

38th Meeting of the International Road Traffic Safety Analysis and Data (IRTAD) Group

's-Hertogenbosch, The Netherlands, 13-14 November 2024

Video recognition Machine Learning for automatic collection of Pedestrian Safety Performance Indicators

George Yannis, NTUA Together with: Stella Roussou, Apostolos Ziakopoulos

Department of Transportation Planning and Engineering, National Technical University of Athens

The PHOEBE Project

- Development of an integrated, dynamic and scalable human-centred predictive safety assessment framework for all road user types in urban areas.
- PHOEBE combines traffic simulation, road safety assessment, human behaviour, mode shift and induced demand modelling and new and emerging mobility data into a harmonised, prospective assessment framework for road safety.

Athens Use Case

- The focus of the Athens pilot is pedestrian road safety.
- To measure it, **profiles** and example travel patterns are defined.
- The analysis critically emphasizes VRU KPIs, such as speed measurements and modal share of pedestrians, cyclists, and similar modes, e.g. e-scooters.
- Different parameters are taken into consideration, such as disability rate, gender, or age.
- Scenarios are also created for different times of the day, such as day- or night time, as well as during peak or off-peak hours.

Video recording details

The video recordings were conducted:

- In 8 locations,
- for 1-hour peak time,
- for 1-hour off-peak time,
- for 2 working days of a week, (Tuesday - Thursday)
- for 2 weeks of a month.

In total 64 hours of video were collected, 8 hours for each location, with **smartphone cameras** emphasizing the ease of transferability of the proposed approach, without the requirements of specialized, costly, or heavy equipment.

The algorithmic logic

The system uses a multi-step tracking logic including:

- Object detection YOLOv8 detector
	- A neural network-based object detection framework, detecting objects including pedestrians and vehicles.
- ResNet-50 and Re-Identification network
	- Maintain consistent tracking of objects across multiple frames.
- Hungarian Algorithm
	- Detected objects are matched with tracked ones, which is crucial for maintaining consistent identities.
- Kalman filter-based prediction
	- Kalman filter tracks continuous movement, objects can become **occluded or temporarily** disappear from the scene (e.g., a pedestrian walks behind a vehicle).

Homography and Ground Plane Projection

- Homography transformation
	- Maps images coordinates to real-world ground plane coordinates.
	- Project points from the 2D image space (the video frames) into a real-world 2D plane (the ground plane).

This projection is necessary for accurately determining whether pedestrians or vehicles are *inside* certain regions, like **crosswalks**, which are defined in real-world coordinates.

Traffic light detection component

Traffic Light Detection

The traffic light detection component isolates the regions corresponding to the traffic lights using Regions of Interest (ROIs) and applies color segmentation to determine whether the light is red or green.

Projected Object Behavior Analysis

- The algorithm checks their positions relative to ROI.
- If a pedestrian is found inside the crosswalk during a pedestrian red traffic light, their behavior is flagged as illegal.
- Similarly, vehicles entering the **crossing area** during a pedestrian green traffic light are flagged as illegal.

Results (1) – Legal and Illegal Behavior Detection

Without the use of the detection algorithm With the use of the detection algorithm

Results (2) –Speed and TTC Calculation

- To ensure realistic speeds, the algorithm imposes a **maximum plausible speed**: 10 m/s for pedestrians and 40 m/s for vehicles.
- If the pedestrian and vehicle are moving toward each other, the TTC is positive, indicating a potential collision.
- The real-time positions of pedestrians and vehicles, detected from the on-street video, are **projected** onto the Google Maps image.
- Objects detected in the video frames are accurately placed on the ground plane of the map, reflecting their actual locations in the real-world coordinates.

Traffic Light Status Detection

- A comparison between the algorithm and the manual observations was conducted. The algorithm achieves accuracy levels mostly between 50% - 70%.
- After manually reviewing the videos, the lower accuracy in some cycles was not primarily due to incorrect color identification (e.g., mistakenly detecting red instead of green or vice versa).
- Instead, the main issue was the algorithm's detection of an 'unknown status' in certain situations, likely caused by challenging conditions such as low light, temporary obstructions, or camera movements due to wind.

Traffic Light Status Accuracy Detection

Illegal crossing detection

- A clear relationship emerges in the way extended red phases correlate with increased illegal crossings.
- Both manual and automated methods detect a marked rise in non-compliance during prolonged red-light intervals.
- Reflecting a trend where pedestrians, faced with longer waiting times, are more likely to cross against the signal.
- A high number of pedestrians chose to cross illegally when the street had lower traffic flow.

Traffic light status with the illegal pedestrian crossing histories

Manual vs Automated Detection

- Results show an almost perfect count of illegal pedestrian crossings, with only a 2.61% overcount.
- In contrast, a larger discrepancy of 25.71% is observed for illegal vehicle counts, which may be due to the greater difficulty in tracking vehicles, given the high variability of modal split (i.e., cars, mopeds, motorcycles, buses, trucks).

Disaggregated comparison between manual and automated counts of illegal pedestrian crossings

Speed and Time to Collision (TTC) (1/2)

- A clear inverse trend is visible: TTC decreases as speed increases, which aligns with expectations.
- At lower speeds (0 to 5 m/s), TTC values are relatively high, often exceeding 100 seconds and occasionally reaching 1000 seconds.
- At higher speeds (35-40 m/s), TTC values are much shorter, indicating less time to prevent a collision.
- Notably, there is greater variability in TTC at higher speeds, suggesting that vehicles moving faster experience a **broader range of collision times** - likely due to differences in distance and driving dynamics.

TTC by vehicle speed

Speed and Time to Collision (TTC) (2/2)

- Considerable speed variations are recorded by the algorithm
- Higher speeds during illegal vehicle crossings can significantly *increase* the likelihood of **severe injuries** if a collision with a pedestrian occurs.
- This greater dispersion suggests that *illegal* crossings are associated with a broader range of behaviors or situational factors.
- For any given speed, the TTC values for illegal vehicles are consistently lower than those for legal vehicles, indicating that illegal crossings increase the likelihood of collisions with pedestrians.

TTC by vehicle speed, differentiating between vehicle status (i.e., legal and illegal)

Overview and KPIs

- The developed algorithm tracks pedestrians and vehicles and integrates Traffic Light Status Detection
- It determines road user legal/illegal behavior with respect to traffic lights
- It calculates the Time-To-Collision (TTC) via an advanced multi-stage approach.
- It opens new road user behavior research venues through Surrogate Safety Measures
- It can be used for higher accuracy of speed monitoring by authorities.

38th Meeting of the International Road Traffic Safety Analysis and Data (IRTAD) Group

's-Hertogenbosch, The Netherlands, 13-14 November 2024

Video recognition Machine Learning for automatic collection of Pedestrian Safety Performance Indicators

George Yannis, NTUA Together with: Stella Roussou, Apostolos Ziakopoulos

Department of Transportation Planning and Engineering, National Technical University of Athens

