An AR Inspection Framework: Feasibility Study with Multiple AR Devices

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Abstract

We present an Augmented Reality (AR) based re-configurable framework for inspection that can be utilized in cross-domain applications such as maintenance and repair assistance in industrial inspection, health sector to record vitals, and automotive/avionics domain inspection, amongst others. The novelty of the inspection framework as compared to the existing counterparts are three fold. Firstly, the inspection check-list can be prioritized by detecting the parts viewed in inspector's field using deep learning principles. Second, the back-end of the framework is easily configurable for different applications where instructions and assistance manuals can be directly imported and visually integrated with inspection type. Third, we conduct a feasibility study on inspection modes such as *Google Glass*, *Google Cardboard*, *Paper based* and *Tablet* for inspection turnaround time, ease, and usefulness by taking a 3D printer inspection use-case.

Index Terms: H.5.1 [Information Interfaces and Presentation]: Artificial, Augmented, and Virtual Realities—; [Human-centered computing]: Ubiquitous and mobile computing—Ambient IntelligenceH.5.2 [Information Interfaces and Presentation]: User Interfaces—Interaction Styles I.4.8 [Computing Methodologies]: Image Processing and Computer Vision—Scene Analysis

1 Introduction

With the advancement in camera technologies and data streaming protocols, AR based applications are proving to be an important aid for inspection, training and supervision tasks in various operations including automotive industry, health-care, education etc.. We present a flexible AR platform for such scenarios which can work across different devices and can be easily configured for different applications.

An inspection is an organized examination of particular equipment/process. Inspection typically involves a set of checks to be performed in accordance to a guideline provided by the product, or an equipment in an industry. The objective of these checks is to verify that no defects are present and all compliance tests have been performed.

The other areas where inspection is carried out employing complex checks for safety, quality are – oil refineries, petrochemical complexes, chemical plants, cement plants, cross-country pipelines, in shipping industries, for wind mill towers and fabrication shops [15]. Such a wide variety of inspection scenarios impose a number of requirements. From an inspector's perspective (a) an optimal guided path around the object of inspection should be provided, (b) precise check-list for the part under inspection should be available, (c) priority of the check should be known, (d) part specification should be available when required and (e) accurate recording of observed inconsistencies should be possible. From the perspective of a company, the requirements include (f) inspection tasks should be completely quick and accurate (g) it should be possible to change priorities of checks due to external factors and (h) all inspection records should be available easily [6] [7].

In this paper, we propose a framework for AR based inspection that is designed to meet the above requirements. The key contributions of our work are:

1 Display of relevant check-list with priorities. The priority of the check-list may be dynamic and driven by object detection paradigm. Refer Sections 3.2 and 3.4.

2 Marker-less AR Guided inspection sequence adaptable to any domain with minimal modifications in the back-end (see Section 3.3).

3 Accurate recording of status of inspection through evidence capturing of images, audio, notes, and videos. The same client software runs on all Android devices evaluated (Cardboard with mobile phone, Google Glass and Tablet).

The organization of the paper is as follows: In Section 2, a literature survey on AR based inspection is discussed. Section 3 describes the proposed framework and architecture, user interaction and marker-less object detection. Section 4 discusses experiments and results through objective and subjective metrics. Finally, Sections 5 and 6 conclude with discussion and summarizing the contributions.

2 Previous Work

We review the different methods of inspection spanning from Paper-based to Google Glass based inspection and in each case highlight the advantages and disadvantages of the same. Traditionally, paper inspections were performed that require data entry, often leading to duplication of labour, with one person completing the inspections and another staff member typing the data into spreadsheets, reports, or work flow systems [3]. This evolved to Digital check-lists that ranged from a simple editable Adobe check-list, to forms with links from the line items to supporting information, to systems which communicate directly with the main office [1]. All these systems lack object parts detection mechanism and automatic recording of inspection evidences on the remote server.

AR technologies enhance our perception and help us see, hear, and feel our environments in enriched ways. With the use of AR to incorporate instruction and assistance manuals interactively and directly within the task domain, and directly referencing the equipment at which the user is looking, has the potential to eliminate the current need for personnel to continually switch their focus of attention between the inspection task and its separate documentation in Paper-based or Tablet-based instructions [9]. It is reported that during repair and maintenance tasks, the use of AR increases productivity, reduces personal risk when working in difficult environment and also helps in performing complex tasks faster with less errors. The scientists at Boeing Corporation developed an experimental AR system to help workers put together wiring harnesses – AR Tablet based inspections were 30% faster and 90% more accurate than desktop or Paper-based inspection methods [17]. BMW uses AR

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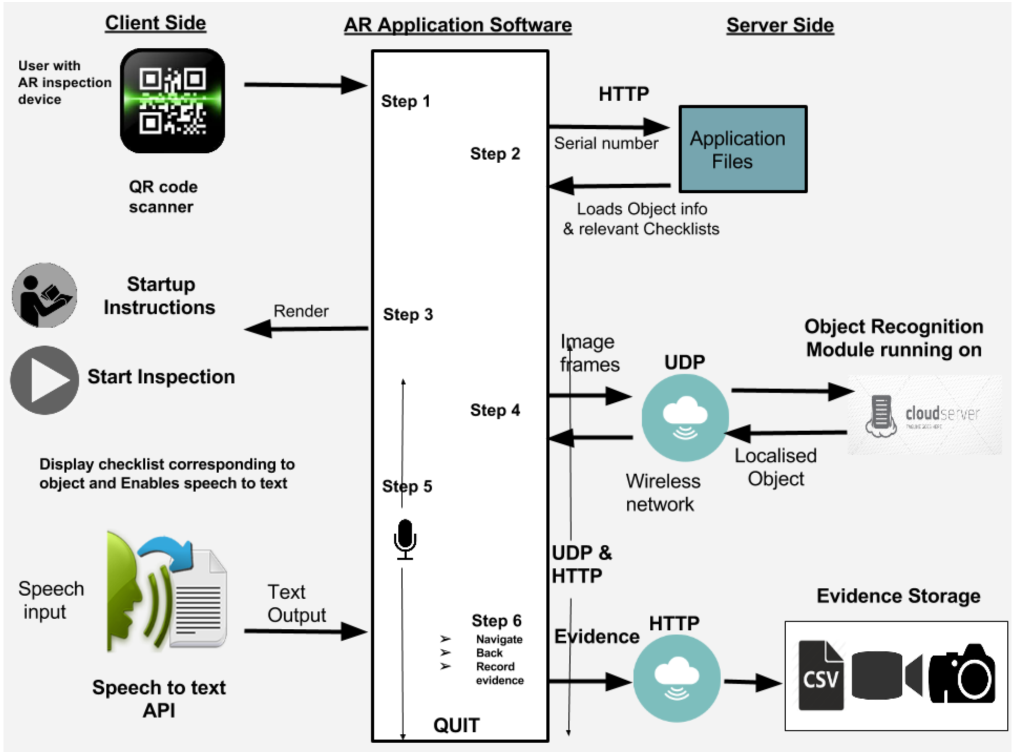


Figure 1: Block diagram showing the various components of the proposed inspection framework

glasses that can assist their mechanics to perform maintenance on the company's high-performance cars. The glasses read the field of view, point out the part that needs replacing and instruct/overlay how to do so [2].

Reference [10] demonstrated desktop based Airline maintenance use-case with efficient ontology-oriented resource management of the knowledge base; our approach employs QR code driven loading of inspection data and efficient object detection driven fetching of context aware information (Section 3.2). It is simpler for both handheld/hands-free device to scan QR code to obtain relevant data compared to generating ontology instances and modelling ontology schema. Telepresence based expert advise proposed in [12] is relevant for assembly tasks. [12] uses marker based tracking which is not economically viable and time consuming to calibrate markers. These markers always need to be present in the FoV and cannot be obscured by other objects during the augmentation [5] to estimate the camera pose. To overcome these problems with marker based AR, we use deep learning based marker-less object detection and tracking (Refer Section 3.2).

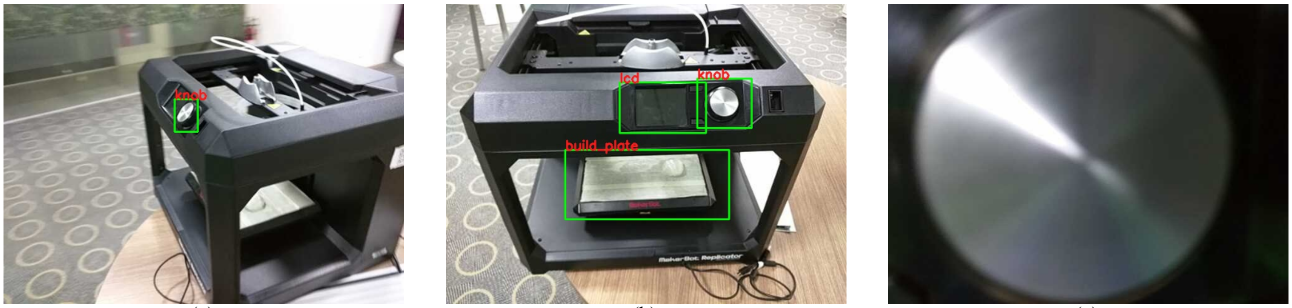
We take into account the following challenges/requirements of developing an inspection framework (a) The inspection time frame; an inspection is to be performed in a limited time and usually time to complete inspection is correlated with the user satisfaction in addition to the type of overlays (b) A large number of check-lists pertaining to a specific model and variant of the product would have to be addressed; some checks may need to be prioritised – prioritisation is typically hard-coded but we also introduce a strategy of object-detection driven check-list priorities (c) The *Google Cardboard* is explored for marker-less AR which hitherto was used for VR applications.

3 Proposed Framework

Our solution aims in developing inspection framework where users can perform complex inspection tasks. To achieve this, we use combination of android mobile and wearable gadgets such as *Google Cardboard*, *Google Glass* and Tablet. The small opening at front pad of the cardboard enables us to capture real-world through device camera allowing developments in AR. The stereoscopic vision of the camera feed on the mobile screen enables the mobile application to be used with Google Cardboard.

Our hardware set-up comprises of (i) QR codes for authentication and obtaining relevant product/object information; (ii) An android phone with a wearable (*Google Cardboard* or *Wearality*) or a *Tablet* or a *Google Glass*; and (iii) A remote system server which can handle live video stream from user device, implements object detection, and having a reliable connection for evidence storage during inspection. Figure 1 shows the view of our AR based inspection framework. The individual steps in the framework are described below.

- In the *Step 1*, the application detects the QR code (using Zxing's library [4]) attached to the device to be inspected and extracts the Serial Number encrypted within the code.
- In the *Step 2*, we query to match this serial number with the entries in back-end server and extract the relevant device information such as; while inspecting a printer its make, type, year of manufacture and inspection history are retrieved along with corresponding check-lists to be performed during inspection.
- In the *Step 3*, the safety instructions and part manuals are displayed on the user device screen; then a system request to start the inspection process is shown. These three initial steps make sure that all the relevant contents for the device are extracted and the user is aware of the complete inspection process.



(a) (b) (c)

Figure 2: Printer part detection: (a) and (b) show sample detection of the printer parts through a bounding box overlay. (c) shows blurry dial where the inspector is observing the part too close, in this situation, inspector is suggested to move slightly away and then resume inspection.

- The *Step* 4, 5 and 6 are specific to the inspection steps and checks to performed on the device. Inspection is performed by a combination of graphic and augmented interfaces, object detection on a remote server, a speech recognition module, and user gestures – *touch* and *tap* for Tablet and *Google Glass* respectively. The AR device's camera captures the scene and is sent to the remote server. We track different objects in this stream (Section3.2) which guides the display of part/object specific information including the check-lists. The speech recognition module recognizes the user commands and helps in choosing options similar to Interactive Voice Recognition (IVR), for authoring the comments and recording the inspection evidences. Section 3.1 describes the possible user interaction techniques utilized. Once the user completes all checks, the inspection data is transferred to the remote server.

3.1 User Interaction

Our application supports various modes of user interaction based on the device used for the inspection. These include voice based interaction on Android devices is achieved through the Google speech recognition API service (works well with Android 4.2 and above). This service continuously listens for user voice input through the device microphone and immediately returns the text output. This text output is then compared with the predefined keywords to execute the relevant task. Google speech recognition service relies on the internet connectivity through which it sends speech data to the server and it subsequently outputs the text. A virtual overlay of on-screen selection buttons can be used for tablet display through which user can easily switch between multiple options. Google Glass uses its touch pad located at the side of the device for user interaction.

3.2 Object Detection and tracking through deep learning

We have demonstrated R-CNN [13], a recent deep learning architecture, based object detection for identifying the parts of a printer obviating the need of marker based methods. The object detection was found to be almost 100% accurate with only one object part missing out of 70 test images owing to extreme blur. In this Section, the details of image collection used for evaluation is presented. Figure 2 shows sample detections of the printer parts. Figure 2 (c) was captured too close and as a result of the image being outside the depth of field – the image is rendered blurry. We employ the non-referential blur detection based on cumulative probability of blur detection suggested by Narvekar et al [11] to quantify the level of blur in an image. When an image's blur is beyond a reasonable threshold, we then suggest the inspector to move back to resume inspection.

For tracking of parts in subsequent frames, we use simple tracking by detection approach, i.e. we run our R-CNN based part detector on continuous frames which identifies position of different parts appearing at all scales. We are not using any explicit model for data association between different frames as R-CNN based detector has shown perfect accuracy in detection performance. Further, occlusion is a not an issue in present scenario as the application software is expected to display information for only those objects which are visible in the view. The RCNN based object detector comprises of following three steps:

1 Generation of category-independent object proposals: Object proposals are the regions/segments of all sizes in the captured images which has atleast one dominant object part in the segment. The label of the segment is defined based on the dominant object part.

2 Feature extraction for object proposals: Training a deep convolutional neural network to extract fixed-length feature-representation of each of these candidate object proposals

3 Classification model for recognizing the proposals: Training a class-specific SVM utilized to find out the score for each extracted feature-vector.

For evaluation purposes, we focussed on 7 object part classes (Build plate, Printer back, Extruder, Filament Spool, LCD, USB Port, and Knob) corresponding to printer inspection use-case. The dataset comprised total 140 images with 20 images of each class where 10 images were used for training and 10 for testing.

The candidate windows i.e. object proposals where generated using selective search's fast-mode [16]. This resulted in around 2000 candidate object proposals of varied sizes which were warped to size 227 X 227 pixels in the next step. Subsequently, each object proposal was forward propagated through a Convolutional neural network (CNN) in order to read off features from the desired layer. Then, for each class, we score each extracted feature vector using the SVM trained for that class. Given all scored regions in an image, we apply a greedy non-maximum suppression (for each class independently) that rejects a region if it has an intersection over-union (IoU) overlap with a higher scoring selected region larger than a learned threshold. We have used default CNN Hyper-parameters as provided in the Fast R-CNN implementation shared by the authors in [13].

3.3 Data handling

Data handling in our inspection framework involves (i) fetching the relevant check-lists and object information from the server post QR code scanning; (ii) sending live video stream to the server for object detection and tracking with the help of fast data transmission User Datagram Protocol (UDP); and (iii) accurate storing of inspection evidence in the form of text, audio, and images on the server through HTTP with reliable TCP connection.

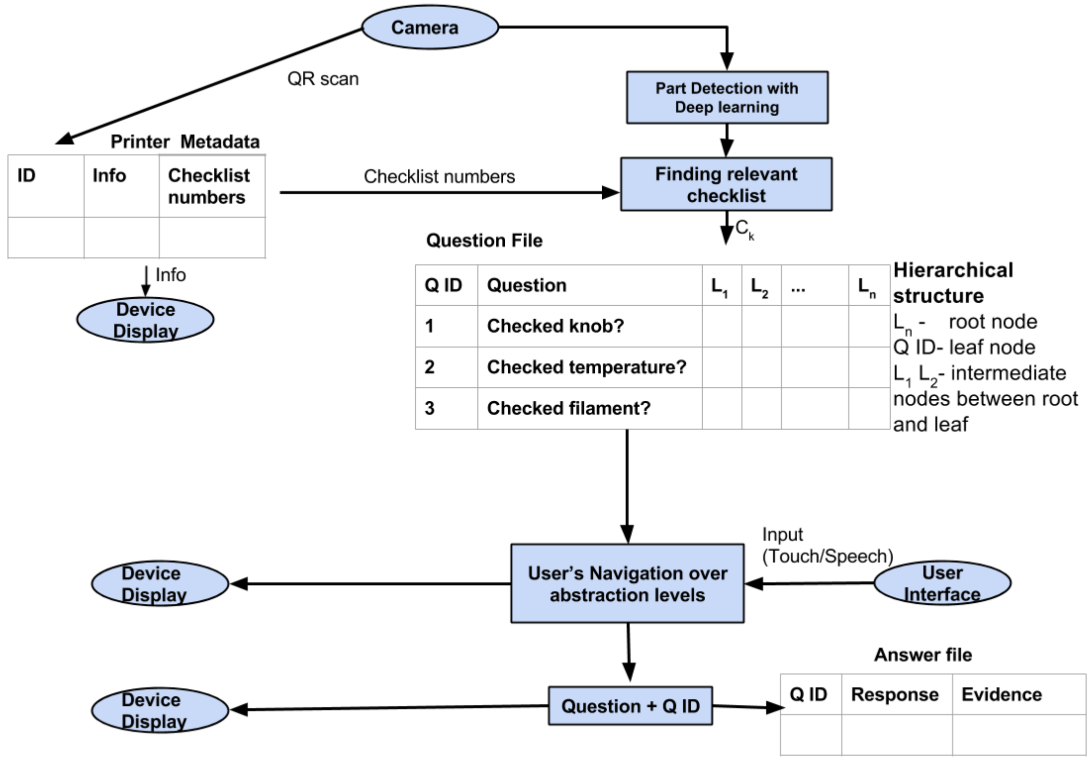


Figure 3: Data handing during inspection process

Figure 3 illustrates the storage architecture of re-configurable back-end with 3 types of file structures (metadata, questions, answers files) for printer use-case. A representation of hierarchical data is shown in the questions file. This can be reused for other use-cases in an identical manner with the same attributes of files. Hence irrespective of the inspection type, the query to access information covered in the multiple levels of the file remains the same. Files for inspection data are stored in csv (comma separated values) format. Three types of files maintained as a part of the application -

1. Printer's metadata file: The details/meta data of objects to be inspected is contained in this file, where a particular object is represented by unique QR/ID number. First column is QR Number/ID number of the object. Second column gives object's information such as Make, Type and Year for Printer Inspection use case. Last column contains checklist numbers to be followed during the inspection for that object.

2. Questions File: Each check-list is associated with its own questions file. Each question in this file has a unique id, and all the nodes information in the hierachical structure as shown in the Figure 3.

3. Answer file: The first column is QID. Second and third column contains Response and Evidence. Where Response can be only YES/No, and evidence is used for multimedia record containing inspection information such as snapshot, video and audio of the scene.

All the files are stored on the remote server and all the relevant check-lists are loaded into application once the QR code is scanned. The questions are grouped in a hierarchical structure, where each level of hierarchy represents the abstraction of the groups. The abstraction levels can be configured for different applications where the leaf nodes are the questions and the abstraction layer above the leaf nodes define the first level grouping of questions. Number of abstraction levels are decided by the steps in inspection process.

3.4 Prioritisation of Check-list based on objects viewed in FoV

In typical inspection process, a large number of check-lists pertaining to a specific model and variant of the product would have to be addressed; some checks may need to be prioritised – prioritisation is typically hard-coded and is usually determined by management. To introduce more flexibility into the inspection, we also introduce a strategy of object-detection driven prioritisation of check-list.

For an optimal guided path around the object of inspection and to change priorities of checks due to external factors, the inspector views the object part of interest. Fig 3 illustrates how a precise check-list for the part to be inspected is made available. The Part Detection model gives a relevant check-list(C_k) to follow for that particular part inspection. It refers to the Question file of C_k check-list. The questions pertaining to that object part are displayed sequentially till the list goes empty. User also has the liberty to manually traverse the abstractions in both directions and address a particular question. The exploration on questions is achieved at User interface. Against each question responses are recorded in Answer file. This

Table 1: Comparison of Inspection Methods in terms of interaction interface

Method	AR	Description
Paper-based	No AR	Utilize pen and paper to record inspection evidence, hand- held
Google Cardboard	AR	Speech to text input, overlay in field of view, wearable
Google Glass	AR	Swipe and tap input, overlay on side, wearable
Tablet	AR	Touch input, overlay on screen, hand-held

helps in overriding the usual full mode inspection route for quick and essential checks that are required when performing a complex inspection task under severe time constraints.

4 Experiments and Results

Table 1 depicts the various inspection methods. The evaluation of inspection process was carried out in a research lab setting illustrating the process on a 3D printer. The subjects carried out as a series of user experiments in which they were tasked with conducting an inspection of a 3D printer. Twenty engineers and research staff from an industry research lab were selected as participants, comprising 12 male and 8 female, and the ages spanned from 22 to 40 with average 28 years. Their proficiency level was novice to intermediate with respect to usage of Google Glass, Google Cardboard, and the 3D printer which is to be inspected. The inspection consisted of check-lists with multiple questions clustered based on printer parts.

A set of subjective and objective metrics were obtained that measure both usability and user experience. These indicators measure human performance and user satisfaction. The subjective metrics are – (1) User preference of a particular inspection method (2) Since user preference constrained the users to vote for a single mode, users ratings were also collected on each mode of inspection using a five-point Likert scale [14] ranging from 1 to 5 (1 - Very Poor, 2 - Poor, 3 - Fair, 4 - Good, 5 - Very Good). The Likert scale is commonly used in surveys as it allows the subjects to quantify opinion based items [8, 14].

Section 4.2 captures a number of subjective metrics. Most important one being, the usefulness of the method when used for complex inspection process involving huge number of check-lists, and user manuals have to be referred many times by the novice users doing maintenance tasks. The ease referred to the user-friendly interaction that reduced the stress while carrying out an inspection process. The objective metric is the turnaround time for each inspection method. The results obtained conform to the requirements of statistical significance of data obtained by subjective metrics.

4.1 Inspection turnaround time

The turnaround time is recorded for inspection process for each subject. Table 2 shows (i) the time for carrying out the inspection averaged over for all the subjects, (ii) the votes received by each based on initial experience of novice users carrying out an inspection. The tablet based approach takes the least amount of time; this is followed by the paper-based and Google Glass taking almost the same time. The Tablet based approach was also the most-preferred mode of inspection, followed by the Google Glass. Since user preference constrained the users to vote for a single mode, users ratings were also collected on each mode of inspection using a five-point Likert scale as described in Section 4.2.

4.2 User Rating

In our experiment, the Likert scale (Rating from 1 to 5) was used measure opinion on five questions/statements:

1 Was the inspection set-up useful with object recognition and display of relevant object parts?

Table 2: Average time taken and Votes received for Inspection

Method	Time(secs)	Votes
Paper-based	168	3
Google Cardboard	193	3
Google Glass	169	6
Tablet	104	8

2 How easy was it to perform inspection?

3 Was there a lag in display of Virtual content?

4 Was there trouble with interaction input method ?

5 Rate the trouble experienced wearing/using the device?

Table 3 shows the mean Likert scale ratings over 20 subjects for all the modes of inspection. We note that *tablet* was easiest for subjects to use when compared to all other modes of inspection. Overall, we can conclude Tablet is rated well for parameters such as usefulness, smooth display and ease. The Google Glass stands in second place for the aforementioned parameters.

4.3 Hardware set-up

The server-hardware configuration: Tesla C2075, CUDA Driver Version : 7.0, Computing Capability : 2.0, Total amount of Global Memory : 5375 Mbytes 14 Multiprocessors, 32 CUDA Cores per MP, Max no. of threads per MP : 1536, and Max no. of threads per block : 1024. The Google Glass Explorer 1 configuration: Texas Instrument OMAP 4430 SoC, 1.2 GHz Dual ARM 7 processor, 1GB RAM, 12GB Internal Memory, 5MP Camera, 802.11b/g WiFi Standard, and Android 4.4 kitkat OS. Nexus 6 Android phone and Samsung Galaxy Tab 4 were used to conduct experiments.

5 Discussion

An inspection framework with fast RCNN for object part detection and subsequent accurate display of overlays is presented. The objective evaluation of inspection framework is done through inspection turnaround time with AR devices. The time taken by tablet based inspection is on an average 50% lesser than Google Cardboard which was unanticipated to be a faster method before experiments owing to its speech-to-text interface for recording inspection results.

Through the questionnaire and post-experiment informal discussions with individual participants, we found that tablet is the preferred choice for most of the users. We note a direct correlation between the time taken to inspect and the user preference. Lesser the time taken, more preferable the inspection method was found to be. Tablet based inspection garners over 40% of the votes when compared with other three methods. The Tablet based application is highly preferred to other approaches for the following reasons mentioned by our subjects:

Table 3: Mean Likert scale ratings of subjective metrics

Method	Usefulness	Ease	Smooth Display	Interaction Input	Easy to Wear/Use ?
Pen-Paper	Not Applicable	3.4	Not Applicable	4.1	3.5
Google Cardboard	4	3.1	3.2	3.1	2.6
Google Glass	4.1	4	3.5	3.6	4.2
Tablet	4.5	4.4	4.2	3.7	3.8

- Subjects found it intuitive to use Tablet as they experienced ease in using the tablet in inspection task where extensive use of hands were not required.

- Google Cardboard was not preferred as it induced simulation/eye sickness to the subject and claustrophobic. The fidelity of speech recognition in Google Cardboard with Android device is not always high especially in a crowded environment. Google Cardboard/Wearality frame with Android device are video-see-through devices whereas Google Glass is optical-see-through device. The video-see-through suffers from the limitations such as the the low resolution of phone camera caused problems in interpretation of the text written on object parts as the text in small font looked too blurry. We explored inspection using Cardboard could get dangerous as user FoV is limited, and he cannot be aware of his surroundings. Inspectors with eye correction (defects) reported difficulties with using cardboard. Having said all the limitations of Google Cardboard, vendors are working on the better optics with advanced head tracking to overcome simulation sickness. Google Cardboard being lowest priced AR solution can be used for short duration inspection applications in indoor environment especially if the solution involves speech interface.

- Glass involved many swipes and taps; it was confusing for novice users to remember the swipe pattern and also fitting Glass over the spectacles was found to be hard. However, Google Glass is more convenient than the tablet especially in the cases when both the hands are required to perform inspection/maintenance tasks and in situations where economy is not a huge concern.

6 Conclusion

An AR inspection framework that can be utilized in cross-domain applications and with multiple devices is presented. We reviewed our inspection framework taking a 3D printer use-case. The key contributions as compared to the existing inspection framework are: (a) check-list prioritization by detecting the parts viewed in inspector's field with the aid of the *state-of-the-art* recurrent neural networks that works close to human performance and at real-time (b) Marker-less AR Guided inspection sequence adaptable to any domain with minimal modifications in the back-end (c) Feasibility study of inspection modes such as *Google Glass*, *Google Cardboard*, *Paper based* and *Tablet* for inspection turnaround time, ease, display lag, interaction methods, and usefulness. From the study with multiple AR devices using subjective and objective metrics concur with tablet-based inspection as a preferred inspection mode. This is due to its simplicity, inspection turnaround time, and wide screen.

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