APPLICATION OF AUGMENTED REALITY TO DIMENSIONAL AND GEOMETRIC INSPECTION

by

Kyung H. Chung

Dissertation submitted to the Faculty of the
Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Industrial and Systems Engineering

APPROVED:

Robert C. Williges, Chair

Brian M. Kleiner

John P. Shewchuk

Deborah Hix

Jose A. Pesante-Santana

February 2002
Blacksburg, Virginia

Keywords: Virtual Environment, Augmented reality, Variable Inspection, Dimensional and Geometric Inspection

Application of Augmented Reality to Dimensional and Geometric inspection

Kyung H. Chung

ABSTRACT

Ensuring inspection performance is not a trivial design problem, because inspection is a complex and difficult task that tends to be error-prone, whether performed by human or by automated machines. Due to economical or technological reasons, human inspectors are responsible for inspection functions in many cases. Humans, however, are rarely perfect. A system of manual inspection was found to be approximately 80-90% effective, thus allowing non-confirming parts to be processed (Harris & Chaney, 1969; Drury, 1975). As the attributes of interest or the variety of products increases, the complexity of an inspection task increases. The inspection system becomes less effective because of the sensory and cognitive limitations of human inspectors. Any means that can support or aid the human inspectors is necessary to compensate for inspection difficulty.

Augmented reality offers a new approach in designing an inspection system as a means to augment the cognitive capability of inspectors. To realize the potential benefits of AR, however the design of AR-aided inspection requires a through understanding of the inspection process as well as AR technology. The cognitive demands of inspection and the capabilities of AR to aid inspectors need to be evaluated to decide when and how to use AR for a dimensional inspection.

The objectives of this study are to improve the performance of a dimensional inspection task by using AR and to develop guidelines in designing an AR-aided inspection system. The performance of four inspection methods (i.e., manual, 2D-aided, 3D-aided, and AR-aided inspections) was compared in terms of inspection time and measurement accuracy. The results suggest that AR might be an effective tool that reduces inspection time. However, the measuring accuracy was basically the same across all inspection methods. The questionnaire results showed that the AR and 3D-aided inspection conditions are preferred over the manual and 2D-aided inspection. Based on the results, four design guidelines were formed in using AR technology for a dimensional inspection.

Dedicated to my wife, Young Sun

ACKNOWLEDGMENTS

I would like to thank my committee members for their help and advice through the process of completing this dissertation. Without them, especially Dr. Williges and Dr. Shewchuk who encouraged me to work for several publications and shared valuable experiences in research with me, this study could not have been successful. I wish to thank Kelcie Bower and Jeff Snider of the Industrial and Systems Engineering Department of Virginia Tech for manufacturing the parts used in this experiment. I also wish to thank Brian Walters and Chuck Perala who helped me with the proof reading of this dissertation. Finally, I owe a debt of gratitude to my wife Young, who always has believed in me more than I have. Without her, my research career would not have been possible.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1. INTRODUCTION

The dimensional and geometric inspection designates the processes to measure the linear, angular magnitudes, or geometric characteristics of parts. The purpose of these measurements is to confirm and determine the compliance of parts with the design specifications. Examples of such attributes include length, height, depth, angle, flatness, roundness, etc. Dimensional and geometric inspection, particularly in the metalworking industry, constitutes a dominant portion of total inspection work (Farago & Curtis, 1994).

Traditional manual methods for information acquisition are often time-consuming and error-prone. The inspection tasks consist of a set of operations: studying part drawings, marking, measurements, recording values, decision, and disposition. Each operation needs different information to accomplish the inspection task. Such information can include setup instructions, tool and equipment lists, inspection procedures, measurement locations and sequence, quality standards, and disposition instructions.

Augmented reality offers a new approach to design an inspection system in which AR is used as a supplementary means or aid to support inspectors: a means to augment the cognitive capability of inspectors, a means to improve the time-shared performance, and a means to direct inspectors' attention. The spatial proximity, or closeness in space, should facilitate parallel processing between different channels (i.e., inspection parts, engineering drawings, routing sheets, etc.). It provides the potential of an effective inspection method for inspectors who conduct visual inspection to measure the dimensional properties of products. Inspectors could determine the measuring points without referring to the engineering drawings, since AR overlays the drawing onto the product to be inspected. An additional advantage is that AR allows a higher possibility of acceptance from workers, since it can be used to support workers rather than to replace them. The inspectors are able to have a freedom in using AR as a supplementary means or aid at any point in an inspection. Inspectors perform the integral part of the inspection task and AR is only used to aid the inspectors when cognitive demand is high.

Augmented Reality (AR) is a growing area in virtual environment (VE) research. A visible difference from an immersive virtual reality (VR) is that AR augments the real world scene, necessitating a user to maintain a sense of presence in the environment. Therefore, AR supplements reality, rather than completely replacing it. This characteristic of AR provides users with new possibilities unlike those of immersive VR. Because AR can help users interact with a real world environment, it has a great potential to support a wider range of tasks in manufacturing processes that transform the physical forms and properties of raw materials to value added products. Despite the potential of AR technology, little research has been performed to investigate the use of AR in manufacturing and/or inspection. The potential of AR will not be realized until several technical challenges are overcome (Azuma, 1997). Early work with AR focused on military applications. For many years, AR technology has been used for head-up displays (HUDs) and helmet mounted sights (HMS) in military aircraft and helicopters to superimpose vector graphics over the pilot's view of the real world. Recently, AR has been recognized as a promising technology for information transfer in many fields and subsequently, several frontier applications are currently being investigated. Medical, manufacturing, entertainment, and military industries have been the most popular application areas of AR technology. Bajura et al. (1992) used AR technology to superimpose an ultrasound image on the image of the patient. Physicians could apply AR for visualization and surgical training. Feiner et al. (1993) built a laser printer maintenance application, where the application was designed to show a repairman how to open the cover and remove the paper tray. In the manufacturing arena, the European Computer-Industry Research Center (ECRC) developed a visual model of an automobile engine to annotate its parts.

However, most AR research has focused on the potential applications of AR. Few studies have attempted to determine the actual performance gains possible via the use of AR technology. One AR project that investigated performance issues was Boeing's "wiring jet set" (Sims, 1994). Using a crude AR prototype, workers were able to complete a wiring task in significantly less time than with previous methods. This resulted primarily from the fact that they no longer had to look at parts lists. Despite the encouraging results, the researchers noted that the project was exploratory in nature and that it has not yet been determined how the results could translate into overall cost savings on jetliner construction.

The possibility of an AR-aided inspection was investigated by Chung, Shewchuk, & Williges (1999). They developed the AR-aided inspection that conveys measurement location and sequence data to inspectors performing thickness inspection using height measurements. The AR was used to show the inspector exactly what and where measurements must be taken on a part. The AR-aided inspection was compared with the manual inspection and the computer-aided inspections based upon two performance criteria: inspection speed and accuracy. It was found that the AR-aided inspection could reduce inspection time about 45-65 % with the same accuracy. The greatest time savings were achieved by the elimination of marking and cleaning functions. Though an AR-aid showed a very promising result, the potential benefits of AR to the dimensional inspection has not yet been fully explored. The selected task for the case study was a specific case of a thickness inspection task not requiring the manipulation of the part orientation, since all measurement points were placed on a single surface of the part to be inspected. A typical dimensional inspection task that includes multiple geometric and dimensional attributes needs to be explored to evaluate the benefits of AR technology.

OUTLINE OF RESEARCH

The design of any system should be systematic in order to optimize the performance. The benefit of the systematic approach is that it can help system designers understand what steps and functions are required to achieve the target system or goals. Practicing with this tool greatly increases the probability that the final application provides the acceptable level of quality (Drury, 1992).

The systematic design procedure consists of task analysis, function allocation, and the evaluation of system performance. The dimensional inspection task can be divided into component functions (i.e., operations) with the task analysis of visual inspection found in the literature. Information needed to support each function can then be analyzed. The possible design change of the inspection system can be evaluated by considering the cognitive demands of each function and the capability of humans.

In order to assess the effectiveness of AR technology for a dimensional and geometric inspection task, the performance differences between the manual, 2D-aided, 3D-aided, and AR-aided inspection were compared. The results obtained from these comparisons provided a discussion on which dimensional attributes are beneficial from AR as well as the overall performance change of the inspection system.

Work areas conducted to meet the research goals were as follows:

<u>Background Literature</u> [Chapter 2]

- The visual inspection studies were reviewed to identify the genetic functions and design problems of inspection systems. The models and theories related to the search and decision functions that decide the performance of inspection were reviewed in detail.
- The functional elements of dimensional and geometric inspection were identified based on the visual inspection studies. Task analysis was performed to determine task demands and the typical errors of each function.

<u>Development of an AR-Aided Dimensional Inspection System</u> [Chapter 3]

- An AR-aided inspection system was designed by using the systematic design procedure. Possible changes to support each inspection function were examined by considering when and where AR would be effective.
- Augmented reality was used as a supplementary means to aid inspectors rather than as a replacement of any function. It was expected that an AR-aided inspection would improve the reliability of the inspection function and reduce inspection time.

Experimental Method [Chapter 4]

- A 4×2×4 mixed factors design was used to evaluate the effectiveness of AR technology for dimensional and geometric inspection. Inspection Method (manual, 2D, 3D, and AR-aided inspections) was the between-subject factor, while Part Shape (prismatic and rotational parts) and Measuring Attribute (point, exact point, line, surface) were within-subjects factors.

Results and Discussion [Chapter 5 and 6]

- The overall performance differences among the manual, 2D, 3D, AR-aided inspections were compared to validate the viability of AR technology with ANOVA. Then, the differential affects of AR for part shapes and dimensional attribute were discussed. It was also discussed how AR affected the inspection functions and reduced inspection time.
- The trade-off between time and measurement accuracy was analyzed to understand the inspection strategy of the four inspection conditions. The individual differences within the same inspection conditions as well as the group differences between the different inspection methods were discussed.
- In addition, the body part discomfort and mental workload of the four inspection methods were analyzed with questionnaires. Users' preference of the inspection method was discussed based on the questionnaire results.

Conclusion [Chapter 7]

- Four design guidelines to design an effective AR-aided inspection system were developed based on the experiment results. It was intended to provide the system designers with the design guidelines of when AR is an appropriate tool to improve the performance of a dimensional and geometric inspection.

CHAPTER 2. BACKGROUND LITERATURE

Inspection can be classified into attribute and variable inspection according to the nature of the information that can be gathered by the inspectors. The attributes inspection is a measurement on nominal and ordinal scales of whether the inspected products possess the attributes or not, for example, a missing capacitor of PCB or a classification of apples according to their grades (Sinclair, 1979). Variable inspection is a measurement on interval or ratio scales where values correspond to the magnitude of measurements, for example, a length in millimeters as in dimensional inspection.

In the context of inspection, most research was done with the attribute inspection commonly called visual inspection. Studies of variable inspection appear less often in the literature. Many studies assumed that variable inspection is an obvious candidate for automation, since machines can take complex measurements and calculate the values of interest rapidly with higher accuracy (Drury, 1992).

With the present lack of research related to variable inspection, the visual inspection studies were reviewed to identify the generic functions of an inspection system. Though there is a basic difference in the type of information of interest between the attribute and variable inspections, visual inspection studies are useful to understand the design problems of the dimensional and geometric inspection, since the nature of the task is the same.

VISUAL INSPECTION

Visual inspection is the process by which an inspector examines parts to determine whether or not the parts possess the attributes of interest. The magnitudes of flaws on the parts are measured and judged cognitively by inspectors. Parts which pass inspection can move on to subsequent operations, while parts that fail inspection must be reworked, scrapped, or dealt with accordingly. A binary classification of attributes is useful for most cases of visual inspection. Items arriving at the inspection system have two outcomes, either they are conforming or nonconforming. Different industries use different names for these outcomes such as accept/reject, fitness/unfitness, good/faults, effective/defective, etc.

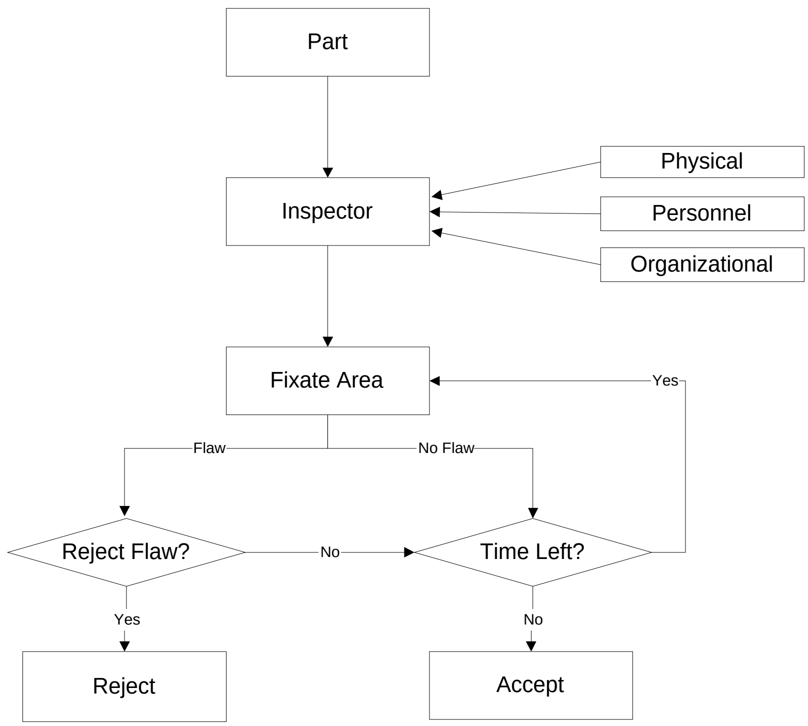


Figure 1. First-fault inspection model (Drury, 1992).

The most common type of visual inspection in manufacturing is 'first fault inspection'. Figure 1 shows a block diagram of the first fault inspection model. The first fault inspection is the process where an inspector detects any nonconformity of parts that are prevented from further processing. Only accepted parts are processed, while defected parts are scrapped or reworked. After a part is presented to the inspectors, it is searched for flaws. If a flaw is found, the part is rejected if it is judged to be outside specifications. Parts are accepted if the inspectors do not find any flaws within a certain time.

Performance Measures

Performance measurement is one of the fundamental elements of any inspection system. The ability to make sound decisions in designing an inspection system is directly related to the availability of adequate measures to determine the effectiveness of various alternatives.

Drury (1992) suggested that the inspection function must fulfill four essential characteristics: accuracy, speed, flexibility, and stability. Accuracy and speed are two essential criteria to determine the effectiveness of the inspection system. In many studies, the primary goals are the minimization of inspection time and inspection errors. Flexibility and stability are rarely used to evaluate the performance of an inspection system because they deal with the qualitative aspects of the system. However, they are also important criteria in determining the effectiveness of an inspection system. An inspection function should be flexible in detecting multiple defect types, since there might be more than a single nonconforming condition and the defect types of current interest can be changed. Finally, the inspection system should be stable and must not be changed with time. The inspection device should not require frequent recalibration and humans who are inside the inspection system should not be subjected to stress. These criteria are useful to assess the effectiveness of alternative inspection systems.

Taxonomy of Visual Inspection

Functions or activities of the inspection can be defined by considering the task demands in the system. The generic functions in the inspection task found in the literature are shown in Table 1.

TABLE 1. Taxonomies of the Visual Inspection Task.

Harris & Chaney (1969)	Drury (1992)	Hou, Lin, & Drury (1993)	Drury & Prabhu (1994)
Monitoring	Present	Present	Setup
Scanning	Search	Search	Present
Measurement	Decision	Decision	Search
	Action	Action	Decision
		Recording	Response

Drury (1992) suggested four distinctive functions for a generic visual inspection. Those four functions are present, search, decision, and action. Each function can be assigned to either a human or an automated machine, since each component can be designed independently of each other. The central elements of the four functions are search and decision-making. Search and decision functions are subject to errors with either human or automatic inspection devices (Drury, 1992). The remaining functions are largely mechanical in nature and are highly reliable. As seen in Table 1, other authors have similar lists or equivalent components that contain the same central element: search and decision.

Sinclair (1984) and Wang & Drury (1989) developed an expanded functional list with the human skills required for inspection as shown in Table 2. Their functional list is useful to relate these generic functions to the given inspection problem. Different skills and cognitive abilities are related to different inspection functions. For instance, search and decision functions depend mainly on the mental abilities of inspectors, but other functions depend on manual skills.

TABLE 2. Inspection Function and Required Human Skills (from Wang & Drury, 1989).

Function	Major Type of Skill	Mental Attributes Required
Orient the item	Manual	
Search the item	Perceptual	Attention, perception, memory
Detect a flaw	Perceptual	Detection, recognition, memory
Recognize/classify	Perceptual	Recognition, classification, memory
Describe status of the item	Perceptual	Judgment, classification, memory
Dispatch item	Manual	
Record of information about the item	Manual and perceptual	Memory

Visual Inspection Model

Drury and Prabhu (1994) conceptualized the inspection system as a sequential progression of inspection functions along with skill/rule/knowledge-based behaviors. The inspection model suggests a linear sequence of inspection functions, though there might be some branches or re-entries in practice.

As shown in Table 3, an inspector functions as low-level and high-level cognitive components in the inspection system. Skill-based behavior represents a psychomotor behavior that consists of an automated routine without conscious control. Information for skill-based behavior is the signal that may activate the automated behavior routines of humans (Rasmussen, 1983). Rule-based behavior represents a conscious goal-oriented behavior guided by rules and procedures for action. The information for rule-based behaviors is a sign that depicts situations or environments. Knowledge-based behavior represents goal-oriented, problem-solving behavior in unfamiliar situations. It requires a functional understanding of the system, analysis of the current state, and advance reasoning while using feedback control for error correction. During knowledge-based behavior, the human perceives information as a symbol that can be used for reasoning.

TABLE 3. Three Levels of Cognitive Skills for Inspection Functions (modified from Drury & Prabhu, 1994).

	Setup	Present	Search	Decision	Response
Skill Level	Follow routine procedure	Present to inspector	Successively fixate areas	Immediate decision	Take action on item and process
Rule Level	Adjust to setup to current conditions		Decide on search plan	Follow rules on measurement and classification	
Know-ledge Level	Change setup rules for device		Optimize search plan	Optimize rule for current situation	

Reason (1990) identifies errors associated with these behaviors as skill-based slips, rule-based mistakes, and knowledge-based mistakes. Slips are the failure to implement the intended action correctly, while mistakes are the failure to form correct intentions. Table 4 shows common errors that could occur at each function. Reducing inspection errors at each function by using human factors' techniques has been the primary objective of many studies.

TABLE 4. Inspection Functions and Common Errors (from Drury and Prabhu, 1994).

Function	Functional Goal	Errors Types
Setup	Calibrate inspection system	Incorrect equipment
		Non-working equipment
		Incorrect calibration
		Incorrect system knowledge
Present	Present item to inspection system	Wrong item presented
		Item miss-presented
		Item damaged by presentation
Search	Detect and locate all possible non conformities	Indication missed
		False indication detected
		Indication miss-located
		Indication forgotten before decision
Decision	Measure and classify all indications located by search	Indication incorrectly measured
		Indication incorrectly classified
		Wrong outcome decision
		Indication not processed
Respond	Act correctly specified by decision	Non-conforming action taken on conforming item
		Conforming action taken on non-conforming item

The inspection model suggested by Drury and Prabhu (1994) provides a useful framework in understanding the required cognitive skills and logical errors of the five inspection functions.

Setup

During setup, the measurement devices, decision aids, and recording devices are prepared, checked, and calibrated. At the skill-based level, a sequence of psychomotor skills is used to check the inspection system according to a predetermined procedure. Possible errors at the skill-based level are repetition, reverse, and omission (Hollnagel, 1989). Checklists are useful as job aids to prevent errors at the skill-based level.

Rule-based behavior is a change of setup according to different products or process conditions. The setup of the inspection system is adjusted to accommodate the current situation. Errors occur when an inspector misapplies rules within multiple conditions.

Knowledge-based reasoning is rarely required at a setup. However, it can occur if new products are introduced, the current inspection system is changed, or a diagnosis of the inspection device is required. Errors occur if an inspector fails to understand the new inspection product, process, or device. This type of error is common in the process control (Moray, Lootseen, & Pajak, 1986).

Present

Though the present is typically a machine function, it can be manually given to the inspector if automation is not practical. It requires psychomotor skills for picking up, orientation, placing, and disposing. The reliability of this function is high, with errors due to either misperception of the orientation, or slips in the manual-handling (Holding, 1981). A standardization of inspection tasks and training in manual skills can improve the reliability of this function (Salvendy & Seymore, 1973; Kleiner & Drury, 1993).

Search

Visual search is a cognitive behavior driven by the selective attentions with which humans seek information and search targets (Wickens & Hollands, 1999). Visual search is a sequential process that proceeds as a series of fixations linked by eye movements, terminating upon successful detection of a target in the visual field (Drury, 1992). In the inspectors' field of view, a target is only visible within a small region of the visual field, which perceives the detail.

The amount of information that can be extracted over time is determined by a useful field of view (UFOV) and a dwell time. A UFOV is the circular area around the fixation point from which information is extracted (Mackworth, 1976). Dwell time is how long the eye is fixated on the location. The difficulty of information extraction affects the dwell time. Dwell time increases while reading unfamiliar words or a more difficult context (McConkie, 1983). Displays that are less legible or contain denser information require a longer dwell time (Mackworth, 1976). Harris & Christhif (1980) found that pilots fixated longer on critical instruments than subsidiary instruments. In a target search task, Kundel & Nodine (1978) found that an inspector used a shorter survey dwell to locate targets, and a longer examination dwell for a detailed examination of targets.

One of the main interests of many studies was to develop a visual search model that determines the time to detect targets and the probability of detecting targets in a given period of time. Drury (1992) investigated the visual search model that assumes a random search to predict the time it takes to detect a flaw in the sheet metal inspection.

According to the model, the probability of detection (p_t) is the function of mean inspection time, as shown in the following equation:

$$p_t = 1 - \exp\left(-\frac{t}{\bar{t}}\right)$$

$$\bar{t} = \frac{t_0 A}{apn}$$

Where $\bar{t}$: Mean search time

t_0: Average time for one fixation

A: Area of object searched

a: Area of the UFOV

p: Probability that the target is detected if it is fixated

n: Number of targets on the part

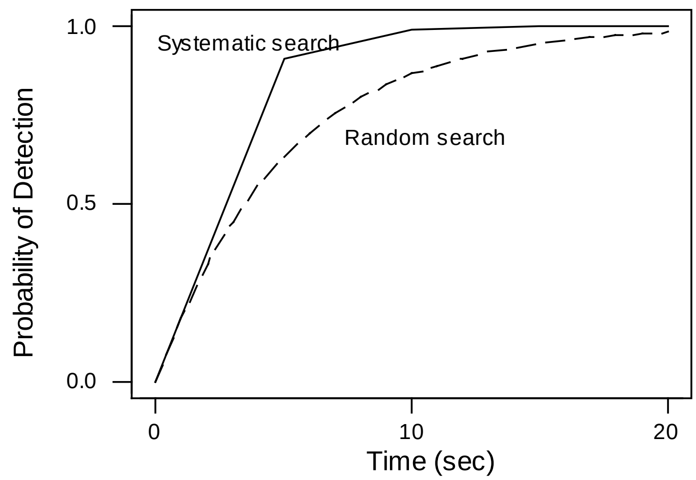


Figure 2. Search time distribution (Drury & Prabhu, 1994).

The relationship between the probability of detection and time can be seen in Figure 2. The model predicts that the probability of locating targets increases with more search time. The probability of locating targets increases at a diminishing rate because a target may be fixated upon more than once without being detected, and search strategies do not cover the whole field even though enough time is given. The model implies that the inspection time can be determined by the cost of the time and the cost of misses. With the search model, Drury (1992) could determine the optimal inspection time with the given probability of fault ratio and desired overall accuracy. Industrial applications of the model showed that search time varies according to the difficulty of the search. The average search time varied from 0.7 to 2.5 sec. for easy flaws, and 1.5 to 8.5 sec for difficult flaws (Drury, 1992). This result implies that search time can be shortened if the conspicuity of a target is increased against the background. Conspicuity is defined as the amount of parts searched in a unit time.

A search pattern is assumed by either a fixed systematic process or a random process (Morawski, Drury, & Karwan, 1980). A target search is described as a free field search in which an inspector locates a target randomly. On the other hand, a systematic search in which an inspector scans the whole inspection area in a systematic manner could reduce inspection time, as shown in Figure 2. Each fixation is only placed in unsearched areas in a systematic search. The eye movement study showed that the search pattern depends on tasks. For example, a random search is used for the circuit board inspection, while the combination of a systematic search and a random search is used for the knitwear inspection (Megaw, 1979).

To a large extent, a visual search is a skill-based behavior. Experienced inspectors perform a visual search automatically without any cognitive effort (Drury Prabhu, 1994). Errors at the skill-based level are failures to detect a target or detection of a non-target as a target. As shown in the search model, the size of UFOV influences both the probability of detection and the search time. It was found that several factors have influences on the UFOV: lighting conditions (Blackwell, 1970), conspicuity of the target against the background (Chaney & Teel, 1967), the size of the flaw, the distance between the flaw and the eyes of the inspector (Overington, 1973), aging (Ball, Beard, Roenker, Miller, & Griggs, 1988; Scialfa, Kline, & Lyman, 1987), training (Ball et al., 1988), and task demand in the fovea region (Williams, 1989). Often the simple positioning of lights or the changing of viewing angles can enhance the detectibility of a particular flaw. Colored lights have proven to be helpful in the color matching inspection (Kantowitz & Sorkin, 1983). The elderly take smaller UFOV from the scene and scan samples slower than the young, but training can enlarge UFOV and all age groups can benefit from training. Also, adequate time breaks or rest time prevents the decrease of the sensitivity of the system.

Errors at the rule-based level occur if an inspector uses a search plan that does not lead to the target. Knowledge-based behavior is related to the search strategy which determines the search plan and search time (Schoonhard, Gould, & Miller, 1973). Errors at this level consist of: neglecting target areas and stopping a search too early. Humans do not search an entire area in exhaustive fashion and can miss targets within the UFOV (Abernethy, 1988; Kundel & Nodine, 1978). A target search is driven by the expectancy of where a target is likely to be found (Wickens & Hollands, 1999). For instance, an inspector often searches a certain location first based on prior experience concerning the likelihood of a target being there. This cognitive characteristic of visual scanning behaviors has been used to account for differences between novices and experts. The expert examines first and more closely those areas where targets are likely to appear, while the novice tends to search whole area evenly (Kundel & Lafollette, 1972).

Decision

The decision component of various inspection tasks was examined by many studies (Adam, 1975; Craig & Colquhoun, 1975; Drury, 1975; Drury & Prabhu, 1994; Hou et al., 1993). These studies modeled the decision function, which has four outcomes associated with probabilities. Correct decisions are correct accept (accept a conforming item) and hit (reject a nonconforming item), while errors are miss (accept a nonconforming item) and false alarm (reject a conforming item). These two errors are often called type II and type I errors, respectively. The probability of these four outcomes are defined as follows:

p_1: Probability of accepting a conforming item

p_2: Probability of rejecting a nonconforming item

$1-p_1$: Probability of accepting a nonconforming item (Type II error)

$1-p_2$: Probability of rejecting a conforming item (Type I error)

p': Actual defect rate of an item

Average values of p_1 are around 0.90 to 0.99, while average values of p_2 are around 0.80 to 0.90 depending on industries (Sinclair, 1984). A useful measure to evaluate the inspection performance is the effective fraction nonconforming (p'_e) that is the probability of total rejected parts. If the inspection system is perfect, p'_e is equal to the actual defect rate of the item (p').

$$p'_e = (1 - p_1) - p'(1 - p_1 - p_2)$$

These measures can be used to evaluate and diagnose the inspection system. Also, they can be used to evaluate the system design process to ensure that a new design fulfills its objectives.

TABLE 5. Attributes and Probability of Inspection Outcomes (from Drury, 1992).

Inspection Decision	True State of Item		Total
	Conforming	Nonconforming	
Accept	Correct accept	Miss	
	$p_1(1-p')$	$(1-p_2)p'$	$p_1+p'(1-p_1-p_2)'$
	a	$-b$	
Reject	False alarm	Hit	
	$(1-p_1)(1-p')$	p_2p'	$(1-p_1)-p'(1-p_1-p_2)$
	$-c$	d	
Total	$1-p'$	p'	1

As the four outcomes can be associated with the probabilities, these outcomes can also be associated with costs ($-b$, $-c$) and rewards (a, d). Table 5 includes a payoff matrix which shows the cost and reward structure of inspection.

Signal detection theory (SDT) is useful in understanding the decision process and optimization of the expected payoff. In SDT, inspectors may be described in terms of their response bias. Risky responders detect most nonconforming items (i.e., hits) but produce many false alarms, while conservative responders make few false alarms but miss many of the non-conforming items. Signal detection theory is able to prescribe how to determine the optimal response bias in a given condition as related to the probability and payoff matrix of the four outcomes (Green & Swets, 1988; Swets & Pickett, 1982). The decision can be optimized by controlling p_1 and p_2 which an inspector adjusts according to the payoff matrix.

The signal detection theory explains that p_1 and p_2 vary in two ways. If the inspector and the task are kept constant, the inspector shifts the response bias so that the probability of accepting a conforming item (p_1) increases while the probability of rejecting a nonconforming item (p_2) decreases. The balance between p_1 and p_2 depends on payoffs and a nonconforming rate (p'). The changes to the inspectors or tasks increase both p_1 and p_2 by influencing the inspectors' discriminability between conforming and nonconforming items (Drury & Prabhu, 1994).

Signal detection theory explains that inspectors' perception of the costs of making an error is important in adjusting the decision criterion to an appropriate level. The actual value of the decision criterion (β) can be computed from the probabilities of hits and false alarms. Laboratory (Chi, 1990) and field studies (Drury & Addison, 1973) showed that inspectors modified their decision criterion toward the optimal level. However, another laboratory study suggested that the adjustment of a decision criterion is less than the optimal level (Wickens & Hollands, 1999). The sluggish beta (β) is more pronounced when beta is manipulated by probabilities than by payoffs (Green & Swets, 1988). The sluggish beta phenomenon has been demonstrated clearly in the laboratory, where precise probabilities and the payoff matrix can be specified to inspectors. The sluggish beta phenomenon in the field study was reported by Harris & Chaney (1969). They reported that inspectors failed to lower beta when the defect rate fell below 5% in a Kodak plant. This sluggishness is explained by the humans' misperception of probability. People tend to overestimate the probability of very rare events, while underestimating the probability of very frequent events (Sheridan & Ferrell, 1974).

Several studies tried to apply incentive schemes to inspection, because early studies found that the reward structure was a determining factor of the balance between type I and type II errors. In laboratory experiments, the reward structure based on type I and II errors changed the performance as expected. However, there is little evidence from industry that incentives based on the type I and II errors are effective (Drury, 1992). Incentive schemes provide rewards for inspectors as well as feedback on performance. It was found that the rapid feedback of inspectors' performance reduced type I and type II errors (Drury & Addison, 1973; Wiener, 1984; Micalizzi & Goldburg, 1989). These studies suggest that the feedback may be the most effective way to control inspection performance.

Feedforward information, detailed information about incoming material minute-by-minute, can influence the response bias. In the laboratory experiment, inspectors could control p_1 and p_2 according to the true defect rates (Wiener, 1984). Feedforward information was also effective for a multi-defects inspection task (Drury, 1990).

Signal detection theory makes a conceptual distinction between the response bias and the inspectors' sensitivity, the resolution of the detection mechanism. For most situations, sensitivity varies between 0.5 and 2.0 (Swets, 1964). A departure from the optimal level results from the inspector's forgetfulness of the precise characteristics of the target. When memory aids are provided to remind the inspector what the targets are, sensitivity approaches optimal level (Wickens & Hollands, 1999). Decision errors can be reduced by providing standards for inspectors in complex inspection tasks. Given the limit standards, the decision task can be changed from absolute judgment to a more accurate comparative judgment. Photographs of typical defects can reduce inconsistency between inspectors and prevent a drift of decision criteria over time. Limit standards could act as memory aids which remind the inspector of what the defects are (Harris & Chaney, 1969; Kelley, 1955).

The decision function can be an automatic process in the case of severity or the absence of any defects, because the decision becomes trivial and skill based. For instance, missing components in assembly will automatically trigger a rejection response. Errors for rule-based behaviors are slip errors, since misses and false alarms are failures to implement the intended action correctly. In general, however, a decision is mainly rule-based behavior. Inspectors make a decision based on rules which are passed on by job experience from senior inspectors or written documents. Errors can be due to misapplying the rules. Drury & Sinclair (1983) provided a typical example in roller bearing inspection tasks where inspectors misapplied rules because of the confusion of defect names. Rule-based decisions can be improved by training and job aids for complex rules (Kleiner & Drury, 1993).

Knowledge-based decisions can be improved if inspectors have accurate information about the costs of false alarms and misses. Inspectors can form an optimal strategy that maximizes the expected values across the decision outcomes (McNichol, 1990). Knowledge about defect types and their probable occurrence rate (Sheehan and Drury, 1973) and performance feedback (Drury and Addison, 1973) can improve the reliability of decision.

Respond

When a defective item is removed from the production system, the inspector needs to record the data related to the action taken. Only skill-level behaviors are required for response, and errors are slips rather than mistakes. To improve the reliability of the respond function, human factors principles can be applied to workplace design. Within the three-dimensional envelope of a workplace, specific design decisions need to be made by considering the inspection task. The horizontal work surface areas to be used by seated or sit-stand inspectors should provide for manual activities to be within a convenient arm's reach (Barnes, 1963). Enough space should be left for rejected items to be stored, so as not to discourage a rejection response because of a tiring action. Data recordings might be more reliable if the automated data capture is achieved.

DIMENSIONAL AND GEOMETRIC INSPECTION

Dimensional and geometric inspection is closely related to visual inspection. The nature of the task and the function in the manufacturing system are almost identical. However, the dimensional and geometric inspection can be differentiated from the visual inspection in three aspects.

First, dimensional and geometric inspection is interested in the variable, the real number representing the measurement. Since the dimensional and geometric inspection uses quantitative data, the decision function becomes highly reliable with a computer. In terms of function allocation, the decision function is an obvious candidate for automation.

Second, the existence and location of targets (i.e. flaws) are not known in visual inspection, while the existence and location of targets (i.e., measuring dimensions) are known in the dimensional and geometric inspection.

Third, dimensional and geometric inspection has no time limit. Inspection is continued until all the dimensions of interest are measured. Inspection time is the criterion that determines the performance level of the inspection system rather than constraints. On the other hand, Drury's first-fault model (1992) includes time constraints. If a critical flaw is not found in the given time, it is assumed the part is conforming.

The inspection process of a generic dimensional and geometric inspection can be depicted as shown in Figure 3. Though the inspection process is different from visual inspection to determine defects, the inspection process can be conceptualized from a first-fault model where any nonconformity (e.g., out of tolerance) of a part prevents that part from being processed further. The part is removed from the inspection system as soon as any nonconformity is found without any more effort to find another nonconformity. If any attribute is out of tolerance, the parts will be scraped or sent back for rework. This diagram model will be used as the basis to design an AR-aided dimensional inspection system.

In the case of variable inspection, measurement variation often becomes one of the most important criteria in determining the performance of the inspection system along with inspection time. It was known that distributions of measurement variation are often approximated by normal distribution. The true distribution can be compromised by bias and imprecision (Mei, Case, & Schmidt, 1975). If the inspection error is independent of the value of the product measurement, the average measurement variation is determined by the average bias and average imprecision. The measurement of bias and imprecision is rarely reported in the inspection literature because the results depend on the characteristics of products measured and the measuring instrument (Drury, 1982). With the improvement of precision in the measuring instrument, the reliability of the measurement function can be improved.

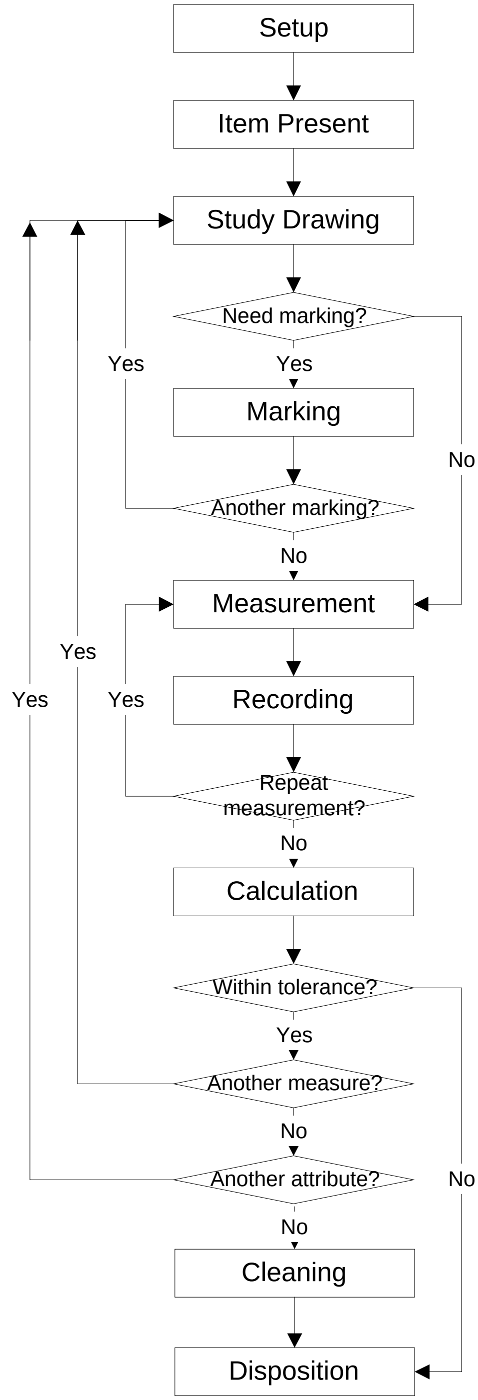


Figure 3. Dimensional and geometric inspection model.

Structured Search

There are two different types of visual sampling behaviors in the literature: visual sampling of unknown targets and of known targets. The visual sampling behavior of unknown targets has been studied in the context of the visual inspection of flaws, such as a flaw on a piece of sheet metal. Inspectors scan the intended areas or objects to detect the target of which the existence and location are unknown. The search is driven by cognitive factors related to the expectancy of where a target is, and the visual search pattern becomes less structured than that of known targets. The visual search model of unknown targets proposed by Drury (1975) is often called free field search or visual search.

The search model of known targets in which the visual sampling is guided by the expected events among different channels is called structured search (Wickens & Hollands, 1999). The search pattern of the dimensional inspection is very similar to the structured search, where inspectors determine the measuring dimensions according to engineering drawings in the dimensional and geometric inspection. Unfortunately, however, research on the search model of dimensional and geometric inspection (i.e., study drawing: selecting a dimension of interest on engineering drawings by referring to inspection reports) is not found in the literature.

The visual sampling behavior of known targets has been studied in supervisory control. The operator scans the various displays and allocates attention to them through the structured visual sampling. The probability of missing an event is directly related to event frequency and uncertainty. Frequent events are more likely to be missed, as they are not sampled, or the timing of events is uncertain. According to Wickens & Hollands (1999), humans use a mental model of the statistic properties of the events (how frequently and when the event will occur) to guide a visual sampling. However, the sampling rate is not adjusted enough for frequent and rare events as much as it should be as seen in the sluggish beta phenomenon. This imperfect sampling is explained by imperfect memory: humans tend to oversample the rare events because of forgetfulness. The general findings of the visual sampling studies are well summarized by Moray (1986).

Structured visual sampling behaviors have also been applied to the design of computer-based menu systems (Somberg, 1987). The basic concept is to structure the menu in such a way that the target can be found in the minimum time. The linear visual search model (Neisser, 1963) was used to determine the search time. These studies could provide a useful understanding of the structured search, though they could not succeed in developing a model that can predict the exact search time.

Since information or cueing can be used to guide in the structured search, it is possible to direct an inspector's attention to appropriate areas. It appears that cues can direct the spotlight of attentions and the correct cueing reduces errors. Cueing increases the sensitivity to a target location and results in fewer errors (Kinchla, 1992; Downing, 1988).

Augmented reality can influence the structured visual sampling behaviors via directing attention and spatial proximity. The effectiveness of intelligent cueing which directs the users' attention to a certain target in the see-through HMDs is investigated by Yeh, Wickens, & Seagull (1998). The finding was that cueing reduces target detection time for expected targets, but increases detection time and the number of errors for unexpected targets. When the cue was unreliable, it directed attention to unwanted objects (Downing, 1988). These results imply that intelligent cueing can be effective for various tasks, but that humans might depend too heavily on the cues.

The benefits of spatial proximity have also been proven in driving and aviation applications using head-up displays (HUDs). Goesch (1990) found that an automobile HUD could facilitate the parallel processing between two channels by superimposing a view of a speedometer on a view of a road. Sojourner & Antin (1990) compared driver performance between HUDs and head-down displays to find that HUDs have an advantage for detecting cues presented in the road sign. In aviation applications, a HUD could improve the control of positioning during landing when the view and runway were obscured by clouds (Wickens & Long, 1995). Martin-Emerson & Wickens (1977) also reported that the alignment of the display object to the real object helped the human divide attention and reduce the tracking error. However, some experimental data suggests that spatial proximity will not always guarantee parallel processing (Becklen & Cervone, 1983; Neisser & Becklen, 1975). Neisser & Becklen (1975) conducted experiments on whether or not subjects can detect the critical events on the two games in which one is superimposed over the other. They found that subjects had difficulty when detecting events in the two games at once, and failed to see unusual events in one game while monitoring the other game. Similar results were observed in aviation (Goesch, 1990; Steenblik, 1989). When a HUD was used to facilitate the simultaneous processing of inside and outside information in the cockpit, a pilot might treat the two distances as different attention channels. The pilot's cognition became occupied in processing information on the HUD while ignoring critical cues from outside the aircraft. Also, Wickens & Long (1995) reported that an unexpected obstacle was more poorly detected with the HUD than without it. The HUD facilitates the parallel processing of scenes and symbology when the pilot expects the stimulus.

Another factor affecting the spatial proximity is the conformal nature of symbology, the correspondence between objects and the position of the objects as related to the real world (Wickens & Long, 1995). It was found that the alignment of the display object to the real object helped the pilot divide attention between the display and the scene of the world, and thus reduce tracking error (Martin-Emerson & Wickens, 1977). In AR studies, this is often called a registration problem of virtual objects.

Although spatial proximity may allow parallel processing, it also imposes the potential for confusion between the scenes momentarily wanted and those momentarily unwanted. Several studies have found that subjects failed to focus attention because of this confusion (Wickens & Andre, 1990; Holahan, Culler, & Wilcox, 1978). The critical variable in predicting performance is the degree of spatial separation of irrelevant items in the field of view. Separation might be defined by not only the difference of the visual location, but also by the nature of the perceived activity. If two perceptual channels are close together, they will both be processed, even if only one is desired. If the implication for action is incompatible, intrusion/distraction would increase. On the other hand, if both have common implications for action, perceptual competition would be minimized between the two channels. Many failures occur when divided attention is mandatory rather than optional. Parallel processing will help a task performance only if the task requires parallel processing.

Taxonomy of Dimensional and Geometric Inspection

In the context of dimensional and geometric inspection, the taxonomy of inspection has not been differentiated from that of visual inspection in the literature. However, a useful list of dimensional inspection functions is found in a coordinate measuring machine (CMM) and an automated visual inspection system (AVIS). The functions of the automated inspection system provide useful insight in identifying the functional list of dimensional and geometric inspection, since automated inspection must logically fulfill all of the inspection functions (Farago & Curtis, 1994). Though the functions do not represent the natural breakdown for dimensional inspection, a compatible functional list of CMM, AVIS, and visual inspection are useful in identifying the functions of dimensional inspections, as seen in Table 6.

TABLE 6. Relationship Between Automated and Human Functions.

CMM	AVIS	Visual Inspection	Dimensional Inspection
Object Handling	Object Handling	Present	Present
Probing	Scanning	Search	Study Drawing
Computer	Signal Processing Computer	Decision	Measurement Calculation Decision
Object Handling	Object Handling	Response	Response

Human functions found in the inspection literature are still valid for the automated inspection (Harlow, Henderson, Rayfield, Johnston, & Dwyer, 1975) and the dimensional and geometric inspection. However, there are basic differences between visual inspection and dimensional inspection in search and decision functions.

For dimensional and geometric inspection, search corresponds to study drawing, while decision function needs to be classified into measurement, calculation and decision since each one requires different cognitive and motor skills in order to complete the inspection task. In the flaw inspection, the magnitude of flaws is measured and judged cognitively by inspectors, and the cognitive measurement is included in the part of decision function. On the other hand, dimensional inspection requires an actual measurement of the magnitude with measuring devices. After the measurements, an average value of the measured dimensions needs to be calculated to decide the disposition of parts. Measurement and calculation become distinctive components of decision in dimensional inspection. Marking and cleaning are supportive functions for measurement. Not every dimensional inspection necessarily includes all of these functions. Marking and cleaning functions are not required when the exact measuring point is not critical in the measurements of the attribute.

As a result, eight functions can be identified, as shown in Table 7. The eight functions include present, study drawing, marking, measurement, recording, decision, cleaning, and disposition. It is necessary that the designers should understand how AR influences the performances of various inspection functions to realize the potential of AR. The usefulness of AR can be determined by considering if AR is an effective tool to support the cognitive demands for each function. Table 7 shows required physical skills and cognitive resources to perform each function. The list of logical errors is also very useful, since system designers determine which errors occur and when they occur. Reducing inspection errors at each function should be one of the primary objectives of this study through the systematic design process. The compensation of the inspection error results in a redesign of the inspection system by considering the capability of human inspectors and the required cognitive abilities of each function.

TABLE 7. Functions, Required Skills and Logical Errors of Dimensional Inspection.

Function	Required Resources	Logical Errors	AR Aids
Present	Manual	Wrong item presented	
		Item miss-presented	
		Item damaged by presentation	
Study Drawing	Perception	Confusion on measuring attributes	×
	Attention	Miss attributes of interest	×
	Memory	Forget measuring attributes	×
		Forget measuring locations	×
Marking	Manual	Incorrect marking	×
	Attention	Miss marking	×
	Memory	Forget marking locations	×
Measurement	Manual	Incorrect measurement	
	Attention	Wrong read out instruments	
	Memory	Forget the measured values	
		Incorrect instrument knowledge	×
Recording	Manual	Incorrect recording	
	Memory	Incorrect calculation	×
Decision	Attention	Select wrong values	×
	Memory	Fail to recall the recorded values	×
		Decision not processed	
Cleaning	Manual	Forget to clean marked spots	×
Disposition	Manual	Wrong action for disposition	

Present, recording, and disposition are mechanical functions. Psychomotor skills, such as, setting up measuring devices, placing an item, and writing the measured value, determine the performance of these functions. Since these functions depend mainly on manual skills, AR does not support these functions.

The search pattern follows a structured or focused search (Wickens & Hollands, 1999) in which inspectors search the known target (i.e., measuring dimension) from engineering drawings. Then the inspectors locate the measuring points on the parts by referring to temporarily stored information, and measure the dimension of interest. The performance of study drawing depends largely on selective attention. For proper dimensioning, inspectors refer to engineering drawings and select only the relevant information for the current measures. Errors can be caused because of a discrepancy between the three-dimensional real parts and two-dimensional representation of the real parts. Another logical error is that inspectors might miss or become confused by the current measuring variable due to multiple measurements on various dimensions. AR can be used to highlight or direct inspector attention in determining the measuring variable. It is useful in reducing inspection time and slip errors.

Decision function performs the same role as in visual inspections for flaws. The disposition value is compared with design specifications to see if it is acceptable or not. Decision performance depends mainly on attention and memory. Errors occur when inspectors forget what the measured value was, or make mistakes in calculation. The reliability of a decision can be improved with AR aids since errors are mainly caused by forgetfulness. By providing the spatial proximity between the measured and the compared value, errors can be reduced. However, the decision is made with ratio scale data (e.g., cm, mm) rather than with nominal scale data. The decision is relatively easier than the decision-making with the nominal scale data, since it uses quantitative data. The decision functions can benefit from automation, since the decision-making algorithm can be highly reliable with the quantitative data. Since a computer is a component of the AR system, it can support data storing and mathematical calculation though those capabilities are rarely used for AR applications.

Note that marking and cleaning are not needed anymore in the AR-aided inspection system. By superimposing the measuring information over the real parts, these functions can be eliminated from the inspection task. The pilot study (Chung et al, 1999) showed that the greatest time saving was achieved by the elimination of these two operations.

Automated Inspection

With advances in sensors and computers, automated inspections are one of the logical solutions to improve the performance of inspection systems. Even in a fully automated system, humans are still required for supervisory control and monitoring in an outer loop. Inspectors are responsible for setup, calibration, and supervisory control, while machines are responsible for complex measurements and calculations in an automated inspection.

The performance of an automated inspection system can be measured with the same criteria that are used for the manual inspection. Accuracy and speed are important measures to compare the effectiveness, though the cost must be included to compare the cost-benefits of the two methods (Drury & Prabhu, 1994). Accuracy can be measured by the probability of accepting a conforming item and the probability of rejecting a nonconforming item. In the case of variable inspection, the measurement accuracy is often used to measure the performance of an inspection system. Often studies evaluate the accuracy of the inspection system by its capability to detect small defects (Hara, Okamoto, Hamada, & Akyama, 1980)

There is a scattered body of literature on AVIS. Automated visual inspection systems typically use sensors to capture images of the inspection components, image processing systems to take measurements, and objects handling systems to transport parts. However, many AVIS has failed because of the stability of environments. Several factors such as illumination levels, types of illumination, reflectivity, and contrast affect the performance of the inspection system. For instance, cloth brightness can be changed due to ambient illumination (Takatoo, Takagi, & Mori, 1989). Lighting intensity should be sufficient to nullify the interference from ambient sources.

Currently, the automated inspection of flaw detection has not provided fruitful results. The performance difference between experienced inspectors and an optical inspection device was compared with high-precision metal parts (Drury & Sinclair, 1983). Both the humans and the machines conducted search and decision on four different types of faults. It was found that human inspection was better than automated inspection in terms of false alarm and hit rates. The main finding was that the automated system was better at locating the defect (i.e., search), while the human was better at decision making. With these findings, they concluded that there is a good possibility of using machines for the searching function, while leaving the decision function to the human. In automated inspection, the relation between detection effectiveness and false alarm is not well understood. An automated inspection system can detect very small defects by increasing gain that reduces a detection threshold, but most detection devices and algorithms of the automated visual inspection system suffer from high false alarm rates (West, 1984). Defects on simple visual fields are relatively easy to detect. Difficult products to inspect are those that contain complex visual patterns such as a printed wiring board and photomasks for integrated circuits and hybrid circuits (Drury & Prabhu, 1994). Because the finding of the automated inspection studies show that neither the human nor the automated system achieved satisfactory results, inspection studies in the literature tried to optimize inspection performance by allocating inspection functions properly between humans and machines. The ground rule was to assign tasks to the human that humans excel at and assign tasks to the machine that machines excel at by considering the capabilities and limitations of each subsystem. Hou et al. (1993) designed five different inspection systems for an automotive electronic company: human inspection, computer-search human-decision, human-computer decision-sharing, and automated inspection. They designed two different hybrid inspection systems by changing the degree of function allocation between humans and machines. In a computer-search human-decision, if the computer detects defects, it shows the defects to inspectors who decide about the status of the defects. In a human-computer decision sharing, the computer performs both search and decision, but the inspector takes over the decision if the confidence level is low. The false alarm rates and hit rates were used to compare the overall system performance among these inspection systems. The result showed that the two hybrid inspection systems have a better performance than the automated inspection. The human inspection was also significantly better than the automated inspection, a result consistent with the finding of Drury & Sinclair (1983). There was no significant performance difference between the human inspection and the hybrid inspection. However, the computer-search human-decision system (0.9460) had the marginally higher sensitivity value than the human inspection (0.9457) and the human-computer decision-sharing system (0.9071).

On the other hand, an automation of variable inspection such as dimensional inspection achieved visible progresses. Two types of automated inspections have been explored in the literature of variable inspection. Bosch (1987) suggested the advantage of the CMM and electro-optic technologies in the dimensional inspection system, though the performance of these systems was not reported. One of the common industrial 3D geometric inspection methods involves tactile sensing, using CMM. The part is initially fixed in a given position in the CMM, and the location of certain points is measured. The CMM can provide a high degree of measuring accuracy. However, the CMM are slow in operation because a single touch probe is used to take many individual readings from the surface of the inspected object and inspectors have to guide the tactile probe to these measuring points. Such a machine requires detailed programming for each of the different objects. Thus, especially when small quantities of certain parts need to be inspected, the CMM becomes very time consuming and inefficient.

Some AVIS applications found in the literature are a 3D machine vision for the inspection of the surface form of cylindrical parts (Reid & Rixon, 1985) and a visual gauging system for the inspection of the dimensional location of automobile parts (Mahdvieh, 1987). Skaggs & Meyer (1985) developed an optical metrology system which can inspect various dimensions of parts, such as length, hole diameter, width, and the angle of two lines. They reported that the average inspection time for each dimension was 0.8-3.6 seconds and the measurement variation was less than 0.0003 inch. Lim, Swaminathan, Woo, Chan, & Wonh (1997) developed the automated inspection and dimensional measurement for optoelectronic components. They reported that the system was capable of measuring the dimension with an accuracy of 30 μm by using CCD cameras. However, most of AVIS can solve the limited class of dimensional inspections. Most successful applications are found in measurements that can be measured with 2D perspectives, for instance PCB, and sheet metal inspections. Because of technological limitations, many 3D vision systems often suffer from measurement accuracy (Martin, 1992). Another disadvantage of AVISs is that AVISs only can check visible features. Any feature that cannot be seen by the cameras cannot be measured.

In cases where automation is not economically viable or desirable, measurements must be done manually. In custom job shops, a manufacturing system needs high flexibility under the condition in which there are various products with a small amount of quantity. Workstations are arranged without emphasis on any particular routings, making them equally able to handle various products with different routings. With the rapidly changing characteristics of orders, highly skilled workers perform machine setup, fabrication, assembly, material handling maintenance, and inspection tasks. Between these tasks and/or during the last step, inspections are conducted to check if all dimensional and geometric attributes of the products conform to design specification. Accordingly, an inspection system needs a high degree of flexibility to deal with various products, and automation does not become a practical solution. An inspection is conducted with generic types of inspection instruments (e.g., vernier caliper) rather than with automated instruments for specific products.

Intervention Techniques

Various intervention techniques are found in the literature. Though the effectiveness of the intervention techniques was mainly tested in visual inspection, these techniques are also applicable for the dimensional inspection.

Drury (1992) suggested that the three possible design changes to improve the inspection performance are product, process, and person. Process change means the redesign of the inspection process, work place, job, etc. Procedure changes include lighting (Faulkner & Murphy, 1975), standards (Kleiner & Drury, 1993), visual or ergonomic aids (Kleiner, 1983), search strategy (Bloomfield, 1975), feedback (Drury & Addison, 1973), speed (Drury, 1979), and job enrichment (Maher, Overbach, Plamer, & Piersol, 1970).

Inspector changes are done to make the inspector fit well to the inspection system by training (Czaja & Drury, 1981; Gramophdhye, Bhagwar, Kimbler, & Greenstein, 1998) and selection (Tiffin & Roger, 1941). Training is effective and necessary, while selection is not. A major problem related to selection is that it has been difficult to devise selection or placement procedures for inspections. Several inspection tests were suggested, but the validity of these tests was not determined (Wiener, 1975). On the other hand, good standard training has proven very effective to bring novices to an experienced work standard. Studies showed that not only can a visual search be improved with the controlled practice, but also decision making and discriminability can be trained (Embrey, 1979). Kleiner & Drury (1993) showed that training could provide a performance improvement for experienced inspectors, too. Inspectors who had a job experience for 2 to 14 years could achieve a better performance with a two day training program which contains seven sections: naming of parts, naming of flaws, handling, standards, search, decision-making, and process interface.

Product change means the change of the inspected items. However, no study was found in the visual inspection literature, though examples are available in other manufacturing tasks.

The most commonly used intervention approaches were training, lighting, and visual/ergonomic aids and these approaches were very successful in various inspections. Some studies applied several intervention approaches together (Chaney & Teel, 1967; Kleiner & Drury, 1993), and their results were usually better than using any single one.

All of these intervention techniques are useful for the dimensional and geometric inspection, but the selection of intervention techniques is decided by considering application domains, tasks, parts inspected, etc.

VIRTUAL ENVIRONMENTS FOR MANUFACTURING TASKS

Virtual environment (VE) technology has been recognized as having a potential that has a wide range of applications, and there are increasing discussions of its feasibility in industrial applications. Many pioneering studies have focused on the development of brand new applications to prove the technological possibility of VE. Applications of VE technology in manufacturing are just beginning to emerge. The manufacturing industry has assessed VEs as an affordable technology that has a potentially wide range of applications (Wilson, Brown, Cobb, D'cruz, & Eastgate, 1995). Several studies showed that VE technology is a powerful means of information provision for a wide variety of manufacturing tasks (Dai, 1998; Wilson et al., 1995; Wilson, Cobb, D'Cruz, & Eastgate, 1996). These applications are directed toward using VE technology as a means of improving performance for a wide variety of manufacturing tasks involving inspection. Although relatively few manufacturing applications of VE and even fewer empirical studies that evaluate these applications exist, the potential for using VE in manufacturing is greatly based on current VE demonstrations.

Taxonomy for Virtual Environments

To discuss VEs in manufacturing in an organized manner, some type of taxonomy is required to classify the VEs. Various classification schemes of VEs have been suggested in the literature as shown in Table 8. These authors classified the taxonomy of VE according to the fidelity (Zeltzer, 1992), presence (Sheridan, 1992), and experience (Naimark, 1992; Robinett, 1992) associated with VEs. Even though they suggested quite different dimensions to classify VEs from each other, all of them tried to quantify the degree of users' perception and experience in VEs.

Zeltzer (1992) proposed the taxonomy of VEs, based on three components: autonomy, interaction, and presence. He suggested that the AIP cube can be used as a useful tool to contrast VEs, as well as graphic simulation systems. Similarly, Sheridan (1992) proposed three principle determinants of a sense of presence which are an extent of sensory information, a control of the relation of sensors environments, and the ability to modify the physical environment. He suggested that these dimensions can be represented as three orthogonal axes to determine the perceived presence in VEs. Zeltzer (1992) and Sheridan (1992) tried to classify the VEs according to the users' perception, while Naimark (1992) and Robinett (1992) tried to classify the VEs according to the physical properties of the system.

TABLE 8. Suggested Taxonomies for Virtual Environments.

Investigator	Dimension of Taxonomy	Viewpoint
Zeltzer (1992)	Autonomy	Measure of fidelity
	Interaction	
	Presence	
Sheridan (1992)	Extent of sensory information	Operational measure of presence
	Control of relation of sensors environments	
	Ability to modify physical environment	
Naimark (1991)	Monoscopic imaging	Recording and reproducing visual experience
	Stereoscopic imaging	
	Panoramics	
	Surrogate travel	
	Real-time imaging	
Robinett (1992)	Causality	Synthetic experience associated with HMD based systems
	Model source	
	Time	
	Space	
	Superposition	
	Display type	
	Sensor type	
	Action measurement type	
	Actuator type	

Milgram and Drascic (1997) suggested a taxonomy for VE representations, in which the degree of reality and virtuality is described on a reality-virtuality continuum. The four major components of this continuum include reality, augmented-reality, augmented-virtuality, and virtuality. Reality defines the environment as consisting solely of real objects observed via a video display such as telepresence using video cameras. Augmented reality is an augmented environment where computer-generated images are added to the real environment. Most augmented-reality systems are coupled with see-through head-mounted displays (HMDs) and head trackers. Task-related or analog information is provided from the computer to support the operators who are executing tasks in the real environment. The success of AR applications depends mainly on the way information is transmitted to the operators rather than the immersive feeling or fidelity in the VE. This class of applications can support tasks requiring the physical manipulation of real objects. The concept of augmented virtuality is almost the same as augmented-reality except the primary virtual environment is enhanced through some additional real world image. Augmented virtuality provides a partially immersive environment where real physical objects interact in a virtual world. An example of augmented virtuality is where a user reaches forward in the virtual world and grasps a virtual object on a VE workbench that provides a large projection screen, or in a Cave Automated Virtual Environment (CAVE) that provides a VE room. Virtuality is a completely immersed environment and is commonly referred to as virtual reality. Many applications are implemented using a HMD to provide complete immersion. The main uses of virtuality are training and applications requiring simulation that do not allow the operator to interact with real objects. The success of these applications depends on the level of immersive feeling and the degree of fidelity of the VE.

These taxonomies provide a qualitative tool for contrasting VEs, but there is no agreed classification scheme among them. The problem with using the current taxonomies is that these taxonomies are independent of one another and are very difficult to apply to the manufacturing domain.

Virtual Environment Methods

Chung, Shewchuk, & Williges (submitted) classified four VE methods for manufacturing by considering the way of information provision. The four VE methods are visualization, simulation, information provision, and telerobotics.

Visualization occurs when users navigate in a VE. Although visualization requires a 3D representation of objects in the VE, the difference between visualization and traditional 3D computer-aided design (CAD) is that visualization concentrates on the high degree of perception rather than on the pure quality of the graphic (Wilson et al., 1996). Visualization can be employed for almost all types of manufacturing tasks but is particularly well-suited for the design of manufacturing facilities and the product as well as for the planning. The process of designing and validating products via a real-time graphics system that allows the user to be immersed in and to interact with the product, is known as virtual prototyping (Dai & Göbel, 1994; Flaig & Thrainsson, 1996).

Simulation is applicable when users need to control the virtual objects and change their state in the same way as they do in the real world. Virtual objects act like real objects in response to unscripted user actions. The critical component of the VE simulation is the interaction between users and virtual objects. It requires more than realistic visualization; it also requires realistic physical behavior on the part of the virtual objects. Therefore, most VE simulations employ multi-modal displays to support realistic interaction between users and the VE. Simulation holds particular promise for training operators to execute manufacturing activities and to evaluate the design of equipment, systems, and tasks that either do not exist in the real world or for which actual usage would be impractical or cost-prohibitive.

Virtual environments can be used to guide and support users to complete their work more efficiently by means of information provision. Task-related information, such as instructions and data, can be conveyed to the users both when and where needed via VEs. Augmented reality is a useful tool for providing information for the execution of real-world tasks, because it provides the composite view of virtual and real scenes. Information-provision is particularly well-suited for aiding in controlling & monitoring. The performance enhancement can be achieved by reducing operators' workload and facilitating parallel processing.

Telerobotics is used when the user interacts with virtual or real objects in an unscripted manner. The remote environment is reconstructed by using VE to provide a sense of telepresence for operators. Virtual environment supports operators to conduct real tasks via a robot or some other electromechanical device. It is typically useful in helping to remove an operator from a hazardous environment. Telerobotics is employed for the physical processing in manufacturing.

The choice among different VE methods for a given task depends on the information requirements of the task. The manufacturing process consists of various tasks that are determined by the nature of the products to be made. Every manufacturing process, however, is comprised of planning, physical process, and control and monitoring. Six major manufacturing tasks can be identified based on functional and implementation views over the life cycle of a manufacturing process (Shewchuk, Chung, & Williges, 2002). These six major tasks are design of manufacturing tasks, design of manufacturing facilities, training, control and monitoring, planning, and physical processing activities. Since each of the six types has different information requirements, the suitable VE method for each will also differ.

Chung et al. (2002) grouped the various VE applications found in the literature according to the manufacturing task and VE methods, as shown in Table 9. This classification is useful in deciding whether a certain method is appropriate or not for a certain task in the systematic manner. Table 9 shows that there is a certain relationship between manufacturing tasks and VE methods: a certain VE method might be superior over other methods for a certain task. For example, *visualization* is a useful method for all types of manufacturing tasks except the physical processing task. On the other hand, *information provision* and *telerobotics* are useful for the physical processing tasks which require physical interaction with real objects.

TABLE 9. VE Methods for Manufacturing Tasks (from Chung et al., 2002).

Manufacturing Tasks	VE Methods			
	Visualization	Simulation	Information Provision	Telerobotics
Design of Manufacturing Tasks	4			
Design of Manufacturing Facilities	2			
Training for Manufacturing Tasks	2	4		
Planning	19	4		
Control and Monitoring	3		2	
Physical Processing			10	8
Total	30	8	12	8

Based on this framework, it was found that the information provision method is suitable for an inspection task which is included in control and monitoring tasks. Virtual environment, especially AR, is an effective means to transfer the task information for inspectors, because it allows inspectors to see both virtual and real objects together. It can help reduce operator workload and facilitate multitasking.

Chung et al. (1999) found that AR technology could enhance a visual inspection performance via directing attention and spatial proximity. They developed an AR-aided height inspection system that could provide spatial proximity between real parts and engineering drawing. Since the measuring information was superimposed on parts with AR, all the measurements can be taken without marking. The AR-aided inspection took significantly less time than the manual or computer-aided inspection in the case of a height inspection task. They compared the inspection times for three different parts which are flat, convex, and stepped parts, and found that the flat part took significantly less time than the convex or stepped parts, whereas inspection times for the convex and stepped parts were not significantly different from each other. An interesting find was that the AR-aided inspection was not influenced by the part shapes: inspection times were nearly identical over all part shapes. On the other hand, inspection times with manual and computer-aided inspections were significantly increased as part shapes become more complex. With these observations, they concluded that AR was very promising for inspection tasks, where tasks are more involved and parts much more complex.

The potential of AR has not been fully proven yet. The previous test showed the possibility only for a specific case of thickness inspection not requiring the manipulation of the part. The typical inspection task, which includes multiple dimensional attributes, should be evaluated to determine the benefits of AR.

Potential Benefits of AR

In the context of inspection, some special methods of improving search efficiency include overlays and blinking inspection. Overlays are special patterns with which the difference between the pattern and parts is enhanced by projecting the overlays over the part. Overlays were very effective for the printed circuit board (PCB) inspection task (Teel, Springer, & Sadler, 1968). Blinking inspection uses a similar method, but the difference appears to flash on and off by the rapid alternation of a perfect part and a part to be inspected. Blink inspection uses a temporal alternating of an item with a known perfect item, both items being registered on the same visual field. A difference between the two items will appear to blink, while the rest remains steady (Liuzzo & Drury, 1980). They reported a 30% reduction in error and a 60% increase in throughput using video blinking, but also negative effects such as stress and eyestrain among inspectors. These applications could achieve the performance improvement by increasing the conspicuity of targets against the background. The inspectors' sensitivity, the resolution of the detection, could be improved with a separation between the noise and the signal.

The concept of using AR is somewhat different from that of the blinking inspection and overlays. Augmented reality offers a new perspective, a supplementary aiding, in designing a visual inspection system. Three distinctive characteristics of AR are useful to improve the performance of the manufacturing and inspection systems.

First, AR can be used to augment the senses and cognitive abilities of operators. In many manufacturing applications, AR can be used as an intelligence amplification (Brooks, 1996) to make a task easier to perform. Augmented reality is presented to enhance users' perception by transferring information that the users cannot directly detect with their own senses.

Second, AR can improve the time-shared performance of two concurrent tasks by providing a spatial proximity of two information channels. For instance, AR is applicable when an inspector has to pay attention to the engineering drawings and the inspection part simultaneously. The same scenario can easily be applicable to the assembly, monitoring, and supervisory control tasks.

Finally, AR can be used to direct inspectors' attentions. It can guide the inspectors during the inspection task by providing task information according to the task sequence. For instance, studying a drawing requires the selective attention which decides the appropriate cues among various aspects of the parts' information. Because AR can provide the information that is only related to the current subtask, inspectors can focus on the useful cues easily without being distracted by inappropriate cues that stand out.

When inspectors need to refer to an inspection manual, tolerances, or standards, AR can provide the required information. Through the use of AR, operators can acquire task specific information in a more efficient, timely, and accurate manner.

Limitation of AR Technology

The usefulness of AR technology depends on the nature of the tasks and the required information. As seen in Table 10, the criteria that can be used in deciding the applicability of VE to manufacturing tasks were suggested by Chung et al. (submitted).

If the task demands attention for two spatially separated channels, AR has a high potential for the task. On the other hand, skilled-based tasks with which users need little task information gain no great benefits from AR. The task requiring fine work might not be a good candidate for an AR application. The visual pixel resolution of the-state-of-the-art HMDs is about 3.75-5 minutes of arc per pixel with 120°×60° field-of-view (FOV) (Ellis, 1995), while the human eye can perceive 1 min of arc (Kroemer, Kroemer, & Kroemer-Elbert, 1994) with wider FOV. Since commercially available HMDs have far less resolution with a narrow FOV, tasks requiring a high degree of visual accuracy are not appropriate.

TABLE 10. Criteria to Decide the Applicability of VE to Manufacturing Tasks (from Chung et al., 2002).

Attributes	Criteria	Consideration
Task	Type of skill	The degree of requiring a high level of skill (mental ability vs. physical skill)
	Fineness of task	The degree accuracy (e.g., resolution) required to perform a task
	Interaction	The degree of requiring interaction with real objects
	Task interference	Possibility of task interference caused by VE systems
Information	Modality	Type of human sensory domains employed such as visual, auditory, haptic senses, or a combination of these
	Information Type	Analog, prepositional, or distributed representation
	Volume	Amount of information associated with the VE application

The benefits of interactivity to performance are often reported in the literature, but the conclusions are not yet decisive (Burdea & Coiiffet, 1994; Kalawsky, 1993; Stanney , Ronald, & Kenny, 1998). While many researchers assumed the benefits of interactivity, interactivity has a differential effect depending on the task workload. Interactivity improves users' navigation performance under normal workload conditions, while it affects negatively under high workload conditions (Williams, Wickens, & Huchinson, 1994). Since interactivity increases the workload demands, user performances could suffer from a very high interactive system. The interactivity is beneficial to the extent that it is maintained within human information processing limitations (Card, Moran, & Newell, 1983). The types and levels of interactivity should be matched to the given task profiles. Virtual environment applications, which have achieved successful results until now, can be characterized by a low degree of interaction between users and the system. Much of the fruitful results were achieved in the architectural walkthrough, or information visualization which requires a low degree of interaction. Some of those examples are virtual wind tunnel (Bryson, 1997), virtual data visualization (Robertson, Card, & Mackinlay, 1993; Risch, May, Thomas, & Dowson, 1996), scientific exploration (Dede, Salzman, & Loftin, 1996) and virtual prototyping (Finger et al., 1997; Flaig & Thrainsson, 1996). Research using a high degree of interaction is underway, but these more complex applications have not yet shown great results (Bowman & Hodge, 1998). Many interactively complex applications of immersive VEs have suffered from the usability problems. Only some visible success has been achieved in less immersive VE applications such as desk-top VEs (Wilson, Brown, Cobb, D'cruz, & Eastgate, 1995; Wilson, Cobb, D'Cruz, & Eastgate, 1996). Chung et al. (1999) demonstrated an AR-aided inspection in which subjects use a keyboard to interact with the VE. The users need to memorize several command keys to manipulate the virtual objects and number keys to input the data. Even though they used a typical keyboard, they could develop a very useful and usable application with a small number of wisely selected commands and functions.

A dominant element of VEs is visual displays. Though auditory and haptic displays are often used, they are used as a supplementary means to a visual sense. Therefore, the tasks associated mainly with visual and spatial senses (e.g., layout, maintenance) have a higher feasibility than the tasks associated with psychomotor skills or haptic sense (e.g., fabrication). Among different types of visual information, analog (e.g., graphic) information has generally more promising results than alphanumeric data or texts. The efficacy of the AR representations depends on the type of information they are intended to provide. Preece et al. (1994) discriminated three types of representation to represent knowledge: analogical representation, prepositional representation, and distributed representation. Analog representations are picture-like images or 3D graphic images. Prepositional representations are abstract and language like statements that make assertions. Distributed representations are networks of nodes where knowledge is implicit in the connections between nodes. Augmented reality could be beneficial for the system that requires the analog information, but less useful for the system that requires prepositional and distributed information.

The volume of information is also critical, because it is one of the main factors of feedback lag. Human operators will suffer control difficulty if time lag is greater than 250 ms (Ellis, 1995). Rendering time, tracking and other computation like collision detection are major factors for the feedback lag of VE applications (Zachmann, 1998).

The technological limitations of AR should be reviewed carefully, since they confine the ways of presenting information. Even with the state of the art technology, it is not possible to build a fully implemented VE system (Furness & Barfield, 1995). The proper alignment and registration of virtual objects to the real world is difficult to satisfy with existing equipment. Since even tiny errors in registration are easily detectable by the human visual system, most applications assume a static viewpoint (Azuma, 1997). Also, AR equipment, such as HMDs, wires, etc., can interfere with users' tasks. With the development of non-intrusive equipment, however, these problems will be minimized. Any application using AR technology should avoid these technological limitations to design an effective inspection system. The number of the AR or VE elements needs to be reduced and, then the remaining elements need to be optimized for the task at hand with a systematic design approach.

CHAPTER 3. DEVELOPMENT OF AN AUGMENTED REALITY-AIDED DIMENSIONAL INSPECTION

The typical approach to analyze the inspection is to view the inspection as a system. Drury (1992) suggested using the system design concept for the design of any system in order to avoid sub-optimization of the system. The steps for a systems approach are: system goals are written, the logical system functions to achieve the goals are deduced, each function is allocated to a human or machine and each function is designed in detail, and then, the system is tested and evaluated before manufacturing and delivery.

SYSTEM GOAL

The system goal is the overall performance (i.e., speed and measurement accuracy) improvement of a dimensional inspection task. It is intended to reduce the cognitive demands of the task and to support inspectors with AR aids.

To determine the geometric dimensioning of a part, inspectors should know what needs to be measured and where the measures are to be taken. Since two channels, real and virtual scenes, provide supplementary information to complete the task, the AR will be used to facilitate a parallel processing. Parallel processing will improve the inspection performance in high demand environments, but it also causes the failure of focused attention. The need to maintain a spatial proximity of the two channels might interfere with the inspection performance. Design challenge is how to minimize the confusion between two channels and the cognitive demands to perform the task.

TASK ANALYSIS

The dimensional attribute defines the linear and angular magnitudes of the parts, while the geometric property defines the forms or features of the parts. Table 11 shows that these attributes can commonly be found in any dimensional and geometric measurements (Farago and Curtis, 1994).

The geometric shape of parts can be classified into prismatic and rotational shapes. Commonly, the prismatic shape has two bases, and three or more lateral polygons (Giesecke, Mitchell, Spencer, Hill, & Dygdon, 1986). The rotational shape includes cylinders, cones, and spheres. The typical dimensional attributes of each geometric shape are useful to understand the difference between two part shapes in inspection. The geometric and dimensional properties of prismatic parts include length, height, thickness, angle, flatness, squareness, parallelism, etc. On the other hand, the geometric and dimensional properties of rotational parts include length, thickness, diameter, contour, roundness, etc. The same attributes can appear in both the prismatic and rotational parts. Often, a part can have both geometric and dimensional properties of the prismatic and rotational shapes, if it consists of the combination of two shapes.

TABLE 11. Dimensional and Geometric Attributes and Required Information Form.

Property	Dimension	Related Dimension	Measuring Instrument
Dimension	Length	Width	Rules, Tapes
		Height	Vernier caliper
			Micrometer
			Go-no go gage
	Thickness	Height	Vernier caliper
			Height gage
			Ultrasonic thickness gage
	Depth	Length	Vernier depth gage
			Depth micrometer
	Diameter		Vernier caliper
			Go-no go gage
	Angle		Universal bevel protractor
Geometric Form	Flatness	Straightness	Dial indicator with base
	Perpendicularity	Squareness	Height gage stand with guideways
			Steel squares
	Profile	Contour	Dial indicator with base
			Contour gage
			Optical comparator
	Parallelism		Dial bench gage
	Roundness	Circularity	Dial indicator, V-blocks, mandrel
		Concentricity	
		Coaxiality	
		Form regularity	
Location	Coordinate location		Vernier caliper
			Coordinate measuring machine (CMM)

As seen in Table 12, every attribute can be measured by any of four types of measurements: point, exact point, line, and surface measurements.

Point measurement is used to measure the length, width, diameter, etc., since they are measurements of the shortest distance between two corresponding surfaces on the part. When the measured part has a flat bottom, often height, depth, and thickness can be measured at a point.

TABLE 12. Part Shape and Typical Dimensional Attributes.

Part Shape	Property	Dimensional Attribute
Prismatic	Point	Length, Width, Height, Depth, Thickness, etc.
	Exact point	Height, Thickness
	Line	Angle
	Surface	Flatness, Parallelism, Squareness, Straightness, Perpendicularity, etc.
Rotational	Point	Length, Height, Wall thickness, Diameter, etc.
	Exact point	Height, Thickness
	Line	Angle
	Surface	Roundness, Circularity, Concentricity, Coaxiality, Form regularity, Straightness, Parallelism, etc.

Exact point measurement is the special case of the point measurement. There are two methods in placing measuring instruments: proximal and exact device placing. In proximal device placing, the measurement can be taken at any two points on the surfaces. For example, length is not sensitive to the measuring location, as long as two surfaces are parallel. In exact device placing, a measuring device should be placed on the specific point. Note that the marking function is needed for only the exact placing of the measuring device.

The angle is a line measurement that is formed by two intersecting lines. Surface measurement is used for the geometric property which defines the geometric forms and interrelationships of surfaces defined by such concepts as straightness, perpendicularity, parallelism, roundness, etc. The surface measurement requires the movement or the rotation of the measuring devices or the measured parts to determine values.

FUNCTION ALLOCATION

The functions of dimensional inspection were identified by the task analysis. An inspection system must perform all of these inspection functions, whether performed by humans or machines, or by the combination of these two. In the system design sense, each function can be assigned to either human or machine components.

Fitts list was the first analytical attempt used to allocate functions between humans and machines. The rule for functional allocation was that functions in which humans perform better were assigned to humans and functions that favored machines were assigned to machines. He viewed humans and machines as two competitive subsystems to perform various functions within the system. However, the Fitts list had little impact on the engineering design practice, because of a lack of good allocation algorithms.

An alternative technique is to allocate as many functions as possible to machines (Chapanis, 1970). This approach could improve the overall system performance, but leftover functions became an unreasonable set of tasks or an underload task set for humans. The operators fail to build an appropriate mental model, when the functions left over for the humans do not form a coherent set of tasks. A designing strategy assigning the maximum number of functions to machines is likely to produce an underload for humans. Stress is created when task demands do not match human capabilities.

Bailey (1982) suggested a balanced approach in which allocation can be classified into categories because of the practical design situation: allocation to machines by management, allocation to humans and machines by requirements, allocation by systematic procedure, and an inability to allocate. A balanced approach captures a favor of designers at work, but does not offer any quantitative guidelines to allocate functions.

Many visual inspection studies tried to improve the performance of an inspection system through the Fitts approach (i.e., hybrid inspection) or Chapanis's approach (i.e., automated inspection). However, the automated inspection and hybrid inspections have not provided fully satisfied results, though the hybrid inspection showed a possibility of performance improvement, as seen in the literature.

A more promising design approach for an inspection system might be a complementary approach. Jordan (1963) set forth the premise that humans and machines should be considered not comparable, but rather complementary. Activities to perform a function should be shared by a man and machine without separation. Function allocation should be determined on how to provide affective and cognitive supports for the human in the system (Sanders & McCormick, 1993). Affective support refers to the emotional part of humans, such as job satisfaction and motivation. Cognitive support refers to design considerations that promote the development of an adequate mental model, and that ensure an appropriate level of involvement in the task.

Augmented reality technology can be used for augmenting or assisting functions when inspectors show cognitive limitations. Using AR technology is intended not as a replacement of a certain function but as an aid to support the function necessary to complete an inspection task. The inspectors perform the integral part of inspection tasks, and AR technology can support the functions when cognitive demand is high. With the supplementary approach, AR can allow a dynamic function allocation in which the system can be designed to allow workers to make allocation decisions at any given point in time during the system performance (Kantowitz & Sorkin, 1983). Augmented reality can provide the freedom for inspectors whether they deploy AR or not. Since AR can be used as a supplementary means, an inspector can override an AR system anytime, if it is desirable. This property might make AR more attractive and acceptable to workers**.**

Another advantage of AR is flexibility. The flexibility of an inspection system is also one of the important performance criteria, even it is rarely measured because of the lack of appropriate measures. It is rare that an inspection system has a single nonconforming condition. More often, an inspection system deals with multiple defect types, and changes the strategy to detect particular defect types of interest. Since AR is a very flexible medium to modify the information by reprogramming, the inspection system can accommodate any change (e.g., change in products, defects types) easily.

One of the foreseeable drawbacks of AR is the wearing of HMDs for a long period of time, yet no one reported any discomfort during the pretest experiment.

However, the effects of prolonged exposure to AR need to be identified for real applications in the work place. The subjects experienced only about 30 to 45 minutes in the pretest experiment; this short one-shot experience for users might not be enough to judge the negative effects of AR. To prevent this problem, AR aids need to be designed in a less intrusive way so that the weight of HMDs is supported by a stand. The similar examples are a watch repairman using a magnifier to repair a watch, or an inspector inspecting a small cylinder with a magnifier (Kleiner, 1983).

Possible changes to support each inspection function were reviewed by considering the cognitive demands of each function and the capabilities of AR to support these demands. Four inspection methods that were designed by the systematic design were manual, 2D-aided, 3D-aided, and AR-aided inspections. The manual inspection uses the typical dimensional inspection method that includes engineering drawings and inspection reports. The 2D-aided inspection uses a computer to transfer the inspection information rather than engineering drawings. The graphic information on the computer screen was the same as that of the engineering drawing, but measuring attributes appeared one-by-one according to the inspection sequences. Inspectors could conduct inspection without spending time for a search with this sequential delivery of measuring information. Also, the calculation for mean value and the decision processes were automated with the computer. The 3D-aided inspection was the same as the 2D-aided inspection except for the graphic representation of parts. All the parts and measuring information were drawn with isometric perspectives. The AR-aided inspection used the same graphic representation of the 3D-aided for parts. However, all the information was delivered to inspectors using HMDs. The composite view of the parts and measuring attributes should enable parallel processing between the two channels.

It was expected that the AR-aided inspection would improve inspection performance by increasing the reliabilities of the search and decision functions and by eliminating the marking and cleaning functions. The AR-aided inspection helps reduce inspection time and errors. To test the suggested hypotheses, the experiment was designed to assess the performance differences of these four inspection methods.

RESEARCH OBJECTIVES

The main objective of this study is to improve the performance of dimensional inspection that includes various dimensional and geometric attributes by using AR aids. The secondary objective is the development of guidelines in designing an AR-aided inspection system. These design guidelines can help the system designers understand ways in which information is presented with AR. It is expected that the design guidelines can be applicable for various manufacturing tasks, though the scope of this study is limited to the dimensional inspection.

To achieve these objectives, the performance data of the AR-aided inspection and other comparable technological alternatives need to be obtained with regard to their effects on inspection time, measurement accuracy, and the user's preference.

Research Hypotheses

Research hypotheses that can be used to evaluated the validity of the AR-aided inspection and to form design guidelines were established. The research hypotheses being tested by this study are:

Hypothesis 1: AR-aided inspection improves inspection performance. Augmented reality helps decrease inspection time and improve measurement accuracy.

Hypothesis 2: The benefit of AR is dependent on part shapes. The performance improvement of prismatic parts with AR is different from that of rotational parts.

Hypothesis 3: The benefit of AR is dependent on measurement attributes. The performance improvement of point measurement with AR is different from that of exact point, line, or surface measurement.

Hypothesis 4: The subjects who use the AR-aided inspection have a higher preference to their inspection method than the subjects who use the manual inspection.

CHAPTER 4. EXPERIMENTAL METHOD

SUBJECTS

All subjects were recruited from the students who have taken or are taking the Manufacturing Processes Laboratory (ISE 2214) course of Industrial and Systems Engineering Department at Virginia Polytechnic and State University in the Fall of 2001. Twenty-four subjects with 20/20 visual acuity and normal color vision were selected by using a vision tester (BAUSH & LOMB).

Then, since the inspection task requires a visual search and cognitive ability to understand how the 2D figures turn into 3D objects, cognitive capability tests were given to all subjects before the experiment. The visualization test was given to measure the ability to manipulate or transform the image of spatial patterns into other forms. The visualization scores ranged from 10 to 20 with an average of 15.4. According to the related study (Ekstrom, French, & Harmon, 1976), no subject had a serious problem in visualization capability.

To minimize the variation of inspection skills among subjects, the experiment was performed after each subject completed the inspection of a pulley and a base plate in the class. Inspection practice consisted of inspecting various dimensional and geometric attributes with measuring instruments, recording the required information on a part inspection report, and determining the acceptance of the attribute. Also, prior to performing the experiment, each subject was given about an hour of instruction and practice, under controlled conditions. Since all subjects have enough knowledge to understand the complex engineering drawings and dimensional inspection processes, the training time could be minimized.

EXPERIMENTAL DESIGN

A 4×2×4 mixed factors design was used to evaluate the effectiveness of AR aids for dimensional inspection tasks

Independent Variables

Inspection Method with four levels (manual, 2D-aided, 3D-aided, and AR-aided inspections) was the between-subjects factor, while Part Shape with two levels (prismatic and rotational parts) and Property with four levels (point, exact point, line, and surface measurements) were the within-subjects factors. As shown in Table 13, twenty-four subjects were randomly assigned into four different inspection methods: six subjects for each of the manual, 2D-aided, 3D-aided, and AR-aided inspection methods.

TABLE 13. Treatment Conditions for the Mixed-factors Design.

Part Shape	Property	Inspection Method			
		Manual	2D	3D	AR
Prismatic	Point	S_1-S_6	S_7-S_{12}	S_{13}-S_{18}	S_{19}-S_{24}
	Exact Point	S_1-S_6	S_7-S_{12}	S_{13}-S_{18}	S_{19}-S_{24}
	Line	S_1-S_6	S_7-S_{12}	S_{13}-S_{18}	S_{19}-S_{24}
	Surface	S_1-S_6	S_7-S_{12}	S_{13}-S_{18}	S_{19}-S_{24}
Rotational	Point	S_1-S_6	S_7-S_{12}	S_{13}-S_{18}	S_{19}-S_{24}
	Exact Point	S_1-S_6	S_7-S_{12}	S_{13}-S_{18}	S_{19}-S_{24}
	Line	S_1-S_6	S_7-S_{12}	S_{13}-S_{18}	S_{19}-S_{24}
	Surface	S_1-S_6	S_7-S_{12}	S_{13}-S_{18}	S_{19}-S_{24}

Dependent Variables

The two dependent variables are average inspection time and measurement accuracy. Also, a subjective questionnaire was used to evaluate the physical stress and user satisfaction of the four inspection methods. Inspection time is the average time to complete the inspection of each dimensional property. The measurement accuracy is defined as the deviation from the true dimensional value. The subjects were instructed to measure each attribute one by one: to measure the next attribute, they must complete all the required processes of the current attribute. This experiment condition gave a conservative result in terms of the inspection time. Often, inspectors can take measures in a more efficient way in the real inspection situation for all four inspection methods. They can determine multiple measuring points together or take multiple measures together regardless of the attributes. Since the subjects measure attributes in turn, the given task might include some additional manipulations of parts: the different attributes which appear on the same surface could not be measured at once.

The physical and mental workloads of the four inspection methods were measured with Likert-type scaled subjective questionnaires at the end of the experiment. The body part discomfort diagram (Wilson, 1998) was used to measure the physical workloads, while the modified NASA task loading index (TLX) was used for the mental workload. The NASA TLX (Hart & Staveland, 1988) and Subjective Workload Assessment Technique (SWAT) (Reid & Nygren, 1988) permit the operator to rate the task on the basis of multiple dimensions. The subscale of NASA TLX are mental demand, physical demand, temporal demand, performance, effort, and frustration level, while the subscale of SWAT are time load, mental effort load, and psychological stress load. The original TLX takes into account the individual differences of these subscales by asking each subject to indicate the subscale which affects the workload the most. The weighted average of each subscale is obtained by a pair-wise comparison of subscales. The SWAT uses a similar process to determine the relative effects by rating subscales with a three-points scale. However, (Nygren, 1991) reported that there was no psychometric basis for calculating the weighted average for TLX. Also, other studies suggested that either the weighted average or the derived SWAT score is not superior to the average of subscales (Christ et al., 1993)

EQUIPMENT

The augmented reality equipment, inspection parts, and measuring instruments that were used in this experiment are as follows:

Augmented Reality Equipment

The HMD employed was Virtual i-glasses (Virtual i.O, Inc.), a binocular HMD system equipped with a head tracker. The unit employs a liquid-crystal display (LCD) with 640x480 VGA resolution, a 60 HZ refresh rate, and a 30° field-of-view (FOV) for each eye. A complete set of technical specifications for the unit was presented in Table 14.

TABLE 14. Head-Mounted Display (i-glasses) Specifications.

Parameter	Performance
Field of view	30° horiz.$\times$22.5°vert. with full overlap
Resolution	VGA (640$\times$480)
Convergence	25 feet from viewer
Focal distance	12 feet from viewer
Maximum brightness	10 foot-lamberts
Maximum contrast ration	100:1
Vertical scan rate	60 or 70 Hz
Weight	8 Ounces

For this experiment, however, the unit was used in a monocular mode and the head tracker was not employed. The pilot study showed that binocular vision made the computer images appear to “float” in front of, rather than merge with, real objects. This made it difficult to use the images to “mark” the part surfaces, as required by the inspection task. To avoid this problem, the non-dominant eye was blocked by a filter in the eyepiece, resulting in monocular vision. With both eyes open, subjects were asked to make an alignment between a 1-foot-long black vertical line about 10 feet away and their thumb. Then, each eye was blocked individually to check when the alignment was broken. For example, if the alignment was broken when the right one was blocked, the right eye was dominant.

The head tracking capability of the unit was found to be inadequate for the precise alignment requirements of this study, and thus was not used. Instead, the inspectors simply control the position of the AR display as necessary to align the image with the real object. The default eye-to-part distance of a computer-generated wire-frame is about 35.5 cm, which corresponds to a normal reading distance. To ensure that the image had the same orientation as the real object with respect to the viewer, the ability to rotate the image via keyboards was incorporated into the application program. The application program was developed using WorldToolKit by Sense8 and executed on an Intergraph TDZ-310 workstation.

Inspection parts

A total of six parts, three prismatic parts and three rotational parts, were used in this experiment, as seen in Figure 4. The dimension of all parts ranges less than 5×5×5 inches. Six parts which include the dimensional properties and attributes of interest were selected from various machining tools. The three prismatic parts were the safety key, the finger guide, and the tool holders, while the three rotational parts were the step pulley, the holder, and the roller stud (Giesecke et al., 1986). These parts included the various measuring attributes that are typical for the prismatic and rotational part of interests. The dimensional and geometric attributes, and the tolerances of each part are shown in the engineering drawings (see Appendix D).

Since the properties are embedded in the parts, the measurable properties depend on the part. Each part includes little difference in measuring attributes, as seen in Table 15. For example, length, width, and height appear more often on the prismatic parts, while diameter, roundness, and concentricity appear more often on the rotational parts.

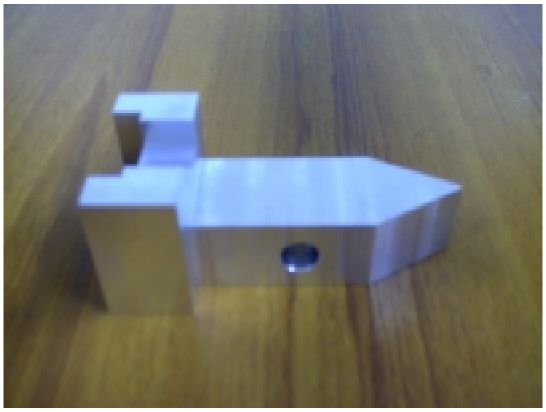
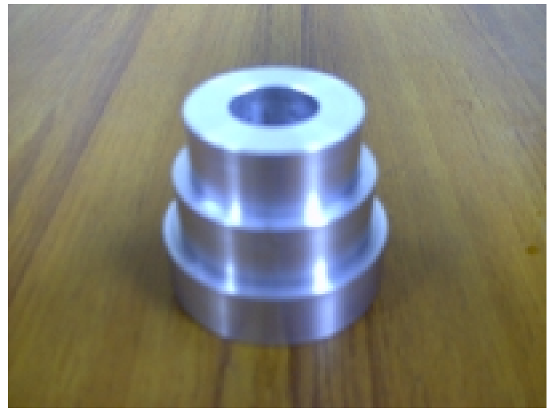
Prismatic Part (P)	Rotational Part (R)
 P-1. Safety Key	 R-1. Step Pulley
 P-2. Finger Guide	 R-2. Holder
 P-3. Tool Holder	 R-3. Roller Stud

Figure 4. Inspection parts used in this experiment.

TABLE 15. Inspection Parts and Dimensional Attributes of Interest.

Part Shape	Parts	Property	Attributes
Prismatic	Safety key	Point	Length, Width, Diameter, Depth
		Exact Point	Height
		Line	Angle
		Surface	Flatness
	Finger guide	Point	Length, Width
		Exact Point	Thickness
		Line	Angle
		Surface	Parallelism
	Tool holder	Point	Length, Width, Diameter
		Exact Point	Height
		Line	Angle
		Surface	Flatness
Rotational	Step Pulley	Point	Length, Width, Diameter
		Exact Point	Not available
		Line	Not available
		Surface	Flatness, Roundness
	Holder	Point	Length, Width, Diameter
		Exact Point	Height
		Line	Angle
		Surface	Roundness
	Roller Stud	Point	Length, Width, Diameter
		Exact Point	Not available
		Line	Not available
		Surface	Concentricity

Measuring Instruments

The selection of measuring instruments depends on the inspected parts' shape, size, volume, the tolerance rate, etc. Table 16 shows the measuring devices for the dimensional attributes that were used for this experiment. The general types of devices which are commonly used to measure each dimensional attribute were used for the experiment.

TABLE 16. Measuring Devices and Attributes.

Device	Model	Attribute
Dial caliper	Mitutoyo 505-644-50	Length, Width, Height, and Diameter, Hole Diameter, Depth
Height gage	Mitutoyo 509-313	Thickness and Height
Bevel protractor	Mahr 106	Angle
Dial gage with base and surface plate	Peacock SPI 20-3333	Flatness, Parallelism, Roundness, and Concentricity

The attributes that share common properties can often be measured with the same measuring instruments, though the effectiveness of the instruments for each attribute might be different according to the measuring situations. A vernier caliper is commonly used for all kinds of point measurements. Often, however, each attribute can be measured with a certain measuring instrument which is designated to measure a certain attribute depending on the parts. A height gage is useful for surface plate work as a layout tool, for marking off vertical distances and for measuring height differences between various steps. Sometimes, specialized devices, for example a go no-go gage, can be used for a certain case if only the nominal scale (e.g., go no-go) is of interest rather than the ration scale (e.g., inch, or mm).

The selection of measuring devices was decided by considering how each attribute is measured in a real situation. A dial caliper was used for the measurement of length, width, and inner/outer diameter. A height gage was used to measure the height/thickness in the center of the part. A depth gage was used to measure the depth. The universal protractor was useful for an angle, and the dial gage was useful for other surface measurements (e.g., flatness, roundness, etc.).

EXPERIMENTAL PROCEDURE

In the training session, the experimenter explained and demonstrated how to use different measuring devices. The training session continued until their performance satisfied the standard values (inspection time:15 min., inspection error: 0). If any inspection error was found, subjects were asked to measure that attribute again at the end of the practice.

Normally, a complete counterbalancing or Balanced Latin Square is used to order experimental conditions. Unfortunately, the order of property cannot be controlled by the experimenter, because the property is embedded on the part. Six parts were randomly presented one-by-one to subjects to eliminate the order effect of within-subject factors.

At the beginning of the experiment, subjects were instructed to conduct the inspection task accurately and quickly with the standardized operation (see Appendix B). Each attribute was measured one to six times at different measurement points on the part with the corresponding measuring instruments. The measuring resolution of all instruments was 0.001 inches except the universal bevel protractor (5 min.). The acceptable bounds of each attribute are called tolerances. The two types of tolerances, dimensional and geometric tolerances (Shewchuk, 2001), are related to these attributes. Dimensional tolerances are used to specify the bounds on the nominal dimension. Thickness, depth, diameter, and length belong to this category. The bilateral tolerance that includes the magnitude along with an upper and lower bound was used for this experiment. Geometric tolerances are used to specify the bounds on the geometric features of a part. Two types of geometric tolerances are form tolerance and location tolerance. Form tolerances bound on geometric attributes, while location tolerances bound on the position of features. The limit dimensions that define only the bounds were used for the tolerance of the surface measurement.

At the end of the experiment, the subject was asked to fill out the subjective questionnaire. The total experiment time, including instruction, inspection, and answering the questionnaire, took about 3 hrs.

The four inspection methods that were used in this experiment are as follows:

Manual Inspection

The engineering drawings and the inspection report forms (see Appendix D) along with test parts were given to a subject. The inspection for each part consisted of a set of steps, which were the study of drawing, marking, measurement, decision for conformation, and data recording, as shown in Figure 5. The subjects measured all attributes on the part exhaustively, and recorded the readings on the inspection reports, along with any required calculations. The average value of each attribute was calculated. Then, the subjects compared their disposition values to the engineering drawing to decide whether the attribute was acceptable or not.

The inspection sequence of the manual inspection is as follows:

1. Place the current part on the inspection station and set up the measuring devices.
2. Study the engineering drawings and the part inspection reports to decide the measuring attributes on the part.
3. Decide if the marking is required to measure the current dimensional or geometric attribute of interest: only the exact point measurement (e.g., height measurement in this experiment) needs marking. Then, mark measurement points on the part surface with a pencil according to the engineering drawings.
4. Measure the attribute of interest, record the value, and calculate the average values.
5. Compare the disposition value with the given geometric dimensioning tolerance on the engineering drawing. Then, record the rejection or acceptance of the current attribute on the inspection report form.
6. Repeat steps 4 to 5, until all measurements have been taken and recorded.
7. Remove all markings from the part surface, if the part was marked.
8. Place the next part and repeat steps 1 to 7.

.

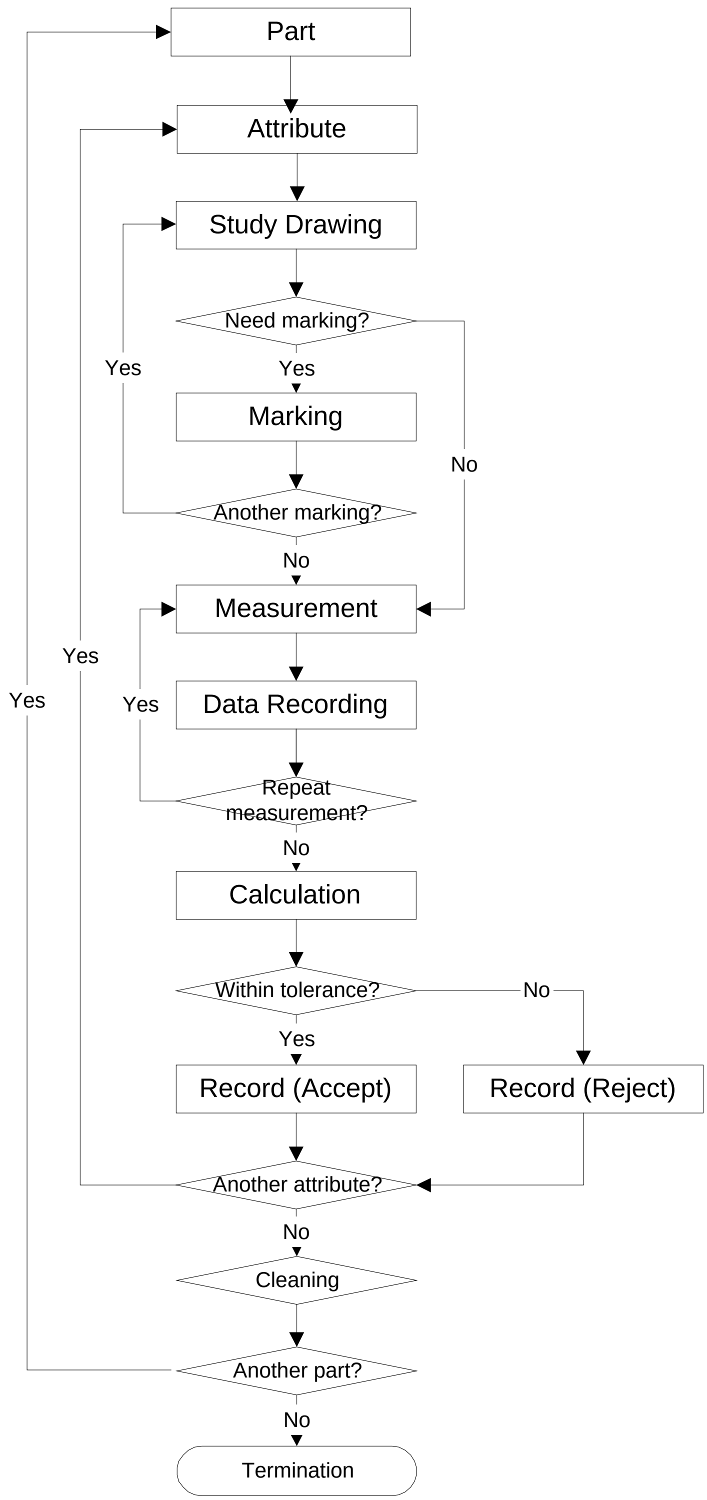


Figure 5. Manual inspection process.

2D-aided and 3D-aided Inspections

The contents of information were the same as that of the manual inspection, but only the selected information which was directly related to the measurement of interest was provided by a computer. The subjects measured attributes on the part according to the information on the screen and keyed readings. Then, the computer decided the disposition of the part by comparing the calculated average value with the specification. The study of drawing and calculation among the inspection processes were no longer needed for the 2D-aided and 3D-aided inspection conditions, since the computer provides the measuring information one-by-one with average values for the decision as shown in Figure 6.

The 2D-aided and 3D-aided inspections were basically identical. The only difference was the way in which information is presented. The 2D-aided inspection used 2D perspective figures (e.g.. engineering drawing) as seen in Figure 7, while the 3D-aided inspection used isometric perspectives as seen in Figure 8. For the 2D-aided inspection, the function that could be used to change the projection of parts was included. Each part could be viewed in at least two of three views: top, front, and side. In the case of the 3D-aided inspection, the wire-frame model of a part could be rotated around two mutually orthogonal axes so that subjects changed the viewpoint of the part according to their needs.

As a result, the performance difference between the 2D and 3D-aided inspections should be caused by the difference in understanding the 2D and 3D figures mentally.

The inspection sequence of the 2D and 3D-aided inspections is as follows:

1. Place the current part on the inspection station and set up the measuring devices.
2. Select (2D) or rotate (3D) the viewpoint of the part as needed.
3. Decide if the marking is required to measure the current dimensional or geometric attribute of interest: only the exact point measurement (e.g., height measurement in this experiment) needs marking. Then, mark measurement points on the part surface according to the information on the computer screen.
4. Measure the attribute of interest. Then enter the reading via the keyboard.
5. Repeat steps 3 to 4 until all the attributes have been taken and recorded.
6. Remove all markings from the part surface, if the part was marked.

7. Place the next part and repeat steps 1 to 5.

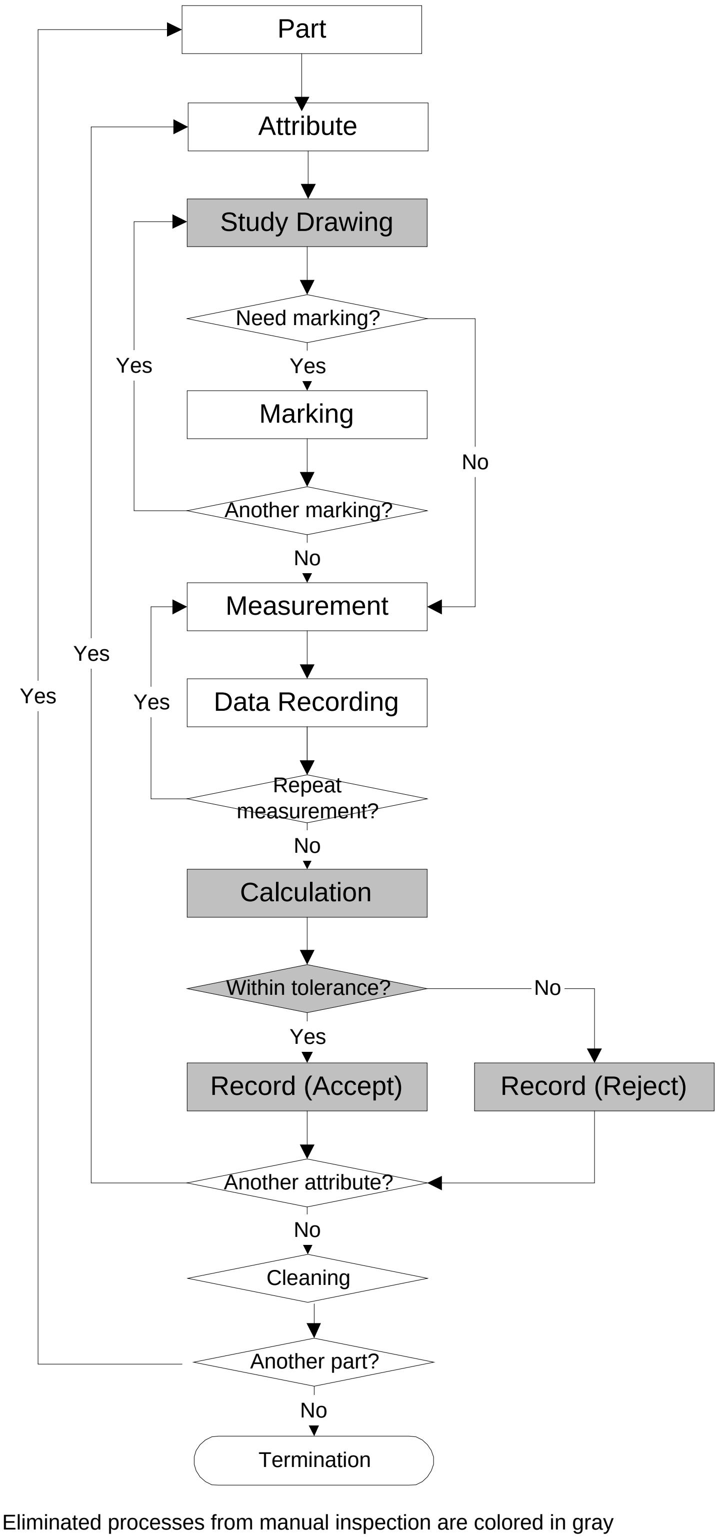
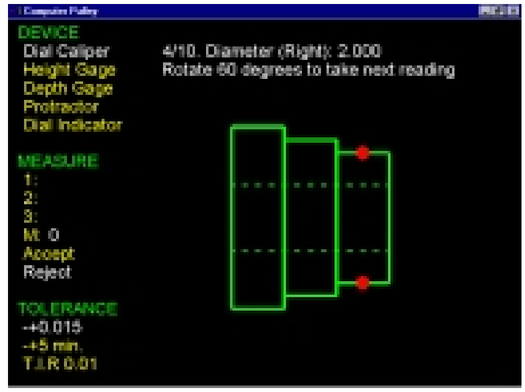


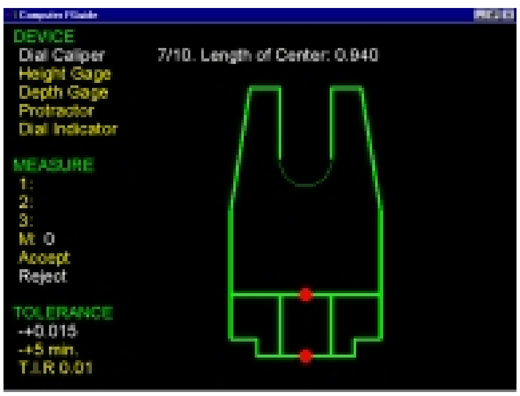
Figure 6. 2D-aided and 3D-aided inspection processes.

Prismatic Part (P)	Rotational Part (R)

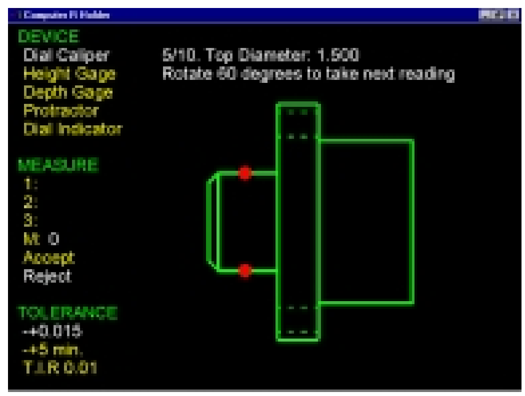
P-1. Safety Key



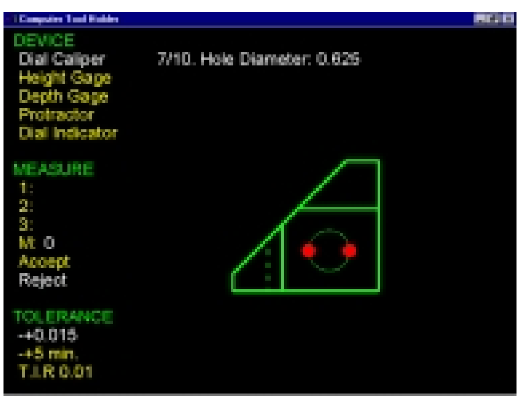
R-1. Step Pulley



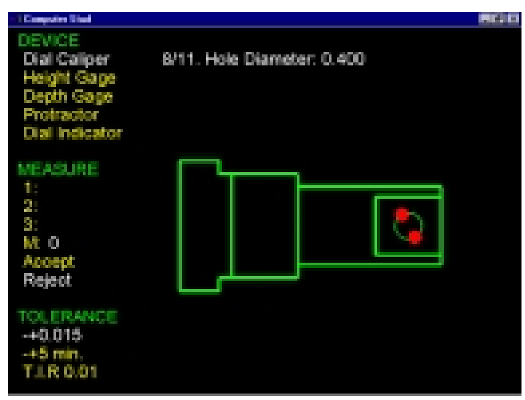
P-2. Finger Guide



R-2. Holder



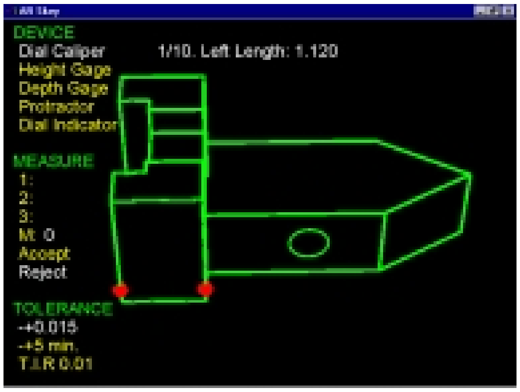
P-3. Tool Holder



R-3. Roller Stud

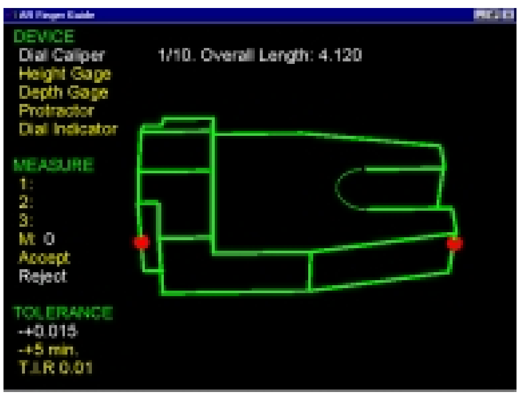
Figure 7. 2D perspective of parts: 2D-aided inspections.

Prismatic Part (P)	Rotational Part (R)

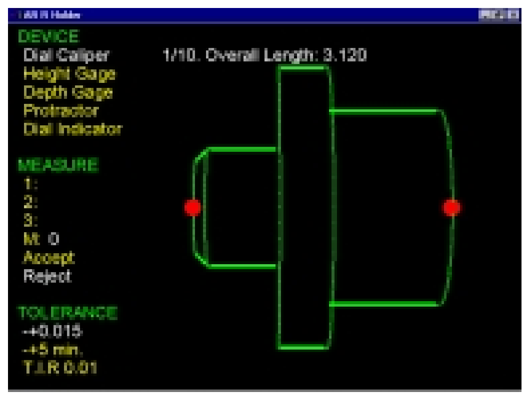


P-1. Safety Key

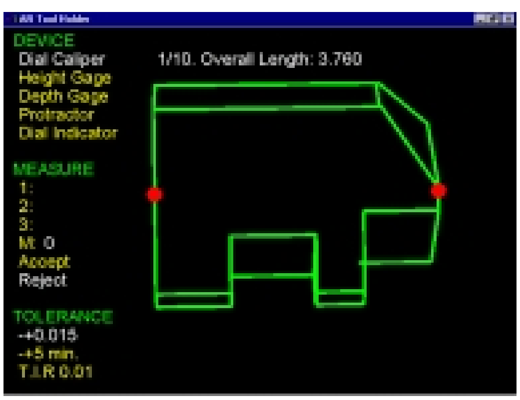
R-1. Step Pulley



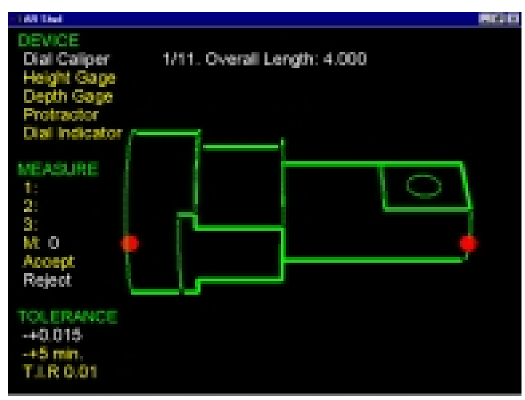
P-2. Finger Guide



R-2. Holder



P-3. Tool Holder



R-3. Roller Stud

Figure 8. Isometric perspective of parts: 3D-aided and AR-aided inspections.

AR-aided Inspection

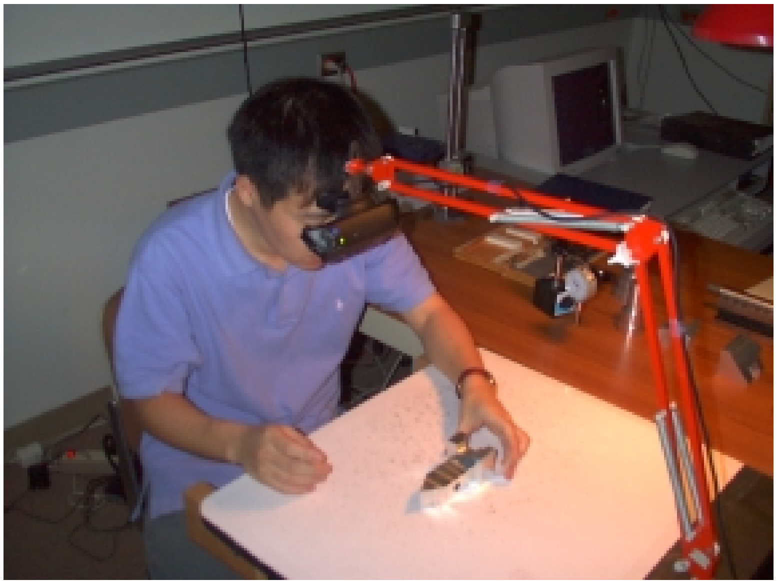
The AR-aided inspection used the same graphics as the 3D-aided inspection. The contents and formats of information were identical to the 3D-aided inspection.

The only difference from the 3D-aided inspection was that the subject used a see-through head-mounted display (HMD), which integrates two information channels together: the computer screen and the part as seen in Figure 9. The wire-frame model was superimposed over the actual part along with the measuring information. This allowed the subject to see the measurement locations on the part directly, as if the part itself had measuring information. The view of a part along with its' measuring attributes could be rotated with keys so that subjects can make an alignment between a part and the wire-frame model, or examine the parts according to their needs.

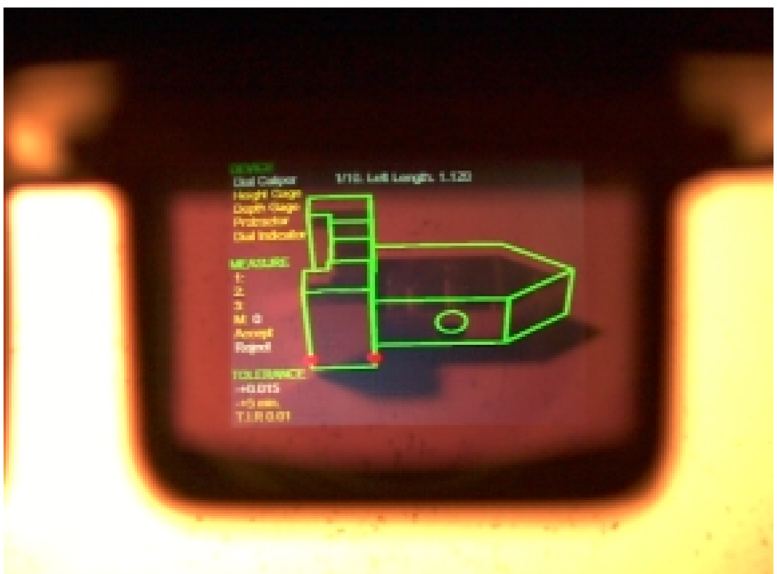
The subjects measured attributes on the part and recorded the readings by using a keyboard. Then, the computer decided the disposition of the part by comparing the calculated average value with the specification. The processes of the AR-aided inspection can be seen in Figure 10. Some steps that were required for the other inspection methods such as study drawing, marking, calculation, and cleaning are no longer needed for the AR-aided inspection condition.

The inspection sequence of the AR-aided inspection is as follows:

1. Place the current part on the inspection station and set up the measuring devices.
2. Rotate (3D) the viewpoint of the part as needed.
3. Control the HMD as required to ensure that the wire-frame image of the part is correctly superimposed over the edge of the part.
4. Measure the current attribute according to the information on the screen. Then enter the reading via the keyboard.
5. Repeat steps 3 to 4 until all the attributes have been taken and recorded.
6. Place the next part and repeat steps 1 to 5.

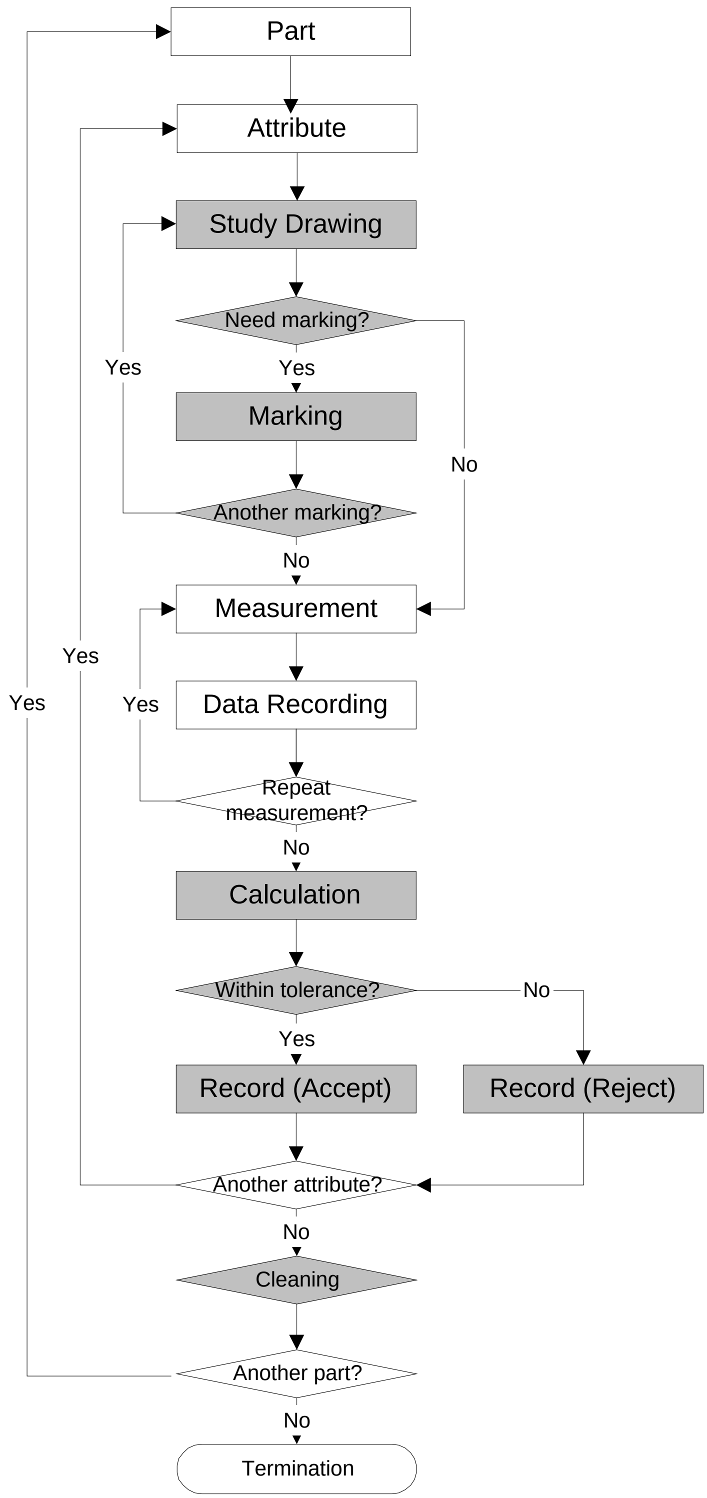


(a) An inspector performs an inspection with AR displays



(b) Scene through the AR display

Figure 9. AR-aided inspection scenes



Eliminated processes from manual inspection are colored in gray

Figure 10. AR-aided inspection processes.

CHAPTER 5. RESULTS

An analysis of variance (ANOVA) was conducted on each of the two performance measures: inspection time and measurement accuracy. The inspection time was the average time (i.e. seconds) spent inspecting the dimensional attribute of interest, while the measurement accuracy was the measurement deviation that was defined as the ratio (i.e., percent) between the deviation and the specification value.

INSPECTION TIME

The ANOVA results show that the Inspection Method significantly affects the inspection time as shown in Table 17

TABLE 17. ANOVA Summary Table of Inspection Time.

Source	df	SS	MS	F	*p*-value
Between Subject					
Method (M)	3	136647.1	45549.0	13.36	0.000*
Subjects (S/M)	20	68182.1	3409.1		
Within Subject					
Part Shape (P)	1	441.0	441.0	1.86	0.1880
M×P	3	538.6	179.5	0.76	0.5317
P×S/M	20	4748.2	237.4		
Attribute (A)	3	456272.0	152090.1	149.80	0.000*
M×A	9	86367.2	9596.4	9.45	0.000*
A×S/M	60	60916.5	1015.3		
P×A	3	2265.5	755.2	3.58	0.0189*
M×P×A	9	2051.8	228.0	1.08	0.3901
M×P×A×S/M	60	12655.4	210.9		
Total	191	907403.5			

The Bonferroni *t*-test shows that the AR-aided inspection takes significantly less time than the 3D and manual inspections ($p < 0.05$), as seen in Table 18. The 2D-aided inspection takes significantly less time than the manual inspection. However, there are no significant differences between the AR-aided and 2D-aided inspections, between the 2D-aided and 3D-aided inspections, and between the 3D-aided and manual inspections.

TABLE 18. Paired Comparisons of Inspection Methods (CD_B=34.886, $p < 0.05$).

Inspection Method	AR	2D	3D	Manual
Means	92.000	117.417	131.875	165.813
AR	-	25.417	39.875*	73.813*
2D		-	14.458	48.396*
3D			-	33.938
Manual				-

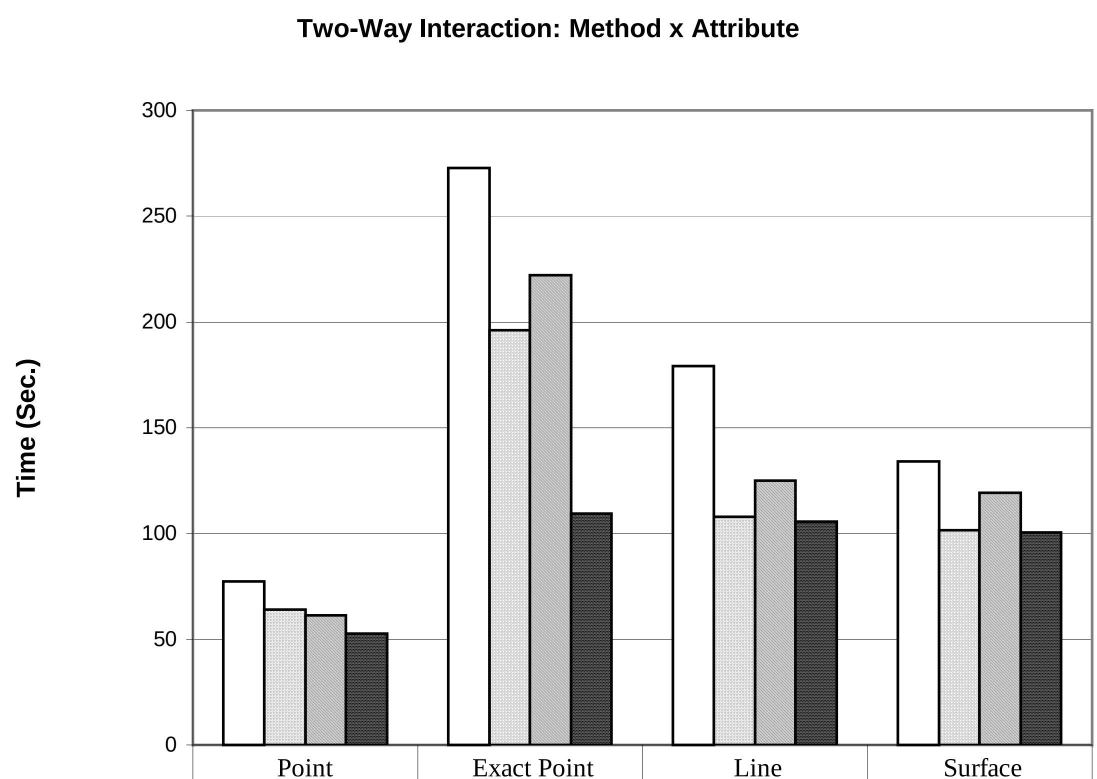
The effect of the Part Shape on inspection time is not significant. There is no significant difference between the mean inspection times of the prismatic part (mean: 125.260 sec.) and that of the rotation part (mean: 129.295 sec.).

The effect of the Attribute on inspection time is significant. The inspection time of each attribute is significantly different from each other except between the line and surface measurements, as seen in Table 19. The point measurement takes the shortest time whereas the exact point measurement takes the longest time.

TABLE 19. Paired Comparisons of Attributes (CD_B= 17.747, $p < 0.05$).

Inspection Method	Point	Surface	Line	Exact Point
Means (Seconds)	63.833	113.875	129.333	200.063
Point	-	50.042*	65.500*	136.230*
Surface		-	15.458	86.188*
Line			-	70.730*
Exact Point				-

The ANOVA results show that the two-way interaction of Method and Attribute is significant. Figure 11 shows that the AR-aided inspection is always fastest regardless of the measuring attributes. The adjusted Bonferroni *t*-test indicates that for the point and surface measurements, the Inspection Method has no significant effect on the inspection time, as seen in Table 20. However, for the exact point measurement, Inspection Method has a significant effect on the inspection time. The manual inspection takes longer than the 2D-aided and 3D-aided inspections, and the 2D-aided and 3D-aided inspections take longer than the AR-aided inspection. For the line measurement, the manual inspection method takes longer than the other three inspection methods. The inspection time of the three methods for line measurement is not significantly different from each other.



	Point	Exact Point	Line	Surface
Manual	77.42	272.67	179.17	134
2D-aided	64	196.08	107.92	101.67
3D-adied	61.33	222	124.92	119.25
AR-aided	52.58	109.5	105.55	100.58

Figure 11. Average inspection time of each inspection method.

TABLE 20. Unconfounded Comparisons of Two-Way Interaction: Method × Attribute.

Method	Point (A_1)	Exact Point (A_2)	Line (A_3)	Surface (A_4)
Manual (M_1)	929	3272	2150	1608
2D-aided (M_2)	768	2353	1295	1220
3D-aided (M_3)	736	2664	1499	1431
AR-aided (M_4)	631	1314	1264	1207

(M_1A_1)-(M_1A_2)	2343*	(M_1A_1)-(M_2A_1)	161
(M_1A_1)-(M_1A_3)	1221*	(M_1A_1)-(M_3A_1)	193
(M_1A_1)-(M_1A_4)	679*	(M_1A_1)-(M_4A_1)	298
(M_1A_2)-(M_1A_3)	1122*	(M_2A_1)-(M_3A_1)	32
(M_1A_2)-(M_1A_4)	1664*	(M_2A_1)-(M_4A_1)	137
(M_1A_3)-(M_1A_4)	542	(M_3A_1)-(M_4A_1)	105
(M_2A_1)-(M_2A_2)	1585*	(M_1A_2)-(M_2A_2)	919*
(M_2A_1)-(M_2A_3)	527	(M_1A_2)-(M_3A_2)	608*
(M_2A_1)-(M_2A_4)	452	(M_1A_2)-(M_4A_2)	1958*
(M_2A_2)-(M_2A_3)	1058*	(M_2A_2)-(M_3A_2)	311
(M_2A_2)-(M_2A_4)	1133*	(M_2A_2)-(M_4A_2)	1039*
(M_2A_3)-(M_2A_4)	75	(M_3A_2)-(M_4A_2)	1350*
(M_3A_1)-(M_3A_2)	1928*	(M_1A_3)-(M_2A_3)	855*
(M_3A_1)-(M_3A_3)	763*	(M_1A_3)-(M_3A_3)	651*
(M_3A_1)-(M_3A_4)	695*	(M_1A_3)-(M_4A_3)	886*
(M_3A_2)-(M_3A_3)	1165*	(M_2A_3)-(M_3A_3)	204
(M_3A_2)-(M_3A_4)	1233*	(M_2A_3)-(M_4A_3)	31
(M_3A_3)-(M_3A_4)	68	(M_3A_3)-(M_4A_3)	235
(M_4A_1)-(M_4A_2)	683*	(M_1A_4)-(M_2A_4)	388
(M_4A_1)-(M_4A_3)	633*	(M_1A_4)-(M_3A_4)	177
(M_4A_1)-(M_4A_4)	576*	(M_1A_4)-(M_4A_4)	401
(M_4A_2)-(M_4A_3)	50	(M_2A_4)-(M_3A_4)	211
(M_4A_2)-(M_4A_4)	107	(M_2A_4)-(M_4A_4)	13
(M_4A_3)-(M_4A_4)	57	(M_3A_4)-(M_4A_4)	224

$$CD_B = \left[t'(c, df_{error})\right]\left[\sqrt{2n(MS_{error})}\right] = \left[t'(48,60)\right]\left[\sqrt{2*12*1015.27}\right] = 544.94$$

The Part Shape × Attribute interaction is shown in Figure 12. The adjusted Bonferroni *t*-test indicates that the Part Shape has no effect on the inspection time for the point, exact point, and line measurements, as shown in Table 21. Regardless of the part shapes, the inspection time of the same attribute is the same. On the other hand, for the surface measurement, the rotational parts take a longer inspection time than the prismatic parts.

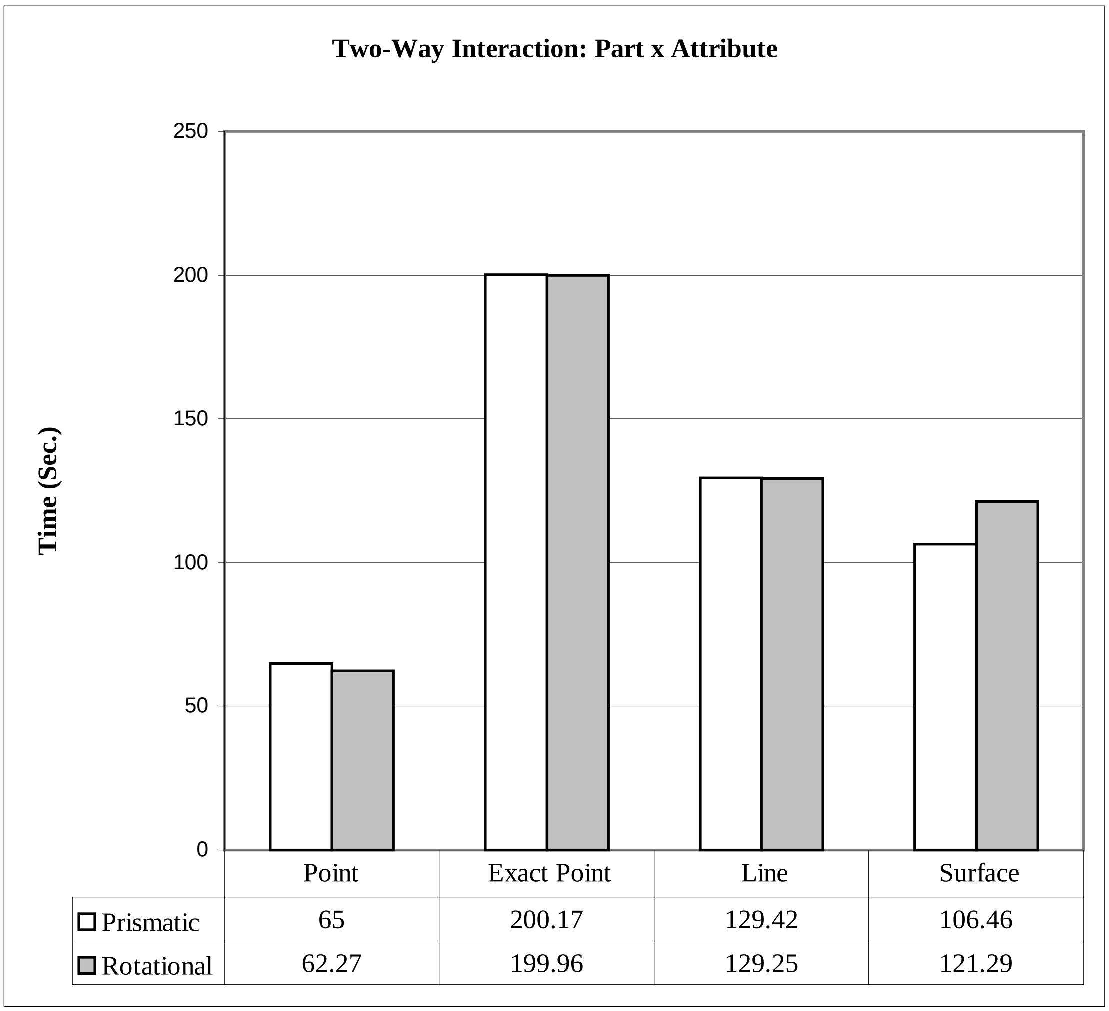


Figure 12. Average inspection time of each part shape.

TABLE 21. Unconfounded Comparisons of Two-Way Interactions: Part $\times$ Attribute.

Part Shape	Point (A_1)	Exact Point (A_2)	Line (A_3)	Surface (A_4)
Prismatic (P_1)	1560	4804	3106	2554
Rotational (P_2)	1494	4798	3102	2910

(P_1A_1)-(P_1A_2)	3244*	(P_1A_1)-(P_2A_1)	66
(P_1A_1)-(P_1A_3)	1546*	(P_1A_2)-(P_2A_2)	6
(P_1A_1)-(P_1A_4)	994*	(P_1A_3)-(P_2A_3)	4
(P_1A_2)-(P_1A_3)	1698*	(P_1A_4)-(P_2A_4)	356*
(P_1A_2)-(P_1A_4)	2250*		
(P_1A_3)-(P_1A_4)	552*		
(P_2A_1)-(P_2A_2)	3304*		
(P_2A_1)-(P_2A_3)	1608*		
(P_2A_1)-(P_2A_4)	1416*		
(P_2A_2)-(P_2A_3)	1696*		
(P_2A_2)-(P_2A_4)	1888*		
(P_2A_3)-(P_2A_4)	192		

$$CD_B = [t'(c, df_{error})]\left[\sqrt{2n(MS_{error})}\right] = [t'(16,60)]\left[\sqrt{2*24*210.92}\right] = 317.57$$

MEASUREMENT ACCURACY

The ANOVA results of Table 22 show that the Inspection Method does not affect the measurement accuracy. Measurement accuracy is equal across all four inspection methods ($p < 0.05$). Conversely, two other main effects, Part shape and Attribute, significantly affect measurement accuracy. The prismatic parts (0.39%) include higher measurement variations than the rotational parts (0.30%). The Bonferroni *t*-test results show that the measurement accuracy of the point and surface measurements is higher than that of the exact point and line measurements (Table 23). The point and surface measurements show less measurement deviation than the exact point and line measurements.

TABLE 22. ANOVA Summary Table of Measurement Accuracy.

Source	df	SS	MS	F	*p*-value
Between Subject					
Method (M)	3	0.055559	0.018519	0.32	0.812
Subjects (S/M)	20	1.165477	0.058273		
Within Subject					
Part Shape (P)	1	0.364854	0.364854	9.36	0.006*
M×P	3	0.019979	0.006659	0.17	0.915
P×S/M	20	0.779359	0.038967		
Attribute (A)	3	3.441051	1.147017	34.22	0.000*
M×A	9	0.610134	0.067793	2.02	0.051
A×S/M	60	2.011062	0.033517		
P×A	3	1.837534	0.612511	29.79	0.000*
M×P×A	9	0.929223	0.103247	5.02	0.000*
M×P×A×S/M	60	1.233732	0.020562		
Total	191	12.34797			

TABLE 23. Paired Comparisons of Attributes (CD_B= 0.10197, p < 0.05).

Inspection Method	Surface	Point	Exact Point	Line
Means Variation (%)	0.19767	0.22569	0.47379	0.48343
Surface	-	0.02802	0.27612*	0.28576*
Point		-	0.24810*	0.25774*
Exact Point			-	0.00964
Line				-

Figure 13 shows the two-way interaction of the Part Shape and Attribute. The adjusted Bonferroni-*t* test indicates that for the point and surface measurements, the rotation parts include less deviation, as shown in Table 24. For the exact point and line measurements, the prismatic parts include less deviation.

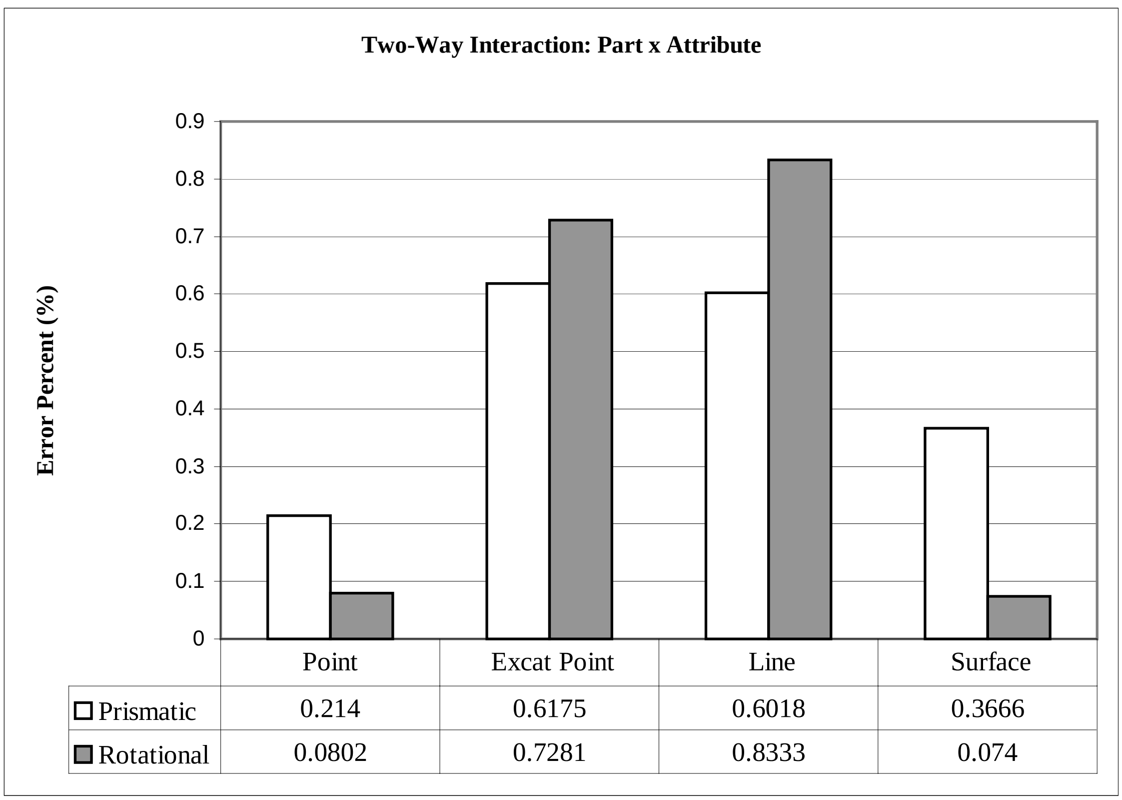


Figure 13. Average inspection measurement deviation.

TABLE 24. Unconfounded Comparisons of Two-Way Interactions: Part × Attribute.

Part Shape	Point (A_1)	Exact Point (A_2)	Line (A_3)	Surface (A_4)
Prismatic (P_1)	5.1360	14.8200	14.4432	8.7984
Rotational (P_2)	1.9248	17.4744	19.9992	1.7760

$(P_1A_1)-(P_1A_2)$	9.6840*	$(P_1A_1)-(P_2A_1)$	3.2112*
$(P_1A_1)-(P_1A_3)$	9.3072*	$(P_1A_2)-(P_2A_2)$	2.6554
$(P_1A_1)-(P_1A_4)$	3.6624*	$(P_1A_3)-(P_2A_3)$	5.5560*
$(P_1A_2)-(P_1A_3)$	0.3768	$(P_1A_4)-(P_2A_4)$	7.0224*
$(P_1A_2)-(P_1A_4)$	6.0216*		
$(P_1A_3)-(P_1A_4)$	5.6448*		
$(P_2A_1)-(P_2A_2)$	15.5496*		
$(P_2A_1)-(P_2A_3)$	18.0744*		
$(P_2A_1)-(P_2A_4)$	0.1488		
$(P_2A_2)-(P_2A_3)$	2.5248		
$(P_2A_2)-(P_2A_4)$	15.6984*		
$(P_2A_3)-(P_2A_4)$	18.2232*		

$$CD_B = [t'(c, df_{error})]\left[\sqrt{2n(MS_{error})}\right] = [t'(16,60)]\left[\sqrt{2*24*0.0201562}\right] = 3.1355$$

INSPECTION STRATEGY DIFFERENCES BETWEEN GROUPS

To understand the inspection strategy of the four inspection methods, the trade-off between time and measurement accuracy was analyzed. Each subject's inspection time and measurement deviation from the real value is plotted in Figure 14. The dashed lines represent the mean values of these two dependent variables. The more observations of the method that appear on the lower left area, the better the performance of that method becomes evident.

Figure 14 shows the inspection strategy difference among the four inspection conditions. A visible difference is that the observations of the exact point and surface measurements are scattered along with x and y-axes. It means that there is a big difference in the individual inspection strategy within the same inspection condition as well as among the four inspection conditions for the exact point and surface measurement. On the other hand, there is no big different for the point and surface measurement. Subjects used a similar inspection strategy for point and surface measurements.

In the case of point measurement, the AR-aided and 3D-aided inspection methods show a small amount of differences within the group. The 2D-aided inspection also shows a distribution similar to the AR-aided inspection except for one subject who spent almost twice as much time. The manual inspection often appears at the top right part. It implies that subjects spent more time with a large measurement deviation in the manual inspection condition. Subjects need to study engineering drawings to find the current attribute of interest and calculate the disposition value in the manual inspection condition.

In the case of exact point measurement, the inspection time difference among inspection methods is eminent. The AR-aided inspection is plotted on the left hand side, the 2D and 3D-aided inspections are plotted in the middle, and then the manual inspection condition is plotted on the right hand side. Subjects spent less time in the AR-aided inspection condition. Undoubtedly, the major sources of the difference between the AR-aided inspection and the 2D and 3D-aided inspection are the marking and cleaning processes that are required for the exact point measurement. Since AR could eliminate these two steps in the inspection processes, subjects could spend less time in the AR-aided inspection condition. On the other hand, the differences between the 2D and 3D-aided inspections and the manual inspection are the automated calculation and decision functions. An interesting finding is that there is a great amount of individual difference regardless of inspection methods. Even in the same inspection condition, each subject uses a quite different inspection strategy. Observed data are scattered in the wide range along with x and y-axes.

In the case of line measurement, the plotted data show that each subject uses a different strategy within the same inspection condition. However, there is a difference between the manual inspection and the other inspection methods. The manual inspection is plotted at the lower right hand part. It means that subjects spent more time with a small amount of deviation in the manual inspection condition, while less time was spent with a large measurement deviation in the other inspection conditions.

In the case of surface measurement, all subjects except one spent the same amount of time with the same amount of deviation regardless of the inspection methods. No individual difference is found within and between the four inspection methods.

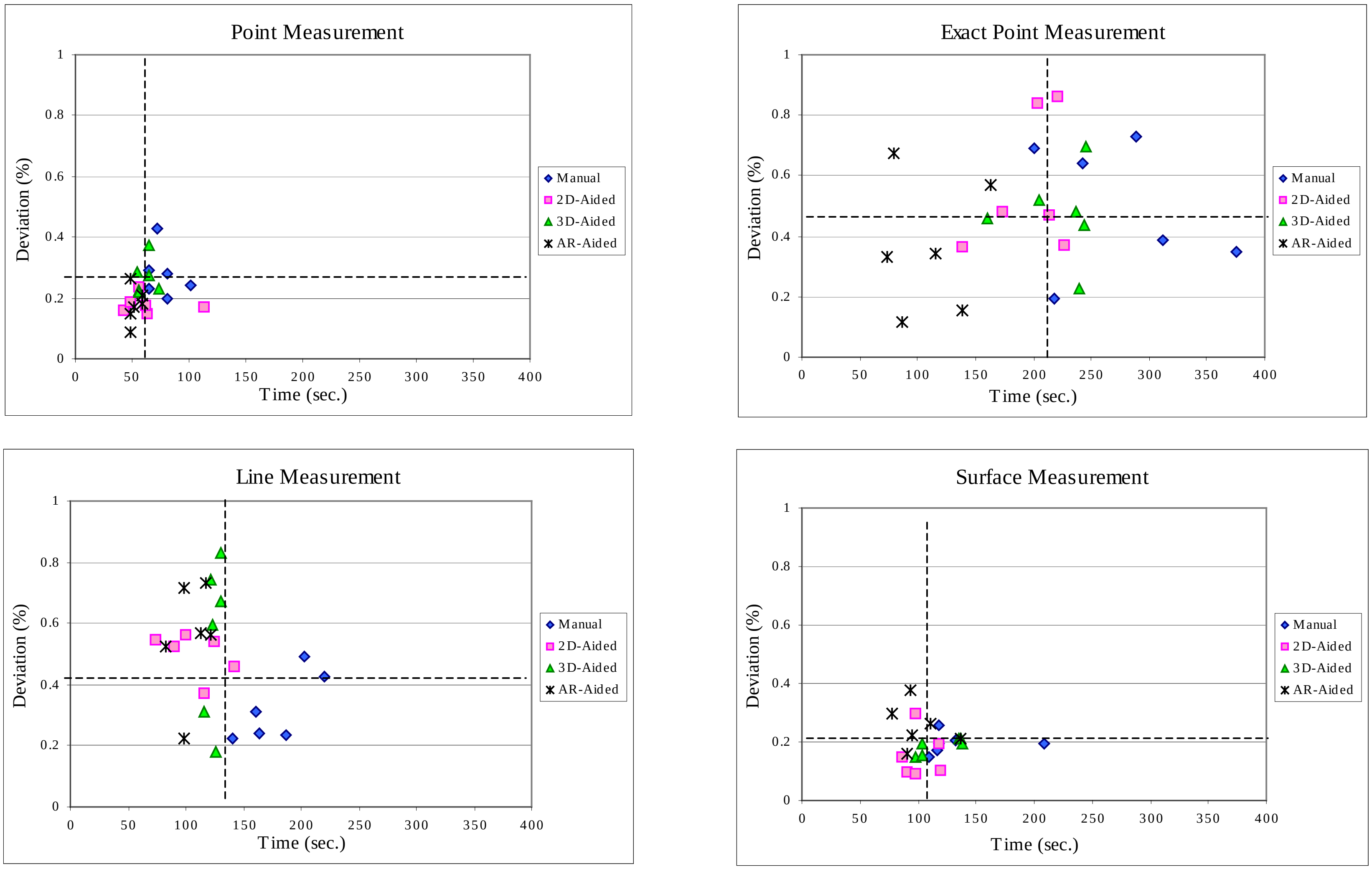


Figure 14. Trade-off between inspection time and measuring accuracy.

ANALYSIS OF THE QUESTIONNAIRE

The analysis results of the questionnaire which consisted of body part discomfort and mental workload are as follows;

Body Part Discomfort

The MANOVA shows that there is no difference among the four inspection methods for questions relating to physical stress, as shown in Table 25. The questionnaire is anchored from 1 to 9; a small value represents a high agreement with the given statement.

The average values of all four inspection conditions are lower than 5.0 (neutral) with the exception of three mean values higher than 5.0. These results suggest that there is no discomfort related to any of the four inspection methods.

TABLE 25. Body Part Physical Stress Difference Among Inspection Methods.

Question	Mean				*p*
	M	2D	3D	AR	
I have experienced no discomfort at all during and after the experiment					
1. Head	3.67	3.00	1.67	2.50	0.38
2. Eye	4.33	2.50	3.42	3.00	0.60
3. Neck	3.83	4.50	3.08	3.83	0.82
4. Shoulder	3.33	3.33	3.58	2.83	0.95
5. Upper Arm	3.17	3.50	2.08	2.17	0.43
6. Elbows	3.50	4.67	1.25	2.17	0.06
7. Lower Arm and Hands	3.17	4.00	3.08	2.83	0.86
8. Upper Back	3.50	5.50	5.08	4.67	0.63
9. Lower Back	4.83	4.17	5.75	4.50	0.79
10. Hip and Thigh	3.50	3.00	1.58	2.00	0.37
11. Knees	3.50	2.83	1.08	2.33	0.19
12. Ankles/Feet	3.50	3.50	1.08	1.08	0.10

To identify the individual differences, the number of subjects who had experienced any discomfort (more than 7 in Likert Scale) was counted with the questionnaire, as seen in Table 26. The upper and lower back discomforts were most frequently reported regardless of the inspection methods. On the average, no discomfort was found, though nine subjects did report physical discomforts. Among inspection conditions, subjects who used the AR-aided inspection reported the minimum number of physical discomfort. On the other hand, subjects who used the 2D-aided inspection reported the highest number of physical discomfort.

TABLE 26. Individual Differences of Body Part Discomforts.

Question	Mean				Total
	M	2D	3D	AR	
I have experienced no discomfort at all during and after the experiment					
1. Head		1			1
2. Eye	1		1		2
3. Neck	1	2		1	4
4. Shoulder	1	1	1		3
5. Upper Arm		1			1
6. Elbows	1	2			3
7. Lower Arm and Hands		2	1		3
8. Upper Back	1	3	3	2	9
9. Lower Back	2	2	3	2	9
10. Hip and Thigh	1				1
11. Knees	1	1			2
12. Ankles/Feet	1	1			2
Total	10	16	9	5	40

Mental Workload

The MANOVA results of Table 27 indicate that there is no difference among the four inspection methods for questions relating to mental workload except for their inspection method preference. The mean values for the mental workload across each group are less than or equal to 5.0. The results suggest that all four groups not only were satisfied with their performance but also perceived that the mental workloads of the given inspection were not high.

A significant difference among the groups is found for the user preference of the inspection method. The Bonferroni *t*-test shows that the subjects who used AR-aided and 3D-aided inspection methods show a higher preference for their inspection method than subjects who used the manual and 2D-aided inspection methods. However, there is no significant difference between the users who used manual inspection and those who used 2D-aided inspection, and between the users who used the 3D-aided inspection and those who used the AR-aided inspection.

TABLE 27. Mental Workloads Difference Among Inspection Methods.

Question	Mean				*p*
	M	2D	3D	AR	
Mental Demand: how much mental activity (e.g., thinking, remembering, calculation, and decision) was required? 1. The inspection task was easy to perform mentally.	3.50	3.17	2.92	2.50	0.704
Physical Demand: How much physical activity (e.g., manipulating, controlling, and handling, etc.) was required? 1. The task was easy to perform physically.	2.67	3.17	3.42	2.50	0.727
Temporal Demand: How much time pressure did you feel due to the pace at which the task or task elements occur? 2. The work pace was slow and leisurely.	4.17	3.83	4.08	3.83	0.990
Performance: How successful do you think you were in accomplishing the task set by the experimenter? 3. I was satisfied with my performance in accomplishing the task.	3.17	2.67	2.58	2.83	0.691
Effort: How hard did you have to work (mentally and physically) to accomplish your level of performance? 4. I could finish the inspection task with a minimum level of effort.	4.17	2.50	3.58	3.00	0.112
Frustration Level: How insecure, discouraged, limited, stressed and annoyed did you feel during the task? 5. I felt secure and interested while performing the inspection tasks.	3.33	3.67	3.08	3.17	0.922
User Acceptance: How did you feel about the inspection method that you did? 6. I prefer the inspection method that I used in this experiment to what I did in class.	5.00	4.67	1.33	2.33	0.001*

TABLE 28. Paired Comparisons of Preference (CDB= 1.7725, $p < 0.05$).

Inspection Method	Manual	2D-aided	AR-aided	3D-aided
Error Means	5.00	4.67	2.33	1.33
Manual	-	0.33	2.67*	3.67*
2D-aided		-	2.34*	3.34*
AR-aided			-	1.00
3D-aided				-

To identify the individual differences in mental workloads, the number of subjects who had experienced higher mental workloads (i.e., more than 7 in Likert Scale) was counted with the questionnaire, as seen in Table 28. Though two subjects reported high workloads for mental and temporal demands, most subjects reported that the mental workloads were not high. Among inspection conditions, four subjects who used the manual or 2D-aided inspections reported that mental or temporal demands were high.

TABLE 29. Individual Difference of Mental Workloads.

Question	Mean				Total
	M	2D	3D	AR	
1. Mental Demand	1	1			2
2. Physical Demand					
3. Temporal Demand:	1	1			2
4. Performance					
5. Effort					
6. Frustration Level					
Total	2	2			4

CHAPTER 6. DISCUSSION AND FUTURE RESEARCH

In this study, the effectiveness of AR for a dimensional inspection task was explored. The inspection task consisted of measuring various dimensional attributes of rotational and prismatic parts with four different types of inspection aids: manual, 2D, 3D, and AR. The results of this experiment strongly suggest that inspection performance can be improved by using AR technology in the design of a dimensional inspection system.

Hypothesis 1: AR-aided inspection improves inspection performance. Augmented reality helps decrease inspection time and improve measurement accuracy.

Hypothesis 1 was partly supported. Hypothesis 1 addresses the overall performance differences among the four inspection methods. Inspection time and measurement accuracy are two performance criteria in determining the effectiveness of the inspection methods.

The ANOVA results support that the AR-aided inspection provides the best performance among the four inspection methods by having the shortest inspection time. The 2D-aided inspection was faster than the 3D-aided inspection, and manual inspection was the slowest. The AR-aided inspection showed a great advantage for the exact point measurement, since the AR-aided inspection does not require marking and cleaning for exact point measurement as shown in the thickness inspection study (Chung et al. 1999). The advantages of the AR-aided inspection for the other dimensional measurements were also shown by the results, though the difference was not as large as for the exact point measurement.

The difference of required skills, capability, and inspection functions for the four inspection methods are summarized in Table 30. Table 30 highlights a different set of functions in the whole inspection task, since the other functions are identical, regardless of the inspection methods.

TABLE 30. Difference of Required Skills and Capability among Inspection Methods.

Function	Skill Type	Manual	2D	3D	AR
Study Drawing	Perception	×			
Divided attention	Perception	×	×	×	
Visualization	Cognition	×	×		
Marking	Motor	×	×	×	
Superimposing	Perception and Manual				×
Recording	Motor	×	×	×	×
Calculation	Cognition	×			
Decision	Cognition	×			
Cleaning	Motor	×	×	×	

In the manual inspection, the visual search pattern of the dimensional inspection follows a focused search. Subjects determine the dimension of interest among the cluster of multiple attributes on engineering drawings. In contrast to the manual inspection, the other inspection methods do not require this search process, because a computer provides information for the measuring attribute one-by-one. Manual, 2D, and 3D inspections require divided attention, since the subjects must attend two different channels for either parts and engineering drawings, or for parts and the computer screen. It was observed that subjects moved their head from the engineering drawings to the inspection part or from the computer screen to the parts to decide the measuring method and location. However, the AR-aided inspection can provide spatial proximity between the two channels by superimposing a view of the computer screen over the real part. Visualization is the ability to reconstruct the figures mentally into components for manipulation while the figure is manipulated in spatial orientation (Ekstrom et al., 1979). Since the manual and 2D-aided inspection use 2D figures, subjects need to reconstruct

2D perspective figures into 3D objects mentally. Marking, cleaning, and superimposing are necessary only for the exact point measurement. Marking is always coupled with cleaning, and cleaning is required only if marking is done. The manual, 2D-aided, and 3D-aided inspections require marking and cleaning for the exact point measurement, while the AR-aided inspection uses superimposing to determine the measuring point. All four inspection methods require some type of data keeping; writing, or keying. Calculation and decision are additional processes for the manual inspection, and are included in the automated routine in the other inspection methods.

Table 30 provides a basis for interpretations of the difference among inspection methods. It is useful to understand the components of inspection time and the sources of inspection errors for each inspection method. The performance differences among the four inspection methods could be caused by the combination of these components. If the processes are performed in series, each with some possibility of an inspection error, fewer processes will take less time with fewer errors. The experimental results support these implications. The manual inspection includes most of these processes and takes longer than the other inspection methods. According to the observed data, subjects spent about 10-30 sec for searching and an additional 10-30 sec for recoding, calculation and the decision process. On the other hand, the AR-aided inspection that only includes the superimposing process and recording, has the shortest inspection times. The advantage of 3D perspective in representing dimensional attributes is not supported in terms of inspection time. According to Table 30, the 3D-aided inspection should take a shorter time than the 2D-aided inspection, but the results of the experiment were opposite from the expectation. A possible explanation is that the part features are relatively simple to understand so that no additional time was required to visualize 2D information into 3D objects. All these processes are not necessarily sequential, and a parallel processing might be possible between some of these processes. An interesting finding is that subjects preferred the 3D representation to 2D representations for the inspection part according to the analysis of the questionnaire results though the 3D-aided inspection takes longer than the 2D-aided inspection.

Six types of inspection errors were identified based on the inspection reports and the experimenter’s observation, as seen in Table 31. Among the six categories, the reading, measurement, and typing errors were included in the same type, because they could not be discriminated from each other. Since each subject inspected only six parts, not enough errors were observed for a statistical analysis. However, the observation results provide an insightful understanding of the differences of inspection errors between the four inspection methods.

TABLE 31. The Observed Inspection Error Types.

Error Types	Manual	2D	3D	AR
Taking Wrong Dimensions	6	2	2	1
Omission of Measurement	1	1	-	-
Omission of Cleaning	-	2	2	-
Wrong Equipment	1	-	-	-
Reading/Measurement/Typing Error	4	4	3	4
Calculation/Decision Error	4	-	-	-
Total	16	9	7	5

Inspection errors increase as the number of processes of inspection methods increases. The manual inspection includes most of these processes, and provided the highest number of inspection errors. The AR-aided inspection showed the least number of total errors, since it includes the least number of processes. Table 31 shows that inspectors take a wrong dimension more often with the manual and 2D-aided inspections. The higher rate of taking wrong dimensions during the manual inspection suggests that subjects were more often confused by attributes of interest because of the clustered information. Some marginal amount of errors might be caused by the misperception of 2D figures. Since these two methods use 2D figures, subjects might fail to translate that information into 3D objects correctly.

The number of reading, measurement, and typing errors was almost the same across the four inspection methods. It means that the reliability of the data recoding function (i.e., writing) of the manual inspection is almost the same as that of the other inspection methods (i.e., data keying). The calculation and decision errors were only found in the manual inspection. The results suggest that the reliability of decision function can be improved by the automation, since the difference between manual and other inspections comes from mainly the automated routine of calculation and decision functions with a computer.

The measuring accuracy was basically the same across all inspection methods. Since all inspection methods use the same measuring instruments, the sources of measuring errors (e.g., deviation between real value and measured value) should be the same. The difference of the source of measurement deviation among the inspection methods exists in the exact point measurement. Some portion of the deviation in the AR-aided inspection was undoubtedly introduced by superimposing, while the marking caused the deviation in the other methods. However, the degree of deviation caused by either process is indifferent according to the experimental results.

Hypothesis 2: The benefit of AR is dependent on part shapes. The performance improvement of prismatic parts with AR is different from that of rotational parts.

Hypothesis 2 is not supported. Hypothesis 2 addresses the relative advantage of AR between prismatic and rotational parts. The ANOVA results of the inspection time support that the benefit of AR is the same between the prismatic and rotational parts, as shown in Table 32. The AR-aided inspection provided the best performance. The 2D-aided inspection was faster than the 3D-aided inspection, and manual inspection was the slowest regardless of the part shape. The ANOVA results of measurement accuracy suggest that the affect of AR is indifferent between the prismatic and the rotational parts. These findings suggest that AR aids provide a great advantage in reducing the inspection time regardless of the part shape.

TABLE 32. The Average Inspection Time for Prismatic and Rotation Parts (unit: sec.).

Part Shape	Manual	2D-aided	3D-aided	AR-aided
Prismatic	162.8	114.4	133.0	90.8
Rotational	168.8	120.4	130.8	93.2

The probable explanation of this result is that the characteristic dimensional and geometric inspection depends on the dimensional attribute rather than the part shape. The same attribute is always measured the same way with the same measuring instruments regardless of the part shape.

Hypothesis 3: The benefit of AR is dependent on measurement attributes. The performance improvement of point measurement with AR is different from that of exact point, line, or surface measurement.

Hypothesis 3 was supported. Hypothesis 3 addresses the relative advantage of AR among the four types of dimensional attributes. The ANOVA results of the inspection time suggest that the benefit of AR is different among the dimensional attributes. Augmented reality provided the greatest advantage for the exact point measurement, whereas the benefit of AR was not significantly different from those of the 2D and 3D-aided inspections for the other dimensional attributes.

For the exact point measurement, the major difference between the AR-aided inspection and the 2D and 3D-aided inspection are that the AR-aided inspection does not need marking and cleaning processes. Since the AR-aided inspection could eliminate the most time-consuming processes in the dimensional and geometric inspection, AR could provide a great advantage.

For line measurement, the AR-aided inspections could reduce the significant amount of inspection time with automated calculation and decision processes. Another advantage of AR might be that AR was very useful for subjects to understand which attributes need to be measured. By superimposing the measuring attribute over the real part, subjects could determine the measuring attribute quickly.

For point and line measurements, the AR-aided inspection could not provide a significant amount of time saving, though AR might be helpful to reduce the average inspection time with the automated calculation and decision processes. A possible explanation might be that the calculation of an average value and the decision processes might be relatively easy.

The ANOVA results of measurement accuracy suggest that the affect of AR is indifferent among the four dimensional attributes.

These findings support that AR aids are a good solution to reduce the inspection time, especially for the dimensional attributes which require the marking function, though they may not be a solution for improving measurement accuracy. In addition to this, AR can be useful to eliminate certain types of inspection errors (see Table 30): for instance, taking measures on wrong dimensions, omission, and applying wrong instruments.

Hypothesis 4: The subjects who use the AR-aided inspection have a higher preference to their inspection method than the subjects who use the manual inspection.

Hypothesis 4 was supported. One of the big concerns in designing the AR-aided inspection system for this study was the user's acceptance of the AR-aided inspection. Though the overall inspection performance is the most important criterion in deciding the effectiveness of the designed system, the user's preference of AR-aided inspection cannot be ignored.

The results of the questionnaire suggest that there was no physical stress on any body part across all the inspection methods. All the average values were lower than 5.0 (i.e. neutral) except the upper and lower backs for the 2D, and 3D-aided inspections.

Even though there were no indications of body part discomforts in the overall level (average is lower than 5), nine subjects reported upper and lower back discomforts. Since subjects spent about 2-3 hours in a bent posture, they should experience some discomforts on their back. This result suggests that considerations for individual inspectors are required for all four inspection conditions. Any possible discomfort can be minimized with ergonomic design considerations such as using a height-adjustable inspection table.

An unexpected finding was that subjects who used the AR-aided inspections reported the minimum number of body part discomforts. Since the AR-aided inspection uses AR displays, it was expected that subjects in the AR-aided condition would report the highest number of body part discomforts, especially eye and head discomforts. Surprisingly, no subject who used the AR-aided method reported eye or head discomforts. Three factors might be related to the result. First, since subjects in the AR-aid inspection condition could finish the tasks quickly, they had less chance of experiencing body part discomforts. The subjects spent about 22-43% less time in the AR-aided inspection condition. Second, subjects could minimize the head movements from the parts to the computer screens or to the engineering drawings with AR displays. Third, because the AR displays were supported by a stand, the physical burden of wearing AR displays might be minimized (Figure 9). These positive aspects of AR might outweigh the negative aspects of using AR displays.

The questionnaire related to mental workload suggests that the mental workload is not high for the four inspection methods. Apparently, using an AR technology does not increase the mental workload of users. The subjects using the 3D perspective, however, show a higher preference to their inspection method than those using the 2D perspective. The possible explanation of this result is that subjects prefer the 3D representation for real objects. Since the parts are 3D, inspection methods that preserve that characteristic are easier to understand than a 2D representation. With the manual and computer-aided inspection, subjects need to project the measuring locations onto 3D parts from 2D drawings. A similar kind of display-cognitive compatibility could be explained in part by the proximal compatibility principle (Wickens & Carswell, 1995).

On the other hand, subjects do not show preferences for the one-by-one information of the computer screen to the clustered information of the engineering drawing. Subjects show indifference in their preference between the manual inspection and the 2D-aided computer inspection.

Based on these results, it can be inferred that all groups are satisfied with the given inspection method. Though the physical body stress and mental workloads caused by the four inspection methods are indifferent, the AR-aided and 3D-aided inspections are preferred over the manual and 2D-aided inspections.

Future Research Implication

Though this research showed very promising results with AR in designing a dimensional inspection system, several research issues need to be studied.

Further research to evaluate the effects of AR on inspection errors is necessary. In this study, the performance criteria to evaluate the designed system were inspection time and measurement accuracy (e.g., measurement deviation from the real value). Not enough inspector errors were collected for the statistical analysis because of the limited number of subjects and parts. Though the observed samples agree with the intuitive expectation that AR aids can eliminate the errors related to certain functions and reduce the total amount of inspection errors with the minimum number of functions to complete the inspection task, a larger sample size is needed to support the assumption.

An AR technology can offer an innovative technological solution to the manufacturing processes. To realize such an innovation, however, AR technology should be further developed. Some of the key technological improvements necessary include a faster rendering of 3D graphics, a wider FOV with high resolution, an effective stereoscopic vision system, and an accurate registration with low expense. To avoid the current technological constraints, the registration task was performed by the subjects rather than using head trackers in this experiment. The AR-aided inspection task should have been designed more efficiently, if the current technological limitations were to be resolved.

Finally, it should be noted that all of the findings reported in this research may apply only to a relatively short span of time with students. The cumulative effects of day work need to be considered for a real application in the workplace with real inspectors. Since the level of experiences and skills of real inspectors should be different from those of students who only spent several hours in the class, research investigating the prolonged effects of using AR over 8 hr. for a day of work needs to be conducted with real inspectors.

CHAPTER 7. CONCLUSIONS

The experimental result supports that the AR-aided inspection achieved 22-43% more time saving than the other inspection methods. The advantage of AR was eminent for an inspection task that includes exact measurements. Since this type of measurement was the most time consuming during the whole inspection task, the benefits of AR increased as the portion of the exact measurement increased. On the other hand, AR aids could not help improve the measurement accuracy. The measurement accuracy was the same regardless of the inspection methods used. Another most encouraging finding was that users favored the AR-aided inspection according to the results of the questionnaire. The user's satisfaction of AR aids should provide a positive environment in adopting AR in the workplace.

In this study, experiments were performed to evaluate the effectiveness of AR for a dimensional inspection task. The inspection tasks were typical types of dimensional inspection tasks that include various dimensional attributes. Despite the limitations of the laboratory study with a limited number of subjects, the findings of this research are beneficial in designing a dimensional inspection system using AR technology.

Design Guidelines

With regard to the research hypotheses tested in this experiment, four design guidelines can be formed:

1. Use AR aids when a design objective is to reduce the inspection time and when the current measurement accuracy of the inspection system is acceptable.

   The results of the experiment strongly suggest that AR aids are an effective tool to reduce the inspection time, while AR may not provide any performance improvement for measurement accuracy. Since AR aids do not affect the measurement instrument or the measurement method, there was no change in the measurement function. As a result, the measurement accuracy remains the same in the inspection system. If the critical issue in the design of a dimensional inspection system is measurement accuracy rather than inspection time, another approach which can change the measurement function needs to be used.

2. Use AR aids when the portion of exact measurements is high in total measurement.

   The AR aids show a great amount of time saving in this experiment, but the degree of benefits from AR varied among attributes. Undoubtedly, the great portion of time saving was because of the exact measurement. The relative advantage of AR aids for the other measuring attributes was not eminent, though the AR-aided inspection showed some marginal benefits over the 2D-aided and 3D-aided inspections for the point, line, and surface measurements. Because of its associated costs, AR might not be an economical solution with such a small difference in marginal benefits. If the exact measurement is not required, the 2D-aided or 3D-aided inspections can be an economical solution rather than the AR-aided inspection.

3. Provide the measuring information of interest one-by-one.

   The questionnaire results showed that the subjects are indifferent in their preference between manual (clustered information) and the 2D-aided inspection (one-by-one). However, the experimental results showed a higher rate of taking a wrong dimension in the manual inspection. When too much information appears together, there is a possibility of choosing an inappropriate segment of information, or of a longer search time. By providing the selected information which is only related to the current interest, the inspectors attention can be directed to the immediate action with fewer errors.

4. Automate the decision function by using a computer.

   Because the dimensional and geometric inspection is a measurement of quantitative variables, the decision function can be highly reliable with a computer.
   In the context of flaw detection, the automated inspection system could not provide a satisfactory result because of the lack of a reliable decision algorithm (Drury 1992). However, for the dimensional and geometric inspection, the decision with quantitative value is an obvious candidate for automation. As seen in Table 31, the automation decision process might be useful to eliminate decision errors. In addition, it might reduce the workloads of human inspectors.

REFERENCES

Abernethy, B. (1988). Visual search in sports and ergonomics: Its relationship to selective attention and performer expertise. Human Performance, 1, 205-235.

Adam, S. K. (1975). Decision making in quality control: some perceptual and behavioral considerations. In C. G. Drury & J. G. Fox (Eds.), Human Reliability in Quality Control (pp. 55-69). London: Taylor and Francis.

Azuma, R. T. (1997). A survey of augmented reality. Presence: Teleoperators and Virtual Environments, 6(4), 355-385.

Bailey, R. (1982). Human performance engineering. Englewood Cliff, NJ: Prentice Hall.

Bajura, M., Fuchs, H., & Ohbuchi, R. (1992). Merging virtual objects with the real world: Seeing ultrasound imaginary within the patient, Computer Graphics ACM SIGGRAPH, 203-210.

Ball, K. K., Beard, B. L., Roenker, D. L., Miller, R. L., & Griggs, D. S. (1988). Age and visual search: Expanding the useful field of view. Journal of Optical Society of America, A(5), 2210-2219.

Barnes, R. M. (1963). Motion and time study. New York, NY: Wiley.

Becklen, R., & Cervone, D. (1983). Selective looking and noticing of unexpected events. Memory & Cognition, 11(6), 601-608.

Blackwell, H. R. (1970). Development of procedures and instruction for visual task evaluation. Illuminating Engineering, 65, 267-291.

Bloomfield, J. R. (1975). Studies on visual search. In C. G. Drury & J. G. Fox (Eds.), Reliability in quality control (pp. 31-43). London: Taylor & Francis.

Bosch, J. A. (1987). Automatic dimensional inspection. In The 8th International Conference on Automated Inspection and Product Control (pp. 157-166). Bedford, UK: Cotswold Press.

Bowman, D. A., & Hodge, L. F. (1998). The virtual venue: Use-computer interaction in information-rich virtual environment. Presence: Teleoperators and Virtual Environments, 7(5), 478-493.

Brooks, F. P., Jr. (1996). Computer science as toolsmith II. Communications of the ACM, 39(3), 61-69.

Bryson, S. (1997). The virtual windtunnel on the virtual workbench. IEEE Computer Graphics and Applications, 17(4), 15.

Burdea, C., & Coiiffet, P. (1994). Virtual reality technology. New York, NY: Wiley.

Card, S. K., Moran, T. P., & Newell, A. (1983). The psychology of human-computer interaction. Hillsdale, NJ: Lawrence Erlbaum Associates.

Chaney, F. B., & Teel, K. S. (1967). Improving inspection performance through training, and visual aids. Journal of Applied Psychology, 51, 311-315.

Chapanis, A. (1970). Human factors in system engineering. In K. DeGreen, B, (Ed.), System Psychology . New York, NY: McGraw Hill.

Chi, C. F. (1990). The human as an optimizer in inspection. Unpublished , State University of New York, Buffalo.

Christ, R. E., Hill, S. G., Ayers, J. C., Iavecchia, H. M., Zaklad, A. L., & Bittner, A. C. (1993). Application and validation of workload assessment techniques (Technical Report 974). Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Science.

Chung, K. H., Shewchuk, J. P., & Williges, R. C. (1999). An application of augmented reality to thickness inspection. Human Factors and Ergonomics in Manufacturing, 9(4), 331-342.

Chung, K. H., Shewchuk, J. P., & Williges, R. C. (2002). An analysis framework for applying virtual environment technology to manufacturing tasks. Human Factors and Ergonomics in Manufacturing, 9.

Craig, A., & Colquhoun. (1975). Vigilance: a review. In C. G. Drury & J. G. Fox (Eds.), Human Reliability in Quality Control (pp. 71-87). London: Taylor and Francis.

Czaja, S. J., & Drury, C. G. (1981). Training programs for inspection. Human Factors, 23(4), 473-484.

Dai, F. (1998). Virtual reality for industrial application. NY, New York: Springer.

Dai, F., & Göbel, M. (1994). Virtual prototyping-An approach using VR-techniques. In Proceedings of Computers in Engineering (pp. 311-316) ASME.

Dede, C., Salzman, M., & Loftin, R. (1996). ScienceSpace: Virtual reality for learning complex and abstract scientific concepts. In Virtual Reality Annual International Symposium '96 IEEE Computer Society.

Downing, C. J. (1988). Expectancy and visual-spatial attention: Effects on perceptual quality. Journal of Experimental Psychology: Human Perception & Performance, 14, 344-347.

Drury, C. G. (1975). Improving Human decision making in quality control. In C. G. Drury & J. G. Fox (Eds.), Human Reliability in Quality Control (pp. 45-53). London: Taylor and Francis.

Drury, C. G. (1979). The effect of speed of working on industrial inspection accuracy. Applied Ergonomics, 4, 2-7.

Drury, C. G. (1982). Improving Inspection performance. In G. Salvendy (Ed.), Handbook of Industrial Engineering (pp. 2282-2314). New York: John Wiley & Sons.

Drury, C. G. (1990). The information environment in inspection. In FAA (Ed.), Human Factors Issues in Aircraft Maintenance and Inspection: Information exchange & communication (pp. 98-109). Washington D.C.: FAA.

Drury, C. G. (1992). Inspection performance. In G. Salvendy (Ed.), Handbook of Industrial Engineering (pp. 2282-2314). New York: John Wiley & Sons.

Drury, C. G., & Addison, J. L. (1973). An industrial study of the effects of feedback and fault density on inspection performance. Ergonomics,, 16, 59-169.

Drury, C. G., & Prabhu, P. V. (1994). Human factors in test and inspection. In G. Salvendy & W. Karwowski (Eds.), Design of work and development of personnel in advanced manufacturing (pp. 355-401). New York: John Wiley and Sons.

Drury, C. G., & Sinclair, M. A. (1983). Human and machine performance in an inspection task. Human Factors, 25(4), 391-399.

Ekstrom, R. B., French, J. W., & Harmon, H. H. (1976). Manual for kit of factor-referenced cognitive tests. Princeton: ETS.

Ellis, S. R. (1995). Origins and elements of virtual environments. In W. Barfield & T. A. I. Furness (Eds.), Virtual Environments and Advanced Interface Design (pp. 14-57). New York, NY: Oxford University Press.

Embrey, D. E. (1979). Approaches to training for industrial inspection. Applied Ergonomics, 10, 135-144.

Farago, F. T., & Curtis, M. A. (1994). Handbook of dimensional measurement. New York, NY: Industrial Press.

Faulkner, T. W., & Murphy, T. J. (1975). Lighting for difficulty visual tasks. In D. C. G. & F. J. G (Eds.), Human reliability in quality control. London: Taylor & Francis.

Feiner, S., MacIntyre, B., & Seligmann, D. (1993). Knowledge-based augmented reality, Communication of the ACM, 36(7), 52-62.

Finger, S., Baraff, D., Siewiorek, D. P., Weiss, L., Witkin, A., Sundararajan, V., Wright, P., Cutkosky, M., & Prinz, M. C. (1997). Rapid design: Integrating virtual and physical prototypes. In 1997 NSF Design and Manufacturing Grantees Conference (pp. 41-42)NSF.

Flaig, T., & Thrainsson, M. T. (1996). Virtual prototyping-New information techniques in product design. In 1996 ASME Design Engineering Technical Conferences and Computers in Engineering Conference (pp. 96-DETC/DFM-1417)ASME.

Furness, T. A., & Barfield, W. (1995). Introduction to virtual environments and advanced interface design. In T. A. Furness III & W. Barfield (Eds.), Virtual environments and advanced interface design (pp. 3-13). New York, NY: Oxford University Press.

Giesecke, F. E., Mitchell, A., Spencer, H. C., Hill, I. L., & Dygdon, J. T. (1986). Technical Drawing. New York, NY: Macmillan Publishing Company.

Gillan, D. J., & Richman, E. H. (1994). Minimalism and syntax of graphs. Human Factors, 36, 619-644.

Goesch, T. (1990). Head up displays hit the road. Information display, 7(8), 10-13.

Gramophdhye, A., Bhagwar, S., Kimbler, D., & Greenstein, J. (1998). The use of advanced technology for visual inspection training. Applied Ergonomics, 29(5), 361-375.

Green, D. M., & Swets, J. A. (1988). Signal detection theory and psychophysics. New York, NY: Wiley.

Hara, Y., Okamoto, T., Hamada, N., & Akyama, N. (1980). Automatic visual inspection of LSI photomasks. In Proceedings of 5th International Joint Conference of Pattern Recognition (pp. 273-279).

Harlow, C. A., Henderson, S. E., Rayfield, D. A., Johnston, R. J., & Dwyer III, S. J. (1975). Automated inspection of electronic assemblies. Computer, 4, 130-137.

Harris, D. H., & Chaney, F. B. (1969). Human factors in quality assurance. New York: Wiley.

Harris, R. L., & Christhif, D. M. (1980). What do pilots see in displays? In Proceedings of the 24th Annual Meeting of Human Factors Society Human Factors Society.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of experimental and theoretical research. In P. A. Hancock & N. Meshkati (Eds.), Human Mental Workload (pp. 139-183). Amsterdam: North Holland.

Holahan, C. J., Culler, R. E., & Wilcox, B. L. (1978). Effects of visual distraction on reaction time in a simulated traffic environment. Human Factors, 20(4), 409-413.

Holding, D. H. (1981). Human skills. New York, NY: Wiley.

Hollnagel, E. (1989). The phenotype of erroneous actions: Implication for HCI design. In C. R. S. Weir & J. L. Alty (Eds.), Human-Computer Interaction and Complex System . London: Academic Press.

Hou, T. H., Lin, L., & G., D. C. (1993). An empirical study of hybrid inspection systems and allocation of inspection functions. International Journal of Human Factors in Manufacturing, 3(4), 351-367.

Jordan, N. (1963). Allocation of functions between man and machines in automated system. Journal of Applied Psychology, 47, 161-165.

Kalawsky, R. S. (1993). The science of virtual reality and virtual environment. Reading, MA: Addison-Wesley.

Kantowitz, B. H., & Sorkin, R. D. (1983). Human factors: Understanding people-system relationship. New York: John Wiley and Sons.

Kelley, M. L. (1955). A study of industrial inspection by the methods of paired comparison. Psychological Monograph, 69.9(399), 1-16.

Kinchla, R. A. (1992). Attention. Annual Review of Psychology, 43, 711-742.

Kleiner, B. K. (1983). Ergonomic/Economic design of visual inspection workplace. In Proceedings of Human Factors Society 27th Annual Meeting (pp. 307-309)Human Factors Society.

Kleiner, B. K., & Drury, C. G. (1993). Design and evaluation of an inspection training program. Applied Ergonomics, 24(2), 75-82.

Kroemer, K., Kroemer, H., & Kroemer-Elbert, K. K. (1994). Ergonomics: How to design for ease & efficiency. England Cliff, NJ: Prentice Hall.

Kundel, H. L., & Nodine, C. F. (1978). Studies of eye movements and visual search in radiology. In J. W. Senders, D. E. Fisher, & R. A. Monty (Eds.), Eye Movements and The Higher Psychological Functions (pp. 317-328). Hillsdale, NJ: Erlbaum.

Kundel, H. S., & Lafollette, B. S. (1972). Visual search patterns and experience with radiological images. Radiology, 103, 523-528.

Lim, T. K., Swaminathan, S., Woo, C. K., Chan, C. N., & Wonh, Y. K. (1997). Automated inspection and dimensional measurement of optoelectronic components. In Automatic Inspection and Novel Instrumentation (pp. 32-49). Bellingham, WA: SPIE.

Liuzzo, J. G., & Drury, C. G. (1980). An evaluation of blink inspection. Human Factors, 20(5), 561-572.

Mackworth, N. H. (1976). Ways of recording line of sight. In R. A. Monty & J. W. Senders (Eds.), Eye Movements and Psychological Processing (pp. 173-178). Hillsdale. NJ: Erlbaum.

Mahdvieh, Y. (1987). The development of an on-line non-contact visual gauging system. In The 8th International Conference on Automated Inspection and Product Control (pp. 109-119). Bedford, UK: Cotswold Press.

Maher, J., Overbach, W., Plamer, G., & Piersol, D. (1970). Enriched jobs improve inspection performance. Work Study and Management Services, October, 821-824.

Martin, M. (1992). Computer vision, model and inspection. River edge, NJ: World Scientific.

Martin-Emerson, R., & Wickens, C. D. (1977). Superimposing, symbology, visual attention, and the head-up display. Human Factors(39), 581-601.

McConkie, G. W. (1983). Eye movements and perception between auditory and visual perception. In K. Raynor (Ed.), Eye Movement in Reading . New York, NY: Academic Press.

McNichol, D. (1990). A primer of signal detection theory. London: Allen and Unwin.

Megaw, E. D. (1979). Factors affecting visual inspection accuracy. Applied Ergonomics, 10, 27-32.

Mei, W-H., Case, K. E., Schmidt, J. W. (1975). Bias and imprecision in variable acceptance sampling: effects and compensation. International Journal of Production Research, 13(4), 327-340.

Micalizzi, J., & Goldburg, J. H. (1989). Knowledge of results in visual inspection: Implications for training. International Journal of Industrial Ergonomics, 4, 225-235.

Milgram, P., & Drascic, D. (1997). Perceptual effects in alignment virtual and real objects in augmented reality displays. In Human Factors and Ergonomics Society Annual Meeting (pp. 1239-1243).

Morawski, T., Drury, C. G., & Karwan, M. H. (1980). Predicting search performance for multiple targets. Radiology, 103, 707-718.

Moray, N., Lootseen, P., & Pajak, J. (1986). The acquisition of process control skills. IEEE Transactions, SME-16, 497-505.

Naimark, M. (1992). Element of real space imaging: a proposed taxonomy. In Proceeding of SPI (pp. 14-17)Electronic Imaging.

Neisser, U. (1963). Decision time without reaction time. American Journal of Psychology, 76, 376-385.

Neisser, U., & Becklen, R. (1975). Selective looking: Attention to visually specified events. Cognitive psychology, 7, 480-494.

Nygren, T. E. (1991). Psychometric properties of subjective workload measurement techniques: Implications for their use in the assessment of perceived mental workloads. Human Factors, 33, 17-31.

Overington, I. (1973). Visions and acquisitions. London: Pentech Press.

Preece, J., Rogers, Y., Sharp, H., Benyon, D., Holland, S., & Carey, T. (1994). Human-computer interaction. New York, NY: Addison-Wesley.

Rasmussen, J. (1983). Skills, rules, and knowledge; signals, signs, and symbols, and other distinction in human performance models. IEEE Transactions on Systems, Man and Cybernetics, SMC-13, 257-266.

Reason, J. (1990). Human error. Cambridge, UK: Cambridge University Press.

Reid, G. B., & Nygren, T. E. (1988). The subjective workload assessment technique: A scaling procedure for measuring mental workload. In P. A. Hancock & N. Meshkati (Eds.), Human Mental Workload (Vol. 185-218,). Amsterdam: North Holland.

Reid, G. T., & Rixon, R. C. (1985). 3-D machine vision for automatic measurements of complex shape. In The 7th International Conference on Automated Inspection and Product Control (pp. 129-138). Bedford, UK: Cotswold Press.

Risch, J., May, R., Thomas, J., & Dowson, S. (1996). Interactive information visualization for exploratory intelligence data analysis. In Virtual Reality Annual International Symposium '96 (pp. 230-238)IEEE Society.

Robertson, G., Card, S., & Mackinlay, J. (1993). Information visualization using 3D interactive animation. Communication of ACM, 36(4), 57-71.

Robinett, W. (1992). Synthetic experience: a proposed taxonomy. Presence: Teleoperators and Environments, 1(2), 229-249.

Salvendy, G., & Seymore, J. W. D. (1973). Prediction and development industrial work performance. New York, NY: Wiley.

Sanders, M. S., & McCormick, E. J. (1993). Human factors in engineering and design. (Seventh ed.). New York: McGraw-Hill.

Schoonhard, J. W., Gould, J. D., & Miller, L. A. (1973). Studies of visual inspection. Ergonomics, 16, 365-379.

Scialfa, C. T., Kline, D. W., & Lyman, B. J. (1987). Age differences in target identification as a function of retina location and noise level: Examination of the useful field of view. Psychology and Aging, 2, 14-19.

Sheehan, J. J., & Drury, C. G. (1973). The analysis of industrial inspection. Applied Ergonomics, 2(2), 74-78.

Sheridan, T. B. (1992). Musings on telepresence and virtual presence. Presence: Teleoperators and Virtual Environment, 1(120-125).

Sheridan, T. B., & Ferrell, W. A. (1974). Man-machine system: Information, control, and decision models of human performance. Cambridge, MA: MIT Press.

Shewchuk, J. P. (2001). ISE 2214 Course Pack: Manufacturing Process Laboratory . Blacksburg, VA: Virginia Polytechnic Institute and State University.

Shewchuk, J. P., Chung, K. H., & Williges, R. C. (2002). Virtual environment in manufacturing (pp. 1119-1142). In K. Stanney (Ed.), Handbook of Virtual Environments. NJ: Lawrence Erlbaum.

Sims, D. (1994). New reality in aircraft design and manufacturing, IEEE Computer Graphics and Application, 14(2), 91.

Sinclair, M. A. (1979). The use of performance measures on industrial examiners in inspection schemes. Applied Ergonomics, 10, 17-25.

Sinclair, M. A. (1984). Ergonomic quality control. Workshop document. In International Conference on Occupational Ergonomics .

Skaggs, F., & Meyer, R. (1985). Vision computer based parts measurement system. In The 7th International Conference on Automated Inspection and Product Control (pp. 99-110). Bedford, UK: Cotswold Press.

Sojourner, R. J., & Antin, J. F. (1990). The effects of a simulated head-up display speedometer on perceptual task performance. Human Factors, 32, 329-339.

Somberg, B. L. (1987). A comparison of rule-based and positionally constant arrangements of computer menu items. In Proceedings of CHI & GI '87 Conference of Human Factors in Computing Systems Association of Computer Machinery.

Stanney, K. M., Ronald, R. M., & Kennedy, R. S. (1998). Human factors issues in virtual environments: A review of the literature. Presence, 7(4), 327-351.

Steenblik, J. W. (1989). Alaska Airlines' HGS. Air line pilot, December, 10-14.

Swets, J. A., & Pickett, R. M. (1982). Evaluation of diagnostic systems. New York, NY: Academic Press.

Takatoo, M., Takagi, Y., & Mori, T. (1989). Automated fabric inspection system using image processing techniques. In Automated Inspection and High Speed Vision Architectures II (pp. 151-158)SPIE.

Teel, U. S., Springer, R. M., & Sadler, E. E. (1968). Assembly and inspection in micro electric system. Human Factors, 10, 217-244.

Tiffin, J., & Roger, H. B. (1941). The selection and training of inspectors. Personnel, 18, 14-37.

Wang, M. J. & Drury, C.G. (1989). A method of evaluating inspector's performance differences and job requirement. Applied Ergonomics, 20(3), 181-190.

West, G. A. W. (1984). System for automated visual inspection of bare printed circuit boards. IEEE Transactions on Systems, Man and Cybernetics, SMC-14(5), 767-773.

Wickens, C. D., & Andre, A. D. (1990). Proximity compatibility and information display: Effects of color, space, and objectiveness of information integration. Human Factors, 32, 61-77.

Wickens, C. D., & Carswell, C. M. (1995). The proximity compatibility principle: Its psychological foundation and relevance to display design. Human Factors, 37, 473-494.

Wickens, C. D., & Hollands, J. G. (1999). Engineering psychology and human performance. (2nd ed.). New York, NY: Harper Collins Publishers.

Wickens, C. D., & Long, J. (1995). Object versus space-based models of visual attention: Implications for the design of head-up displays. Journal of Experimental Psychology, 1, 179-193.

Wiener, E. L. (1984). Vigilance and inspection. In J. S. Waren (Ed.), Sustained attention in human performance (pp. 207-245). New York, NY: Wiley.

Williams, H. P., Wickens, C. D., & Huchinson, S. (1994). Fidelity and interactivity in navigation training: A comparison of three methods. In Human Factors Society 38th Annual Meeting (pp. 1163-1167)Human Factors Society.

Williams, L. J. (1989). Foveal load affects the functional field of view. Human Performance, 2, 1-28.

Wilson, J. (1998). Task analysis and work design. In V. Martino & N. Corlett (Eds.), Work Organization and Ergonomics (pp.13-48). Geneva: International Labor Office.

Wilson, J. R., Brown, D. J., Cobb, S. V., D'cruz, M. M., & Eastgate, R. M. (1995). Manufacturing operations in virtual environments (MOVE). Presence: Teleoperators and Virtual Environments, 4(3), 306-317.

Wilson, J. R., Cobb, S., D'Cruz, M., & Eastgate, R. (1996). Virtual reality for industrial application: Opportunities and limitations. Nottingham: Nottingham University Press.

Yeh, M., Wickens, C. D., & Seagull, F. J. (1998). Conformity and target cueing: Presentation of symbology in augmented reality. In Proceedings of the 42th Annual Meeting of the Human Factors and Ergonomics Society (pp. 1526-1530)Human Factors and Ergonomics Society.

Zachmann, G. (1998). VR-technology for industrial applications. In F. Dai (Ed.), Virtual Reality for Industrial Application (pp. 13-27). New York, NY: Springer.

Zeltzer, D. (1992). Autonomy, interaction, and presence. Presence: Teleoperators and Virtual Environment, 1, 127-132.

APPENDIX A: INFORMED CONSENT FORM

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY
Informed Consent for Participants
in Research Projects Involving Human Subjects

Title of Project Application of Augmented Reality to Dimensional Inspection Task

Investigator(s) Kyung Ho Chung, Robert C. Williges (Chair) .

I. Purpose of this Research/Project

Augmented reality (AR) technology is expected to provide enhancements for the manufacturing process. Specifically, AR technology offers great promise over conventional technology for product design, development, manufacturing, assembly, and quality control. The purpose of this experiment is to evaluate the usefulness of AR technology to improve the performance of a dimensional inspection task by providing task specific information.

II. Procedures

In this study you will be asked to conduct an inspection task to determine the conformity of six metal parts. Your task is to take measures of various dimensional attributes to determine their quality with five measuring devices. Four different experimental conditions will be used to compare the performance differences as a function of information transmission modes including manual, 2D-aided, 3D-aided and AR-aided inspections. You will take measures of dimensional attributes by using only one of the three inspection methods. The task completion time and measurement accuracy are recorded to evaluate performance differences among the three modes. This experiment will take approximately three hours including an hour of practice.

III. Risks

There are no risks associated with this study outside of those encountered from using a computer or a see-through display. However, it is known that some people can be susceptible to motion sickness during virtual reality simulation. At anytime, you can withdraw from the participation of this research without penalty, if you feel any discomfort or don't want to continue.

IV. Benefits of the Project

No direct benefits accrue to the participant. However, the results of this research are expected to provide a great knowledge to understand the potential of AR and its applicability to various manufacturing process tasks. No promise or guarantee of benefits has been made to encourage you to participate.

V. Extent of Anonymity and Confidentiality

The data gathered in this experiment will be treated with confidentiality. Your name will not appear on any of the data collected. A random number will replace your name on all documents. You have the right to see your data and withdraw from the study if you so desire. The data will be stored and locked within the Human-Computer Interaction Laboratory (530C Whittemore) and be disposed of after analysis in approximately two months.

VI. Compensation

You will be paid eight dollars per hour for the time actually spent in the experiment. If you do not work in whole hour increments, you will be given an additional two dollars for every fifteen minutes.

VII. Freedom to Withdraw

You are free to withdraw from participation in this research program without penalty. No one will try to make you continue if you do not want to continue, and you will be paid in full for the amount of time you participated.

VIII. Approval of Research

This research project has been approved, as required, by the Institutional Review Board for Research Involving Human Subjects at Virginia Polytechnic Institute and State University, and by the Department of Industrial and Systems Engineering.

______________________________ IRB Approval Date

______________________________ Approval Expiration Date

IX. Subject's Responsibilities

I voluntarily agree to participate in this study. I have the following responsibilities:

I should not volunteer for participation, if I now know I will not be able to complete this experiment.

After completion of this study, I will not discuss my experiences with any other individual for a period of two months. This will ensure that everyone will begin the study with the same level of knowledge and expectations.

X. Subject's Permission

I have read and understand the Informed Consent and conditions of this project. I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent for participation in this project. If I participate, I may withdraw at any time without penalty. I agree to abide by the rules of this project.

______________________________ ______________________

Signature Date

Should I have any pertinent questions about this research or its conduct, and research subjects' rights, and whom to contact in the event of a research-related injury to the subject, I may contact:

_Kyung H. Chung________________________ _231-3193/ kychung@vt.edu
Investigator(s) Telephone/e-mail

_Robert C. Williges_______________________ _231-6270/williges@vt.edu_
Faculty Advisor Telephone/e-mail

__Robert, J. Beaton_________________________ _231-5931/bobb@vt.edu___
Departmental Reviewer/Department Head Telephone/e-mail

David M. Moore 540-231-4991/moored@vt.edu
Chair, IRB Telephone/e-mail
Office of Research Compliance
Research & Graduate Studies

This Informed Consent is valid from ________ to ________.

APPENDIX B: INSTRUCTION KIT

INSTRUCTIONS

This instruction kit includes the inspection task that you are going to perform along with measuring devices, and practice material. You must follow the standardized sequence and measuring methods that are provided by this instruction. At anytime during this session, feel free to ask questions if something is not clear.

TASK DESCRIPTION

This study looks at dimensional inspection performance differences by using three different ways of presenting information. You will conduct dimensional inspection tasks by using one of the three following inspection methods: manual, computer-aided, or AR-aided inspections. Your task is to measure the dimensional properties on six metal parts with five measuring devices: dial caliper, height gage, depth gage, protractor, and dial indicator. You should try to finish your task as soon as possible without sacrificing the correctness of your measurement.

MEASURING ATTRIBUTES AND DEVICES

Each device is designated to measure certain dimensional attributes. The dial caliper is used to measure length, width, and diameter. The height gage is used for height and thickness. The depth gage is used for the depth of holes or the bottom of features. The protractor is used to measure the angular dimensions. Finally, the dial indicator is used to determine flatness or roundness. A certain dimensional attribute can often be measured by more than one device. For instance, when the bottom of a part is flat, it can be measured either with the dial caliper, or with the height gage. However, you must to use the predetermined device that is designated for a certain dimensional attribute of interest by the instructor. Each attribute is coded to match a particular measuring device. The following codes are used for this experiment:

TABLE 1. Dimensional Attribute and Matching Measuring Devices

Code	Attribute	Description of Attribute	Devices
L	Length	Horizontal distance between two points	Dial Caliper
W	Width	Lateral distance between two points	
D	Diameter	Inside/outside diameter of circle	
H	Height	Vertical distance between two points	Height Gage
DT	Depth	Depth of features or holes	Depth Gage
A	Angle	Angular magnitude resulting from intersection of two straight lines	Protractor
F	Flatness	Flatness of surface related to a perfect plane	Dial Indicator
P	Parallelism	Parallelism between two surfaces	
R	Roundness	Uniformity, or deviation from the ideal form	

Suppose the code of measuring dimension is D1, it is the measurement of the first diameter on a part. It is supposed to be measured with a "Dial Caliper" as shown in Table 1.

MEASUREMENT

You must measure each dimension 3 times. The average value of your measurements will be used to decide the conformity of the dimensions of interest according to the given tolerance bounds. Be sure to take three readings with equally paced distances: for instance, one at the center, one about 0.25 in from each end. Rotate the part about 60 degrees, when you measure the attributes of the rotational parts. You must conduct measurements until all attributes of interest are exhausted, even if any nonconformity is found.

DATA RECORDING

The general measuring sensitivity of all devices except the protractor is 0.001 inch with plain reference marks. The measuring sensitivity of a protractor is 5 min (e.g., 1/12°).

All dimensional values should be written in the standardized way. All readings and the averages need to be written in 4 digit numbers, for example 0.340, 1.345, etc. Angular dimensions should be written 45.05, 90.15, etc.

DIMENSIONAL AND GEOMETRIC TOLERANCES

Dimensional tolerances are used to specify bounds on nominal dimensions such as length, width, height, diameter, and angle. All nominal dimensions will be given along with an upper and lower bound. If the deviation of any dimension is within ± 0.015, the dimension of a part is within acceptable bounds. The tolerance bound of an angle is ± 1 min (0.05 degree).

Geometric tolerance is used to specify the bounds on the geometry of a part's feature. Four geometric features, flatness, parallelism, roundness and concentricity, will be measured in this experiment. The deviation of a surface must be at the correct height (nominal dimension + tolerance). The tolerance for geometric tolerance is 0.010.

MANUAL INSPECTION

You will use a pencil, ruler, eraser, calculator and six engineering drawings that show the dimensional attributes of parts along with five measuring devices. You must take readings, record values, calculate averages, and mark on an inspection report whether the dimensional attribute is acceptable or not according to the given tolerance limits.

Inspection Sequence

The following is the standardized inspection sequence for the manual inspection;

1. Place a part on the inspection station and set up the measuring devices.
2. Determine the current measuring dimension according to the inspection report and the engineering drawing.
3. Be sure to determine the measuring locations before taking a reading. Use a pencil to determine the exact points of measurement if it is necessary. All attributes except height can be measured without markings.
4. Use the matching measuring device for each dimension according to the code of the dimension of interest.
5. Record the three readings and calculate the average value to decide whether the dimension is within the tolerance limit.
6. Repeat steps 1 through 4 until all dimensions of interest are exhausted.
7. Erase all marks on the part.
8. Tell the experimenter that you have finished your inspection of the part.

COMPUTER-AIDED INSPECTION

You will use a pencil, ruler, and eraser along with five measuring devices. A computer will show the information related to each dimension on the screen during an inspection task. The computer shows which device is to be used, measuring sequence, tolerance limit, and other information related to the inspection task.

Inspection Sequence

The following is the standardized inspection sequence for the computer-aided inspection;

1. Place a part on the inspection station and set up the measuring devices.
2. The current measuring dimension will appear one by one on the computer screen. Use the measuring device that is highlighted in white.
3. Be sure to determine the measuring locations before taking a reading. Use a pencil to determine the exact points of measurement if it is necessary. All attributes except height can be measured without markings.
4. Take a reading of the current measure and enter the data by using the keyboard.
   - Enter the value in 4 digits and hit the “space bar”. Please locate the measuring device as suggested on the screen.
   - All dimensions should be measured 3 times. Then the target will go to the next measurement dimension
   - If you want to change the previous input data, press “p” key and repeat the previous step.
5. Repeat steps 2 through 4 for all dimensional attributes of interest.
6. When all dimensional attributes are measured, there will be no more “red marks” which represent the measuring locations.
7. Erase all marks on the part, if you made any.
8. Tell the experimenter that you have finished your inspection of the part.

AR-AIDED INSPECTION

You will use a see-through display so that you can see computer-generated images and a real part superimposed together. When you superimpose the green wire-frame exactly over the part, the red target shows the position of the current measurement. However, you do not need to locate the device on the same measuring location that appeared on the display, if the placement of the device does not affect the accuracy of the measurement. The only placement sensitive measurement in this experiment is the height measurement. You must make an alignment between the part and the wire-frame model that represents the physical part.

How to use the see-through display

When you use the see-through display, you can see both the computer-generated image and the real image simultaneously through the goggles. The green wire image on the screen is the replicate of the physical part.

Tips for Superimposing:

- Make the length of the virtual image and the real object the same by controlling the position of the display.
- If the width of the two objects is not identical, rotate the virtual image by using “up” key or “down” key on the keyboard.
- Remember only the height measurement needs the good alignment to take a reading. Other measurements can be taken without perfect alignment.

Inspection Sequence

The following is the standardized inspection sequence for the AR-aided inspection;

1. Place a part on the inspection station and set up the measuring devices.
2. The current measuring dimension will appear one by one on the screen. Select the measuring device that is highlighted in white.
3. Make an alignment of the wire-frame over the physical part for height measurement.
4. Take a reading of the current measurement and enter the data by using the keyboard.
    - Enter the value in 4 digits and hit the "space bar". Please locate the measuring device as suggested on the screen.
    - All dimensions should be measured 3 times. The target will then go to the next measurement dimension
    - If you want to change the previous input data, press "p" and repeat the previous step.
5. Repeat steps 2 through 4 for all dimensional attributes of interest.
6. When all dimensional attributes are measured, there will be no more "red marks" which represent the measuring locations.
7. Tell the experimenter that you have finished your inspection of the part

MESURING DEVICES

Note: The instruction materials were made from the Handbook of Dimensional Measurement (Fargo & Curtis, 1995), Technical Drawing (Geisecke et al, 1986), and ISE 2214 Lab. manual (Shewchuk, 2001).

Dial Caliper

A dial caliper consists of a scale and two jaws, one movable and one fixed. The part to be measured is placed inside the jaws, the jaws are tightened, and the measurement is taken. The measurement is established by reading the scale (each division = 0.1 inch) and adding on the value read in the dial (each division = 0.001 inch). A dial caliper can be used to measure internal and external features. Dial calipers are very commonly used for measuring length and diameter. They can also be used for measuring the size and depth of internal features, such as holes and pockets.

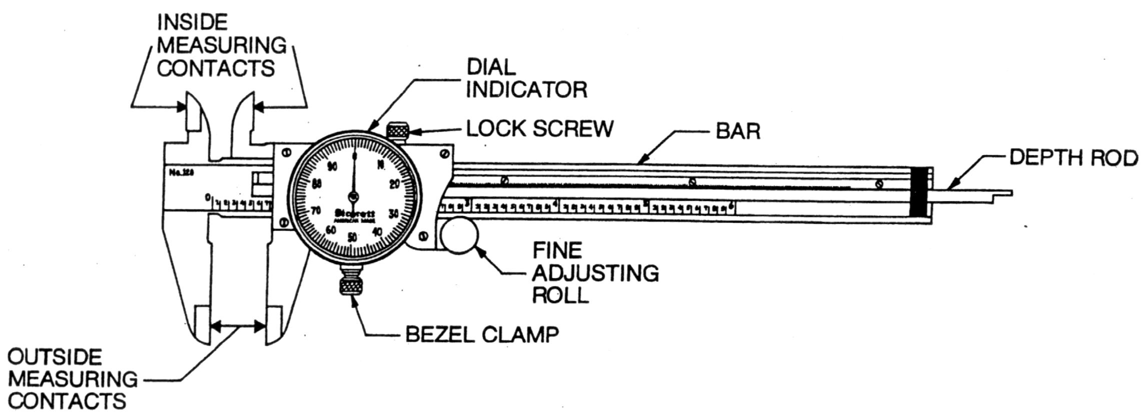


Figure 1. Dial caliper components (from Shewchuk, 2001)

Height Gage

The basic design of the height gage is same as that of the dial caliper. The primary use of height gages in the surface plate work is as a layout tool for marking off vertical distances and for measuring height and thickness difference between steps at various levels. Height gages differ from dial calipers in that they have a single jaw. The height gages are made with wide bases, with bars of cross section, and with dials.

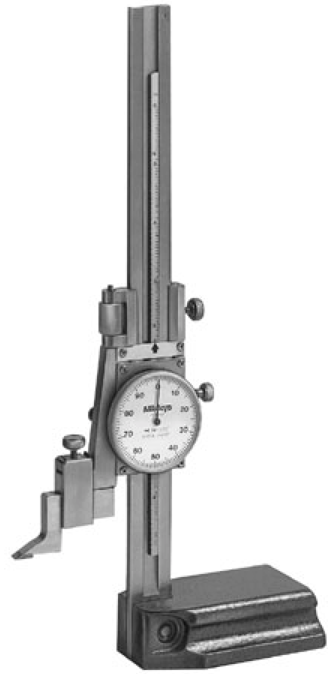


Figure 2. Dial height gage (from www.mitutoyo.com)

Dial Indicator

Dial indicators are simple mechanical devices which convert linear movement to rotation of an indicator needle on a circular dial. The indicator is first zeroed (i.e., the indicator needle is made to point to zero on the scale) with respect to some reference surface, then the part is brought into contact with the contact point. The measurement is read directly from the circular dial. Dial indicators are used with various holding fixtures for measuring thickness, height, straightness, parallelism, roundness, flatness, and runout. The fixture must be located on a solid, flat surface for such measurements to be taken.

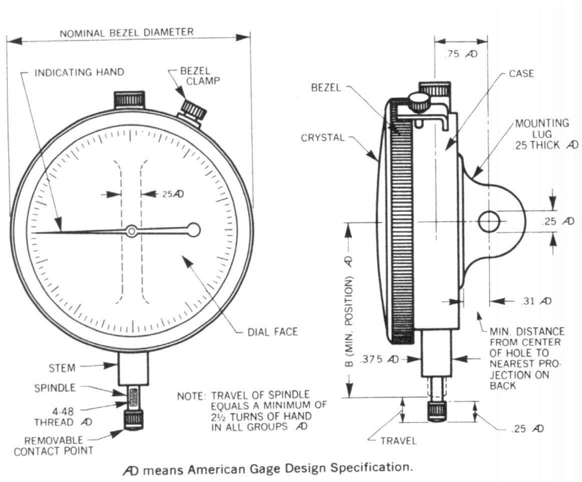


Figure 3. Dial indicator component (from Farago & Curtis, 1994)

Depth Micrometer

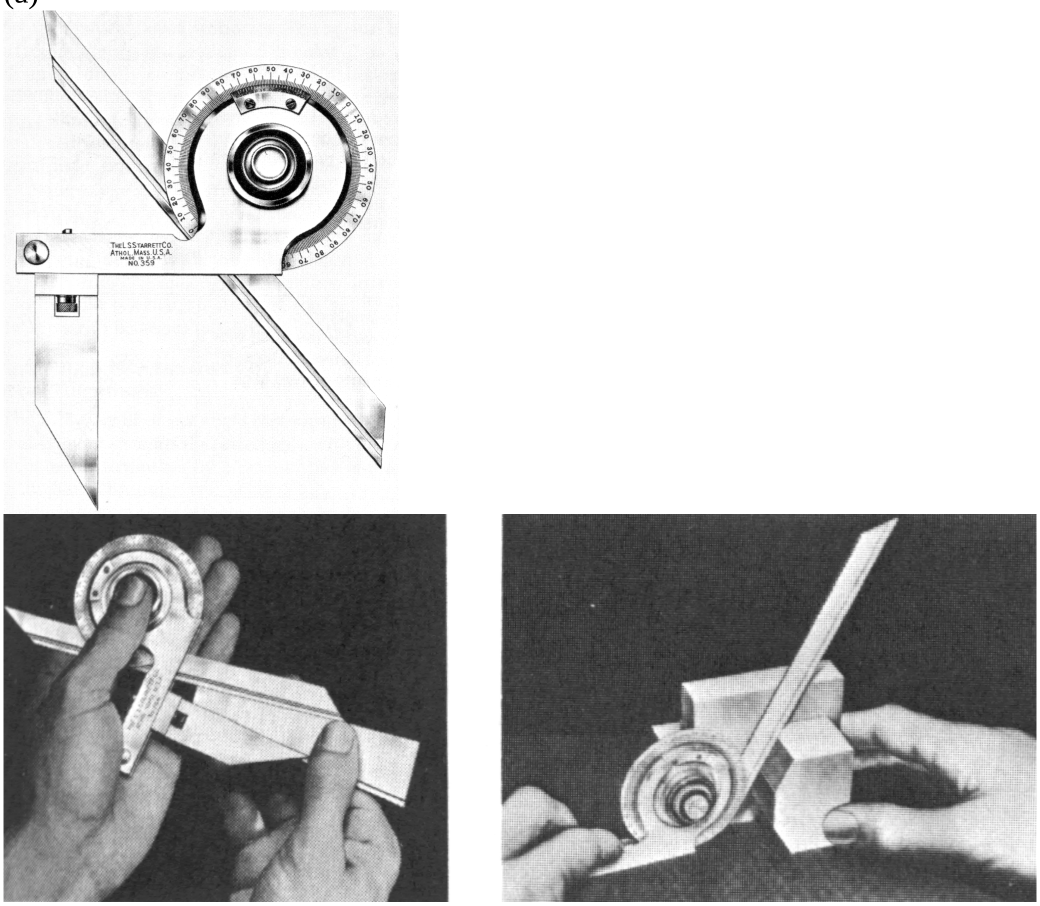
A depth micrometer consists of a threaded spindle inside a T-shaped frame. A graduated thimble and sleeve are located at the end of the spindle: rotating the thimble causes the spindle to move down and protrude from the bottom of the frame. The micrometer base is placed over the feature to be measured, and the spindle turned until it contacts the bottom of the feature.

Figure 4. Depth micrometer and rods (from www.mitutoyo.com)

Bevel Protractor

Universal bevel protractors are equipped with a full circular scale graduated into 360 degrees and complemented by a vernier scale applied to a segment. The segment has 12 graduation lines with special spacing in either directing to permit the subdivision of each one degree interval on the main scale into 12 equal parts corresponding to 1/12th part of a degree; that is, 5 minutes. Figure 5 shows how to use the bevel protractor to measure parts which have different shapes.

(a)



(b) (c)

Figure 5. Bevel protractor and its usage (from Farago & Curtis, 1994)
(a) Universal bevel protractor with thumb nut for fine adjustment
(b) The measurement of a part having a acute angle
(c) The angle being measured is related to that common reference plate

PRACTICE: PULLEY INSPECTION

1. Overall Length (L1)

   Equipment: Dial Caliper

   a. Take three equally-spaced readings of the pulley length: rotate pulley about 60° after each measurement
   b. Record each measurement, and calculate and record the average (as disposition value), on the part inspection report.

2. Pulley Length (L2)

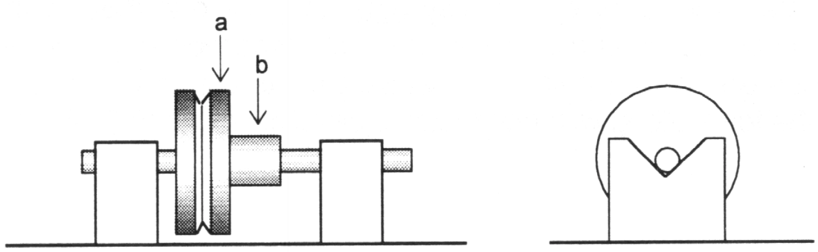
   Equipment: Dial Caliper

   a. Take three equally-spaced readings of the pulley length: rotate pulley about 60° after each measurement
   b. Record each measurement, and calculate and record the average (as disposition value), on the part inspection report.

3. Concentricity (C1) and Roundness (R1, R2)

   Equipment: Dial Indicator, 2 V-blocks, tapered mandrel

   a. Place the pulley on a mandrel
   b. Place the mandrel on V-blocks as shown in below:



   c. Raise the dial indicator contact point above the part height, then locate the contact point at point ‘a’ on the hub. Zero the indicator, using the bezel.
   d. Rotate the mandrel with the pulley and note the range of the dial indicator movement. This is known as T.I.R. (Total Indicator Reading). Record this value (R1) on the inspection report.
   e. Repeat steps c-d using point ‘b’ on the boss. Record this value (R2) on the inspection report.
   f. Calculate the concentricity of boss with hub, C, as follows:

$$C = \frac{|T.I.R._{R1} - T.I.R._{R2}|}{2}$$

4. Hole Diameter (D1)

   Equipment: Dial Caliper (Inside Measuring)

   a. Take three equally-spaced readings of the pulley length: rotate pulley about 60° after each measurement
   b. Record each measurement, and calculate and record the average (as disposition value), on the part inspection report.

5. Hub Diameter: Outside Diameter (D2)

   Equipment: Dial Caliper (Outside Measuring)

   a. Take three equally-spaced readings of the pulley length: rotate pulley about 60° after each measurement
   b. Record each measurement, and calculate and record the average (as disposition value), on the part inspection report.

6. Height (H1)

   Equipment: Height Gage

   a. Determine the measuring location by referring to the coordinates on the drawing. Mark the measuring point to decide the correct placement of the height gage.
   b. Record each measurement, and calculate and record the average (as disposition value) on the part inspection report.

7. Angle (A1)

   Equipment: Universal Bevel Protractor

   a. Embrace two bounding elements of the angle with a protractor.
   b. Record each measurement, and calculate and record the average (as disposition value) on the part inspection report.

8. Parallelism (P1), or Flatness (F1)

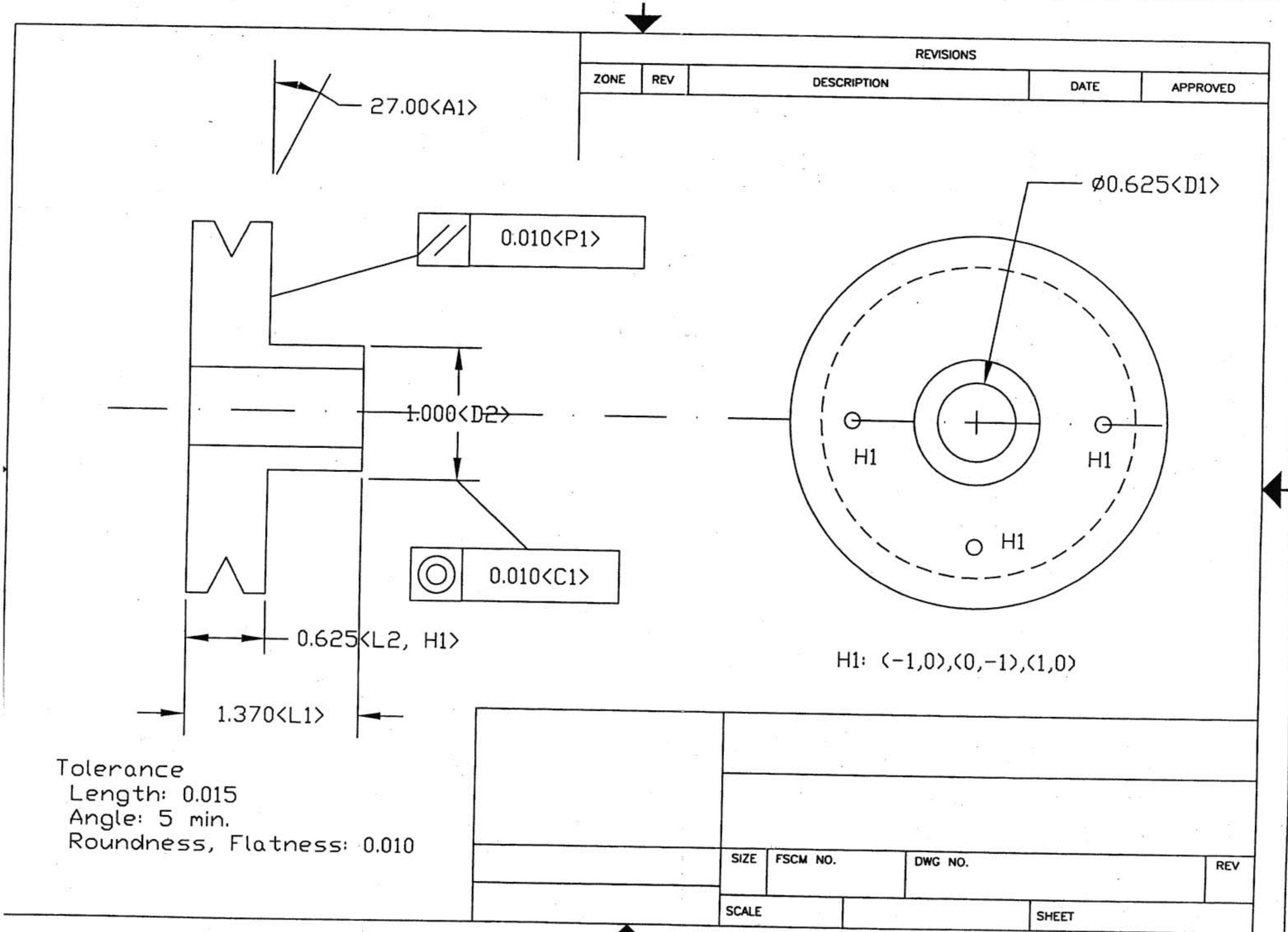
Equipment: Dial Indicator

a. Place the pulley top face up on the table.
b. Position the dial indicator contact point so that it is about 1/8 inch above the part surface, then move it to a position about ¼ inch from the right end of the pulley.
c. Move the dial down, by moving the arm, until the contact point just touches the pulley, then move down about 1/16 inch more.
d. Zero the dial by turning the bezel.
e. Slide the pulley longitudinally until the contact point is at the opposite end. Watch the indicator while moving the pulley and note T.I.R. Record the value on the form.
f. Rotate the pulley about 60° and repeat step a through e three times
g. Record the average value of the three readings as the disposition value on the inspection report.

Part Inspection Report

Part Type: Training Part	
Item No: *Training*	***Part Name:*** *Pulley*
Inspector #:	***Date:***

Attribute	**Results**			**Mean**	**Accept**	**Reject**
	1st	***2nd***	***3rd***			
1. Overall length (L1)						
2. Length of pulley (L2)						
3. Roundness (R1)						
4. Angle (A1)						
5. Hole Diameter (D1)						
6. Outside Diameter (D2)						
7. Height (H1)						
8. Angle (A1)						
9. Flatness (F1)						



REVISIONS
ZONE
REV
DESCRIPTION
DATE
APPROVED
27.00<A1>
0.010<P1>
Ø0.625<D1>
1.000<D2>
0.010<C1>
H1
H1
H1
0.625<L2, H1>
H1: (-1,0),(0,-1),(1,0)
1.370<L1>
Tolerance
Length: 0.015
Angle: 5 min.
Roundness, Flatness: 0.010
SIZE
FSCM NO.
DWG NO.
REV
SCALE
SHEET

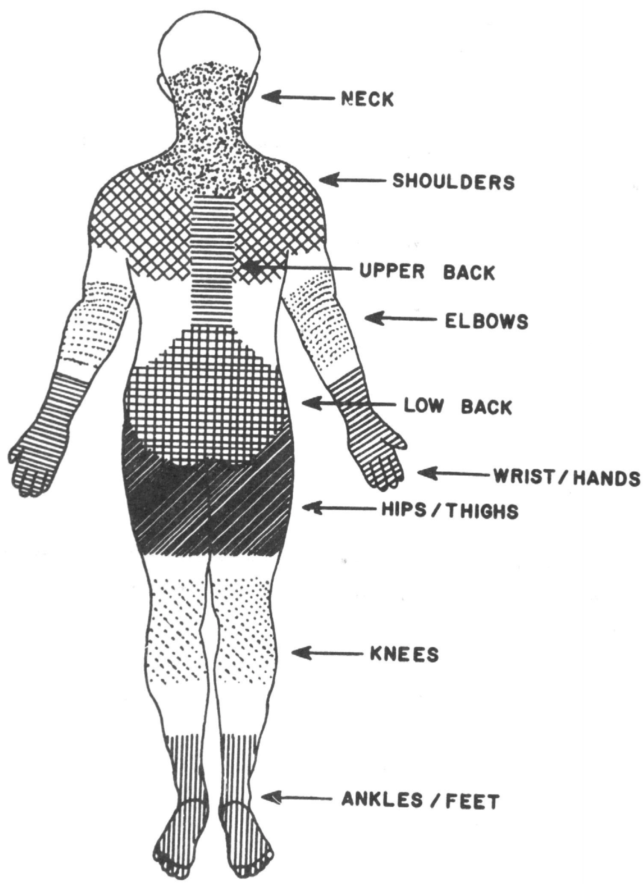
APPENDIX C: QUESTIONNAIRES

Subjective Questionnaires

This questionnaire consists of two parts: subjective judgment of body part discomfort and mental workloads related to the inspection task. Please answer every question by marking an appropriate scale by considering how you personally feel about you work experience with the task.

Part1: Body Part Discomfort

Please use the following picture to map the approximate position of the part of the body referred to in the questionnaire.



1. Head: I have experienced no discomfort at all during and after the experiment

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

2. Eye:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

3. Neck:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

4. Shoulder:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

5. Upper Arm:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

6. Elbows:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

7. Lower Arm and Hands:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

8. Upper Back:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

9. Lower Back:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

10. Hip and Thigh

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

11. Knees:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

12. Ankles/Feet:

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

Part 2: Mental workloads

Please indicate how you personally feel about your work experience with the task by marking how much you agree with each statement.

Mental Demand: How much mental activity (e.g., thinking, remembering, calculation, and decision) was required?

2.1 The inspection task was easy to perform mentally.

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

Physical Demand: How much physical activity (e.g., manipulating, controlling, and handling, etc.) was required?

2.2 The task was easy to perform physically.

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

Temporal Demand: How much time pressure did you feel due to the pace at which the task or task elements occur?

2.3 The work pace was slow and leisurely.

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

Performance: How successful do you think you were in accomplishing the task set by the experimenter?

2.4 I was satisfied with my performance in accomplishing the task.

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

Effort: How hard did you have to work (mentally and physically) to accomplish your level of performance?

2.5 I could finish the inspection task with a minimum level of efforts.

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

Frustration Level: How insecure, discouraged, limited, stressed and annoyed did you feel during the task?

2.6 I felt secure and interested while performing the inspection tasks.

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

User Acceptance: How did you feel about the inspection method that you did?

2.7 I prefer the inspection method that I used in this experiment to what I did in class.

1	2	3	4	5	6	7	8	9
Strongly Agree		Agree		Neutral		Disagree		Strongly Disagree

2.8 I recognized that I have seen the virtual image with one eye during the inspection task (Answer only if you conducted the AR-aided inspection).

Yes/No

Please tell us if you have suggestions or comment related to this experiment.

Questionnaire Results

1. Body Part Discomfort Rating

Subject	Method	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q12	P12
1	1	2	6	5	3	3	3	4	3	6	1	4	4
2	1	6	6	7	7	6	3	5	7	7	6	3	3
3	1	6	8	2	4	4	9	4	3	8	8	8	8
4	1	5	3	6	3	3	3	3	3	5	3	3	3
5	1	2	2	2	2	2	2	2	4	2	2	2	2
6	1	1	1	1	1	1	1	1	1	1	1	1	1
1	2	7	4	3	4	6	7	7	3	4	6	8	8
2	2	1	3	6	3	1	6	1	6	3	1	1	1
3	2	5	3	9	8	7	8	9	9	9	6	3	5
4	2	3	3	7	3	5	5	5	7	7	3	3	5
5	2	1	1	1	1	1	1	1	1	1	1	1	1
6	2	1	1	1	1	1	1	1	7	1	1	1	1
1	3	3	3.5	3.5	1.5	2.5	1.5	1.5	3.5	2.5	1.5	1.5	1.5
2	3	2	1	2	6	3	2	3	8	5	1	1	1
3	3	1	1	3	4	3	1	1	4	7	4	1	1
4	3	1	9	6	7	1	1	5	7	8	1	1	1
5	3	2	5	2	2	2	1	7	7	5	1	1	1
6	3	1	1	2	1	1	1	1	1	7	1	1	1
1	4	1	6	7	6	2	2	3	5	2	1	3	1
2	4	6	3	1	3	3	3	3	9	9	3	3	1
3	4	3	4	6	3	3	3	6	5	7	3	3	3
4	4	1	1	1	1	1	1	1	1	1	1	1	1
5	4	3	3	5	3	3	3	3	7	3	3	3	3
6	4	1	1	3	1	1	1	1	1	5	1	1	1

2. Mental Workloads Rating

Subject	Method	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	1	3	1	6	3	4	4	5
2	1	3	2	5	3	5	3	5
3	1	4	4	4	4	4	4	5
4	1	7	5	7	5	6	5	5
5	1	2	1	2	2	2	2	5
6	1	2	3	1	2	4	2	5
1	2	2	2	8	4	3	5	4
2	2	3	4	3	3	3	4	5
3	2	7	6	5	2	4	6	4
4	2	3	5	5	3	3	5	3
5	2	3	1	1	3	1	1	5
6	2	1	1	1	1	1	1	7
1	3	3.5	4.5	6.5	2.5	3.5	3.5	2
2	3	2	3	1	2	4	2	1
3	3	3	3	2	2	3	1	2
4	3	4	3	3	3	4	6	1
5	3	3	4	6	3	4	3	1
6	3	2	3	6	3	3	3	1
1	4	3	2	4	2	2	3	3
2	4	1	5	3	2	1	3	1
3	4	3	3	3	4	3	2	2
4	4	3	1	5	3	5	3	2
5	4	3	3	3	3	3	3	5
6	4	2	1	5	3	4	5	1

APPENDIX D: INSPECTION REPORT & ENGINEERING DRAWINGS

Part Inspection Report

Part Type: Prismatic	
Item No: *P-1*	***Part Name:*** *Safety Key*
Inspector #:	***Date:***

Attribute	**Results**			**Mean**	**Accept**	**Reject**
	1st	***2nd***	***3rd***			
1. Overall length (L1)						
2. Width of middle (W1)						
3. Length of left (L2)						
4. Hole diameter (D1)						
5. Left inside length (L3)						
6. Overall height (H1)						
7. Height of middle (H2)						
8. Angle (A1)						
9. Flatness (F1)						
10. Overall width (W2)						
11. Width of right (W3)						
12. Top right width (W4)						
13. Inner width (W5)						
14. Top inside width (W6)						
15. Depth (DT1)						

Part Inspection Report

Part Type: Prismatic	
Item No: *P-2*	***Part Name:*** *Finger Guide*
Inspector #:	***Date:***

Attribute	**Results**			**Mean**	**Accept**	**Reject**
	1st	***2nd***	***3rd***			
1. Overall length (L1)						
2. Length of left end (L2)						
3. Length of center (L3)						
4. Inside width (W1)						
5. Overall height (H1)						
6. Height of middle (H2)						
7. Flatness (F1)						
8. Overall width (W2)						
9. Rear inside width (W3)						
10. Right slop angle (A1)						
11. Left slop angle (A2)						

Part Inspection Report

Part Type: Prismatic	
Item No: *P-3*	***Part Name:*** *Tool Holder*
Inspector #:	***Date:***

Attribute	**Results**			**Mean**	**Accept**	**Reject**
	1st	***2nd***	***3rd***			
1. Overall length (L1)						
2. Length of middle leg (L2)						
3. Length of left leg (L3)						
4. Inside length (L4)						
5. Overall height (H1)						
6. Height of middle (H2)						
7. Angle (A1)						
8. Flatness (F1)						
9. Right end width (W1)						
10. Hole diameter (D1)						
11. Left slop angle (A2)						

Part Inspection Report

Part Type: Rotational	
Item No: *R-1*	***Part Name:*** *Step Pulley*
Inspector #:	***Date:***

Attribute	**Results**			**Mean**	**Accept**	**Reject**
	1st	***2nd***	***3rd***			
1. Overall length (L1)						
2. Length to 2nd step (L2)						
3. Length of 1st step (L3)						
4. Diameter of right (D1)						
5. Diameter of middle (D2)						
6. Diameter of left (D3)						
7. Roundness of right (R1)						
8. Roundness of middle (R2)						
9. Roundness of left (R3)						
10. Hole diameter (D4)						

Part Inspection Report

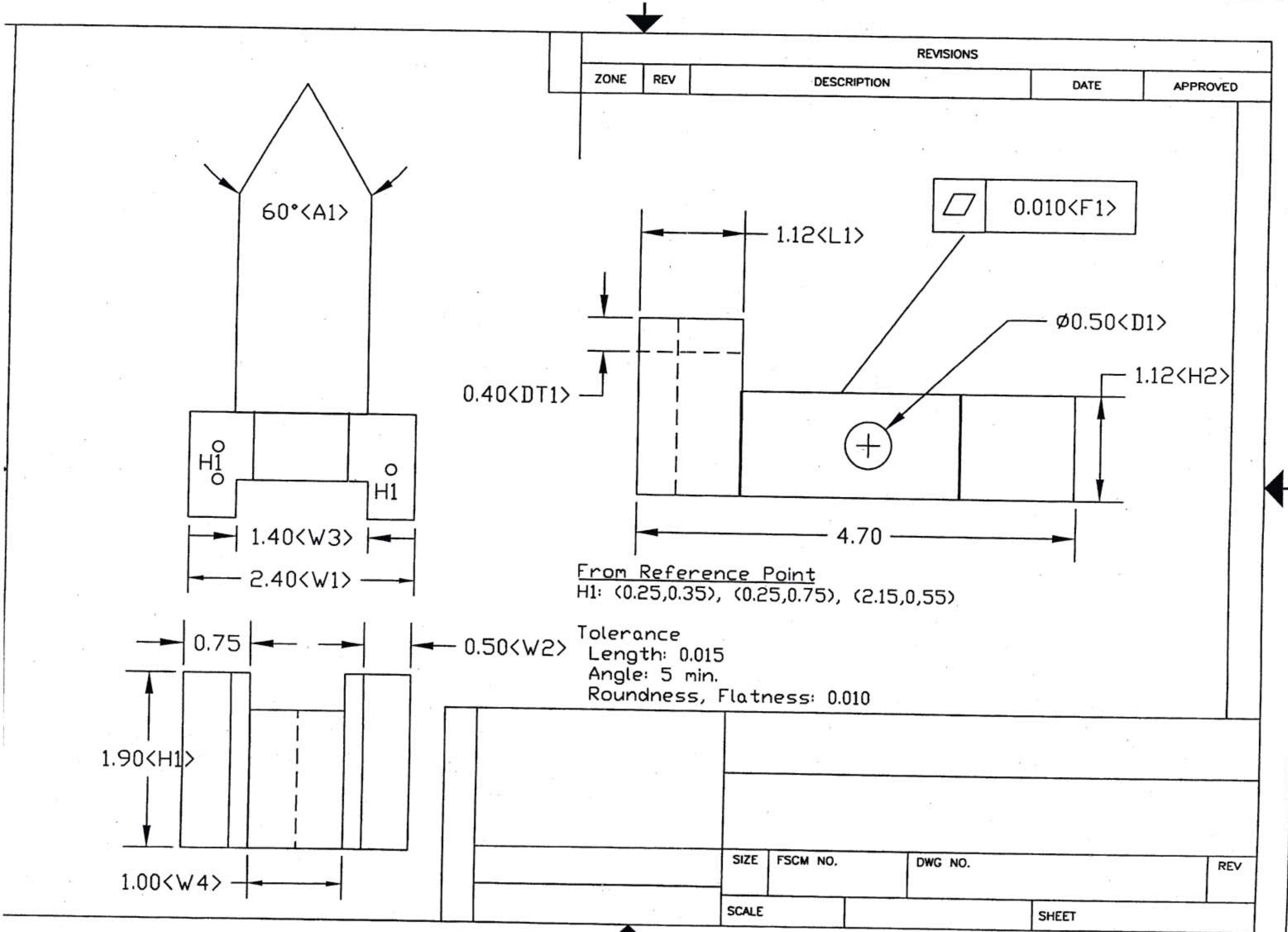
Part Type: Rotational	
Item No: *R-2*	***Part Name:*** *Holder*
Inspector #:	***Date:***

Attribute	**Results**			**Mean**	**Accept**	**Reject**
	1st	***2nd***	***3rd***			
1. Overall length (L1)						
2. Length to shoulder (L2)						
3. Shoulder length (L3)						
4. Base diameter (D1)						
5. Top diameter (D2)						
6. Angle (A1)						
7. Shoulder diameter (D3)						
8. Right hole diameter (D4)						
9. Left hole diameter (D5)						
10. Shoulder height (H1)						

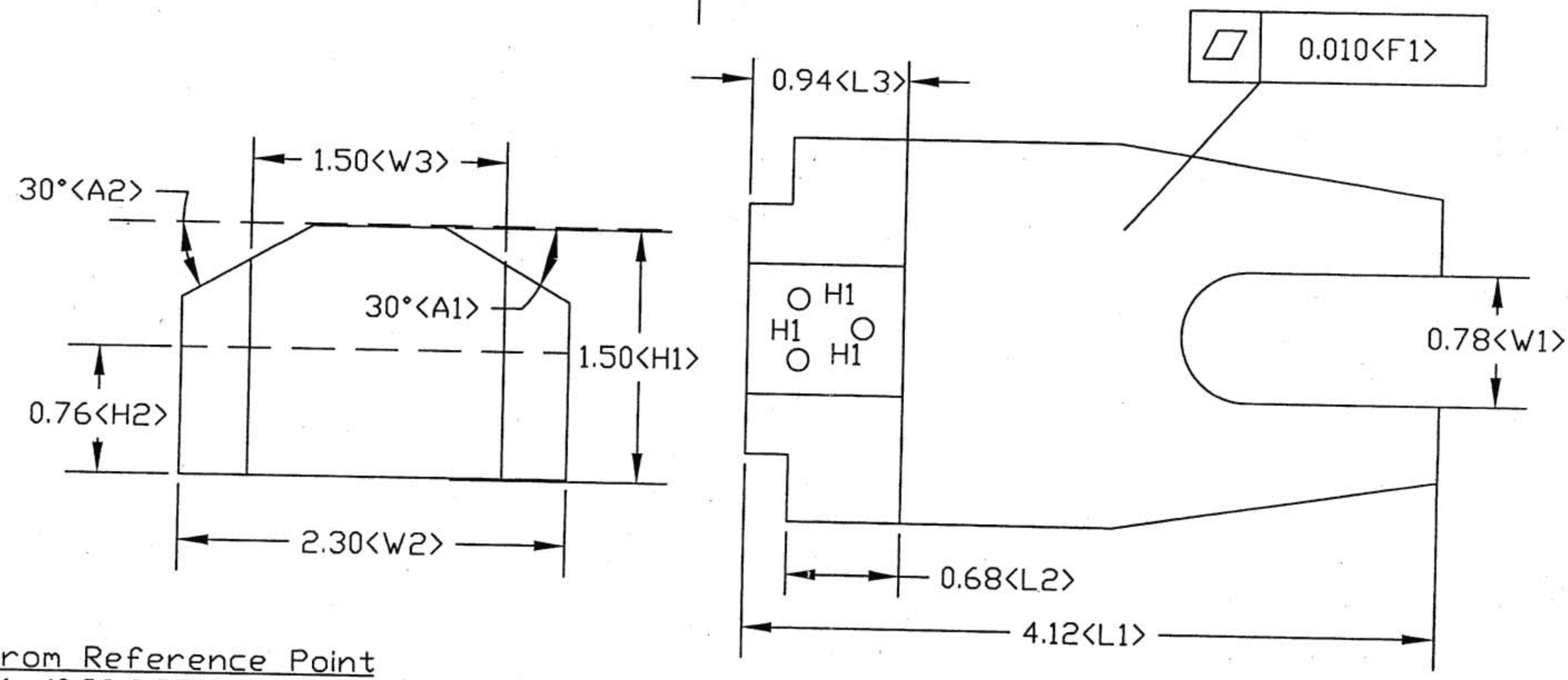
Part Inspection Report

Part Type: Rotational	
Item No: *R-3*	***Part Name:*** *Roller Stud*
Inspector #:	***Date:***

Attribute	**Results**			**Mean**	**Accept**	**Reject**
	1st	***2nd***	***3rd***			
1. Overall length (L1)						
2. Length to upper cut (L2)						
3. Length to lower cut (L3)						
4. Length to 2nd step (L4)						
5. Length to 1st step (L5)						
6. Diameter of right (D1)						
7. Diameter of left (D2)						
8. Hole diameter (D3)						
9. Width of middle (W1)						
Concentricity						
10. Roundness of right (R1)						
11. Roundness of left (R1)						
Difference 10 and 11						


REVISIONS
ZONE
REV
DESCRIPTION
DATE
APPROVED
60°<A1>
H1
H1
1.40<W3>
2.40<W1>
0.75
0.50<W2>
1.90<H1>
1.00<W4>
1.12<L1>
0.010<F1>
Ø0.50<D1>
0.40<DT1>
1.12<H2>
4.70
From Reference Point
H1: (0.25,0.35), (0.25,0.75), (2.15,0,55)
Tolerance
Length: 0.015
Angle: 5 min.
Roundness, Flatness: 0.010
SIZE
FSCM NO.
DWG NO.
REV
SCALE
SHEET

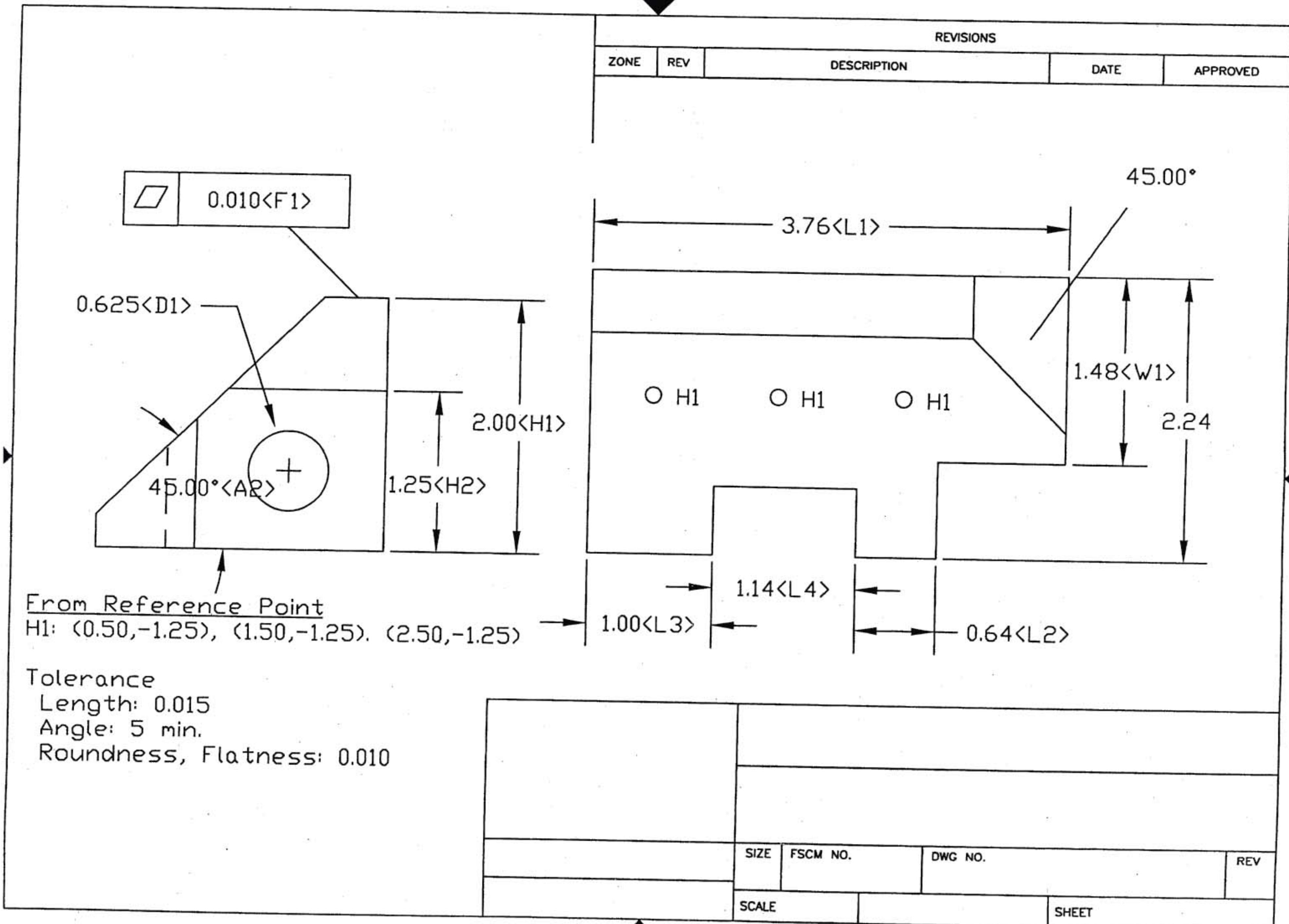
REVISIONS				
ZONE	REV	DESCRIPTION	DATE	APPROVED

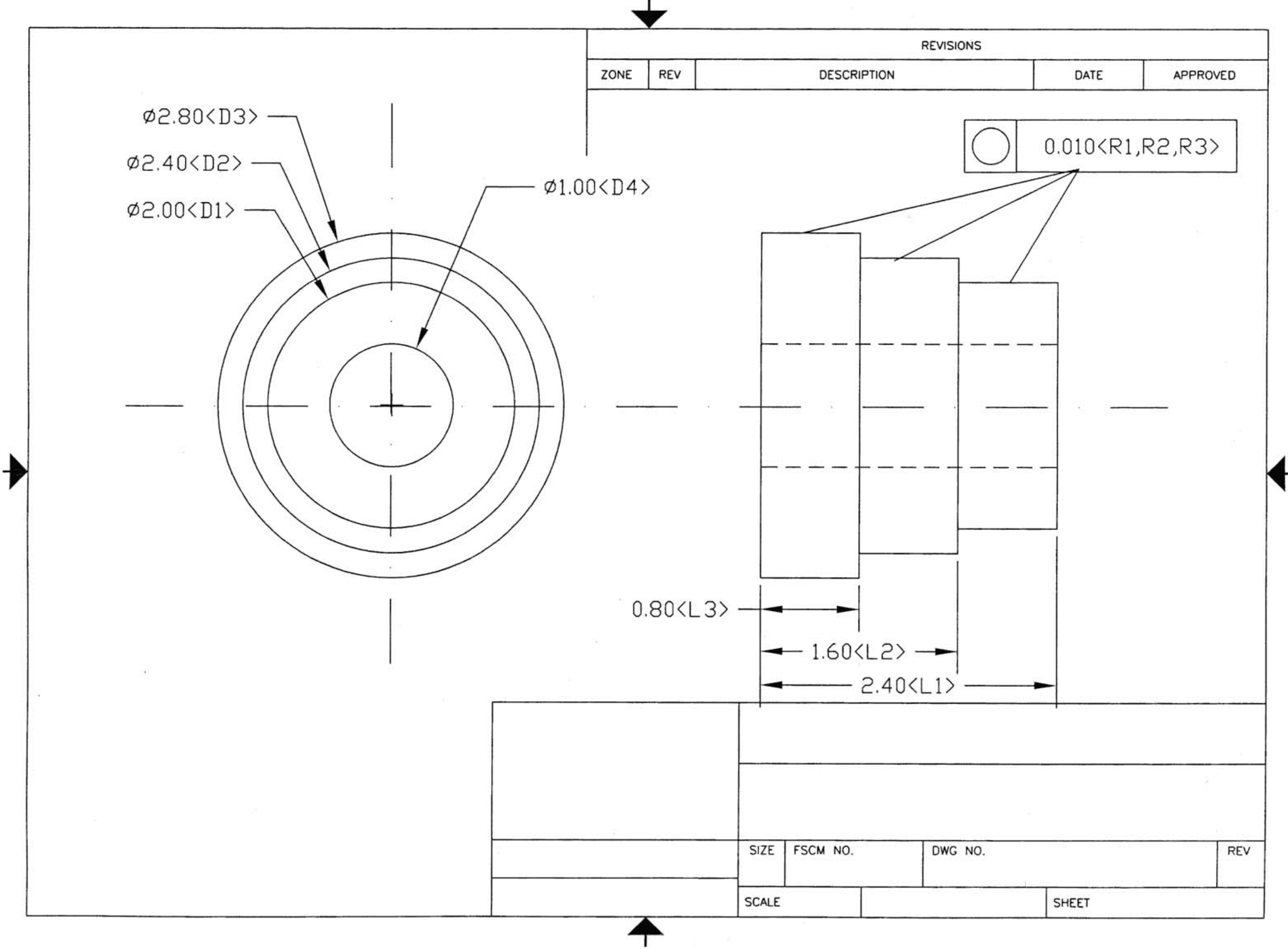


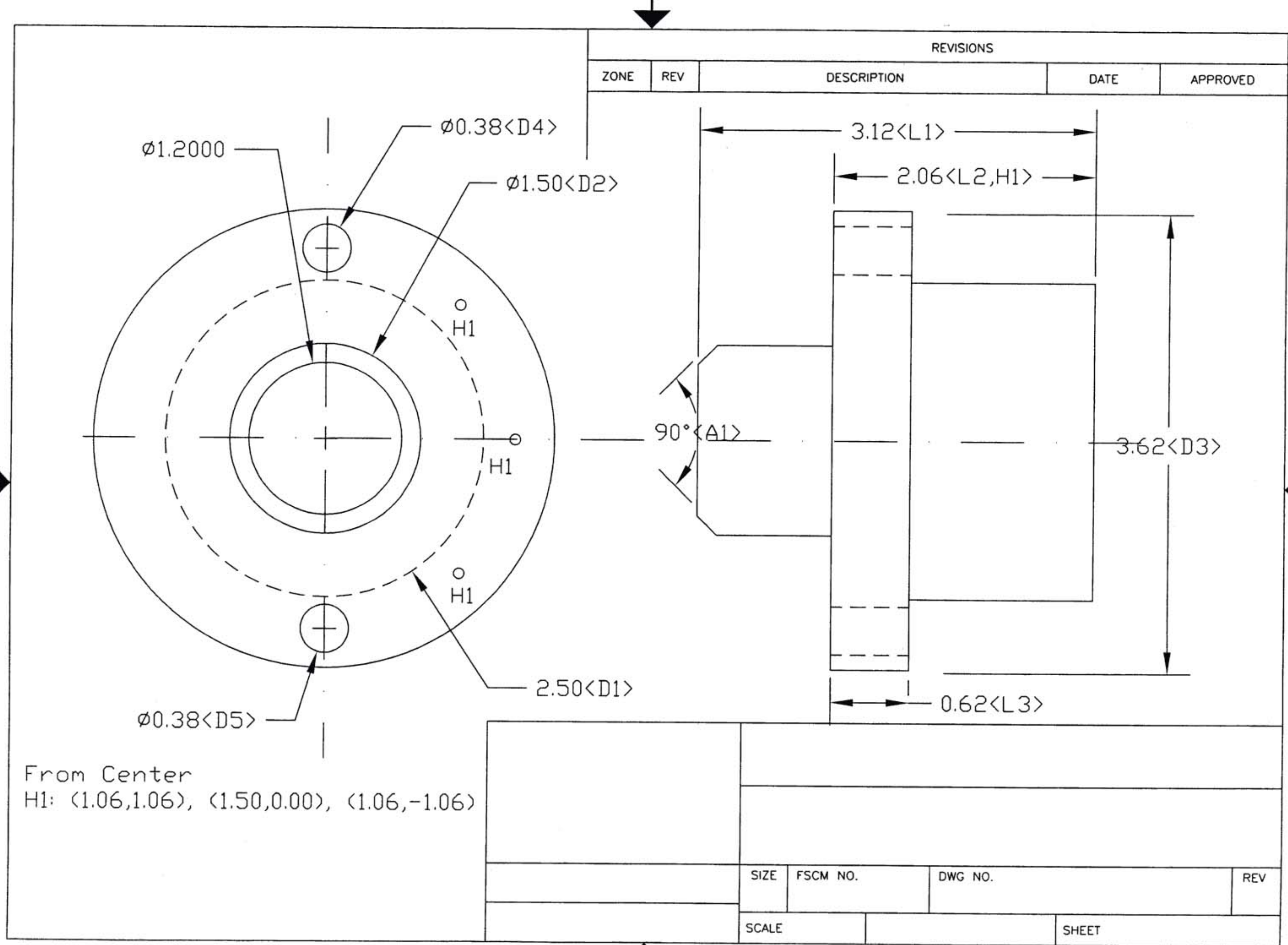
<u>From Reference Point</u>
H1: (0.30,0.95), (0.30,1.35), (0.60,1.15)

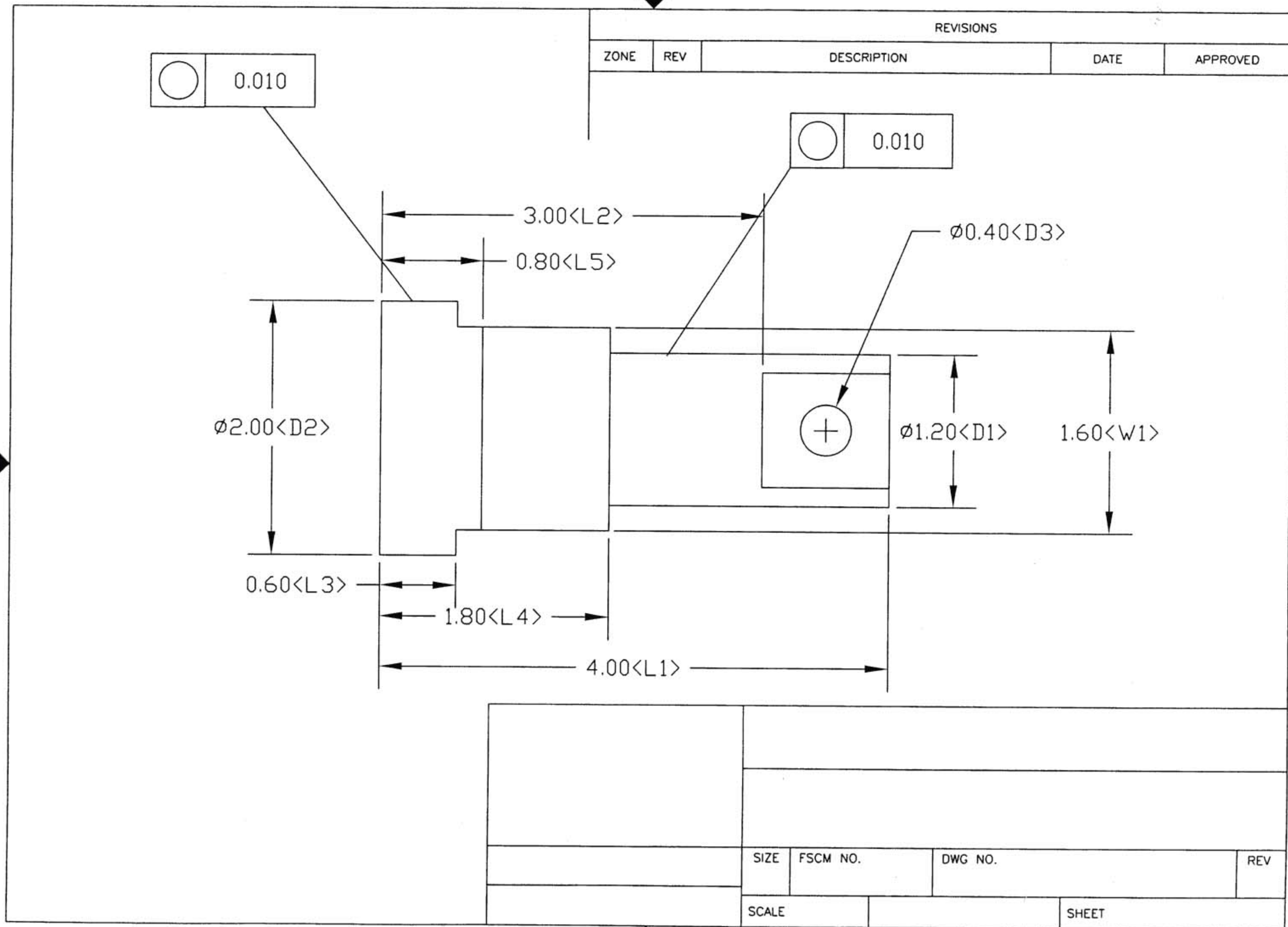
Tolerance
Length: 0.015
Angle: 5 min.
Roundness, Flatness: 0.010

SIZE	FSCM NO.	DWG NO.	REV
SCALE		SHEET	


REVISIONS
ZONE
REV
DESCRIPTION
DATE
APPROVED
0.010<F1>
0.625<D1>
45.00°<A2>
1.25<H2>
2.00<H1>
3.76<L1>
45.00°
1.48<W1>
2.24
H1
H1
H1
1.14<L4>
1.00<L3>
0.64<L2>
From Reference Point
H1: (0.50,-1.25), (1.50,-1.25). (2.50,-1.25)
Tolerance
Length: 0.015
Angle: 5 min.
Roundness, Flatness: 0.010
SIZE
FSCM NO.
DWG NO.
REV
SCALE
SHEET


REVISIONS
ZONE
REV
DESCRIPTION
DATE
APPROVED
Ø2.80<D3>
Ø2.40<D2>
Ø2.00<D1>
Ø1.00<D4>
0.010<R1,R2,R3>
0.80<L3>
1.60<L2>
2.40<L1>
SIZE
FSCM NO.
DWG NO.
REV
SCALE
SHEET


REVISIONS
ZONE
REV
DESCRIPTION
DATE
APPROVED
Ø1.2000
Ø0.38<D4>
Ø1.50<D2>
H1
H1
H1
2.50<D1>
Ø0.38<D5>
3.12<L1>
2.06<L2,H1>
90°<A1>
3.62<D3>
0.62<L3>
From Center
H1: (1.06,1.06), (1.50,0.00), (1.06,-1.06)
SIZE
FSCM NO.
DWG NO.
REV
SCALE
SHEET


REVISIONS
ZONE
REV
DESCRIPTION
DATE
APPROVED
0.010
0.010
3.00<L2>
0.80<L5>
Ø0.40<D3>
Ø2.00<D2>
Ø1.20<D1>
1.60<W1>
0.60<L3>
1.80<L4>
4.00<L1>
SIZE
FSCM NO.
DWG NO.
REV
SCALE
SHEET

VITA

Kyung H. Chung

Education

M.S.	1985	Seoul National University, Seoul, Korea Major: Industrial Engineering/Human Factors
B.S.	1983	Hanyang University, Seoul, Korea Major: Industrial Engineering

Academic and Professional Experience

1996 - Present	Enrolled as a graduate students at Virginia Polytechnic and State University, Blacksburg, Virginia Tech
1994 - 1996	Project Manager Department of Techno-Economic Analysis Electronics and Telecommunication Research Institute (ETRI) Taejon, Korea
1992 - 1994	Senior Researcher Department of Techno-Economic Analysis Electronics and Telecommunication Research Institute (ETRI) Taejon, Korea
1986 - 1992	Researcher Department of Techno-Economic Analysis Electronics and Telecommunication Research Institute (ETRI) Taejon, Korea