Analyzing Human Visual Attention in Human-Robot Collaborative Construction Tasks

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ABSTRACT

Human-Robot Collaboration (HRC) is a promising approach to relieve workers from repetitive and physically demanding tasks and improve safety and productivity in construction. It is critical for robots to understand worker intention in order to adapt their motion to facilitate smooth HRC. Evidence has shown that visual attention reveals human intention. However, it is still unclear how visual attention is distributed in human-robot collaborative construction tasks. In this study, a pilot experiment was conducted to examine human visual attention in a wood assembly task with the assistance of a collaborative robot. A mobile eye tracker was used to collect participants' gaze movements. Data were validated and processed in terms of various metrics to analyze visual attention patterns. It is found that construction workers' visual attention is related to the detailed process of the task – around 30% of the eye gaze is located at the connector areas and the design drawing area, which is primarily relevant to their task. Furthermore, workers' attention could be affected by the movement of the robot, with their gaze following the path of robot arm and gripper during the collaboration. The findings can stimulate further research into attention-aware HRC for intelligent construction.

INTRODUCTION

The construction industry is contending with a skilled labor shortage (Olsen et al. 2012). According to a survey report released by the Associated General Contractors of America (AGC), 80% of contractors have faced obstacles in recruiting skilled workers to fill craft positions (AGC 2018). The reasons for the skilled labor shortage lie in two ways – an aging workforce and a lack of youth involvement (Clarion Energy 2007). The gradual departure of experienced professionals creates pressing challenges in terms of recruitment and replacement of a skilled workforce. Meanwhile, the construction industry doesn't appeal to younger generations due to "outdated" technology and tools used in construction work (Simic 2023). This industry needs new technologies and new approaches to attract more youth and create possibilities for less skilled individuals to conduct construction work.

Advanced robotics and the rapid development of powerful Artificial Intelligence have shown the strength and potential as a future solution in construction (Kim et al. 2021). It could mitigate the impact of skilled labor shortage by encompassing individuals with varying skill levels and underrepresented groups (e.g., disabilities) (Okishiba et al. 2019). Construction robotics and automation could attract the future generation of construction workers as well as meet their aspirations of construction work under the background of Industry 4.0 (Geraci 2021). A vital requirement of construction robotics adoption has emerged. Human-robot collaboration (HRC) in construction tasks is envisioned to be an efficient and productive way on future construction sites to relieve human workers from hazardous and physically demanding tasks (Liang et al. 2020).

In HRC, human workers can maximize their knowledge and judgment to perform high-level planning and decision-making while leaving the repetitive tasks to the collaborative robot (e.g., the collaborative robot can fetch parts and tools timely while the human worker focuses on installation) (Liu and Jebelli 2022). Considering the dynamic and unstructured construction environments (i.e., vehicles, workers, and materials on the same site), such intuitive collaboration requires collaborative robot reacts to human movements timely and adaptively for a successful HRC implementation. Initially, in a human-human collaboration, humans use verbal and visual cues to understand each other, establish communications and react correspondingly, resulting in safe and efficient collaboration. Accordingly, human visual attention can provide collaborative robots with valuable insights into the worker's intentions, priorities, and future motions. This could enable collaborative robots to complete minor steps (e.g., parts fetching) in a construction task efficiently by incorporating the worker's intentions. Additionally, collaborative robots could plan their actions (e.g., trajectory planning) safely and adaptively by accurately predicting human future movements with human visual attention.

It has been proved that eye movements have a relationship with visual attention decades ago (Bridgeman et al. 1975; Pashler 2016). Eye movements can represent an individual's cognitive process, which makes it a perfect approach to identifying and analyzing visual attention (Rayner 1977). Many researchers have explored the application of eye movements in the construction field. Hasanzadeh et al. (2017) proved that the eye movement metrics of construction workers can be used as an indicator of human error in hazard identification tasks. Wang et al. (2023) incorporated eye gaze with hand gesture recognition for robot control by giving the area of interest (AOI) via gaze information and sending control commands via hand gestures. Those studies mainly contributed to methods development for robot control or gaze implementation in construction inspection. However, few studies focus on examining visual attention in human-robot collaborative tasks. Thus, this paper uses gaze tracking to examine human visual attention in HRC implementation in construction tasks. A pilot experiment was conducted to collect gaze data. The results provide insights into human workers' visual attention in HRC implementation in a construction task.

BACKGROUND

Visual attention is the ability that an individual focuses on a perceived stimulus which includes visual and cognitive processes (Fischer and Breitmeyer 1987). This kind of attention has been widely investigated in numerous domains, from behavioral studies and psychology to the robotics field (Vijayakumar et al. 2001; Admoni & Scassellati 2017). The wearable sensor, eye tracker, has been increasingly applied in construction studies. For instance, researchers utilized gaze information to study workers' visual attention and cognitive processes in construction hazard recognition for intelligent construction (Zhang et al. 2023). A study that examined workers' visual attention in building inspection was conducted by Shi et al. (2020) to find the relationship between visual attention and spatial memory.

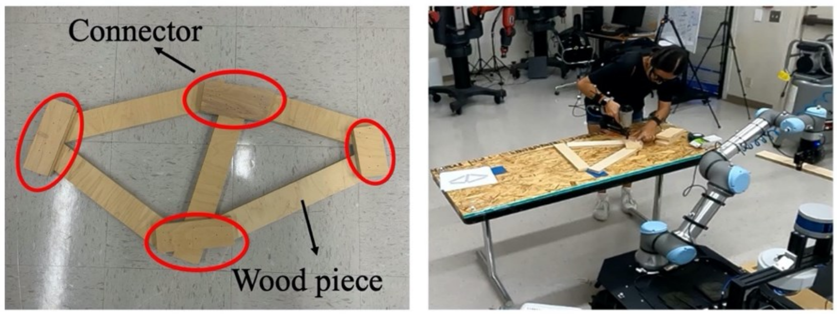
In HRC, gaze-related research explored social eye gaze and attention cues for easy and intuitive interaction between humans and robots. Eye gaze was utilized as a communication cue to trigger robot actions (Palinko et al. 2016). Besides gaze-based control, eye gaze in HRC on a handover task was investigated for understanding shared gaze and human intentions (Ivaldi et al. 2017). Chadalavada et al. (2020) implemented eye gaze to convey information about human intentions (i.e., which way the person will take) to a mobile robot for navigation purposes. In the context of construction, gaze-included HRC has been explored. A hand gesture recognition system involves the human gaze to direct construction machine-of-interest (Wang, Veeramani, and Zhu 2023). User's gaze was expanded and integrated into a virtual reality system for the teleoperation of robotic arm manipulation (Moniri et al. 2016).

These studies provide strong evidence that eye gaze can be an efficient and reliable communication cue for HRC in construction contexts. However, collaboration in construction tasks requires shared knowledge of goals, procedures, and intentions. For example, a robot that helps a construction worker assemble a shed wall needs to perceive the worker's current goals and coordinate actions with the worker's intentions (e.g., fetch toolbox). Few studies focus on revealing the gaze patterns of humans in construction assembly tasks to provide insights for safe and efficient HRC and benefit workforce training to adapt to the HRC context. This paper seeks to answer the following questions: 1) how the construction worker's gaze is distributed in HRC? 2) are their gaze trajectories reflect the sequential procedures of the task? Therefore, this study aims to examine human eye gaze in construction assembly tasks via a pilot HRC experiment.

METHODOLOGY

This study conducted a pilot experiment to examine human visual attention in an HRC assembly task. The participant was tasked to perform a wood assembly task through the collaboration of a ground robot equipped with an industrial arm. In this study, two tasks of varying difficulty levels were formulated. To collect participants' gaze movement, an eye tracker from Pupil Lab was used in each experiment. Using the data obtained from this device, gaze fixations were extracted and mapped onto a reference image. Finally, the processed data was subjected to gaze analysis in order to identify potential patterns of gaze that could potentially indicate participants' intentions and actions.

Experiment Task and Data Collection. A wood assembly task was designed to be performed in a controlled lab environment (see Figure 1 (a)). The design is simplified from real-scale roof trusses on construction sites for practical implication. It contains general tasks (e.g., placing and nailing) for a typical construction project. Each group of one participant and the collaborative robot performed the same task to establish the comparison in HRC. The participant was asked to collaborate with a collaborative robot to assemble the wood structure according to a given design drawing in the HRC. The robot is Husky A200, a mobile robot from Clearpath, with a six-degree-of-freedom industrial arm from Universal Robot, mounted on the top plate of the robot. The robot arm is equipped with a 2-finger gripper to perform the grasp and pick-up works. Figure 1 (b) illustrates the setup for HRC experimental environment. The participant and the robot share the same working space. In the experiment, the participant was tasked to do the assembly according to the given drawing by nailing two wood pieces with a connector using a nail gun. Instead of participants taking care of all the measurements and wood piece placement, the robot picks up each wood piece one at a time and places it on the working bench following the design drawing. The robot places the two wood pieces on the left side first, followed by the middle piece. It places the other two wood pieces on the right-hand side at last. Thus, the participant can start to place and nail the connector once two pieces are placed, while the robot continuously brings and places the left ones.



(a) (b)

Figure 1. (a) The assembled wood structure (red circles show the connectors placed and nailed onto two wood pieces). (b) The participant connects two wood pieces while the robot continuously brings and places more wood pieces on the table.

College students majoring in architecture were recruited, who have basic construction skills (e.g., cutting and nailing) and are trained in the woodshop for hands-on tasks (e.g., carpentry). Most of them will cultivate their careers in the construction and architecture industry. A total of four individuals participated in this experiment, with three females and one male. Training on using nail guns and understanding safety rules was given before the experiment. Gaze data was collected using an eye tracker from Pupil Lab. It is a pair of glass frames with one scene camera with a resolution of 1920 × 1080 and two eye cameras with a resolution of 192 × 192. The scene camera captures the world frame, and the eye cameras capture the movements of the wearer's left and right eyeballs. Before each experiment, the participant was required to wear the eye tracker and complete the device calibration. The data was collected and stored using a laptop, including the fixation data and imagery data. Figure 2 shows the gaze data collected from the eye tracker. The world frame presents the working space from the first view. The images of eyeballs are overlayed onto the world frame.

To verify the validity of gaze data, a post-interview was performed after the experiment. The gaze-overlaid video was played back and viewed by the participant and the researcher jointly. In the interview, the researcher first explained what the world frame is and how the gaze point is displayed in the video. After the explanation, the participants were asked to confirm their gaze positions according to their recalls at each time the researcher paused the video. The participants were primarily asked when they were nailing to connect two wood pieces.

Eye Tracker Calibration. Considering the individual difference, eye tracker calibration was required for each participant before the experiment started. A screen-based calibration was used due to the limited working space. In this calibration, a marker appears at different positions on the screen of a laptop. The participant is asked to focus on the center of the marker each time it appears on the screen and only move eyeballs to follow the marker. In our calibration, the participant stood at the front of the working bench (i.e., where the participant stood at the beginning of the experiment), and the laptop was placed at the center area of the working bench. The participant looked a litter bit down to focus on the markers shown on the screen (4 positions at the corners of the display, 1 position at the center of the display), which reflected the same head movement in the experiment. The accuracy of the calibration was tested by observing the fixation position shown on the screen when asking the participant to focus on the marked blue points on the surface of the working bench.

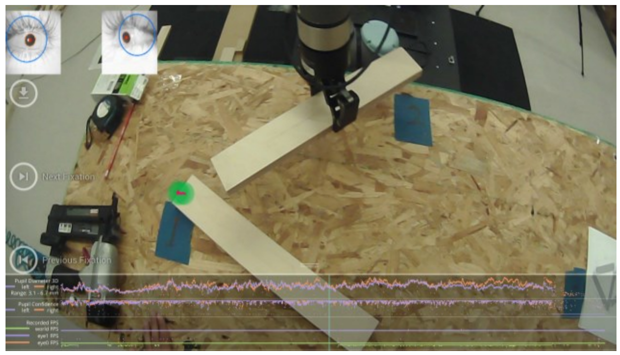


Figure 2. Visualization of gaze data collected from the eye tracker. The scene captured by scene camera is shown. Frames captured by eye cameras are shown on the top left (blue circle presents the 3D model of eyeball). Green dot shows the gaze of the participant.

DATA ANALYSIS

This study uses several gaze metrics to analyze the gaze data, including AOI, fixation, hit any AOI rate (HAAR), and scan path (Jacob and Karn 2003). AOI is the area of display that the research is interested in and thus defined by the researchers. Fixation refers to a relatively stable eye position with a typical threshold of dispersion and a minimum duration. In this study, the Pupil Lab eye tracker uses 1.5° of dispersion and 80 milliseconds of minimum duration in a dispersion-based method to calculate the fixations (Kassner, Patera, and Bulling 2014). The fixation duration means the time duration of one fixation. HAAR is the rate that a gaze hits any AOIs, which reflects the importance of the elements (i.e., AOIs were defined by the research team). Scan path presents a trajectory of a series of fixations in a spatial display. It is used to show the spatial arrangement of a portion of fixations for visualization.

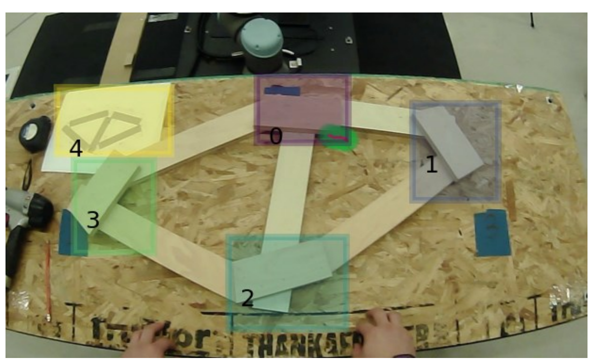


Figure 3. The AOIs – four AOIs for the connectors and one for the design drawing. The number of AOIs is indicated in the picture.

The fixation data of all participants was exported from the eye tracker. During the experiment, this study is interested in finding out how the participant's visual attention was distributed according to the specific wood assembly task using HRC, especially when the participant was doing the nailing. Hence, five AOIs – four AOIs for the connectors and one for the design drawing – were defined (see Figure. 3). Considering the dynamic aspects of the world frames, a mobile gaze mapper was used to map fixations onto the reference image (MacInnes et al. 2018). To cover the whole wood structure, a snapshot of assembled end product was extracted from the world video for each experiment. The position of AOIs may vary in different participants (e.g., some participants like the design drawing placed one the left-hand side, other may like it placed on the right-hand side), but the sequence of AOIs stays the same. Once the fixation data reference to the reference image is prepared, quantitively analysis was performed to get more insights of fixations during the HRC assembly task. HAAR was calculated based on the five AOIs.

RESULTS

The eye gaze data of all participants was analyzed to study how the participant's visual attention was distributed between the AOIs (i.e., the places where connectors were placed and where the design drawing was placed) in this wood assembly HRC task. Fixations from all participants were extracted, and a table of general description of the fixations is presented (see Table 1). The fixation count varies significantly from the smallest number of 2243 to the largest number of 4756. This could be because the completion time of each experiment for each participant is different – some participants spent more time ensuring the placement of wood pieces was correct according to the design drawing. Interestingly, the mean of fixation duration among all participants is relatively similar, with a total mean of 145 milliseconds. This shows that the participants' eyes rest on an object in the surroundings for a relatively similar time duration.

Table 1. General description of fixation data.

Participant	ID1	ID2	ID3	ID4
Fixation count	4004	4756	2243	3288
Mean of fixation duration (milliseconds) (total mean = 145)	134	137	151	156

To better visualize the gaze data collected from participants, a scan path of a portion of gaze points from participant ID2 was drawn (see Figure 4). It shows the spatial arrangement of gaze positions on the surface of the reference image. A big portion of the gaze points is located on the top left of the reference image because it is the pickup location where the robot moved its arm to pick up lumber. It means that when the robot arm moves, the participant moves his or her gaze to that position accordingly. In addition, there are certain portions of gaze points shown sequentially on the wood pieces, on the design drawing, and then on the connectors. This indicates that the participant gazed at the design drawing and lumbers back and forth to verify that the placement was correct. After the verification, the participant focused on the connector for nailing.

To investigate how the visual attention is distributed related to the wood assembly task, five AOIs were defined, and gaze points were mapped to the reference image accordingly to analyze the HAAR within different AOIs (see Table 2). The AOIs of #0, #3, and #4 account to most of HAAR among all participants. That means the visual attention of all the participants is mainly located at the connector placed on the top of the middle lumbers, at the design drawings, and at the most left connector area. This could be because the robot picks up the lumber from the pickup location and, moves to the center of the working bench, then places the lumber in the desired location. Thus, the participants' gaze followed the movement of the robot. It is also reasonable that the design drawing has a high HAAR. The participants need to gaze at the drawing and ensure the lumber placement is correct according to the drawing. This indicates that the visual attention of construction workers is related to the detailed process of the assembly task. The HAAR at AOI #1 of participant ID2 is zero. It may be because the gaze point shown in the video is outside of the bounding box. There could be minor displacement between actual attention and captured point due to the eye ball's conditions of the user (e.g., shortsighted). Individually, participant ID4 has the highest HAAR at AOI #0. There was a minor collision when the robot tried to place the lumber in the middle during the experiment, which caused the participant to gaze at AOI #3 more prolonged than others.

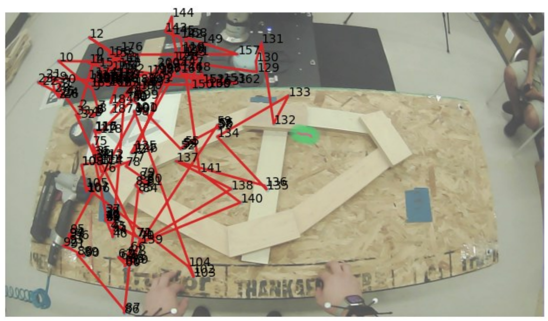


Figure 4. Scan path of a portion of gaze points from one participant.

Table 2. HAAR within five AOIs from all participants.

AOI	0	1	2	3	4
ID1	3.14%	1.29%	0.40%	13.10%	13.26%
ID2	1.76%	0.00%	1.11%	10.22%	10.93%
ID3	7.22%	1.99%	9.44%	3.93%	3.14%
ID4	22.57%	4.30%	1.77%	2.18%	5.12%

CONCLUSION

This study examined the visual attention of construction workers through eye gaze analysis in a pilot experimental assembly task using HRC. Five AOIs related to the wood assembly task were defined. A gaze confirmation interview was conducted after each experiment to get valid gaze data. This study analyzed gaze data based on several gaze metrics, including AOIs, fixations, HAAR, and scan path. It illustrates the worker's gaze in an HRC from 1) the eye gaze distribution in this assembly task; 2) the gaze movement during task procedures.

It is found that construction workers' visual attention is related to the detailed process of the task – around 30% of the eye gaze is located at the connector areas and the design drawing area. Interestingly, workers' gaze movement could be affected by the collaborative robot when performing an HRC assembly task. The workers also gazed at the pick-up area where the robot fetched the lumber from and on the robot gripper sometimes when the robot arm was moving. It can be told from the scan path analysis that the worker's gaze movement followed a certain sequence in the task. The gaze moved between lumber and design drawings, then it focused on the connector the worker was about to work on. It proves that workers' visual attention is significantly affected by the robot's movement and task procedures.

The findings of this study have significant implications for HRC-related research. The demonstrated gaze distribution of workers suggests that the gaze can reflect the workers' areas-of-interest in an assembly task. The integration of eye gaze in a HRC could smooth the collaboration process by sharing the current status of human workers with the robot simultaneously. Additionally, the observed gaze movement of workers hints that the eye gaze could be implemented as gaze commands to trigger certain motions of the collaborative robot. For instance, in this assembly task, the robot may continuously bring more lumber when the participant gazes between the pick-up area and the design drawing back and forth. These findings not only advance the understanding of workers' gaze in an HRC task but also stimulate further research into the HRC in construction regarding eye gaze communication.

Limitations exist in this study. Firstly, the small sample size has limitations in understanding the general visual attention among construction workers. More data from a well-balanced gender distribution will be included in ongoing research. Second, bounding boxes are used to define the AOIs, which is not precise. To provide more precise visual attention (e.g., actual areas of the object the worker is interested in) between humans and robots, object segmentation should be applied in further research. Additionally, the small-scale wood assembly cannot represent the construction works on real construction sites. A real-scale wood structure should be considered in future research.

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