Gentlemen on the Road: Effect of Yielding Behavior of Autonomous Vehicle on Pedestrian Head Orientation

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Abstract

Autonomous vehicles can improve pedestrian safety by learning human-like social behaviors (e.g., yielding). We conducted a virtual reality experiment with 39 participants and measured crossing times (seconds) and head orientation (yaw degrees). We manipulated AV yielding behavior (no-yield, slow-yield, and fast-yield) and the AV size (small, medium, and large). Using Dynamic time warping and K-means clustering, we classified head orientation change of pedestrians by time into 6 clusters of patterns. Results indicate that pedestrians’ head orientation change was influenced by AV yielding behavior as well as the size of the AV. Participants fixated on the front most of the time even when the car approached near. Participants changed head orientation most frequently when a large size AV did not yield (no-yield). In post-experiment interview, participants reported that yielding behavior and size affected their decision to cross and perceived safety. For autonomous vehicles to be perceived more safe and trustful, vehicle-specific factors such as size and yielding behavior should be considered in designing process.

Keywords: Pedestrian-vehicle Interaction, Autonomous Vehicles, Trust in Automation, Virtual Reality
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Autonomous driving is an ever-fast developing technology world-wide. While recent successful cases of autonomous cars on the public roads signal exciting news, it raises safety concerns at the same time. Korea is one of the leading countries in developing autonomous driving technology, yet it has the highest pedestrian fatality rates. The number of deaths in traffic accidents per 100,000 population in Korea was 4.1 in 2014, which is three times the OECD average (1.4). In the same year Korea had the highest rate of pedestrian fatalities anywhere in the OECD and the number of elderly fatalities per capita was triple the OECD average (Adler and Ahrend, 2017). However, letting autonomous vehicles drive on the real road can lead to multiple challenges not only in the context of driver-vehicle interface, but also in pedestrian-vehicle communication. In addition, social acceptance of AV and public trust should precede operating AVs on public roads. Researchers have shown more interests on human-AV interactions recently (Ackermann et al., 2019; De Clercq et al., 2019; Dey and Terken, 2017). However, much of this research focused on looking at pedestrian reaction from a driver’s perspective. There is a lack of studies focusing on the pedestrian perspectives. It is necessary to examine communication means people use in the face of vehicles on the road.

Trust in AV

When an artificial agent sends a social signal (e.g., greeting), our expectation that it will continuously show more human-like social response increases (Reeves and Nass, 1996). But when the agent’s behavior is hard to interpret (e.g., "Will that driver stop in front of me or not?"), our trust in the agent decreases. Studies show that the more uncertain the vehicles’ intentions are, the less the pedestrians trust them (Jayaraman et al., 2019). Pedestrians showing trust in the vehicle’s intention to ensure their safety generated reduced crossing speed, less frequent staring at vehicles, and shorter distances to collision at signalized crosswalks (Asaithambi et al., 2016; Rasouli et al., 2017; Tom and Granié, 2011). In unsignalized crosswalks, the rules may not be clear which of the
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cars and pedestrians should go first. In signalized crosswalks, people rarely engage in interacting with vehicles because both parties are expected to follow the traffic signals. We wanted to see how pedestrians interact with the AVs when there is no clear rule of who goes first. We focused on interactions in unsignalized crosswalks. We expect that pedestrians will engage more in communicating with the approaching vehicle in an unsignalized crosswalk than in a signalized crosswalk.

Movement as Intent Communication

Movements and gestures are important to coordination and performance of joint activities with which they communicate intentions. When given dot points moving, human can derive one’s own interpretation of their purpose, cause, and expected results (Dittrich et al., 1996; Heider and Simmel, 1944). Movement is used as a way to express socially appropriate behavior or to communicate intent to creat social distance (Ekman and Friesen, 1969). Autonomous robots also use movement as a communication method (Lehmann et al., 2015; Thompson et al., 2011). Social signals delivered via movements such as nodding, shaking hands, advancing or retreating from others can be interpreted in different ways depending on the situations. Teaching machines to behave in socially appropriate ways can make cooperation with humans smoother in several cases like manufacturing, sports, and even a jazz ensemble (Hoffman and Ju, 2012). Recently, there have been increasing cases of research on AV’s socially appropriate movement gesture as effective non-verbal communication means affecting pedestrian trust (Asaithambi et al., 2016; Risto et al., 2017). In crosswalks, it is difficult to verbally communicate, so both pedestrians and drivers put efforts on interpreting each agent’s movements. Studies show that pedestrians use many nonverbal communication means such as raising hands, staring, race walking, and bowing (Guéguen et al., 2015; Rasouli et al., 2017; Ren et al., 2016). These messages can be also understood differently depending on the culture and locations. Pedestrians assume that the AV will ensure the safe distance between them, and if this social agreement is violated, they react accordingly (e.g., staring, putting up a hand).
Intent Communication of AV: Yielding Behavior

Autonomous vehicles (AVs) need the ability to communicate their intent with pedestrians. Previous studies on human-AV interaction, however, have mainly concerned communication between the driver and AV (Bellem et al., 2018; Buckley et al., 2018; Lee et al., 2019; Seppelt and Lee, 2019). It is crucial for the related fields to study how pedestrians perceive safety and use both verbal and non-verbal communication means to safely cross. Studies show that AVs that have an interface showing its intent of waiting or passing were perceived more safe than those without it (Böickle et al., 2017; Habibovic et al., 2018).

Keeping a safe distance and showing the desire and intention of doing so will be regarded as socially appropriate manners. If AVs behave like how good-mannered human drivers would yield, this behavior could increase the trust and perceived safety in pedestrians as well. To make AVs socially appropriate, we should regard vehicles as social entities that can affect the behaviors and psychological states of pedestrians. A vehicle approaching without slowing the speed invades the comfort boundaries and thus evokes pedestrians’ emotional responses such as fear (e.g., stopping or running) and discomfort (e.g., staring). Many pedestrian responses to drivers rely on subtle and non-verbal cues, which sometimes lead to miscommunication or perceived risks.

However, only a limited number of studies investigated pedestrian-AV interaction. Recent approach on studying pedestrian-AV interaction are on-site observation of pedestrian reaction to "driverless" vehicles, which were driven by human drivers hidden behind a car seat (Dey et al., 2019; Palmeiro et al., 2018; Risto et al., 2017; Rothenbücher et al., 2016). Previous studies mainly focused on vehicle factors that affected pedestrian behaviors such as vehicle appearances, speed, and presence of crosswalks (Rasouli and Tsotsos, 2019; Schmidt and Faerber, 2009; Sucha et al., 2017). Recent studies on pedestrian-AV interactions focused on manipulating Head Mount Displays (HMD) in order for vehicle to deliver its intent (e.g., yielding, passing ; Habibovic et al., 2018; Mahadevan et al., 2018). However, HMDs are useful only when pedestrians are always watching the front of the vehicle. It is known that pedestrians rarely look at the human-driven vehicles until it "misbehaved" by approaching aggressively and not slowing its speed.
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(Rothenbücher et al., 2016). Pedestrians showed a blind trust in the driver and did not notice until the vehicle advanced and did not yield. In other field study by Risto et al., 2017, pedestrians showed discomfort by staring at vehicles when they did not keep a safe enough distance between them. We on the other hand will focus on the vehicle movement, yielding. And to make it more human-like, we will manipulate the speed of yielding behavior so that the AV 'intends' to give a sufficient safe distance from the pedestrian.

Intent Communication of Pedestrians: Head Orientation

Pedestrians were mostly viewed as moving articles in many past studies. Therefore, motion itself has served as a strong parameter of the pedestrian movement and safety. Commonly observed trusting behaviors of both drivers and pedestrians include lack of monitoring the AVs (e.g., low gaze ratio and head movement (Hergeth et al., 2017; Jayaraman et al., 2019). For pedestrians in specific, this lack of monitoring may lead to risky behaviors such as jaywalking and allowing close distances to the vehicles, which are the instances of overtrust (Parasuraman et al., 1993).

Recent approach to pedestrian intent communication and estimation has suggested looking at non-verbal parameters such as hand wave, eye contact, and verbal expression. head orientation has served as an important index for pedestrian crossing intent (Kooij et al., 2019; Kwak et al., 2017; Rasouli et al., 2017; Rasouli and Tsotsos, 2019; Schulz and Stiefelhagen, 2015). Here we suggest using head orientation of a pedestrian as an indicator of cautionary behavior - hereinafter expressed as 'looking around behavior' measured by 'head orientation'. Individual differences in head orientation is expected as we as pedestrians do not share identical behavioral patterns while crossing: some people do not look at the vehicles at all whereas someone others are more careful about crossing. Using machine-learning based clustering classification method, we expect to identify several different types of cautionary behaviors in Korean pedestrians.
Present Study

We used a virtual environment to simulate a road condition that is similar to the typical Korean one-lane road. Using virtual reality, one can measure various factors that can affect pedestrian behavior. Recent body of research use virtual reality as an alternative to the pre-existing methods. Studies on crossing safety education, and human-robot collaboration used virtual reality (Matsas et al., 2018; McComas et al., 2002; Whitney et al., 2018; Zanbaka et al., 2007). In virtual reality, people also exhibit a natural response to the virtual character/agent so we expect that pedestrians in our virtual crosswalk setting will do so. To ensure this, we will also conduct a user-test to check whether the environment itself did not hinder the VR experience.

Research shows that simple addition of a factor in a dynamic traffic situation can lead to catastrophic consequences (Rasouli and Tsotsos, 2019). Hence, it will be difficult to experiment in simulated roads with real vehicles. Using virtual reality, one can derive both motion and non-motion reactions of pedestrians. Virtual reality can safely reproduce different countries, road sizes, and weather, allowing you to test factors that affect pedestrian safety. Simply adding realistic settings such as buildings or landmarks that exist in reality into virtual reality settings can increase the sense of realism and presence. As researchers, we can consider different environmental and contextual factors as manipulating variables such as country settings, volume of traffic, and even hazardous weather conditions.

Methods

Participants

A total of 37 people participated in the study ($M_{\text{age}}=24.14$, $SD_{\text{age}}=4.92$, $N_{\text{female}}=17$). Only participants who reported no experience of dizziness, nausea, or vomiting following any virtual-reality related experiences were eligible to participate. The study was approved by the Institutional Review Board of Seoul National University (IRB No.1807/002-012) and carried out in accordance with the approval including all guidelines. Participants informed us of their consent after safety instructions were given.
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Materials

We used a HTC Vive Pro head-mounted-display (HMD) with resolution of 2880 x 1660, a viewing angle of 110 degrees, and a frequency of 90 Hz. We set up a TPCast wireless VR adapter for wireless connection of VR equipment. Head tracking was achieved in real time. Participants were able to listen to the sound via the headphone equipped to the HMD. We set two Lighthouse sensors diagonally across the room to track head orientation. For safety reasons, 4 barricades were put at each corner of the room.

The virtual crosswalk task (VCT) was executed on a desktop computer with an Intel Core i7-7700CPU, with 16GB of RAM and an NVIDIA GeForce GTX 1070, running Windows 10 and DirectX 11. We used Unity 2017 3D software to simulate typical look of downtown and rural road in Korea. We used the Steam VR library to design components such as buildings, landscapes, and crosswalks.

«Figure 1»

Design

Yielding Behavior. Initial speed was randomly set among 3.33 m/s, 5.56 m/s, 4.17 m/s. When participants were detected, all AVs slowed down to 1.11 m/s. In slow-yield and fast-yield trials, AVs stopped when participants were within a close distance of 0.5m. If no participant were present, AVs proceeded without yielding. All AVs had a maximum speed of 19 km / h and an acceleration of 0.80 km / h. The recognition distance was set at 4.5 m for fast-yield and 7.0 m for both no-yield and slow-yield. In fast-yield condition, break power was set to 6.0, and 3.0 for AVs in both no-yield and slow-yield conditions. In slow-yield, AVs stopped for 2 seconds in order to see the presence of participants within the given range of 0.5 m. In no-yield condition, all AVs passed slowly in crosswalk with a speed of 4.0 m/s.

AV Size. There were 3 different sizes of AVs used: small, medium, and large. AVs were replications of typical sizes of compact AVs, medium sedans or vans, and trucks, respectively.

«Figure 2»
Procedure

Participants were first informed of the general procedure and safety instructions regarding the experimental room setup. At each corner of the experimental room, we installed four barricades. As participants put the HMD on, researchers adjusted the amount of pressure in order for a proper fit. Two researchers were assigned to each experiment: one monitored the HMD connection and observed what participants viewed and the other safely guarded participants. We also instructed participants to walk as if he/she were walking on a real crosswalk and not to get hit by the AV. Participants were randomly assigned to at least 2 instances of 9 conditions: 3 yielding behavior (no-yield (control), slow-yield, and fast-yield) x 3 AV size (small, medium (control), large). We conducted a total of 3 practice trials with no companion, small size AVs, and city downtown setting of virtual crosswalk. In test trials, participants crossed zebra crossings that were are located in either one of three settings: 2 urban and a rural one-lane roads.

Figure 3 shows a general procedure of a single trial in the virtual crosswalk. When the trial started, a "ready" sign appeared and 3 seconds of waiting time was given. After the waiting time ended, the trial started and a time-counter indicating the time limit for each trial started. Time limit was 20 seconds for each trial. At the start of the trial an instruction saying "cross the road and receive a coin at the end of the crosswalk" was shown. We put time-counter and a coin-based reward system in order to keep the experiment interesting and not to subject participants to experience boredom quickly. At the end of the crosswalk, there was an arrow indicating the end-point. If the participants succeeded at the trial, the message "success" was shown and a button pressed by the participant set up the next trial. Participant then had to turn around in order to start the new trial. A new arrow then appeared either at the same location that the participant just arrived at or at the opposite side so that a new crosswalk is made throughout the room in diagonal direction. Within 200 ms, an AV started to appear and the participant could hear the sound of the AV initiating the engine. The AV then turned around the corner and started approaching to the crosswalk. Then, when the distance between the AV and the participant was 0.5 m, the AV stopped in slow-yield and fast-yield conditions. The AV did not stop at all in
no-yield condition trials. The location of the vehicle was randomized to either left or right side of the participant. Throughout the experiment, we measured total duration of crossing time, success rate, and head orientation (0 to 360 degrees) by 200 ms which were measured automatically by HMD. When finished, we conducted post-experiment interviews.

We asked participants to give their opinions about the overall experience. Two questions to check validity of VR experience were asked: 1) how realistic the virtual crosswalk was (Simulation Realism) and 2) how similar their crossing behavior was to the one in real life (Realistic Behavior). Participants were also asked to provide subjective ratings on the effect of AV’s size and yielding behavior on their crossing behavior. We also asked to describe in detail any attempt to communicate or take caution when faced with AVs in the experiment.

Results

Success Rate and Crossing Time

All 37 participants attempted to cross the crosswalk within the time limit. We excluded 23 trials that were either ‘fail-to-cross’ or ‘timeout’ (0.02% of our sample). Average success rate was 98.7%. Participants crossed the crosswalk on average of 8.76 seconds (SD = 4.23 sec). The shortest time was less than 1 second and the longest was 19.99 seconds. Participants’ mean crossing time were calculated. Mean crossing time per conditions is illustrated in Table 1. Participants took longest time to cross when Large AVs did not yield (M = 10.63, SD = 5.65), whereas they took shortest when AVs were small and yielded fast (M = 8.38, SD =3.57).

Head Orientation

We regarded head orientation as an indicator of taking caution when crossing by looking around. We examined whether the number of looking around behavior depending on the AV size
and yielding behavior. Specifically, we divided each time sequence into 4 periods according to the occurrences of these following events: when the AV was shown within the sight of the participant ('appears'), when the AV approached near the crossing line('approaches'), and when the AV stopped in front of the crossing line('stops'), and when the AV waited (or passed) the crossing line('waits'). In polar coordinate degree, we defined head drift between 90 degree and 270 degree as front.

For clustering head orientation change patterns, we used Dynamic time warping(DTW), a time series pattern recognition algorithm that measures the optimal similarity between two similar time sequences. It is widely used in fields like speech recognition, futures trading in systems, and graphic or video pattern recognition. It matches the two time series in a direction that minimizes the distance between them. As shown in Figure 4, when two time series are matched using DTW, it can be appropriately matched to a set of waveform that are partially distorted, unlike when using the Euclidean distance method (Keogh et al., 2001). For our analysis, we used Soft-DTW (Cuturi and Blondel, 2017), a time-series pattern classification algorithm based on DTW which has shown better performance recently. We measured the angle of head orientation in every 200 ms. The range of angle (yaw) was 0 to 360 degrees. We then converted it into a range of two thresholds, -180 and 180 degrees. Assuming 0 degree as facing straight upfront, we coded the head orientation to the far right as -180 degrees and 180 degrees as head orientations to the far left.

«Figure 4»

We found great individual differences in crossing time, the shortest being 1 second and the longest being 19.9 seconds. In each trial, it took 3.5 seconds on average for the AV to appear and start approaching. We observed that participants showed a wide range of different time and even the same participant showed greater difference of crossing time by trials. In order to conduct time series classification, time sequence before 2 seconds and after 10 seconds were normalized into total 10 seconds. A total of 248 sequences were analyzed for head orientation patterns.

Prior to classification, average of time sequences with respect to dtw £ discrepancy were computed. Each dtw $x, y$) was divided by $m_i$, the length of $y_i$ in Equation 1. We used k-means
clustering to extract commonly observed head orientation change patterns and number of each patterns observed by conditions. K-means clustering is a machine learning based classification method for grouping data based on the similarity of average points. As formally stated in Equation 2, generalization of Loyld algorithm for k-means clustering (Lloyd, 1982) was conducted in each centering and clustering allocation step according to the dtw\_lambda discrepancy (3, See Cuturi and Blondel, 2017).

\[
\min_{x_1, \ldots, x_N \in \mathbb{R}^{p \times n}} \sum_{i=1}^{N} \frac{1}{m_i} \min_{j \in [k]} \text{dtw}_i(x_j, y_i) \tag{1}
\]

\[
\min_{x \in \mathbb{R}^{p \times n}} \sum_{i=1}^{N} \frac{1}{m_i} \sum_{j \in \mathbb{R}^{p \times n}} \frac{1}{m_i} \text{dtw}_i(x, y_i) \tag{2}
\]

\[
k^* = \arg\min \sum_{i=1}^{k} \sum_{j \in S_i} |x_j - \mu_i|^2 \tag{3}
\]

«Table 2»

«Figure 5»

«Figure 6»

Figure 5 illustrates head orientation change by time of events of behaviors of AV. Table 2 shows description of head orientation of participants on each time of the events. We found 6 clusters of head orientation change patterns (Cluster 1 to 6). In cluster 1 and 2, participants did not show head orientation change. In cluster 3, head orientation was fixed toward the opposite side of the AVs until the end of a trial. Cluster 4 shows the head orientation change only when the AV stopped. In cluster 5, initial head orientation fixation to the approaching AV was shown, but then fixated to the front until the end of the trial. Only participants in cluster 6 showed head orientation toward AVs from the start to the end of the trials. Percentage of each cluster by trials of size x yielding behavior of AVs are illustrated in Figure 6 illustrates.

«Table 3»
Post-experiment Interview

Table 3 shows pedestrians’ mean ratings for each item. Participants provided additional comments about the overall experience of crossing on VR crosswalk.

Realism

Most participants agreed that the virtual crosswalks felt real (3.98 out of 5, with 5 being the very much realistic). Even though the participants were aware of the fact that they were in a virtual reality (a simulated setting), it did not stop them from fully focusing on the problem at hand. Participants reported that even if they knew they were in a simulated world, it did not stop them from being immersed in the situation. One participant said:

"I felt like I was a character in a 3D animated world."

One participant, however, mentioned that he got used to the environment and got bored. The experiment naturally required participants to walk and run repeatedly and as they performed the same action, this could have led to loss of interest.

Similarity to real-world crossing behavior

Most participants reported they crossed similarly to how they usually cross, given that the crosswalk in the task were close replications of a typical alley or small road in Korea. Several participants reported that they were more cautious as they were uncertain about the AV’s intention to yield. These uncertainties were mainly due to the fact that participants could not see the driver inside the AV. Some participants commented:

"I crossed as if I was crossing a real crosswalk. I felt like I had to send some signals to the driver so that I can feel safe. I waved my hands and tried to make eye contact. I acted more carefully after a crash in the beginning of the experiment."

"I couldn’t see the driver in the AV, so I thought the AV wouldn’t yield if it had noticed my presence."

Only few participants admitted that repetitive exposure to the similar crosswalks in the VR made them tired and less vigilant of the AV movement.
Effect of Yielding Behavior of AV

Most of the participants said that yielding behavior of the AV affected their crossing behavior. Participants stated that when the AV stopped quickly, they crossed rather slowly. However, when the AV stopped slowly, it took more time for them to determine whether the AV was stopping to yield and whether it was safe to cross. Some participants reported that the yielding behavior affected their judgment on safety rather than the speed of the AV.

Effect of AV Size

Most participants responded that the size of the vehicle affected their crossing behavior. In particular, the larger the AV, the more carefully they crossed. However, the act of caution was divided into two types rushing ahead before approaching or waiting until the AV completely passed. Interestingly, some participants reported that they perceived smaller AVs more threatening than AVs of different sizes as they seemed to approach faster. Another group of participants reported that as virtual AVs made them willing to take more risky crossing decisions (e.g., crossing without looking at the AV), except for large-sized AVs. Large size AVs were too tall for them to make eye contacts, and thus led to decreased perception of safety. Here, we add part of comments participants provided:

"I didn’t find other AVs threatening except for the large truck. I was scared that the driver inside wouldn’t notice me."

"I found it very overwhelming when the AV was a large truck. I had a car accident when I was a child. So I waited until all cars had fully passed"

"I didn’t think the size of the AV mattered until the large truck appeared. It was scary when it seemed like it passed right in front of my nose."

Discussion

To summarize, we conducted an exploratory study in order to find the impact of autonomous vehicle related variables such as size and yielding behavior on change of head orientation of Korean pedestrians. We used virtual reality simulation to explore the impact of
target variable in order to observe the direct effect of them. To our knowledge, this is the first to
explore vehicle behavior in a virtual reality, especially in the perspective of a pedestrian, as most
of the previous literature was focused on the view of a driver. We also took a novel approach in
analysis by using a machine learning classification, Dynamic Time Warping and K-means
clustering in order to find common patterns of head orientation. We found that size of the AV
affected the change of head orientation while participants crossed. Participants were more
cautious with large AVs of other sizes, showing lowest level of trust. Participants' head
orientation were fixated on the front mostly (cluster 1 and 2). We found different crossing
behaviors by yielding behavior of vehicles. When AVs yielded fast, participants showed more
trust by mostly looking at the opposite side of the AV (cluster 5), except when the size of AV was
large. This can be explained in two ways. First, when the AV is large, one ran without looking
around. As soon as one heard the sound of an engine, they ran quickly towards the end of the
crosswalk. Second, one ran after checking the AV has fully passed or stopped to yield. In this
context, it would be reasonable to conclude that participants did not want to read signals or
intentions from the driver-less large truck. With small AVs, we were able to observe more
frequent head shifts, which could be interpreted as people trying to read the intention of the
driver. In other words, we observed more interaction between the participants and the vehicles
with small AVs. When the AV slowly yielded, we observed that participants took more time to
cross and tried to look into the driver’s seat. The intent of slowly yielding and large sized-AVs
were perceived most uncertain to participants which led to low level of perceived safety and trust.

«Figure 7»

Future studies can consider following topics: 1) Cultural difference in pedestrian intent
communications. In some cultures, raising a hand can interpreted as showing gratitude to the
driver for yielding while in other cultures it can be used to announce their presence. This suggests
that autonomous vehicles should be able to observe a gesture and interpret it accordingly
depending on the culture. The industry has to consider whether the driver’s hand gestures will be
recognized by the pedestrians or whether the pedestrian’s gestures will be ignored. 2) Individual difference in gap acceptance between pedestrians and AVs. In Korea, it is not hard to find instances of pedestrians allowing extremely short distances from vehicles (Figure 7). Especially at crosswalks without traffic lights, one can easily witness pedestrians allowing short distance to the vehicle by walking around the AV (even after the vehicle stops to yield) and approaching near the vehicle to wait (close enough to open the door). Installing sensors for approaching pedestrians and a communication medium, such as LED light strips, text-board, or a speaker, on all sides of the exterior of the vehicle should be considered to accurately detect pedestrians’ intent. 3) Unauthorized crossing (‘jaywalking’). Even in the presence of traffic lights, there are countries with low and high rate of jaywalking frequency. Futures studies should study factors related to pedestrians’ attempt to jaywalk in front of autonomous vehicles.

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Table 1

*Mean Crossing Time of Pedestrians (All)*

| Yielding Behavior | No-Yield* | Slow-Yield | Fast-Yield |
|-------------------|-----------|------------|------------|
| Size              | M         | SD         | M          | SD         | M          | SD         |
| Large             | 10.63     | 5.65       | 9.70       | 5.08       | 8.54       | 3.55       |
| Medium            | 9.61      | 3.69       | 9.14       | 2.80       | 9.04       | 3.48       |
| Small             | 10        | 4.59       | 8.92       | 3.73       | 8.38       | 3.57       |

*Control condition.
Table 2

*Description of Head Orientation Change by Time of the Events of AV Behaviors*

| Cluster(s) | Appears | Approaches | Stops* | Waits* |
|------------|---------|------------|--------|--------|
| 1          | Front   | Front      | Front  | Front  |
| 2          | Left    | Left       | Front  | Front  |
| 3          | Right to left | Left | Left  | Left  |
| 4          | Right to left | Left | Left  | Right |
| 5          | Right   | Right to left | Left  | Right |
| 6          | Right   | Right      | Left   | Left   |

*AVs neither stop nor wait in No-Yield trials.

Descriptions were based on human raters ($n = 3$)
Table 3

*Mean Ratings of Virtual Crosswalk Simulation and Perceived Effect of Yielding Behavior and Size of AV by Pedestrians (N=37)*

| Variables                  | M(SD)  |
|----------------------------|--------|
| Simulation Realism         | 3.98(0.80) |
| Realistic Behavior         | 4.03(0.81) |
| Yielding Behavior of AV    | 4.05(0.81) |
| Size of AV                 | 3.40(0.68) |

*Note:* Simulation Realism rating is on 5-point scale (1 = "Not very realistic", 5 = "Very realistic"). Realistic Behavior rating is on 5-point scale (1="Not very similar", 5 = "Very similar"). Both Yielding Behavior of AV ratings and Size of AV ratings are on 5-point scale (1="Not at all", 5 = "Very much").
Figure 1

Examples of Stimuli Used in the Experiment

Note: Large (top), medium (center), and small (bottom)
Figure 2

Experiment Procedure

1. Car appears
2. Car moves
3. Car stops or moves
4. Car waits or moves
Figure 3

Percentage of Pedestrians Finished Crossing by Time of Events of AV Behaviors

Note: FY, Fast-Yield; SY, Slow-Yield; NY, No-Yield; Small, Small size AVs; Medium, Medium size AVs; Large, Large size AVs
Figure 4

Comparison of Euclidean Distance and Dynamic Time Warping Between Two Time Series Data

Eucledian

Dynamic Time Warping
Figure 5

Result of Head Orientation Change Pattern Clustering using Dynamic Time Warping

*Note:* Blue triangle indicates the time when the AV stopped in front of the pedestrian (except for No-Yield trials).
Figure 6

Percentage of Pedestrian Head Orientation Change Patterns by AV Size and Yielding Behavior

Note: FY, Fast-Yield; SY, Slow-Yield; NY, No-Yield; Small, Small size AVs; Medium, Medium size AVs; Large, Large size AVs
Figure 7

Pedestrian Behavior in Korean Urban Roads