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Classifying Excavator Collisions Based on Users' Visual Perception in the Mixed Reality Environment

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Abstract: Visual perception plays an important role for recognizing possible hazards. In the context of heavy machinery, relevant visual information can be obtained from the machine's surrounding and from the human-machine interface that exists inside the cabin. In this paper, we propose a method that classifies the occurring collisions by combining the data collected by the eye tracker and the automatic logging mechanism in the mixed reality simulation. Thirteen participants were asked to complete a test scenario in the mixed reality simulation, while wearing an eye tracker. The results demonstrate that we could classify the occurring collisions based on two visual perception conditions: (1) whether the colliding objects were visible from the participants' field of view and (2) whether the participants have seen the information presented on the human-machine interface before the collisions occurred. This approach enabled us to interpret the occurring collisions differently, compared to the traditional approach that uses the total number of collisions as the representation of participants' performance.


1 Introduction


Measuring participants' performance while completing certain evaluation scenarios has long been used as a method to measure the effectiveness of information systems (Nielsen and Levy, 1994; Fu et al., 2002). The kind of performance data being collected varies depending on the context of the study and the information system being evaluated. Completion time, number of errors, and reaction time are some frequently used metrics in the context of safety-critical domains, including automotive (Albers et al., 2020) and heavy machinery domains (Sitompul and Wallmyr, 2019).


When using participants' performance as the metric to determine the effectiveness of information systems, designers and researchers need to be open minded in interpreting the collected data, as there could be various reasons that lead to such out-

come (Fu et al., 2002). For example, in many cases, the number of errors was often taken as the face value that represents participants' performance (Cacciabue, 2004). While this approach is generally accepted and any forms of errors should be avoided, it is important to note that errors may occur due to various reasons. For instance, the collision that occurred with an occluded object, where the participant was completely unaware of the object's presence. By understanding the underlying conditions behind an error, designers and researchers could be more reflective in interpreting the collected data. The better understanding would hopefully help designers and researchers to propose solutions for preventing errors in specific underlying conditions.

In this paper, we classified the occurring collisions in the context of heavy machinery based on two visual perception conditions: (1) whether the colliding object was visible from the participants' perspective, either centrally or peripherally, and (2) whether the participants saw the visual supportive information before the collisions occurred. We focused on

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this issue, since visual perception ability plays a crucial role for recognizing possible hazards (Jeelani et al., 2017) and this ability varies among individuals (Ziemkiewicz et al., 2012). In the context of heavy machinery, the relevant visual information can be obtained from the machine’s surroundings and also from the human-machine interface (HMI) that exists inside the cabin (Sitompul and Wallmyr, 2019).

To facilitate the study, we used a mixed reality environment to simulate an excavator operation, where the environment was virtual and projected onto the wall, while the HMI and the controls were physical. The HMI visualized warnings that indicated the presence of an object near the excavator. To measure participants’ visual perception when a collision occurred, we used the data from two sources: (1) an eye tracker that recorded whether the participants saw any warning shown by the HMI before the collision occurred and (2) an automatic logging mechanism implemented in the simulation that recorded whether the colliding object was visible from the participants’ perspective. The timestamps from both sources were then synchronized in order to combine the data.

2 Related Work

To gain more insights on what happened in evaluation scenarios, it is a common practice to collect multiple kinds of data (Holzinger, 2005; Falkowska et al., 2016), such as participants’ verbal feedback, responses on subjective questionnaires, and participants’ physiopsychological status (e.g. eye movement and brain electrical activity). Using multiple kinds of data offers possibilities for designers and researchers to understand participants’ behaviors, which are not only limited to the final outcome, but also how they arrived at such outcome (Ebling and John, 2000; Brehmer and Munzner, 2013). However, the data from different sources were often used as independent metrics, where the data from different sources were then compared to determine whether they supported or contradicted each other (Brehmer and Munzner, 2013; Blascheck et al., 2016). This situation does not only apply to studies that investigated traditional interfaces, but also applies to studies that evaluated immersive interfaces, including augmented reality and virtual reality. See Dey et al. (2018) for the review of evaluations methods used in augmented reality studies and Karre et al. (2019) for the review of evaluations methods used in virtual reality studies.

There are some combination approaches that have been proposed so far (see ElTayeby and Dou (2016) for the review). Pohl (2012) and Reda et al. (2014)

combined interaction logs and recordings from think aloud protocols to help designers and researchers to inspect what users were thinking when performing a task. Crowe and Narayanan (2000) combined eye tracking data and interaction logs (using keyboards and mouses) to investigate what steps that users took and which visual stimuli that led to such actions. Beck et al. (2015) proposed to synchronize eye tracking data and recordings from think aloud protocols to probe what users were seeing and thinking. Blascheck et al. (2016) extended the previous approach by adding interaction logs using computer mouses, in addition to eye tracking data and recordings from think aloud protocols. The combination of three different sources could be used for analyzing user behaviors when using visualization systems. However, the proposed approaches mentioned above were still limited to screen-based interfaces.

3 Mixed Reality Simulation

The mixed reality environment used in this study was originally developed by Kade et al. (2016) using the Unity game engine¹. The images of the virtual environment were projected using a head-worn projection system onto the wall covered by the retroreflective cloth (see No. 5 and No. 6 in Figure 1). The head-worn projection system was made of two parts: (1) a stripped-down laser pico projector, SHOWWX+from Microvision, Inc., with an external battery pack (see No. 8 in Figure 1) and (2) a Samsung S4+ smartphone (see No. 7 in Figure 1) that hosted the virtual environment renderer and tracked the user’s head movement using the built-in gyroscope sensor in the smartphone. The laser projector had a native maximum resolution of 848px × 480px @60Hz and a light emission of 15 lumen. This setup enabled the user to look around within the virtual environment freely. In this study, the distance between the user’s head and the wall was around 2 meters.

3.1 Test Scenario

The test scenario was to drive an excavator through a construction site, while trying to avoid any collisions with construction workers, traffic cones, and other objects (see Figure 2). In total, there were two construction workers and 31 traffic cones along the passage in the virtual environment. All these objects were static, except for the second construction worker that constantly walked back and forth over the passage. While

¹<https://unity.com>

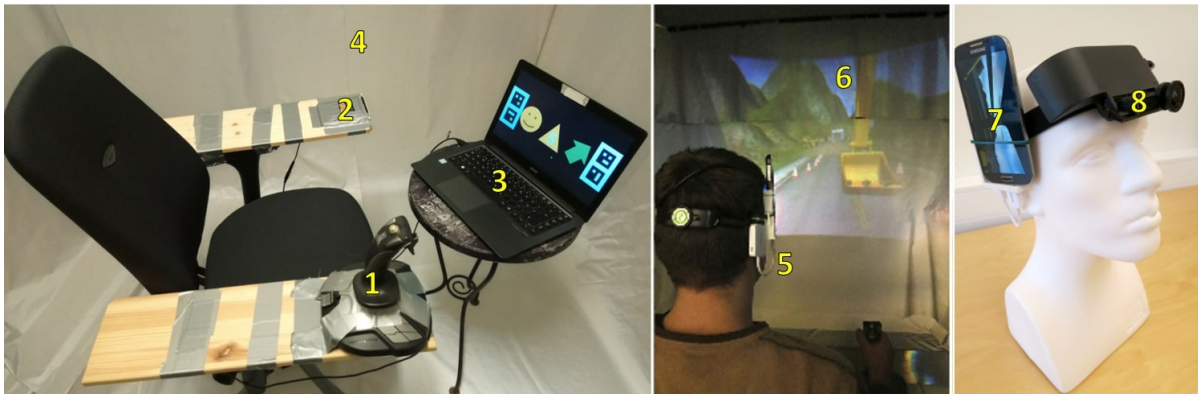


Figure 1: The mixed reality simulation consisted of a joystick (No. 1), a keyboard (No. 2), a laptop that served as the human-machine interface (No. 3), the retroreflective cloth attached on the wall (No. 4), a head-worn projector (No. 5). The head-worn projector consisted of a smartphone (No. 7), a laser projector (No. 8) with a 3D-printed box that hosted the battery. The projected images could be seen on the retroreflective cloth (No. 6).

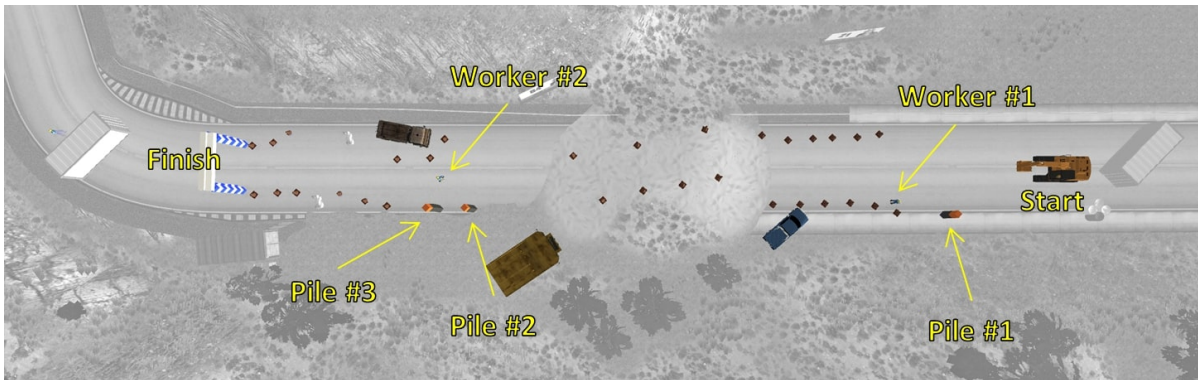


Figure 2: A bird's eye view of the virtual environment. The obstacle objects, such as cones, were colored, while the environment was turned grayscale.

navigating through the passage, the participants were also required to find three piles, which were made of orange and grey cubes. The participants were asked to knock down the orange cubes only, which were located on top of these piles. To finish the scenario, the participants were required to drive the excavator through a gateway that served as the finish line. The test scenario was designed to be difficult in order to give the participants several observable challenges, which could force their attention into several different fields of focus. Nonetheless, it is also not rare for excavators to be used in narrow spaces, for example, in urban areas where obstacles may exist all around the machine.

3.2 Human-machine Interface

To help the participants, the mixed reality simulation was also equipped with an HMI in the form of a laptop monitor that was placed in front of the participants (see No. 3 in Figure 1). The laptop monitor served as

a representation of head-down displays that usually exist inside excavator cabins. The HMI displayed a set of symbols intended to help users to navigate and avoid collisions with the objects in the virtual environment (see the left image in Figure 3). The symbols were:

1. A green arrow that always pointed to which pile of orange cubes that should be knocked down.
2. A yellow triangle warning that indicated that there was an object nearby.
3. A red octagon warning that indicated that a collision was imminent to happen.
4. A yellow circle, which symbolized a face, that appeared if the nearby object was a construction worker.

The triangle warning, the octagon warning, and the symbolized face were shown based on the distance between the nearby object and the excavator. The yellow triangle warning was displayed when there was an object near the excavator. When the excavator was

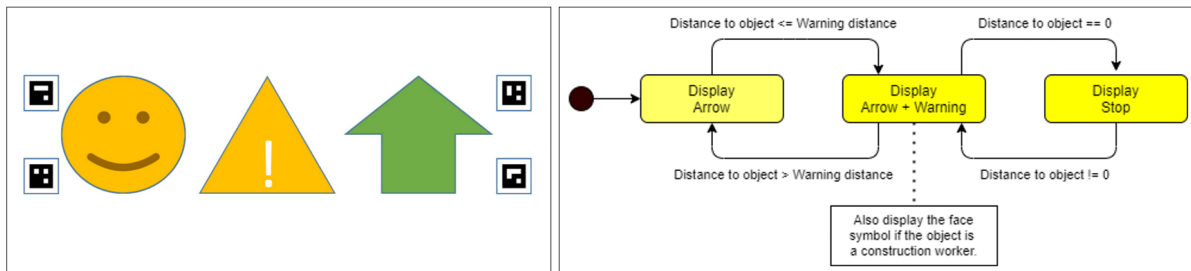


Figure 3: The left image shows the set of symbols presented on the HMI. The markers in the corners are used for enabling the eye tracker to automatically detect whether the user has looked at the presented information. The right image shows a state diagram, which illustrates how the HMI determines which information and when the information should be presented to the user.

about to collide with the nearby object, the yellow triangle warning was replaced with the red octagon warning. The symbolized face was shown together with the triangle warning or the octagon warning, only if the nearby object was a construction worker. See the right image in Figure 3 for the state diagram that shows how the HMI decided which information to be shown to the user. These symbols were surrounded by four markers that enabled the eye tracker to perform surface tracking (see No. 3 in Figure 1 and the left image in Figure 3). More information on the surface tracking is described in Section 4.1.

4 Proposed Data Combination Method

As briefly mentioned in Section 1, the proposed method classified the occurring collisions using two sources of data: an eye tracker and an automatic logging mechanism implemented in the simulation. Here, we describe how the data from both sources were collected, and then synchronized.

4.1 Eye Tracking Data

The eye tracker used in this study was Pupil Core from Pupil Labs². Pupil Core was a head-worn eye tracker with two-eye cameras pointed towards the user's eyes and one front-facing camera that recorded the view in the front of the user. In addition to capturing users' gaze, Pupil Core could also track a pre-defined surface. In this study, the tracked surface was defined with four square markers (see No. 3 in Figure 1). Each square marker contained a unique 5x5 grid pattern that the front-facing camera could identify automatically. Using the four markers, we were able to automatically detect whether the user has seen

²<https://pupil-labs.com/products/core/>

the warning shown on the HMI before a collision occurred.

The eye tracker automatically logged the time intervals when the user's gaze was fixated within the tracked surface regardless of the duration. The logs were exported to a comma-separated values (CSV) file that contained four kinds of information: (1) the timestamp, (2) a Boolean value that indicated whether the user's gaze was inside the tracked surface, (3) the position of the user's gaze, and (4) a float value between 0.0 and 1.0 that indicated the certainty that the position of the user's gaze was correct. The value of 0.0 means the captured data from the eye tracker had 0% certainty, while the value of 1.0 means the captured data had 100% certainty.

There was another alternative to perform surface tracking, which could be done by detecting whether the user has perceived the colliding object from the projected images of the virtual environment. However, this approach was not feasible due to the different frame rates between the eye tracker's camera and the projector in the head-worn projection system. From the eye tracker's view, some parts of the projected images were not visible due to the rolling black bar effect, or also known as flickering.

4.2 Automatic Logging Data

Due to the technical limitation of the eye tracker mentioned in Section 4.1, it was not possible to check whether the user has seen the colliding object from the projected images of the virtual environment. To compensate with this disadvantage, we used the *view frustum* to determine the visibility of the colliding object from the user's perspective (see Figure 4 for some examples). This approach allowed us to determine whether the collision happened with an object that was inside or outside the user's field of view.

When a collision occurred, we recorded the visibility of the colliding object by checking whether the

object was inside the view frustum or not, as shown in Figure 4. The colliding object was classified as *visible* if it was inside the view frustum and there was nothing that blocked the users' sight (see the middle image in Figure 4). The colliding object was classified as *occluded* if it was located outside the view frustum (see the left image in Figure 4) or if it was inside the view frustum, but there was something that blocked the user's line of sight (see the right image in Figure 4). The visibility status of the colliding object was determined and recorded in the time of impact. Whenever a collision occurred, we also logged some details from the HMI, such as which information was presented on the HMI, when the information was presented, and its duration. The automatic logging mechanism was implemented using a custom C# script integrated in the Unity game engine.

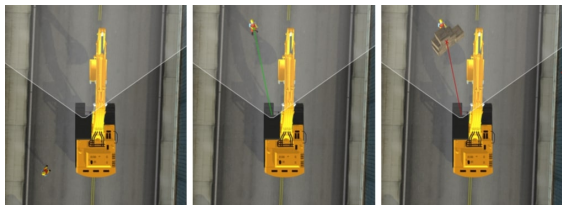


Figure 4: The images depict the excavator from the bird's eye view in three different situations. The left image shows a worker that exists outside the view frustum, thus invisible to the user. The middle image shows a worker that exists inside the view frustum, thus visible to the user. The right image shows that the worker exists within the view frustum, but invisible to the user due to the occluding boxes.

4.3 Data Synchronization

The automatic logging mechanism reported its time in seconds and milliseconds after the simulation was started, and thus the timestamp always started from 0. However, the eye tracker used a separate system for tracking time that counted the number of seconds since the last PUPIL EPOCH³. The last PUPIL EPOCH was set according to the last reboot time of the computer that connected to the eye tracker. Using a C# script, we took the first timestamp that we got from the eye tracker, and then subtracted it with the value of the PUPIL EPOCH. This approach allowed us to make the timestamps from the eye tracker to start from 0 as well. This enabled us to synchronize the data from the eye tracker and the automatic logging mechanism. For each collision that occurred, we could determine: (1) whether the colliding object was visible from the user's perspective and (2) whether the user has seen the presented warning before the colli-

³<https://docs.pupil-labs.com/core/terminology/#timing>

sion occurred.

5 Experimental Procedure

To evaluate how our method could work in practice, thirteen participants (ten males and three females) from the university environment were asked to complete the test scenario described in Section 3.1. The age of the participants was between 26 and 70 years old, while the median age was 31 years old. Two participants had some experience with heavy machinery operations. The participants did not receive any compensation for taking parts in the experiment. An ethical approval was not required for this kind of experiment according to the local law.

Before the experiment started, each participant was informed about the purpose of the study, the equipment that we used for the study, the test scenario that they had to complete, and the data that we collected. After we received the informed consent, each participant was asked to equip the head-worn projection system and the eye tracker. The eye tracker was then calibrated using the on-screen based calibration software, called Pupil Capture⁴. After the calibration has been performed correctly, each participant was given a trial session where they got themselves familiar with the excavator's controls. The experiment was started afterwards.

6 Results

The method that we proposed in this paper classified the occurring collisions based on two visual perception conditions: (1) whether the colliding objects were visible from the participants' field of view and (2) whether the participants saw the supportive information before the collisions occurred. Based on these two conditions, the occurring collisions could be classified into four categories (see Figure 5):

1. The colliding object was visible and one of the warning was seen.
2. The colliding object was visible and no warning was seen.
3. The colliding object was occluded and one of the warning was seen.
4. The colliding object was occluded and no warning was seen.

⁴<https://docs.pupil-labs.com/core/software/pupil-capture/>

The number of collisions based on the conditions when they occurred

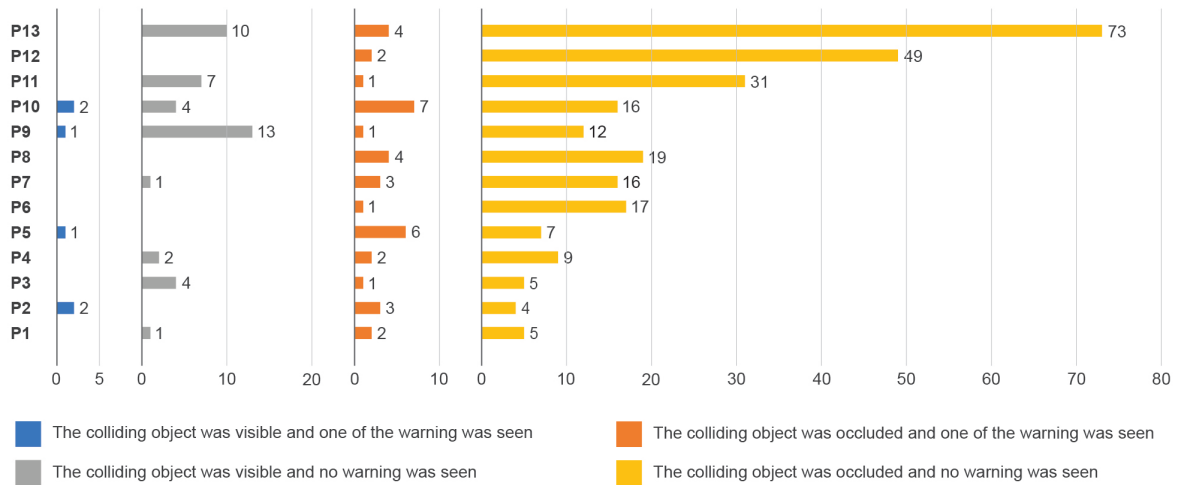


Figure 5: The number of collisions that occurred based on the underlying conditions when they occurred. The different colors represent the various conditions when the collisions occurred. The X-axis represents the participants and the Y-axis represents the number of collisions.

The majority of the collisions occurred when the colliding objects were occluded and the participants did not see the warnings shown on the HMI (see the yellow bars in Figure 5). This finding indicates that the participants were not aware of the presence of the colliding objects and they also did not look at the information shown on the HMI that much. This finding is aligned with prior research in the context of heavy machinery, where operators paid little attention to the information presented on the head-down display inside the cabin (Hägström et al., 2015; Wallmyr, 2017; Szewczyk et al., 2020), since the head-down display is usually placed far from operators' line of sight.

The second most common type of collisions is the collisions that occurred with occluded objects, even though the participants have seen one of the warnings (see the orange bars in Figure 5). We have two assumptions regarding this kind of collisions. The first assumption is that there was very little time between when the participants saw the warnings and when the collision occurred. Therefore, there was not enough time for the participants to avoid the collisions. The second assumption is related to the quality of the warnings. Although the warnings indicated that there was an object nearby, they did not indicate the exact position of the object. Therefore, it was possible that the participants made the wrong action and collided with the nearby object, even though they have seen one of the warnings.

The third most common type of collisions is the

collisions that occurred with visible objects and the participants did not see the presented information (see the grey bars in Figure 5). However, only eight out of thirteen participants who had this type of collisions. Based on the visual perception's perspective, it could be due to a phenomenon called "change blindness", where the participants failed to notice the visible and expected stimuli that existed in their field of view (Jensen et al., 2011), which in this case was the colliding object. There are many factors that could lead to this phenomenon and one of the common factors is the changes in the field of view are not significant enough to what people are currently doing, and thus they fail to detect those changes (Rensink et al., 1997).

The least common type of collisions is the collisions that occurred with visible objects and the participants have also seen the presented information (see the blue bars in Figure 5). From our perspective, this is what we called as obvious errors, since the colliding objects were visible from the participants' perspective and the information was seen as well, but the collisions still occurred. However, as shown in Figure 5, this type of collisions occurred very rarely, since the number of collisions was very small and only four out of thirteen participants who had this type of collisions. This could also indirectly imply that the participants were doing their best to complete the test scenario.

7 Discussion

Our method utilized the occurrence of collisions as the synchronization point between the data collected by the eye tracker and the automatic logging mechanism in the simulation. As such, the data were limited to the collisions that occurred in the test scenario. It would also be interesting to update the method in a way that enables us to determine how many collisions were successfully avoided after looking at the presented warning. By doing so, we could also determine the effectiveness of the HMI in aiding the participants. For example, as shown in Figure 5, P1 and P2 completed the test scenario with less than ten collisions. With the current setup, it was not possible to determine whether their performance was due to the information shown on the HMI or they had some level of expertise in using this kind of simulation. However, we were unable to incorporate this feature in this study, since it was tricky to define the criteria of collision avoidance. For example, since there were multiple objects on both left and right sides along the passage (see Figure 2), it was possible to avoid one object, but accidentally hitting another object.

We believe that the proposed method is also applicable for other studies given that the following requirements are fulfilled. Firstly, due to its nature, our method is only suitable for studies within simulated environments, where it is possible to fully record and observe the event of interest. Although in this study we used a mixed reality simulation, our method can also be applied in a virtual reality simulation, given that the headset being used has a built-in eye tracker, such as Vive Pro Eye⁵. Secondly, here we used the occurrence of collisions as the trigger and the synchronization point for both sources of data. Therefore, it is best to assume that the proposed method would be applicable in studies where participants are expected to make some errors. Thirdly, in order to use the method as what we proposed here, there should be a supportive visualization system as part of the experimental setup. Although the method could still be used without a supportive visualization system as part of the experimental setup, the collision classification would be limited to whether the colliding object is visible from the participant's perspective.

⁵<https://www.vive.com/eu/product/vive-pro-eye/overview/>

8 Conclusion

In this study, we have classified the occurring collisions based on the data from the eye tracker and the automatic logging mechanism in the simulation. The classification was made based on two visual perception conditions: (1) the visibility of the colliding objects from the participants' perspective and (2) whether the participants saw the information presented on the HMI before the collisions occurred. This approach enabled us to interpret the occurring collisions differently, compared to the traditional approach that directly interprets the total number of collisions as the representation of participants' performance. As demonstrated in this study, the collisions could occur due to different conditions. By understanding the underlying conditions behind the collisions, designers and researchers could be more reflective when interpreting the collected data.

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