A robust time-to-collision computation framework for pedestrian-autonomous shuttle interaction

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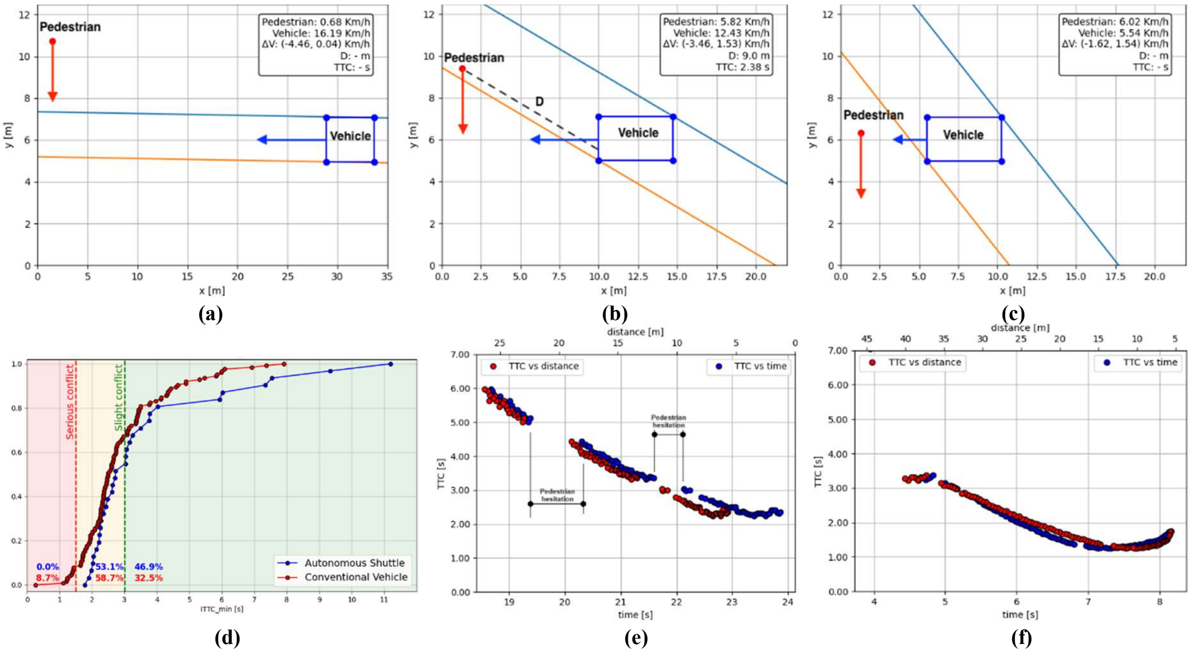
Introduction, research aims and objectives. The Time to Collision (TTC) is instinctively estimated and managed by road users to avoid collisions. TTC is a temporal proximity measure that has been widely used as an indicator of traffic conflict and, more recently, as a surrogate measure of safety. At each instant, TTC is the ratio between the minimum distance D between the potential collision points belonging to Unit 1 (P_1) and Unit 2 (P_2) and their relative speed ΔV. In successive instants, P_1 and P_2 are modified by the changes in speed and direction of the units in conflict due to the evasive manoeuvre(s) that modify the course of their interaction. We propose here a novel processing framework aimed at automatically extracting the TTC value from recorded video frames. This framework includes all necessary pre-processing and data analysis steps, including video acquisition and processing, trajectory extraction, conflict detection and TTC estimation. We have applied this framework to evaluate the TTC between pedestrians and autonomous shuttles (AS) operating in Turin (Italy) between September and October 2022, as part of the H2020 SHOW project (*SHared automation Operating models for Worldwide adoption*). In SHOW, real urban demonstrations with technical validation were carried out using two SAE level 4 AS provided by Navya. The AS circulated in mixed traffic on an authorised route close to the City of Health and Science area (Turin). Videos were collected at an unsignalized crosswalk, during the time when passengers were not allowed to board the AS. The framework was specifically designed and developed to capture the different phases of pedestrian-vehicle interaction, where pedestrians were often hesitant and sometimes reluctant to cross in front of the AS.

Method. After applying the object detection and tracking algorithm to the videos and converting pixel coordinates to real-world coordinates, spatial data analysis was performed to generate the trajectories of each detected object in the scene. Our method automatically matches the type of vehicle with reference spatial dimensions from a pre-defined catalogue to account for different vehicle sizes. Starting from the punctual tracking of the pedestrian and the AS, and after calculating their velocities (V_1 and V_2), we detected the interaction only when the pedestrian fell inside the band identified by the two straight lines passing through the end points of the AS silhouette, oriented according to ΔV (see Figures 1a, 1b and 1c). The conflict bands were delineated and the TTC was calculated only if the pedestrian was inside the bands (no interaction is detected in Figures 1b and 1c, where the pedestrian's speed is zero and the AS has such a low speed, respectively). Our solution advocates conflict detection based on a 2D bird's eye view using a vehicle box representation. This approach leads to an accurate evaluation of conflict measures and thus to a realistic and reliable conflict analysis, even when the pedestrian hesitates to proceed to the crosswalk. Data on pedestrian interaction with conventional vehicles (CV) was also collected. A preliminary sensitivity analysis was carried out to understand and limit the impact of noise in the data due to frame rate (24 fps), pixel size (1920×1080), video processing to remove perspective distortion error, and noise propagation in speeds.

Results, discussion, and conclusions. Figures 1a, 1b and 1c show three different times of the same interaction between a pedestrian (ped) and the AS. The results highlight the effect of the pedestrian's hesitation in the data, as within the same interaction there are instances where it persists and others where it is cancelled out either by the pedestrian's behaviour or by the progressive speed reduction of the AS. Figure 1d shows the cumulative distribution of the minimum instantaneous TTC recorded in the AS-ped interaction. A lognormal distribution was found to be the best function for both the AS-ped (KS test: D = .076, *p* = .985) and CV-ped (D = .110, *p* = .087) interactions. The cumulative density functions of the minimum TTC for the AS-ped interactions showed a similar distribution to that of the CV (D = .168, *p* = .415). However, the two distributions differed at the tails, with more dangerous conflicts (TTC < 1.5 s) for the CV-ped interaction case, mainly due to the lower speed of ASs compared to CVs and the more cautious approach of the pedestrian in front of the AS. Finally, Figures 1e and 1f show the TTC vs distance and time for ped vs AS and CS, respectively. Figure 1e highlights the gaps in the data due to the pedestrian's hesitation in approaching and crossing the road in front of the AS. We argue that if the TTC shows a lack of data for certain time intervals, this needs to be carefully considered when using the TTC to estimate Time Exposed Time to Collision (TET) and Time Integrated Time to Collision (TIT), which were originally defined assuming continuous TTC functions. Furthermore, these results highlight the complex reality of human response while interacting with vehicles of different levels of automation. Pedestrian hesitation when interacting with automated vehicles should also be considered in simulation studies (driving, traffic), as hesitation significantly changes the outcome of the interaction as well as our interpretation of it through indicators such as TTC, TET and TIT, as this study shows.



(a) (b) (c)

(d) (e) (f)

Figure 2. Graphical representation of the interaction computation framework: (a) hesitant pedestrian, (b) crossing pedestrian, (c) almost stationary vehicle. (d) Cumulative distribution of TTC for pedestrian vs. CV and AS. TTC vs. distance and time for ped-AS (e) and ped-CV (f) interactions.