Investigation of Non-Compliance at Pedestrian Crossings of Signalized Intersections Using Computer Vision Techniques

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Abstract. Pedestrian safety at signalized intersections is an important issue in urban areas, especially in areas with high population density, like the city of Athens. The aim of this study is to examine pedestrian non-compliant crossing behavior at a signalized intersection through video data collection via both manual and automated approaches. The automated approach is carried out through a computer vision system that includes object detection, trajectory detection, homography transformation, and Time-to-Collision (TTC) estimation. The aim of this study is to compare the results obtained through manual and automated approaches and examine non-compliant pedestrian crossing behavior at signalized intersections. The study also examines the characteristics of non-compliant pedestrian crossing behavior and pedestrian behavior at signalized intersections. From the results, it is concluded that the performance of automated detection is influenced by factors like occlusion and signal visibility, and pedestrian non-compliant behavior is influenced by factors like signal timing, waiting time, and traffic. The study helps understand pedestrian non-compliant behavior and also demonstrates the potential for analyzing pedestrian behavior at signalized intersections through automated approaches like computer vision.

Keywords: Pedestrian behavior, Video-Based Analysis, Urban Environments, Vulnerable Road Users, Road Safety.

1 Introduction

According to the literature, pedestrian behavior at signalized intersections has been identified as a significant factor contributing to the increase in crash rates [18]. In most cases, data collection is conducted through on-site observations or the use of computer vision technologies, which accurately and automatically analyze metrics in real time.

The way people cross, their walking speed, sudden changes in speed, and the environment, such as the geometry of the crossing and the timing of the signals, are some important factors [1]. Moreover, individual characteristics, encompassing age and gender, psychological factors such as the subjective pressure of time and perceived duration of the green phase, as well as spatial and environmental factors like intersection geometry and pedestrian density, significantly affect speed variability [9],[19],[22].

Additionally, mobile phone distraction was identified as a factor that increases the likelihood of collision by diminishing walking speeds, worsening navigational inefficiency, and decreasing the distances kept from vehicular traffic [2].

Several variables can cause pedestrians to disobey the rules, such as their own traits, the road infrastructure, and the social context. In terms of crossing design, the lack of traffic lights, the longer red phase, and longer wait times have all been linked to a big rise in violations. The long length of the crossing has the same effect [6],[3]. Moreover, deteriorated horizontal markings, the existence of push buttons, the lack of markings, restricted visibility, and parking in proximity to the crossing are significant factors that increase violations [8],[14].

At the individual level, males and young pedestrians are more prone to violations, particularly when influenced by their peers [6], [10], [25]. Social influence is the main factor that affects compliance, as observing people who don't follow the legislation makes it more likely that someone will repeat the same action [12],[16],[17]. Conversely, advanced traffic conditions, including heavy traffic, rush hours, multilane roads, or the existence of tram and bus lanes, serve as deterrents to hazardous behavior [8],[3].

Computer vision applications have improved behavioral studies by extracting trajectories, enabling analyses like heat maps, route distributions, and speed-density correlations [24]. The Longest Common Subsequence (LCS) method makes able to compare the noisy trajectories with real-world variability. Incident detection has achieved an accuracy exceeding 85%, hence validating safety metrics such as Time-to-Collision (TTC) and Post-Encroachment Time (PET) [20].

Long Short-Term Memory (LSTM) models and other deep learning models are very good at predicting dangerous actions. For instance, they can predict red-light violations with 91.6% accuracy and crashes up to two seconds before they happen with 88.5% accuracy [23]. Integrating PET, minimum TTC (mTTC), and Extreme Value Theory (EVT) enhances risk evaluation. Moreover, Gated Recurrent Unit (GRU) models have reached an accuracy of 87.8% (AUC = 0.865), which is better than LSTM models [25]. During this time, methods for finding pedestrians that are based on YOLO have a detection rate of about 81%. These systems help find hazards and control traffic lights so that traffic flows more smoothly and the roads are safer [11],[15].

This paper analyzes pedestrian behavior at signalized intersections using both manual observations and automated computer vision methods. The two methods were used at the same time and location, which allowed for a real-world test of the automated system and a comparison of the data. The main goal was to see how accurate automated detection is compared to manual records, with a focus on figuring out traffic signal phases and sorting crossings into legal and illegal categories. The results aim to provide insights for the development of automated monitoring systems and for improving pedestrian safety at signalized intersections.

Following the introduction, the structure of this paper is as follows. Section 2 presents the methodology, including the study site description, the video data processing procedure, the manual observations, the crossing legality classification process, and the estimation of Time-to-Collision (TTC) for pedestrian-vehicle interactions. Section 3 presents the results of the analysis, including the comparison between manual and automated observations, pedestrian crossing behaviour, and interaction severity analysis. Section 4 discusses the main findings and their implications for pedestrian safety and automated traffic monitoring, while Section 5 summarizes the main conclusions and proposes directions for future research.

2 Methodology

Video recordings were collected at a signalized intersection in Omonia Square, Athens. The camera was positioned to capture pedestrian crossings, vehicle movements, and traffic signal indications. The recorded video data were processed using an automated computer vision pipeline to detect pedestrians and vehicles, track their trajectories, and estimate interaction indicators.

We used an advanced computer vision framework from the Phoebe Project to process the collected videos [34]. The pipeline is based on the object detection, YOLOv8 neural network, which tracks people and vehicles in each frame of the video. YOLOv8 can accurately understand and create a bounding box for the detected object. Following, ResNet-50 was integrated to correctly classify the detected objects and their identities from one frame to the next. We used homography transformation to put the pixel coordinates on the ground plane so that they could be used in the real world. The Hungarian algorithm was also used to match detections from different frames while keeping the object IDs the same. Finally, Kalman filtering was used to make the paths smoother and reduce the effect of noise in the detection.

In parallel, manual observations were conducted using the video recordings. For each pedestrian crossing event, information was recorded regarding crossing legality, signal phase at the start of crossing, pedestrian behaviour characteristics, and interaction conditions. The manual observations were used as a reference dataset for comparison with the automated detection results.

Pedestrian crossing legality was classified based on the signal phase at the start of crossing. Crossings initiated during the pedestrian green phase were classified as legal crossings, while crossings initiated during the red phase were classified as illegal crossings.

To evaluate interaction severity between pedestrians and vehicles, Time-to-Collision (TTC) was calculated for pedestrian-vehicle interactions. TTC represents the time remaining until a potential collision would occur if both road users continued at their current speed and trajectory. Lower TTC values indicate higher interaction severity and increased collision risk.

3 Results

The first step of the analysis involved the statistical description of the dataset derived from the video analysis and manual observations. The descriptive statistics provide an overview of the interaction conditions at the study site and allow an initial understanding of pedestrian and vehicle behaviour at the signalized intersection. The results showed that pedestrian speeds varied depending on signal phase and crossing conditions, while vehicle speeds were generally lower near the crossing area due to signal control and pedestrian activity.

Crossing duration and waiting time also showed variability depending on whether pedestrians crossed legally or illegally. Illegal crossings were often associated with shorter waiting times and higher pedestrian speeds, indicating that pedestrians tend to accelerate when crossing during non-permitted signal phases in order to minimize exposure time on the roadway. In addition, the surrogate safety indicator TTC showed a wide range of values, indicating that pedestrian-vehicle interactions ranged from safe interactions with large temporal margins to more critical interactions with limited temporal separation between road users.

Table 1. Descriptive statistics of main variables (speed, TTC)

Variables	Mean	Std	Min	25%	50%	75%	Max
MinTTC	inf	-	0.06	16.864	40.699	134.65	inf
Confidence_Pedestrian	0.694	0.198	0	0.614	0.741	0.828	0.956
Confidence_Vehicle	0.785	0.157	0	0.712	0.838	0.894	0.964
PedestrianSpeedMagnitude	1.428	1.924	0	0	0.839	1.855	9.999
VehicleSpeedMagnitude	8.314	6.638	0	3.825	7.221	10.973	39.960

The accuracy of pedestrian crossing classification (legal vs illegal crossings) was evaluated by comparing the automated detection results with the manual observations dataset. The results indicated that the automated method achieved moderate accuracy in detecting illegal crossings and slightly higher accuracy in detecting legal crossings. The detection of illegal crossings is more difficult due to uncertainty in signal phase detection and cases in which pedestrians started crossing during transitional signal phases.

The errors in illegal crossing detection were mostly related to uncertainty in signal phase detection, cases in which pedestrians started crossing during the intergreen time, and cases in which pedestrians were partially occluded by a vehicle and in which there were simultaneous crossings by multiple pedestrians. On the contrary, legal crossing detection showed better accuracy due to legal crossing events during more certain signal phases.

The proportion of categorical variables in the MinTTC dataset can provide an understanding of the context in which the potential conflicts between pedestrians and vehicles were observed. A consistent proportion of missing values, about 18%, was observed in different variables, indicating scenarios in which there was not a complete pedestrian-vehicle pair and, consequently, the conditions for the interaction could not be fully determined.This proportion should be considered as a limitation of the dataset, as some interaction characteristics could not be classified.

In terms of legal compliance, the majority of both pedestrians and vehicles were classified as behaving legally at the time of the interaction, while only a small proportion of cases involved illegal behaviour.

Accuracy for the traffic light detection varied significantly between cycles. Most achieved 50-80%, with peaks of 90.5% and 81.5%, but some dropped to as low as 13.7%. The overall accuracy was 62.77%, considered satisfactory but affected by occlusions (buses, trucks blocking the signal) and reliance on color detection, which struggled under poor visibility.

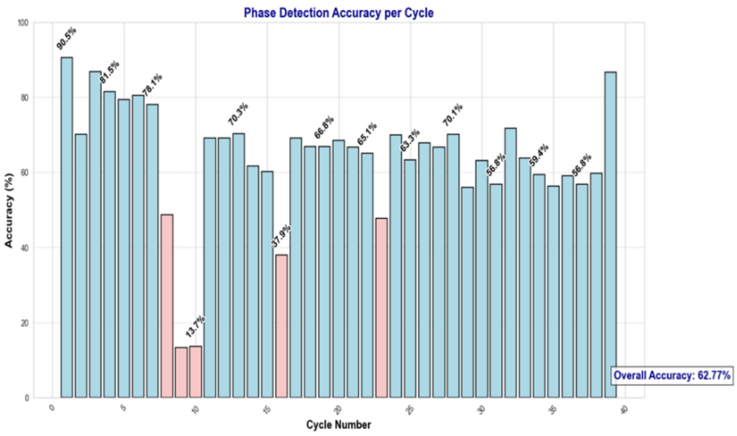

Fig. 1. Algorithm's Detection Accuracy per Cycle.

The automated system achieved 47.54% accuracy regarding the illegal crossing detection, compared to manual observations. The errors arose primarily from the signals obscured by large vehicles, and misclassification of cases where a crossing began on green and ended during the red for the pedestrians, and also red for the vehicles. Moreover, the automated method achieved 64.60% overall accuracy, higher than the ones of illegal crossings. These accuracy results demonstrate the limited performance of the algorithm under obstructions, as it relies on color detection.

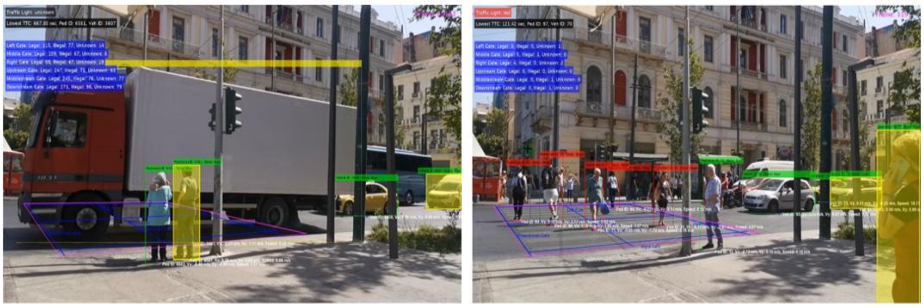

Fig. 2. Algorithm´s Missclassified Cases: Obstacle (left), Crossing on a green signal seconds before it turns red (right)

4 Discussion

This study compared manual observations and automated computer vision detection for the analysis of pedestrian behavior at a signalized intersection in Omonia Square. The automated pipeline processed video data to extract pedestrian and vehicle trajectories and to estimate Time-to-Collision values for pedestrian–vehicle interactions. Manual observations were used as a reference dataset for crossing legality and signal phase detection.

The accuracy of the automatically detected traffic lights was moderate, which decreased when the traffic lights were obstructed by large vehicles such as buses and trucks. The accuracy of the automatically detected illegal crossing was low. This is because the classification of the cases where the pedestrian started crossing during the green light and finished during the red light was low.

The analysis of the behavior of the pedestrians showed that the non-compliant pedestrians crossed the road when the gap between the vehicles was sufficient. This shows that the non-compliant behavior is intentional and depends on the traffic conditions. It is also evident that the pedestrians who did not comply with the traffic signals crossed the road faster. They might have done this to reduce the time spent on the road.

Therefore, the results show that the computer vision can be used to analyze the behavior of the pedestrians. It is evident that the accuracy level needs to be improved. The results can be used to understand the behavior of the non-compliant pedestrians.

5 Conclusions

This study investigated pedestrian non-compliance at a signalized intersection using both manual observations and automated computer vision analysis. The comparison between manual and automated methods showed that automated detection can be used to analyze pedestrian behavior, although its accuracy is affected by signal occlusions and complex crossing situations.

The results showed that violation is related to signal time, waiting time, and gaps in the traffic flow, which means that violation is an intentional decision made by the pedestrians. The use of surrogate measures such as Time-to-Collision helps to further comprehend the severity of interaction and traffic safety.

In the future, the focus should be on the improvement of the automated signal detection, the use of temporal analysis of crossing behavior, and the extension of the analysis to multiple intersections. The computer vision approach with the help of traffic safety indicators can be used for proactive analysis.

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