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Towards a Quantitative Approach for Monitoring and Evaluating Construction Defect Management Inspection Performance using Eye-tracking Technologies

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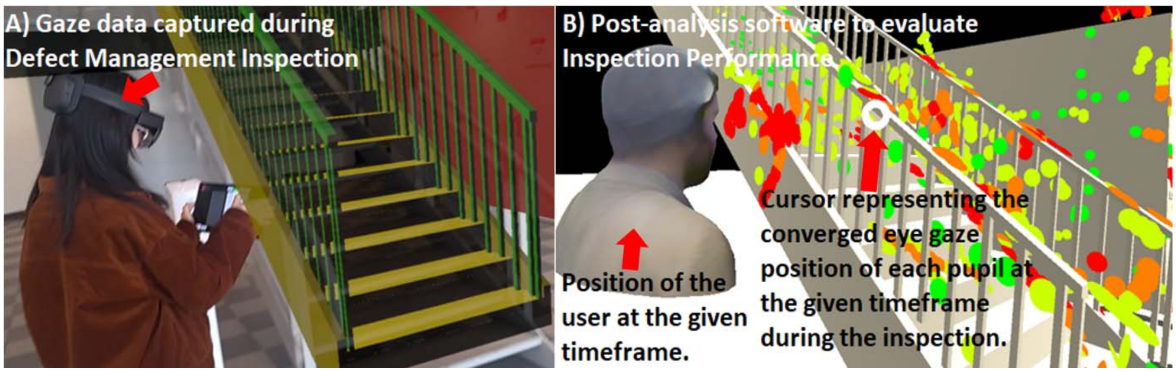

Figure 1: (Left) The inspector conducting a defect management inspection of a building using an experimental AR system. (Right) the presented gaze-based data analysis tool is used to playback the inspection for performance evaluation and analysis.

Abstract

Defect management (DM) inspections play an important role in the overall performance of construction projects. Identifying defects early within the construction project life cycle leads to mitigating significant reworks and potential hazards from occurring later in the building life cycle. Despite the importance of DM inspections in construction, currently, minimal approaches exist to evaluate or assess the performance quality of on-site DM inspectors. To address these issues, we present a novel data analysis tool that incorporates Building Information Modelling technologies to evaluate DM inspection performance using eye gaze data captured during the DM inspection. This paper presents an overview of our proposed data analysis tool, which consists of a four-dimensional (4D) playback visualisation system and a quantitative data analysis simulator. We also present our findings from a pilot study that uses our proposed data analysis tool to comparatively evaluate the performance of two types of DM inspection approaches: conventional paper-based methods, and an experimental Augmented Reality (AR) system. We release our DM data analysis software as an open-source project under the MIT license.

Index Terms: Defect Management Inspections—Building Information Modelling—Construction——Data Analysis—Eye Tracking—Augmented Reality;

1 Introduction

Defect management inspections play a pivotal role in the performance and quality of on-site construction. In a 2004 study, the US construction industry estimated that approximately 57% of a construction projects budget is of non-value (i.e. wasted) [1]. A large portion of the estimated waste can be attributed to construction reworks and delays due to defects going undetected during construction. Therefore, identifying defects early within the construction project can minimise construction reworks and unnecessary delays resulting in saving a significant amount of time, money, and resources at a later stage in the construction project. However, despite the importance of defect management inspections in a construction project, there are limited approaches to determine whether the quality and performance achieved during an on-site construction DM inspection is sufficient. Additionally, no previous approaches exist that can specifically identify potential elements that were not sufficiently inspected during the DM inspection. Therefore, mistakes that may occur during the inspection process can potentially lead to defects going undetected and further leading to significant reworks or potential hazards to occur much later in the building's lifecycle.

Furthermore, the process of identifying defects still remains relatively traditional and is achieved by having an on-site inspector compare the physical construction progress with digital analogue drawings extracted from the geometric Building Information Modelling (BIM) model or CAD model. We believe due to the limited spatial awareness capabilities and difficulties associated with interpreting two-dimensional analogue drawings, this conventional approach is potentially open to errors or defects being overlooked on the construction site. This claim is supported by a recent pilot study conducted by the authors, which demonstrated that the conventional paper-based defect management method operated by non-trained construction workers produced a significantly higher error rate than an experimental AR-based defect management system [4].

BIM technologies have also become a widely adopted technology within the construction industry over the last decade. BIM improves documentation produced during the construction project lifecycle by linking data associated with the project's activities to the three-

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dimensional geometric CAD model. To address the aforementioned issues and mitigate potential defects going undetected during DM inspections, we present a novel system integrating BIM and eye-tracking technologies to monitor, assess, and evaluate DM inspection performance. The presented data analysis system simulates eye gaze data captured during the DM inspection against the virtual BIM model to provide DM inspection performance feedback. The system incorporates two primary components:

1. A four-dimensional (4D) playback data analysis software that replays the on-site DM inspection based on eye-tracking and head-tracking data. A heatmap visualisation is further integrated, providing visual feedback to represent all the fixated points the inspector looked at during the inspection.

2. A data analysis calculation that produces quantitative data associated with the DM inspection performance. An equation is further integrated into the system that outputs a performance rating between 0 to 100 to rate DM inspection performance based on the gaze data. Subsequently, all quantitative data generated by the presented data analysis tool can be linked back to the BIM model using the UnityRev pipeline [3].

In a recent workshop conducted by the authors with construction industry representatives, the representatives claimed that the construction industry is reluctant to adopt new technologies and change its current practices [4]. Therefore, we designed this system to be incorporated as an extension to the current DM inspection processes and practices within the construction industry, as opposed to replacing it. Our hope is that this work will act as an initial step towards adopting new technologies within the construction industry for DM inspection performance feedback.

The specific contributions of this paper are as followed:

1. A system that can be integrated with current DM processes to monitor, evaluate and assess on-site construction DM performance.

2. An investigation that demonstrates the applicability of the developed DM inspection data analysis tool.

In the remainder of the paper, we explore the related works associated with monitoring and evaluating construction performance. Subsequently, we present a system overview of the developed gaze-based DM data analysis system. Two primary components are presented with the intent of representing DM inspection performance for data analysis using both visualisations and quantitative methods. We then present our findings from an experiment that demonstrates the presented system's applicability by using it to evaluate the performance of two types of DM inspection systems. We conclude the paper by discussing some of the outcomes and future directions of our developed system and some final remarks.

We release this software as an open-sourced project under the MIT license[1].

2 Related Work

Currently, minimal research exists to monitor, evaluate, and assess on-site DM inspections. Furthermore, no previous works have utilised gaze-based metrics to evaluate on-site construction performance. Nair et al. [5, 6] developed an approach to predict DM inspection performance quality using two performance metrics. The first metric generates a depth of inspection (DI) score, calculated by dividing the number of defects captured during the inspection against the number of defects captured by both inspection and testing approaches. The score is ranked from 0 (Worse) to 1 (Ideal). Secondly, an inspection performance metric (IPM) is introduced to measure inspection performance based on inspection time, preparation time, number of inspectors, the experience level of inspectors, and the complexity of the project. The main drawback of these metrics is that they cannot measure the inspector's performance for individual elements during the inspection. Therefore, these metrics cannot specifically identify potential defects that went undetected during the DM inspection. This drawback is specifically addressed by the system presented in this paper.

Previous research has also explored the integration of AR technologies with 4D BIM to monitor and track the status of construction projects in relation to the planned schedule [2, 9]. Additionally, mobile AR applications have been developed to monitor construction performance by having on-site workers update their progress in real-time [8].

3 System Overview

The presented gaze-based data analysis prototype consists of two primary components. The first component is a 4D playback visualisation that replays the inspector's head and gaze position at any timestamp during the DM construction inspection. The second component is a data analysis tool that produces quantitative data associated with the performance of the construction inspection. An equation is integrated into the system to predict the overall quality of the inspection based primarily on gaze data inputted into the software. Both components were explicitly designed to provide inspection feedback performance based on gaze data captured during the DM inspection. This section presents a summary of the proposed system, which describes the features and implementation details associated with the two main components. All software was developed using the Unity 3D game engine[2] (Version 2019.3.0b4) and programmed entirely in C#.

Identifying and recording a defect during a DM inspection may not directly correlate with what the inspector is looking at. However, using the presented tool, we can confirm that:

1. The inspector looked at an element that they were supposed to inspect.

2. The inspector looked at an element long enough to have their focus.

3. The inspector looked at an element that was logged as a defect during the inspection.

Based on this criteria, this software attempts to deduce potential defects that may have gone undetected during the inspection based on the gaze data. Furthermore, the software can give an approximation of the overall performance of the DM inspection.

3.1 Data Collection

During the DM inspection, the inspector's head position and rotation vectors, converged eye gaze position vectors of each pupil, and timestamps are autonomously logged and stored within the HoloLens 2 internal storage system as a CSV file. The CSV file is then parsed into the two presented components for data analysis. The collected data was logged to the CSV file every 100ms to ensure an appropriate CSV file size whilst still maintaining a smooth playback rate. Although the data analysis software is not limited to a specific type of eye-tracking hardware, the built-in HoloLens 2 eye tracker was used to capture the gaze and head data collected in the DM inspection experiment presented in Section 4. The MRTK library [3] was used to facilitate the integration of the HoloLens 2 for the data collection process. Vuforia [4] was used to calibrate the alignment of the virtual BIM model and physical building (Figure 2).

[1]https://github.com/kieran196/Unity_AnalysisPlayback

[2]https://unity.com/

[3]https://github.com/microsoft/MixedRealityToolkit-Unity

[4]https://developer.vuforia.com/

This was achieved by having a physical marker placed at a location within the building or construction site that matched the position of a virtual marker within the BIM model. A point cloud of the building or construction site can be additionally utilised to improve accuracy further. The process of aligning the virtual BIM model with the physical building or construction site ensures that the eye gaze data captured during the DM inspection can be simulated against the BIM model at a one-to-one mapping when using the data analysis software.

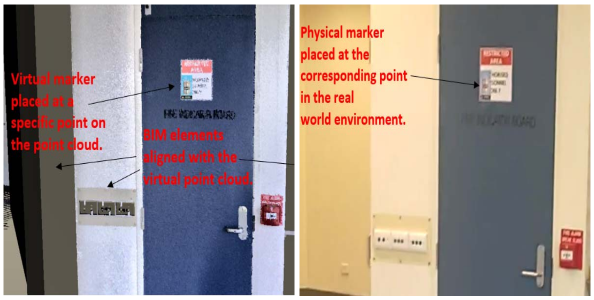

Figure 2: This figure shows the process of calibrating the virtual BIM model with the physical building/construction site. The left image shows a virtual marker placed at a specific location on the BIM model. The right image shows a physical marker placed at the corresponding location in the real-world environment.

3.2 Component 1. Four-Dimensional Playback Visualisation

The 4D playback visualisation tool supports the capability to replay the on-site DM inspection by simulating the inputted gaze data against the virtual BIM model for data analysis. During the analysis process, the user can manipulate a 2D slider on the user-interface to navigate through different timestamps during the DM inspection. Additionally, the playback can be slowed, sped up, or in real-time. A heatmap visualisation is integrated into the system to represent all the fixated gaze points that the inspector looked at throughout the DM inspection. A three-colour gradient palette was utilised for the heatmap, where green represents minimally looked at points, yellow moderately looked at points, and red highly looked at points (Figure 3B). The parameters used to determine the heatmap threshold values can be adjusted by the user. A virtual avatar is used to represent the position of the inspector on the construction site at any timestamp throughout the DM inspection, and a virtual cursor represents the inspector's converged gaze position.

The system can also capture the inspector's physical movements, which are calculated from the head position and rotation vectors. A two-dimensional grid consisting of 1x1 meter tiles is superimposed onto the virtual floor to represent the positions on the construction site that were least and most visited by the inspector based on the movement data (Figure 4A). A numerical value is displayed on each tile to represent the total duration of time the inspector spent walking or idling on the tile. A heatmap visualisation represents the most and least common areas visited by the inspector on the construction site. The parameters to determine the colour-coded threshold values for the heatmap can also be adjusted by the user. An additional line visualisation (Figure 4B) is used to generate the movement paths of the inspector throughout the DM inspection.

The playback component also supports three modes of perspective to watch the playback in (Figure 5):

1. A non-immersive first-person view.

2. A third-person view, where the manager can control the position and rotation of the camera.

Figure 3: This figure demonstrates the playback visualisation of an on-site inspection. The top image shows a user conducting a DM inspection of the building. The bottom image shows the 4D playback visualisation of the DM inspection.

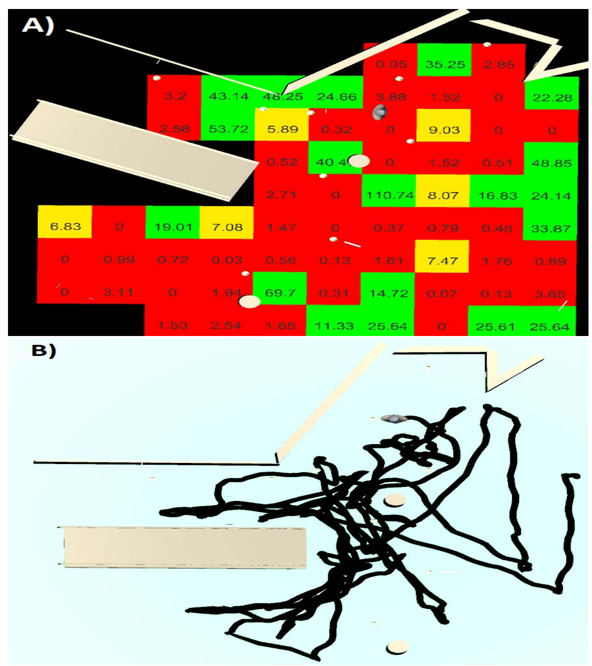

Figure 4: This figure presents two visualisations representing the inspector's physical movements captured during the DM inspection. The top image shows a heatmap visualisation with the heatmap threshold values set as $<= 5s$ Poor, $> 5s < 10s$ Moderate, and $>= 10s$ Excellent. The bottom image shows a line visualisation that represents the physical movement paths of the inspector during the inspection.

3. An immersive first-person Virtual Reality view.

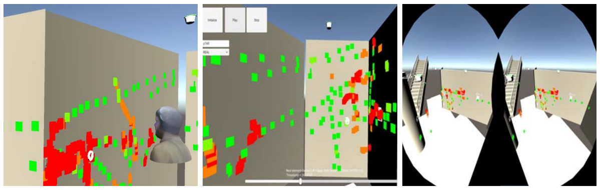

Figure 5: This figure presents the three modes of perspective available in the 4D playback visualisation system. The left-most diagram is a third-person view, the centre diagram is a first-person non-immersive view, and right-most diagram is a first-person immersive Virtual Reality view.

The 4D Playback Visualisation component was developed to provide an intuitive and user-friendly approach for managers to evaluate and track DM inspection performance. An easy-to-use interface with a heatmap visualisation is integrated to assist the manager with understanding how thoroughly elements and areas on the construction site were inspected during the DM inspection. However, the main drawback of the component is that due to the data being represented through visual approaches, data analysis requires interpretation, which can potentially lead to errors. Additionally, due to the DM inspection performance data being represented through visual approaches, the data is unable to be quantified and as a result, cannot be linked back to the BIM model. Finally, the data analysis techniques are potentially time-consuming as they require a manager to go through the entire DM inspection. Therefore, a second component was developed to generate quantitative data associated with the DM inspection for quantifiable data analysis to address these drawbacks.

3.3 Component 2. Quantitative Data Analysis Tool

The second component we present is a quantitative data analysis tool that outputs quantifiable gaze and movement data associated with the DM inspection performance. This process is achieved by inputting the eye gaze data captured during the DM inspection (previously described in Section 3.1) into the software. The inputted gaze data is then processed against the geometric BIM model, and the statistical gaze data is simulated and outputted to a CSV file for analysis. The following metrics are generated by the software:

Total Gaze Data

- Total time spent conducting the DM inspection.
- Total time spent looking at the ground.
- Predicted total gaze performance rating (Based on Equation 1).

Gaze/Movement Data for each BIM element

- The BIM element ID.
- The number of gaze collision points (i.e. is incremented by 1 every time the inspector initially looks at an element)
- Total time spent looking at an element.
- Total time spent dwelling at an element (with a 500ms threshold set)
- Total gaze dwell count of an element.
- Total time spent within the inspector's field of view.
- Predicted gaze-based error rate (based on Equation 2).
- Predicted gaze-based element performance rating (based on Equation 2).
- Time spent on each tile (idle or walking).

To further evaluate DM inspection performance, the data analysis component produces a score ranging from 0 (Very poor) to 100 (Excellent) to estimate the DM inspection performance based on the inputted gaze data. To achieve this, we firstly calculated the element performance rating, which is determined based on the amount of time spent by the inspector looking at an element (Equation 2). Next, we summed the performance ratings of each element to produce an overall performance rating between 0 and 100 (Equation 1). The size of elements for the required gaze fixation time threshold (Equation 3) can be assigned within the software by the user. For our demonstration (Section 4), we categorised large elements within our BIM model as walls and staircases, medium elements as railings and columns, and small elements as lights, signs, and other electrical fixtures. Due to there being no current standardised fixation times for gaze-based inspections, we determined an optimal gaze fixation time as $>= 10s$ for large elements, $>= 5s$ for medium elements, and $>= 2.5s$ for small elements. However, these parameters can also be adjusted by the user depending on the context of the project.

$$PR = \left([\sum EPR]/(EC * 4) \right) * 100 \tag{1}$$

Where PR is the total inspection performance rating, EPR is the individual performance rating of each inspected element, and EC is the elements count (total number of elements within the BIM model).

$$EPR = \begin{pmatrix} 4 & FT \geq RT & Excellent \\ 3 & FT < RT \& \geq RT_1 & Good \\ 2 & FT < RT_1 \& \geq RT_2 & Moderate \\ 1 & FT < RT_2 \& \geq RT_3 & Bad \\ 0 & FT < RT_3 & Poor \end{pmatrix} \tag{2}$$

Where FT is the fixated time spent looking at an element (with a 500ms dwell threshold), and RT is the required threshold which varies based on the size of an element (RT is $>=$ to 10s for large elements, $>=$ 5s for medium elements, and $>=$ 2.5s for small elements). A score is produced from 0 (Poor) to 4 (Excellent) to determine how thoroughly an element was inspected.

$$RT_1 = \frac{RT}{2}, RT_2 = \frac{RT_1}{2}, RT_3 = \frac{RT_2}{2} \tag{3}$$

4 Demonstration

In this section, we demonstrate the applicability of the presented data analysis tools to assess and compare the performance of two types of DM inspection systems (Figure 6).

- DM System 1. The conventional paper-based method which consisted of several orthographic and perspective drawings of the building.
- DM System 2. An experimental AR-based DM inspection prototype previously developed by the authors [4] to superimpose the virtual BIM model onto the physical building.

4.1 Experimental Design

The experiment consisted of a within study design with 11 participants that lacked prior experience conducting DM construction inspections within a professional capacity. During the experiment, participants were required to use both previously described DM inspection systems to complete a mockup DM inspection task within

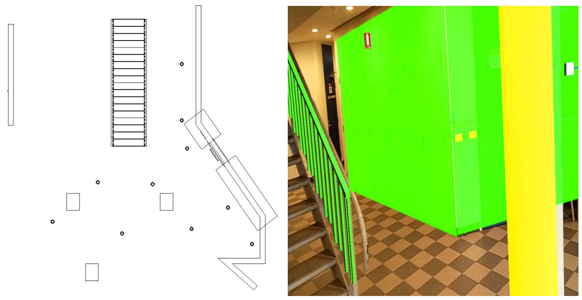

Figure 6: This figure demonstrates the two types of DM inspection systems used in the experiment. The left diagram is one of the several orthographic drawings participants had access to for the conventional DM inspection method. The right diagram represents a first-person view of the experimental Augmented Reality DM system developed by the authors.

a building. In each DM inspection task, participants were required to inspect thirty building elements, where eighteen elements were correct (i.e. no defect), eight building elements slightly differed in position from the virtual element (i.e. minor defect), and four elements significantly differed from the virtual element (i.e. major defect). The types of defects participants were required to identify during the study were whether the placement (position or rotation) of elements in the physical building matched the placement of the virtual elements designed by the architect within the BIM model. Correct elements were defined as virtual elements less than 5cm from the real-world element, minor defects between 5cm and 50cm, and major defects greater than 50cm. While using the conventional paper-based DM inspection system, participants wore a HoloLens 2 HMD with a blank display to capture gaze data.

4.2 Results

To understand how participants engaged with the building using paper-based and AR-based DM inspection systems, we analysed participant's gaze data. This was achieved by using the previously presented DM inspection data analysis tool described in Section 3.

Using the standardised 500ms dwell threshold [7], we calculated the 'total fixation duration', which is defined as the time spent by a participant fixating on a particular element for greater than 500ms, and 'total dwell counts', which is the number of times a participant fixated on an element for greater than 500ms. We also recorded the participant's 'total gaze duration', which is the overall time participants spent looking at each element. All three measures were validated as normally distributed data-sets by the Shapiro-Wilk tests for each condition. Paired t-tests revealed the total fixation duration (in seconds, $t(8) = 3.13$, $p < .05$), total dwell counts ($t(8) = 5.34$, $p < .01$), and total gaze duration (in seconds, $t(8) = 3.98$, $p < .01$) were all significantly higher when using the AR-based system (M = 107, SD = 52.53; M = 161, SD = 44.18; M = 432, SD = 126.94) in comparison to the paper-based approach (M = 45, SD = 32.7; M = 59, SD = 27.17; M = 174, SD = 107.28). The findings from the initial gaze data indicate that when using the AR condition, participants spent significantly more time inspecting elements within the building as opposed to when using the paper-based approach. This demonstrates that when using AR, participants were much more engaged with the building which likely contributed to the AR system producing significantly lower error rates during the inspection tasks.

Next, an estimation of the participant's DM inspection performance based on the participant's gaze data was measured using the performance rating equations previously described (Eqs 1 and 2). The calculated gaze performance ratings for the DM inspection were compared to the actual performance ratings of participants when

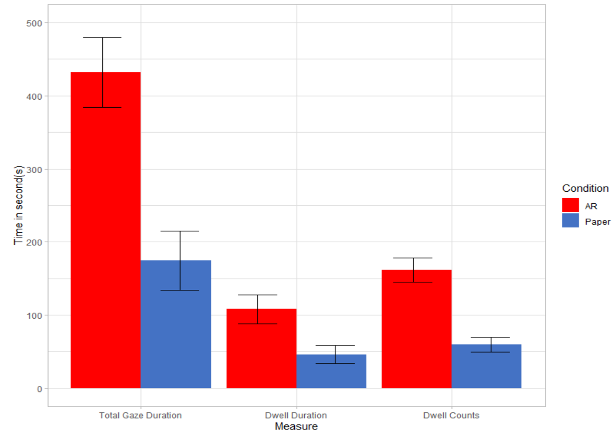

Figure 7: This figure presents the total gaze duration, total dwell duration and total dwell counts of each condition in seconds.

using both paper-based and AR-based DM systems (Table 1). The actual performance ratings were calculated as a percentage of how many elements in the building participants were able to correctly identify and categorise as a non-defect, minor defect, or major defect. The results revealed that the absolute mean error range between the calculated gaze performance ratings and the actual performance ratings for the paper-based system was 14.25 and 11.75 for the AR system. We were unable to find a strong correlation between the calculated gaze performance ratings and the actual performance ratings for either DM system.

Table 1: This table presents the calculated gaze-based performance ratings in comparison to the actual performance ratings for Paper-based and AR-based DM inspection system.

	Paper-based			**AR-based**		
Participant	**Prediction**	**Actual**	**Accuracy**	**Prediction**	**Actual**	**Accuracy**
1	40	60	-20	81	76	+5
2	65	60	+5	81	73	+8
3	63	66	-3	84	70	+14
4	73	53	+20	74	90	-16
5	40	60	-20	74	93	-19
6	37	53	+16	80	73	+7
7	65	60	+5	90	83	+7
8	45	70	-25	75	93	-18
	Absolute Mean Error Rate = 14.25			**Absolute Mean Error Rate = 11.75**		

Further analysis was conducted to determine the impact of gaze on the participant's ability to identify the minor and major defects during the task compared to the actual error rates (Table 2). Our previous findings reported that participants had a significantly lower error rate for correctly identifying minor defects when using AR in comparison to the paper-based system. No significance was found for identifying major defects [4]. To assess the corresponding impact of gaze on the participants ability to identify defects, the gaze-based EPR (Equation 2) was used to calculate a predicted inspection score for each defect element. A Wilcoxon Signed rank test revealed participants produced a significantly higher EPR score ($p < 0.05, r = -0.81$) when using the AR-based system (M = 2.125: Moderate to Good, SD = 0.83) in comparison to the paper-based system (M = 0.25: Poor to Bad, SD = 0.46) for identifying minor defects. In terms of major defects, there was no significance for the EPR scores ($p = 0.08, r = -0.85$) between the AR (M = 3.25: Good to Excellent, SD = 0.95) and paper-based systems (M = 1: Bad, SD = 0.81).

Table 2: This table presents the relationship between the error rate and the predicted gaze-based EPR for participant's identifying defects when using the paper-based and AR-based DM system.

Defect Type	Element Size	Mean Error Rate(%)	Mean Gaze Duration	Mean Gaze Fixation(500ms dwell)	Avg EPR	Avg EPR Score
Paper-based DM System						
Major	Large	63.63%	20.57s	4.288s	2	Moderate
Major	Small	54.54%	0.443s	0.157s	1	Bad
Major	Small	81.81%	0.067s	0s	0	Poor
Major	Med	45.45%	2.944s	0.101s	1	Bad
Minor	Med	63.63%	4.557s	0.748s	1	Bad
Minor	Small	72.72%	0s	0s	0	Poor
Minor	Small	90.90%	0.752s	0s	0	Poor
Minor	Small	72.72%	0.631s	0s	0	Poor
Minor	Small	63.63%	0.416s	0s	0	Poor
Minor	Small	45.45%	0s	0s	0	Poor
Minor	Small	72.72%	0.416s	0.113s	1	Bad
Minor	Large	81.81%	0.524s	0s	0	Poor
AR-based DM System						
Major	Small	9.09%	7.698s	3.18s	4	Excellent
Major	Small	0%	3.917s	1.572s	3	Good
Major	Small	9.09%	2.648s	0.898s	2	Moderate
Major	Small	0%	2.52s	2.52s	4	Excellent
Minor	Large	54.54%	40.459s	4.219s	2	Moderate
Minor	Small	9.09%	2.268s	0.254s	1	Bad
Minor	Small	18.18%	5.505s	1.821s	3	Good
Minor	Med	18.18%	24.472s	1.961s	2	Moderate
Minor	Small	18.18%	4.023s	1.427s	3	Good
Minor	Small	9.09%	21.946s	0.779s	2	Moderate
Minor	Small	0%	2.162s	0.262s	1	Bad
Minor	Small	0%	3.993s	1.448s	3	Good

5 Discussion

The gaze-based performance equations presented in Section 3.3 are an initial step toward using gaze as a performance metric to monitor and evaluate DM inspection performance. A comparison between the gaze performance rating (Equation 1) and actual performance rating demonstrated that the equation could predict DM inspection performance within a margin of 11.75% for AR and 14.25% for paper-based approaches. The error margins demonstrated partial success, however, we were unable to find a statistical correlation between the overall predicted and actual performance ratings. We suspect that chance impacted the results of the gaze-based performance ratings. This was due to participants having a 33.3% chance to correctly categorise an element as a correct, minor, or major defect regardless of whether they looked at the element during the task.

We also looked at the impact of gaze on the participant's ability to identify defect elements within the building. The element performance rating (Equation 2) was used to rate elements from 0 (Poor) to 4 (Excellent) based on the participant's gaze data. In terms of major defects, the EPR produced a mean score of 3.25 (Good to Excellent) for AR and 1 (Bad) for paper-based approaches. Both scores closely correlated with the low error rates when participants used the AR system (4.54%) and high error rates when participants used the paper-based system (61.35%) for identifying major defects. Similarly, when it came to participants' ability to identify minor defects, the EPR produced a mean score of 2.215 (Moderate to Good) for AR and 0.25 (Poor to Bad) for paper-based approaches. Both scores also have a close correlation with the actual error rates when participants used the AR system (15.89%) and the paper-based system (70.44%) for identifying minor defects.

Using the quantitative gaze data produced by the data analysis tool, we also explored the participant's gaze duration and gaze fixation on each building element. The results revealed statistical significance for both total gaze duration and gaze fixation when using the AR system in comparison to the paper-based system. This indicates that participants were much more engaged with the building when using the AR system, which likely contributed to the AR system significantly outperforming the paper-based system. The overall results from the study demonstrate that the gaze-based data analysis system was capable of providing useful insights to evaluate DM inspection performance. However, the process of identifying a defect may not always directly correlate with what the inspector was looking at during the inspection. Further research and testing are still required to validate the system and further understand the reliability of using gaze data as a metric to evaluate inspection performance.

6 Future Directions

The initial gaze-based data analysis prototype was designed specifically to evaluate the performance of on-site construction DM inspections. However, the system could be potentially integrated within other domains associated with the building project lifecycle. Potential examples include construction training, facilities management, education, quality assurance, and safety and risk management. Due to the data analysis system being dependent on the accuracy of the collected gaze data, an indoor environment would be most suitable for tracking purposes. However, as future eye-tracking hardware and tracking algorithms advance, outdoor environments could also be practically used in future iterations. We also aim to explore using alternative and more natural eye-tracking technologies (i.e. Tobii Pro Glasses[5]) to collect gaze data for future research.

7 Conclusion

This paper presented a novel gaze-based data analysis system designed to monitor, assess, and evaluate the performance of construction DM inspections. A summary of the system is presented, which describes the two primary data analysis components built into the system. Subsequently, an experiment was conducted to demonstrate how the presented system could be used to assess the performance of two types of DM inspection approaches. Our hope is that this work will act as an initial step towards adopting new technologies within the construction industry to improve construction performance.

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