Difference between reported crash time and speed disturbances in urban signalized intersections: a case study in Fortaleza, Brazil

Diferença entre horário reportado de acidentes de trânsito e perturbações na velocidade em interseções semaforizadas em Fortaleza, Brasil

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ABSTRACT
The advent of new technologies for monitoring and controlling traffic allows the development of more robust road safety studies, based on the collection of disaggregated traffic data at intervals of 1 to 15 minutes or even in real time. However, in order to relate the crashes to their precursor conditions, applying this type of data requires a better knowledge on the accuracy of crash reported times. This work aims to present an analysis between the reported times of crashes and disturbances in the traffic flow conditions in urban signalized intersections in Fortaleza, Brazil. Vehicle flow disturbances were detected from speed oscillations by using an algorithm based on comparing speeds between "typical" and "crash" conditions and by validating the detections with visual analysis. The results of investigating 291 crashes showed an average difference of 20 minutes (sd = 23 min) between the reported time of crash and the occurrence of the speed disturbance. This is an indication that, while developing road safety disaggregated analyses, one should examine the database accuracy regarding the crash reported time.

RESUMO
O advento de novas tecnologias de monitoramento e controle de tráfego permite o desenvolvimento de estudos mais robustos de segurança viária a partir da obtenção de dados de tráfego desagregados em intervalos de 1 a 15 minutos ou até em tempo real. Entretanto, visando relacionar os acidentes às suas condições precursoras, a aplicação desse tipo de dado demanda um melhor conhecimento sobre a precisão do horário de reportagem dos acidentes. Este trabalho tem como objetivo apresentar uma análise entre horários reportados dos acidentes e perturbações nas condições de fluxo em interseções semaforizadas em Fortaleza, Brasil. As perturbações na corrente de tráfego foram detectadas a partir de oscilações na velocidade com a aplicação de algoritmo que compara as velocidades em condições "típicas" e "com acidentes" e com a validação visual das detecções. A avaliação de 291 acidentes mostrou uma diferença média de 20 minutos (dp = 23 min) entre o horário de reportagem do acidente e o momento da detecção da perturbação na velocidade. Esse achado indica a importância da investigação da precisão dos horários de reportagem dos acidentes de trânsito, principalmente ao desenvolver estudos de segurança viária em escala temporal desagregada.

1. INTRODUCTION

The advent of new technologies for monitoring and controlling urban traffic – such as vehicle detection inductive loops, speed camera equipment and GPS data – provides tools for the development of dynamic traffic flow management. Some of the main benefits of this

approach: reducing the negative impacts of congestions and improving road safety performance, aiming to identify and preferably anticipate the incidents (Roshandel *et al.*, 2015; USDOT, 2014).

Some techniques that use real-time vehicle data are being applied mainly in uninterrupted traffic flow regimes. The Variable Speed Limit, for example, is a strategy that aims to homogenize the speed in the traffic flow, providing a more stable traffic regime therefore reducing traffic conflicts (Yang and Loo, 2016). Another alternative is the ramp metering that aims to control the entrance of vehicles on the highways, promoting reductions of rear-end and sideswipe collisions and congestions in the order of 30% and 8%, respectively (Taylor and Meldrum, 2000). In terms of interrupted flow environment, traffic control measures are mostly focused on the real-time optimization of traffic signals reducing the delays experienced by drivers (Day and Bullock, 2017; Feng *et al.*, 2016).

When it comes to road safety modeling, the most commonly used approach is the development of safety performance functions aiming to evaluate the relationship between exposure and traffic variables, that are usually annually or monthly aggregated, and the frequency and severity of crashes (Cunto *et al.*, 2011; Hauer, 2004; Qin *et al.*, 2005). However, it is observed that this temporal data aggregation may lead to less useful models, especially when the explanatory variables are subject to oscillation within the same day, as well as the average speed and the volume of vehicles.

The availability of disaggregated traffic information enables the development of more robust researches where the effect of speed can be evaluated, for example, on road safety (Abdel-Aty and Pande, 2005; Imprialou *et al.*, 2016) or to apply proactive real-time risk management measures for traffic occurrences (Essa and Sayed, 2019; Huang *et al.*, 2017; Pirdavani *et al.*, 2015). These studies are based on crash precursor indicators, which seek to identify – from aggregated data in intervals of 1 to 10 minutes – disturbances in the traffic flow that may be related to crash occurrences.

The vast majority of crash precursor studies rely on the assumption/estimation of the reported time of the crash in order to estimate the upper limit of the time interval used to define time aggregations (5 min, 10min, 15min, etc). Unfortunately, differences in the reported crash time and the precise crash time may produce another source of bias especially for short time aggregation studies such as 1 minute time interval, sometimes leading to the association of crashes to conditions that are not those prior to the crash or even to scenarios that the condition is already affected by the crash occurrence (Zheng, 2012).

Furthermore, unlike uninterrupted flow conditions, the densely signalized urban environment has systematic interruptions in the traffic flow. Unfortunately, the vast majority of studies on traffic flow disturbances was produced for uninterrupted flow environment, making it difficult for the applied techniques to be transferred to the densely signalized urban environment, such as the city of Fortaleza, Brazil. Thus, pointed out the importance of the crash occurrence time for the development of disaggregated analyses and the absence of related studies for the urban environment, the main objective of this work is to propose a method to detect speed disturbances in the uninterrupted flow environment and to apply it in urban signalized intersections of Fortaleza in order to quantify the differences between crash reported times and the moment of speed disturbances.

This paper is organized into five sections. This section presented the context, the motivation and the goals of this work. The second part brings a review around studies that evaluated the

detection of traffic disturbances. The third section exhibits the proposed method for detecting the moment of speed disturbances in an urban environment and for comparing them to reported crash times. The fourth part presents an application of the method in urban signalized intersections of Fortaleza and a discussion of the findings. The last section brings the study conclusions.

2. VEHICLE FLOW OSCILLATION AND ROAD SAFETY STUDIES

Solomon (1964) presented one of the first studies to investigate the relationship among traffic flow, crash frequency and its severity using speed data collected in the field. The development of new traffic monitoring technologies and statistical techniques has enabled the advancement of researches that, in their state of the art, are aimed at real-time incident risk monitoring strategies (Abdel-Aty *et al.*, 2012; Essa and Sayed, 2019; Pirdavani *et al.*, 2015; Shi and Abdel-Aty, 2015).

At the same time that the use of disaggregated data allows a more robust modeling, there is a need for a higher precision in the crash occurrence time. The use of the times reported by the agents responsible for recording the crash – which may be imprecise – may not correspond to the traffic characteristics considered as precursors to the crash, introducing erroneous cause and effect relationships (Roshandel *et al.*, 2015; Zheng, 2012). Some of the studies developed on this topic did not consider the estimation of the most probable crash occurrence time (Imprialou *et al.*, 2016; Lee *et al.*, 2006; Pirdavani *et al.*, 2015; Stempfel *et al.*, 2016).

Otherwise, some authors have incorporated crash detection techniques into their analyzes. Lee et al. (2002) developed a study on crash precursors considering vehicle density and speed variation indicators with aggregation of 5 minutes in 10 km of freeways in Toronto-CA. The most likely crash occurrence time was identified from speed information aggregated within 1 minute of the upstream detection loop of the occurrence location. The speed profile was visually inspected and the most probable crash occurrence time was assigned when an abrupt drop in the speed was detected.

Zheng et al. (2010) used aggregated data at 20-second intervals of the upstream and downstream detection loops from the crash location to detect the most likely time to evaluate the relationship between traffic oscillations and frequency of freeway crashes. The traffic oscillation identification was based on reductions in the speed of the upstream loop and in increments in the speed and contraction in the volume of the downstream loop. This method – with variations in the temporal data aggregation – is the most common in the studies applied to uninterrupted flow conditions that have continuous inductive loops (Abdel-Aty and Pande, 2005; Lee *et al.*, 2003; Pande and Abdel-Aty, 2006; Zheng, 2012).

Hojati *et al.* (2014) presented a study that evaluates the time difference between the crash occurrence and the return to typical traffic conditions (recovery time) in 14 km of freeways in Queensland-AUS from speed and volume indicators aggregated in 5-minute intervals. The authors used speed data also aggregated within 5 minutes of the upstream detection loop to recognize the precise time of the crash. Average speeds at the time of the crash were compared to typical values on the road and, if substantial reductions (not quantified by the authors) were visually identified in 4 consecutive intervals, then this time was considered.

Another approach applies fixed delays in the reported times in the attempt to obtain the most adequate crash precursor conditions. Christoforou *et al.* (2011), for example, considered a fixed delay of 6 minutes in the crash time to collect traffic characteristics, that is, for a crash reported

at 9:00 am, the authors considered the conditions on the road as of 8h54m. Other researchers adopted the same method with a change in the fixed delay: (i) Golob et al. (2008): 12 minutes; (ii) Quddus et al. (2010): 30 minutes.

Unfortunately, most studies on traffic conditions and road safety that use disaggregated data – and consequently on the relationship of traffic disturbances and reported crash times – were carried out in uninterrupted flow environments using, usually, traffic data from downstream and upstream the crash location. Therefore, there is a gap in the literature researches focused on the urban environment with predominance of interrupted flow, which might add some features around the analyses, like the signal cycle length and the absence of continuous loop detectors.

Moreover, although it is a consensus that fair estimates around the crash occurrence might be considered in disaggregated analyses, there are few studies that evaluated, in quantitative terms, the precision of reported crash times in databases, which is the main purpose of this paper.

3. METHOD

Figure 1 presents the proposed method for the identification of significant disturbances in the traffic flow speed in urban signalized intersections, allowing the development of a comparison with the times reported in the crash database.
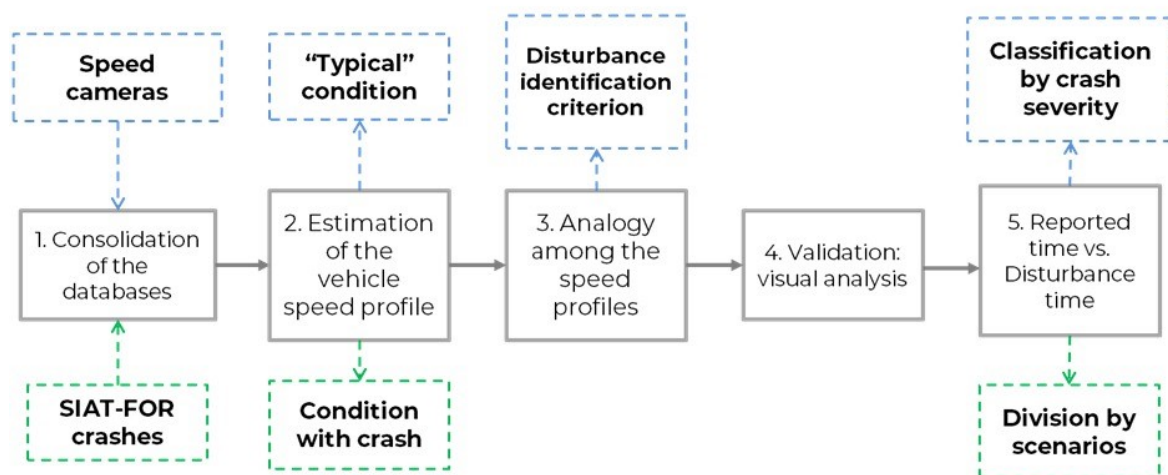

Figure 1. Proposed method for analysis between reported crash occurrence time and disturbances in the speed condition in signalized intersections

The first step of the method consists in the consolidation of two databases: (i) road crashes and (ii) speed camera enforcement system. Fortaleza's Municipal Department of Transportation (AMC) stores the historical data of road crashes in a platform called Traffic Crashes Information System of the City of Fortaleza (SIAT-FOR) since 2004. SIAT-FOR receives crash information from various sources (AMC officers, emergency response system - SAMU, forensic expertise, hospitals, among others), which are treated and georeferenced by the traffic managers. The database provides important characteristics on the occurrences, such as: date, time (hour and minute), severity (property damage only - PDO, injuries or deaths), type of crash (rear-end collision, right-angle collision, sideswipe collision, among others) and involved vehicles (motorcycles or bicycles).

Speed camera enforcement system data is also available in a text file structured in which the following information is recorded for each vehicle passage: equipment code, passing date, passing time (hour, minute and second), passing lane, posted speed limit, speed measured by the equipment, estimated vehicle length and vehicle classification (motorcycle, car, truck or bus).

The consolidation between the two databases intends to associate each speed camera with certain crashes that have occurred (or have been georeferenced) in their vicinity. It was decided to implement some measures so that a greater control of the crash location was possible: (i) selection of equipment located at signalized intersections; (ii) only crashes within a 30-meter radius from the equipment were collected. This was adopted mainly due to the imprecision of the crash georeferencing process caused by the technique of collecting the location of the occurrences by the traffic agents (numbering of the neighboring lot or name of the intersection streets).

After associating the reported crash times to the speed camera equipment, the vehicle speed profiles were used in order to differentiate "typical" conditions and "crash" conditions, i.e., speed profile considerably low when compared to "typical" conditions. Due to the uncertainty around the time reported in the database, it was decided to evaluate a 3-hour interval around each occurrence (reported crash hour, one hour before and after the reported time). To define the "typical" condition in the traffic flow, five days (one and two weeks before and one, two and three weeks after the crash date) were evaluated considering the same 3-hour time window and the same day of the week. Average speeds were determined in the interval of three hours for the five days, where the day that presented the value of the median between the averages was selected as typical.
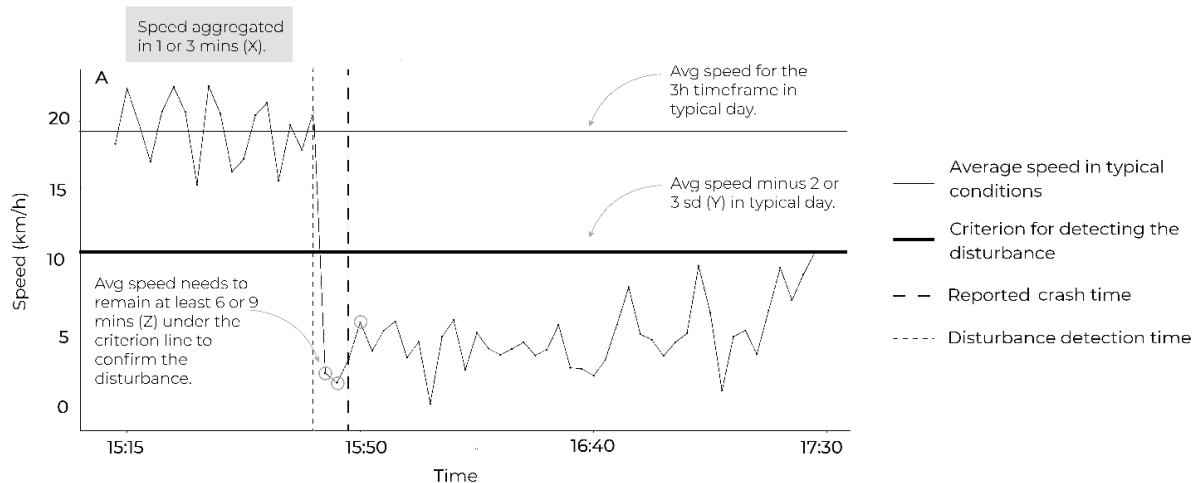

Figure 2. Example of method application for detecting speed disturbances

Three criteria for the speed disturbance identification were tested based on the average and standard deviation of the speed under typical conditions and on the speed aggregation interval: if the aggregated speed in *x* minutes remains below the average value subtracted from *y* standard deviations between the speed observations for *z* consecutive minutes, the subject traffic flow regime is considered as a "disturbance". Each criterion was based on speed aggregations (*x*) in 1 or 3 minutes with subtraction of (*y*) 2 or 3 standard deviations for (*z*) 6 or 9 minutes. A pilot study was developed to determine the most effective criterion of the speed disturbances detection. Figure 2 shows an application of the method in which the speed was aggregated in

3 (*x*) minutes, and the criterion for detecting the disturbance (thick line) obtained with the reduction of the average speed under typical conditions (thin line) of 2 standard deviations between sixty speed observations time slots of 3 minutes each (*y*). For a disturbance to be detected by this criterion, it must remain for 6 or 9 minutes (*z*) below the thick line. In total, the pilot study comprised 8 combinations of the three criteria. The comparisons between typical and crash situations and the detection of the disturbance moment were performed automatically using the software R.

For the crashes in which it was possible to match with speed oscillation triggered by a given combination of criteria, the speed profiles were used to provide additional visual validation of the crash. In this analysis, the graphs corresponding to each crash were observed individually, considering as valid those in which it was possible to detect the exact moment of the beginning of the speed disturbance, corresponding to a sudden change in the graph pattern and, thus, increasing the reliability of the used criterion. The visual validation approach is discussed in more details in the next section. The best combination of average speed aggregation, standard deviation and duration time was the one that produced the highest percentage of automatic detection and number of visually validated cases.

Finally, the reported crash times were compared to the detection time of the speed disturbances, in order to evaluate the difference between them. The results were segregated by crash severity (PDO and injury), by crash type (right-angle and others) and number of approaches with speed cameras that identified the disturbance for the same crash. The last two groups are important because it is assumed that, for example, right-angle collisions (better accuracy of the crash location) and occurrences detected in two or more approaches (possibility of disturbance time validation) would result in more reliable estimates.

4. RESULTS AND DISCUSSION

In this section, the results are presented and analyzed in three steps. Initially, a brief characterization of the database is shown, followed by the results of the pilot study carried out to define the most effective speed disturbance identification criterion. Finally, the algorithm with the selected criterion is applied to the whole crash database leading to an analysis between the differences in the reported crash times and the occurrence of the speed oscillations.

4.1. Consolidation of the speed camera data and crashes database

The speed camera enforcement system of the city of Fortaleza is divided into three main types: signalized intersections, mid-block and exclusive public transportation lanes. As highlighted in the method, in order to increase the reliability regarding the location of the crashes, only signalized intersections equipped with speed surveillance were studied. During the period from 2015 to 2017 a total of 83 speed cameras were active, encompassing 60 intersections in the city. From these, 38 were equipped in only one approach; 21, in two approaches and a single intersection had three devices installed. From a 30-meter radius from each equipment, it was possible to collect 344 crashes in 2015, 384 in 2016 and 229 in 2017; corresponding to a sample of 957 crashes which types and severities are presented in Table 1. Figure 3 shows the spatial distribution of speed cameras and crashes and an example of a 30m-radius buffer around one speed camera in the south of the city. Figure 3 also presents that most of the speed cameras placed in signalized intersections are surrounded by traffic signals, characterizing an interrupted flow environment.

Figure 3. Spatial distribution of electronic control equipment in signalized intersections and crash collection method

Table 1 – Description of the crashes evaluated

Crash type	N	Crash severity	N
Collision with fixed obstacle	14	PDO – Property Damage Only	582
Collision with pedestrian	43	Injury	365
Driver fall (motorcyclist)	37	Fatal	10
Frontal collision	8		
Not identified	296		
Overturning	1		
Rear-end collision	267		
Right-angle collision	101		
Sideswipe collision	190		

4.2. Pilot study to define the criterion of speed disturbance identification

The definition of the speed disturbance identification criterion to be implemented in the algorithm and the temporal aggregation of the speed indicator was performed by applying a pilot study to 200 crashes (randomly selected from the sample set) using the combination of three variables in eight different scenarios. As explained before the evaluated variables were: (i) temporal aggregation of speed in 1 or 3 minutes; (ii) average speed in the typical day reduced by 2 or 3 standard deviations between the speed observations; (iii) disturbance duration for detection of 6 or 9 minutes. Table 2 summarizes the obtained results.

From Table 2, it can be noticed that the combinations that used 3-minute speed aggregation showed detection rates considerably higher than 1-minute aggregations. The high oscillation between consecutive speeds aggregated in 1 minute – possibly due to the traffic signal downstream – provides high standard deviations for the speed, thus generating significantly lower thresholds to identify the disturbance (thick line). Aggregating speeds in 3 minutes smoothens the natural oscillation caused by the traffic signal, reducing the dispersion between observations. These situations are illustrated in Figure 4.

Table 2 – Pilot study summary for the identification of the criteria to apply the speed disturbance detection algorithm

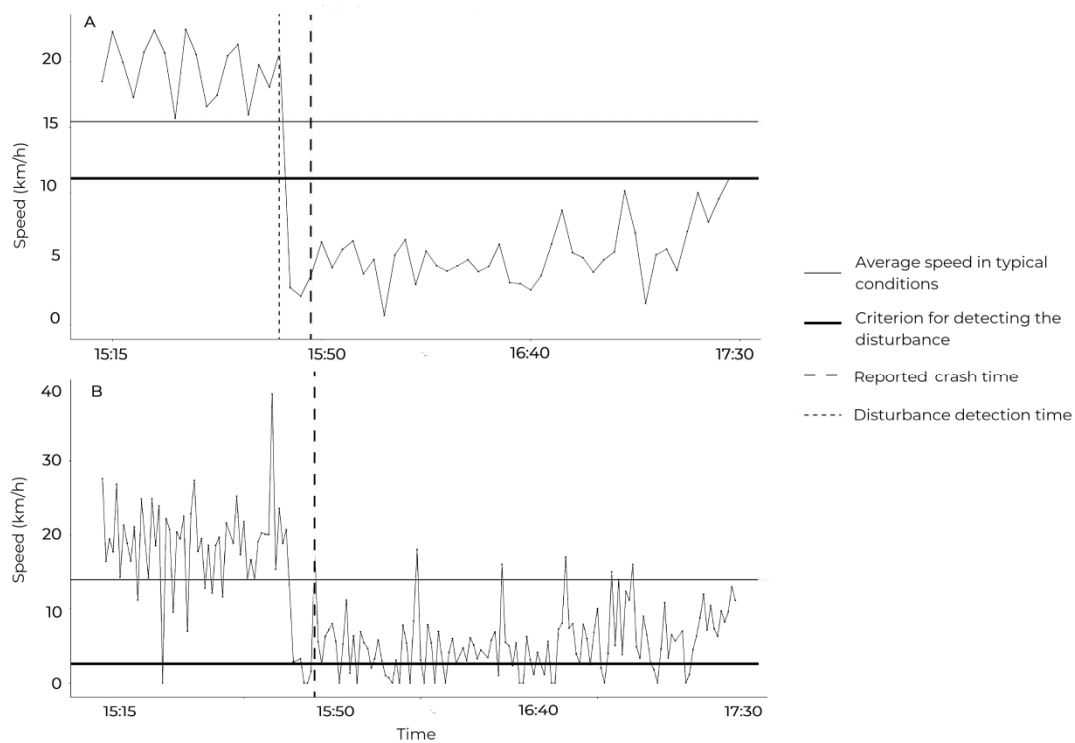| Combination		% Algorithm Detection	% Visual Confirmation
ID	Types		
1	1 min 2 sd 6 dur	10%	70%
2	1 min 3 sd 6 dur	2%	67%
3	1 min 2 sd 9 dur	8%	73%
4	1 min 3 sd 9 dur	1%	100%
5	3 min 2 sd 6 dur	41%	65%
6	3 min 3 sd 6 dur	28%	71%
7	**3 min 2 sd 9 dur**	**36%**	**73%**
8	3 min 3 sd 9 dur	24%	75%

Figure 4. Detection comparison with durations of 3 (a) and 1 (b) minute

When it comes to speed standard deviations and duration time, as expected, the increase in the duration time from six to nine minutes and the use of three standard deviations reduced the percentage of automatic detection, but increased the cases where it was possible to visually validate the crash time.

In addition to not reaching a given criteria, other hypotheses can be drawn to explain the cases where it was not possible to match a given reported crash to the speed profile given by

the speed cameras: (i) some crashes – although georeferenced at the intersection – only impacted the approach without electronic enforcement; (ii) some of the crashes occurred upstream the loop, so only the volume indicator would be impacted; (iii) some crashes with low severity did not affect the speed in the street enough to be detected by the algorithm.

For the visual validation procedure, Figure 5 provides two examples in which speed disturbance was detected by the algorithm, but – during the complementary visual analysis – it was not possible to determine the initial oscillation time, making it difficult to estimate the crash occurrence time. In Figure 5a (rear-end collision) the algorithm detected a disturbance around 10h10m, however, as the speed did not present a constant reduction pattern, it was not possible to specify the crash occurrence time. The speed profile in Figure 5b (sideswipe collision) does not allow to associate some punctual disturbance to the crash occurrence. One hypothesis for such a below-average long-lasting behavior is that the speed reduction may have caused the crash (a lane obstructed by vehicles, for example) rather than the other way around.

Among all combinations, 5 and 7 were the ones that presented the best results. It was decided to adopt the combination 7 (3 min 2 sd 9 dur) to conduct the complete analysis due to the higher rates of visual confirmation. Even though the algorithm's rate of confirmed detection was approximately 26% (36% of detection times 73% of visual confirmation), it is still possible to achieve the central purpose of evaluating the differences between the reported crash times and the speed disturbances, since an extent crash database was considered.
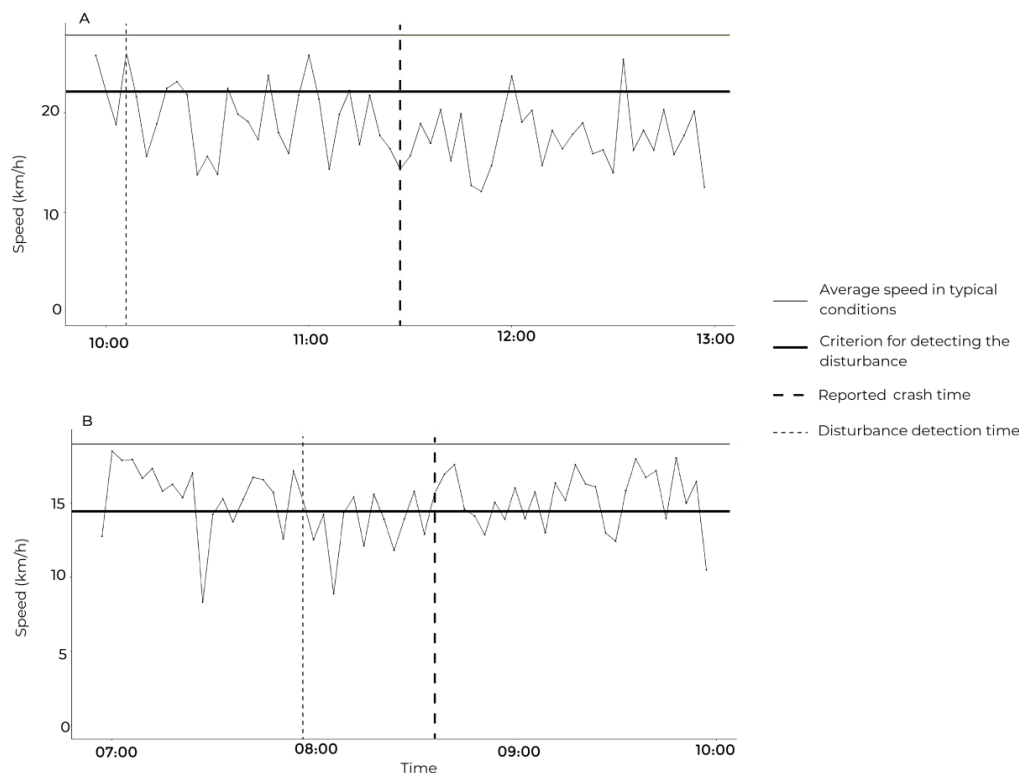

Figure 5. Examples of disturbances detected by the algorithm, but for which it was not possible to specify the initial times of the oscillations: (a) rear-end collision; (b) sideswipe collision

4.3. Analysis of speed disturbances and comparison with reported crash times

The analysis of the traffic disturbances was divided into four scenarios according to the type of crash and to the number of approaches with loop detectors that identified the disturbance: (1) disturbances detected by at least two approaches associated with right-angle collisions; (2)

disturbances detected by at least two approaches associated with other types of crashes; (3) disturbances detected only by one approach associated with right-angle collisions; (4) disturbances detected only by one approach associated with other types of crashes. This division reflects – in descending order – the confidence level to estimate the most likely crash time. For example, scenario 1 allows the most likely crash occurrence time to be validated from the information in one of the approaches. In scenario 4, on the other hand, the confidence regarding the georeferencing of the crash is smaller, and may impact the detection quality. It should be noted that approximately 31% of the crashes registered in the database were classified only as "collision", thus being included in the *Other Types* category.

In general terms, from the 957 investigated crashes, speed disturbances were automatically identified in 412 (43.1%) of them by using the proposed criteria combination 7. From the crashes detected by the algorithm, the complementary visual analysis allowed the exact detection of the speed disturbance moment in 291 (70.6%) of them, maintaining the performance close to the one obtained in the pilot study. Figure 6 shows a summary of the detections per scenario.
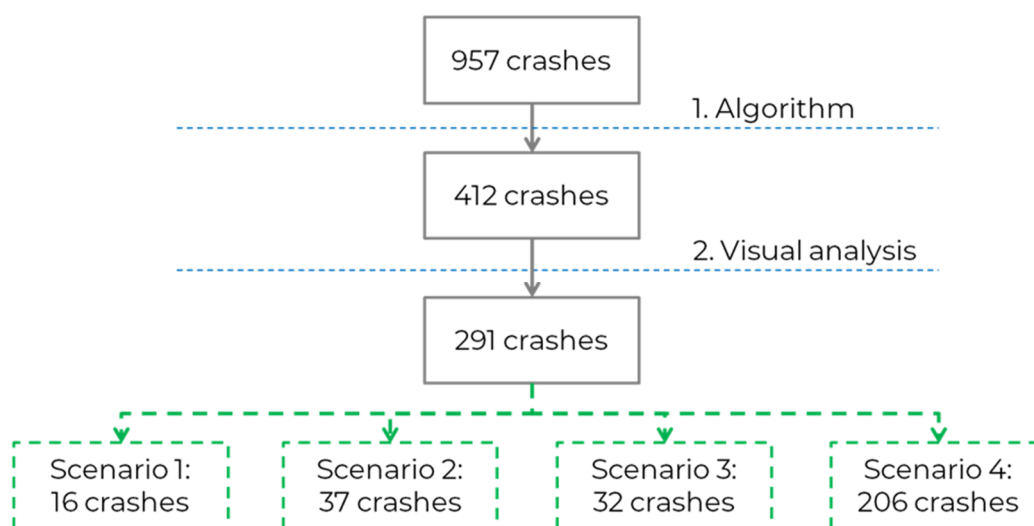

Figure 6. Summary of disturbance detections per stage and per scenario

Figures 7a and 7b provide the speed profile for two approaches of the same intersection at the time when a right-angle collision was reported. It is verified that the two loops detected the speed disturbance in the same hour, 3 minutes after the reported one. Most of the disturbances detected and visually validated for scenarios 1 and 2 followed the profile presented in Figure 7, allowing the precise identification of the disturbance time.

Figure 8 shows two disturbances detected and confirmed by visual analysis in only one loop (scenarios 3 and 4). Figures 8a (right-angle collision) and 8b (sideswipe collision) show situations in which it was possible to determine precisely the moment in which the speed disturbance was triggered.

Table 3 shows the observed differences between the reported crash time and speed disturbance per scenario. For the case of a higher confidence for the difference (scenario 1), there was an average delay of 12 minutes in relation to the time reported in the database and the speed oscillation occurrence. Considering all 291 crashes, the difference was higher:

average delay of 20 minutes. It was also verified that in all the scenarios there were crashes reported before the disturbance identification (estimated difference less than zero). Figure 9 presents a right-angle that the speed disturbance was detected 24 minutes after the reported crash time.
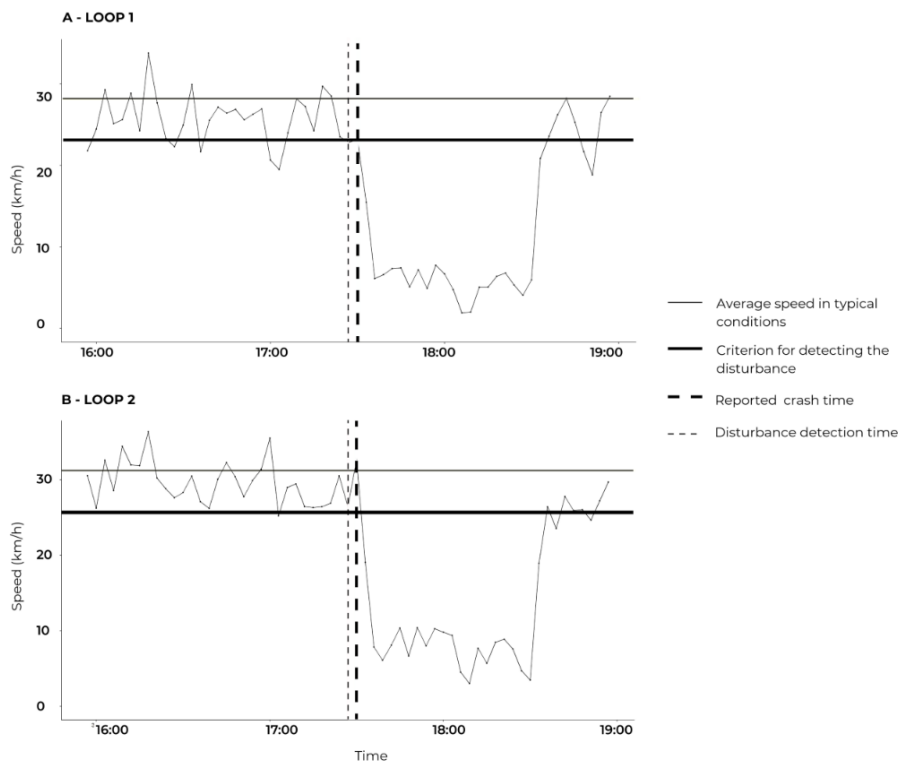

Figure 7. Disturbances detected by two loops at similar times – right-angle collision: (a) loop 1; (b) loop 2
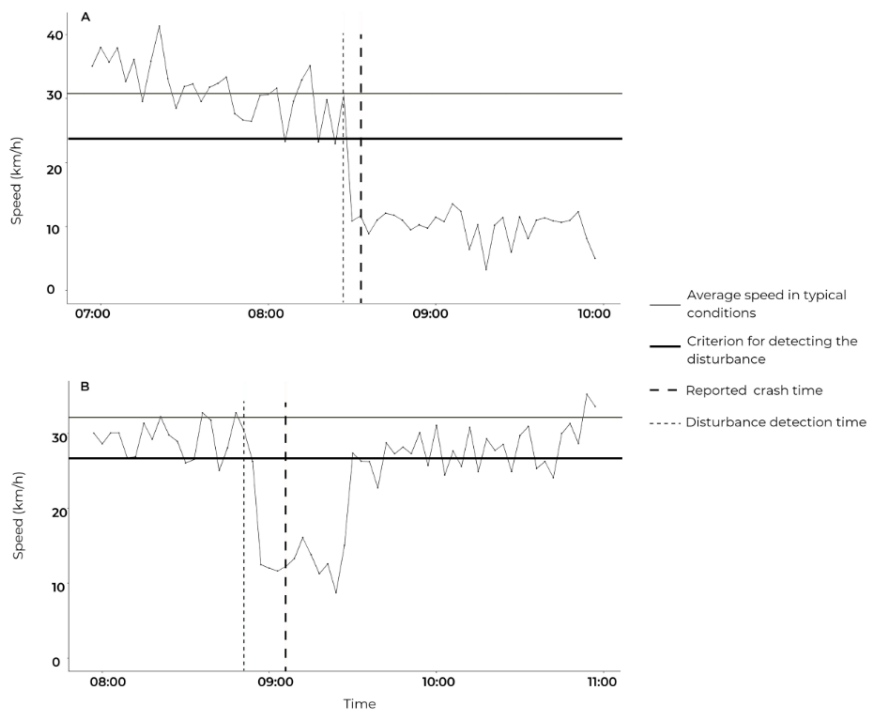

Figure 8. Disturbances detected by only one loop: (a) right-angle collision and (b) sideswipe collision

Table 4 shows the statistics of the differences by crash severity. It is observed that there is a difference in the average between crashes with injuries and deaths compared to those only with property damages (p-value = 0.07), evidencing comparatively lower emergency response time for crashes with victims. The lower average verified for scenario 1 in the previous analysis may be related to the preponderance of crashes with injuries in this scenario.

Table 3 – Statistics between the differences between the reported crash time and speed disturbance by scenario

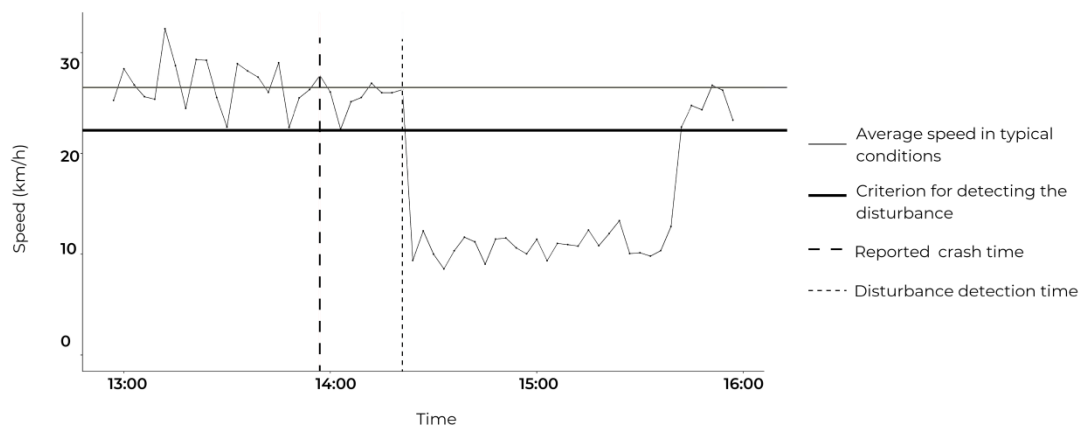| Scenario	#Crashes	Statistics of the estimated differences (minutes)						Crashes severity		
		Average	Standard Deviation	Min.	25º Perc	75º Perc	Max.	PDO	Injured	Fatal
1	16	12	18	-9	3	14	60	5	9	2
2	37	22	24	-9	6	33	81	26	11	0
3	32	10	22	-30	-1	20	84	18	12	2
4	206	21	24	-33	6	35	105	136	68	2
All cases	**291**	**20**	**23**	**-33**	**3**	**33**	**105**	**185**	**100**	**6**

Figure 9. Example of speed disturbance detected after the reported crash time

Table 4 – Statistics between the differences between the reported crash time and speed disturbance due to crash severity

Crash Severity	#Crashes	Statistics of the estimated differences (minutes)					
		Average	Standard Deviation	Min.	25º Perc	75º Perc	Max.
PDO	185	21	24	-33	3	33	105
Injuries and fatalities	106	16	21	-30	3	24	84

The results found for the city of Fortaleza indicate differences around the crash occurrence reported time provided in the databases and the estimated time of serious disturbances in traffic. These divergences would impact severely the validity of studies that evaluate crash precursor conditions. For example, if one while conducting a research with data aggregation of five minutes applies a fixed "correction" to the crash time of 33 minutes (75º percentile), one would relate about 25% of the crash sample to erroneous precursor conditions that might be impacted by the crash existence. To further illustrate, take a crash that was reported at 20h40m, but its real occurrence was at 20h00m; if one employs a correction of 33 minutes – or even worst: uses the reported time – one would associate the crash to post-crash circumstances. Therefore, one feasible solution for this issue is to consider only the crashes which the identification of the most probable occurrence time was possible.

5. CONCLUSION

This work presented an evaluation of the difference between reported crash times and disturbances in vehicle flow conditions in urban signalized intersections in the city of Fortaleza-Brazil. The detection of vehicle speed disturbances was performed using an algorithm that compared speeds at typical days (without crashes) intervals with the interval at which the crash was reported. Then, a complementary visual analysis validated the identified disturbances automatically.

A comparison between the level of disturbance detections considering speed aggregations of one and three minutes showed that the first one is not indicated for the signalized environment, since the short timeframe is impacted by the signal cycle. Aggregations of three minutes were able to minimize the signal cycle effects in the average vehicular speed. The best performance algorithm presented a 43.1% disturbance detection rate, from which 70.6% were visually validated. Disturbances close to the occurrence time of right-angle collisions, which were detected in two approaches (two loop detectors), were considered the most reliable ones for estimating the difference between the reported time and the disturbance, showing an average value of 12 minutes (sd = 18 min). Based on all crash (291) and speed disturbance scenarios, the average difference between occurrence and disturbance was 20 minutes (sd = 23 min).

Due to the observed differences, the main recommendation of this study is that before the development of disaggregated road safety analyses one might explore the crash reported times registered in databases, aiming to evaluate possible differences between this time and the moment that the crash probably occurred. Otherwise, one takes the risk of associating the crashes to conditions that were not prior to them.

The main limitation of the proposed method is that it only considered the speed indicator to detect disturbances in the traffic flow, not contemplating the traffic volume indicator. So, in some crashes that happened upstream the loop detectors only the traffic volume would be impacted. Then, performing the analyses with both indicators would probably increase the algorithm disturbance detection rate.

In future works, it is recommended the application of techniques that consider both speed and traffic volume indicators and the development of similar studies in other cities and countries aiming to measure the differences around the reported crash times the moment of disturbances in the traffic flow. Another possibility is a deeper investigation around the features that impact the value of those differences, like location of the crash, traffic flow conditions before the crash, time of day, day of the week and other elements. One step forward would be the association between the crashes that the most probable time of occurrence were estimated and their precursors conditions, such as speed, traffic volume, vehicular headway, and others considering short temporal aggregations. The development of studies of this type in urban signalized environment would help to fill an existent gap in the literature.

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