a second opinion approach. This process eliminates errors at the start and prevents misses from occurring altogether during subsequent visual inspection. In fact, Boeing, BMW, and Volkswagen have demonstrated success incorporating augmented reality on the assembly line to monitor process improvements (Dillow, 2009).

Additional augmented reality usability studies need to be implemented to understand the extent of virtual assistance required for various processes. Factors such as user interface, system ease of use, and deviation from traditional visual inspection practices could impact human-machine interaction. Ultimately, the objective for augmented reality during visual inspection is to simplify the user's tasks and reduce reliance on tribal knowledge not contained in traditional work aids.

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