An Automated Surrogate Safety Analysis at Protected Highway Ramps Using Cross-Sectional and Before-After Video Data

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Abstract

This study presents a method for surrogate safety analysis to investigate the safety of limited-access highway facilities. The proposed methodology is based on automated trajectory collection and behavioural analysis from surrogate safety measures (in particular, time-to-collision). The methodology is applied to a sample of urban highway sections at on-ramps and off-ramps to study the effectiveness of a lane-change ban treatment in Montreal, Canada. To the authors' knowledge, this is the largest automated video-based surrogate safety analysis of real sites. The applicability of the methodology is explored using (i) a cross-sectional comparison and (ii) a before-after comparison. Video data is collected using the highway traffic surveillance system and a mobile video camera unit. Various methods of aggregating the data, spatially and temporally, are explored. Although the treatment does not have a statistically significant impact on the TTC distributions, it is found empirically that lane changing interactions are less predominant than rear-end interactions at these highway ramps, lane changes across the protected side of the treatment (infractions) occur in great numbers regardless of the implementation of the treatment, and that the start of the treatment produces an artificial critical point in the highway stream causing increased lane-change interactions at this point.

Keywords

Driver behaviour, highway ramps, surrogate safety, time-to-collision, road user interactions, trajectories

1. INTRODUCTION

An important area of research in road safety is the identification of the safety effectiveness of various transportation facility designs and countermeasures. Typically, this type of research relies on collision data collected at many sites over long time periods to overcome the problem of long return periods between collision observations. However, this methodology proves insufficient when evaluating new designs or countermeasures for which little historical data exists, when environmental factors change significantly over time, or when collision data collection programs become prohibitively expensive or unreliable. In addition, the unknown conditions of newly proposed designs or countermeasures further the challenge of collecting sizeable amounts of historical data as practitioners are reluctant to experiment on the public beyond focused pilot projects. In a broader sense, we still face the challenge of evaluating road safety without waiting for collision events occur. To this end, more proactive analysis techniques need to be introduced to maximize interpretation of rich datasets of observations collected over shorter periods of time.

The surrogate safety approach substitutes the long return period of collision observations with observations of road user interactions under typical driving conditions. An interaction is the relationship between pairs of road users within the area of study. The surrogate safety approach relies on the existence of some quantifiable relation between collisions and interactions or indicators derived from their observation.

This approach can be traced back at least to the late 1960’s (Perkins and Harris, 1968) where interactions without a collision, called conflicts, were studied and characterized using “severity” measures (Häkkinen and Luoma, 1991). However, the use of this conflict analysis in road safety studies is so far less popular than historical collision-based diagnosis. The primary arguments against the approach typically include the cost of manual data collection, the subjectivity of conflict interpretation or observation, the difficulty in defining universally comparable measures of interaction safety, and the unknown relationship between conflicts and collision frequency or collision severity (Chin and Quek, 1997). Many papers in road safety have argued for and against the use of conflict analysis as a reliable safety measure, both on the standpoint of collision severity and frequency. The reader is invited to consult (Svensson and Hydén, 2006) for an extensive overview of early attempts at conflict studies and (Laureshyn, 2010) for a comprehensive overview of the Swedish conflict analysis technique.

Part of the data collection and subjectivity issues are being solved thanks to advances in computer vision. This paper presents a complete practical methodology for surrogate safety analysis, including video data collection from traffic cameras as well as from a purpose-built mobile camera system, and for the interpretation of road user trajectories and interactions. This methodology is applied to a case study of safety inside highway merging zones that involved the collection of a large video dataset. More specifically, the objective of this research is to develop a methodology for evaluating vehicular interactions for a particular road element (highway ramps). The use of the proposed methodology is demonstrated using a before-after and cross-sectional comparison of interactions for a sample of sites with a design countermeasure: a particular lane-change ban along highway ramps in Montréal, Québec.

The paper is organized as follows: the next section will cover previous research, followed by an overview of the methodology, a description of the case study, and, finally, some experimental results.

2. BACKGROUND

The problem of acquiring low-cost, objective, and consistent trajectory data has been solved in part by advances in computer vision and cheap video equipment. Computer vision allows for the procedural acquisition of rich road user trajectory data: position in time and space of every road user inside of camera space, such as applied in the NGSIM (Kim et al., 2005) and SHRP2 (Gordon et al., 2012) projects. Computer vision applied to surrogate safety has been developed and used extensively by several research groups. Sayed, Saunier, and Ismail developed video analysis tools primarily for road safety analysis at intersections in North America, including vehicle-vehicle interactions (Saunier et al., 2010) and pedestrian-vehicle interactions (Ismail et al., 2009), (Ismail et al., 2010). Meanwhile, Hydén, Svensson, Laureshyn, and Ardo, among others, have developed a computer vision framework in Europe, as early as 1996 (Hydén, 1996), and more recently using background subtraction and hidden Markov models (Laureshyn et al., 2009). More recently, surrogate safety analysis has been applied for recent before-after studies (Phillips et al., 2011), (Autey et al., 2012). The reader is invited to consult (Buch et al., 2011) for a survey of computer vision for urban transportation applications. Video analysis provides the trajectories of all road users in the camera field of view (or a subset depending on resolution and angle). This detailed microscopic data at high temporal resolution (typically between 15 and 30 measurements per second, depending on the chosen frame rate) is used to characterize road user interactions, computing, for example, relative distance, velocity, etc.

Although there has been a lot of research since the end of the 1960's first in traffic conflict techniques and more recently in more general surrogate safety analysis, there is still a lack of agreement over the methods and their interpretation, and a lack of guidelines. Considerable work has been done to define conflicts, and in particular the most serious ones (the conflicts most similar to collisions) using several indicators and to validate their relationship to safety. The essential idea is to observe all road user interactions (benign and risky behaviours alike) that can be analyzed to produce some kind of safety diagnosis. In this quest, a large number of indicators or surrogate safety measures have been proposed to quantify the road user interactions according to position and time. Speed (particularly absolute speed) has already been widely used as a catch-all surrogate safety measure in the field of road safety. Other measures have emerged, notably Time-to-Collision (TTC) and Post Encroachment Time (PET). Gettman and Head have published extensive summaries of additional surrogate safety measures (Gettman and Head, 2003) commonly used in the literature such as Gap Time (GT) and Proportion of Stopping

Distance (PSD) among others. Laureshyn has compiled and even more thorough list of measures (Laureshyn, 2010), though many are scenario specific or their significance is loosely defined in a more general context (e.g. speed or “steering”). Among these, TTC is probably the most commonly used and encompasses the core concept of a conflict situation where “a collision is imminent if [the road users’] movements remain unchanged” (Amundsen and Hydén, 1977). It relies on the prediction of the motion of road users at a given time to identify potential future collision points assuming events such as driver reaction or emergency breaking fail to take place. In practice, most methods rely on motion prediction at constant velocity. This unrealistic assumption is being questioned in recent work since many paths may lead interacting road users to a collision (Mohamed and Saunier, 2013).

A large number of surrogate safety studies have been conducted in simulated environments using, for example, the Surrogate Safety Assessment Model (SSAM) which uses trajectories extracted from microsimulation, and thus relies on simulated driver behaviour. So far, studies applying surrogate safety to real trajectories have remained small and experimental in scope (typically a case study at one or two sites) such as (Svensson et al., 2011) and (Guido et al., 2010). Of particular note is (Autey et al., 2012) which examined four slip lane sites in a before-after study. This paper applies the latest developments to a cross-sectional case study of eight sample highway sites (ramps), as well as a before-after study of one of these sites. To the authors’ knowledge, this is the largest surrogate safety analysis ever carried out.

3. METHODOLOGY

The proposed steps to analyse road user interactions are summarized as follows:

1. Collection of a sufficiently large video data set for each site.
2. Spatial calibration of the camera image space to the roadway ground plane using aerial imagery.
3. Trajectory data extraction:
    a. Feature tracking (moving pixels).
    b. Feature grouping into road users and empirical error filtering (feature trajectories are grouped together for each road user they represent based on proximity and motion similarity (Saunier and Sayed, 2006)).
4. Interaction classification, motion prediction, potential collision detection, and interaction measurement analysis.
5. Interaction measures summary, comparative analysis, and interpretation according to choice of chosen interaction measure.

3.1 Measures and interaction types

This study breaks down traffic flow into *interactions* which define the relationship at every moment in time between every pair of two road users within the same study area using the extracted road user trajectories. For every time step *t* during which the two road users coexist, various measures can be introduced to characterize the interaction between the two road users, whether they are directly observed, such as distance, speed, etc. or they depend on predicting their future positions, such as TTC.

TTC is defined as the remaining time, from every point in time *t* until any pair of two road users (or a road user and a fixed object) following their future predicted paths would collide (Laureshyn et al., 2010). The general form of TTC is simply understood as the closing distance to the predicted point of collision divided by the velocity. TTC is the main indicator measured in this research for several reasons: it has an intrinsic relationship with driver reaction time, it evolves continuously over the course of each interaction, it can exist for all interaction types, it is simple to calculate, and it already has some objective research behind it (Saunier et al., 2010).

For the purposes of illustrating the methodology using motion prediction, this paper makes use of the simplified motion prediction method with constant velocity. In practice, we can make this simplification as we observe that vehicular motion on straight highway segments tends to be linear, even when changing lanes. Sudden changes in speed or direction mostly occur in emergency situations, such as reacting to an already existing serious conflict. The term “vehicle” is used in the remainder of the paper to refer to motor vehicles, since the presented study deals with highways and on-ramps. The methodology however applies to other road users, using different motion prediction methods depending on the context.

For interactions that converge in both space and time—that is, vehicles are predicted to collide with each other given enough time and according to their predicted paths—TTC can be measured. The algorithm used to make TTC measurements is based off of the work by (Laureshyn et al., 2010) and some basic geometry calculations.

Each interaction is classified by type according to relative position of the vehicles with respect to one another and their lanes. Vehicles following each other experience rear-end interactions (type A) when their paths are converging (when the velocity of the leading car is inferior to the velocity of the following car), while vehicles in different lanes experience diagonal interactions (type C) when their paths cross and projected positions overlap (see **Figure 1**).

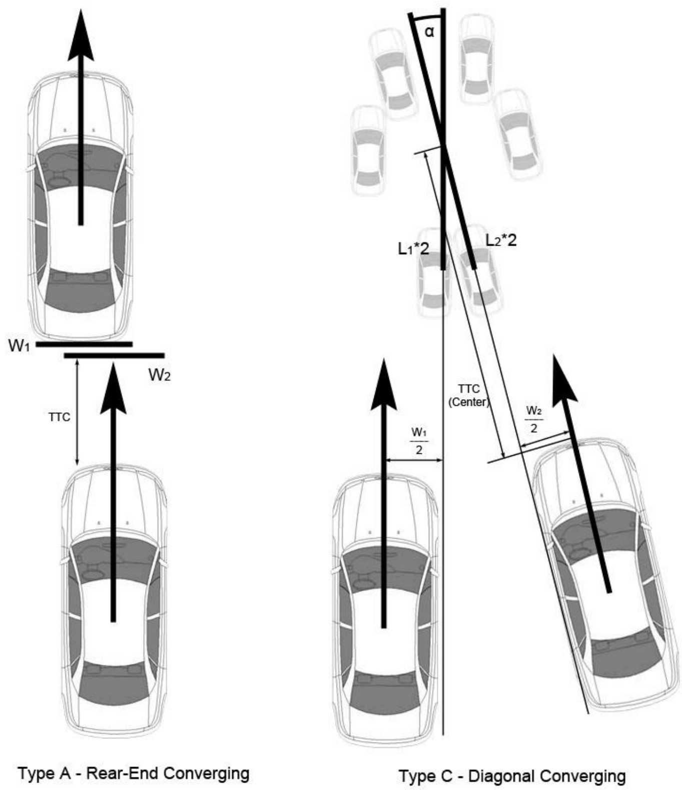

Figure 1
Highway interaction types according to relative position and collision angle.

In situations where the vehicles are not predicted to collide and TTC does not exist, but paths still overlap (typically for lane changing), a predicted PET (pPET) measurement is recorded instead (this measure is analogous to the GT measure used in the literature for intersections (Gettman and Head, 2003) but the term is avoided so as to not confuse with terminology used when discussing highway following distance). It should be noted that highway interactions occur at very sharp angles, so pPET interactions are quite rare. Additionally, for all measures of TTC, the position (x, y) of each predicted collision point CP is recorded. **Figure 2** illustrates the organisation of interaction type classification and associated interaction measures.

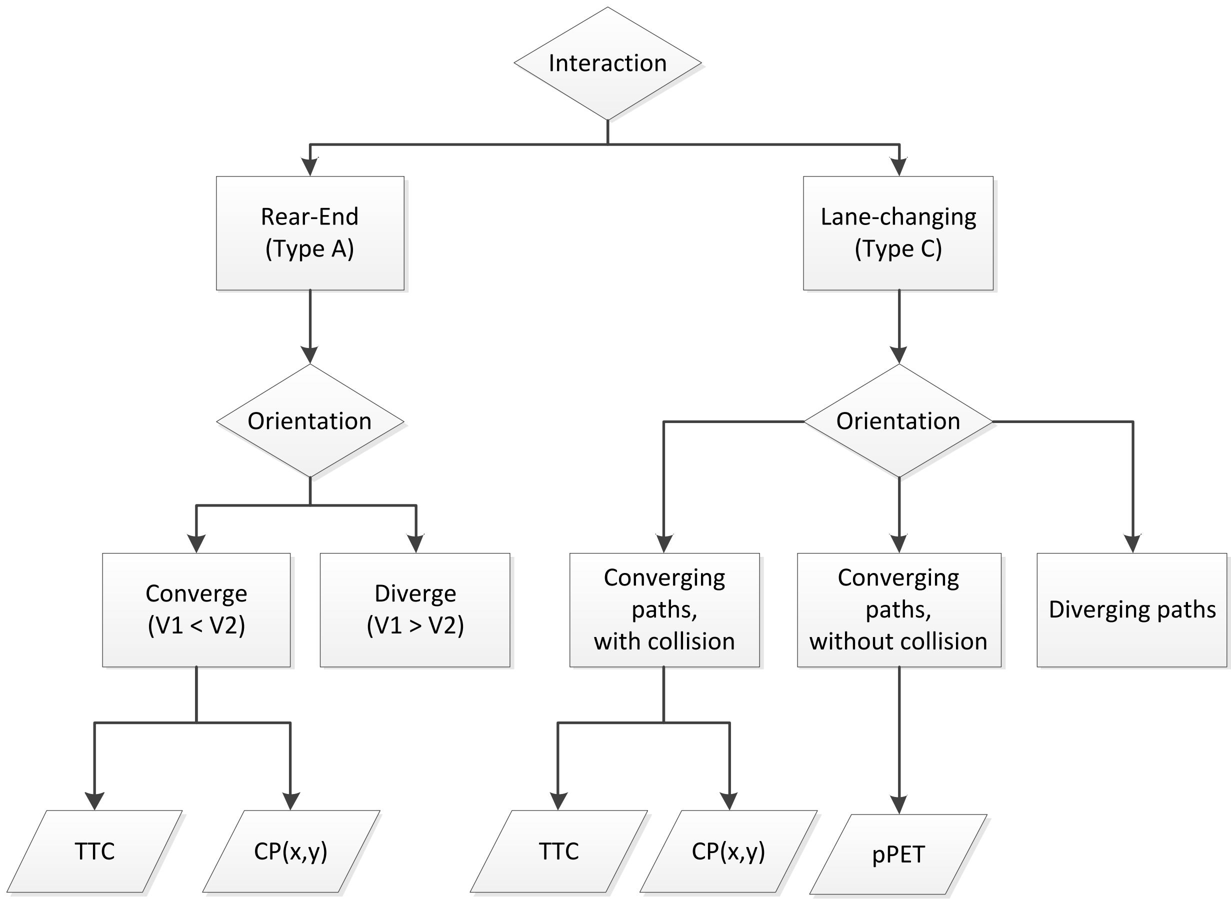

Figure 2
Interaction classification and data extraction flowchart. V1 and V2 represent the velocities of the lead and following cars respectively in a car-following scenario.

3.2 TTC Analysis and Interpretation

An observation (of TTC) is one measure of TTC between any unique pair of vehicles at any time t, that is, over a time step $\Delta t = 1/\text{framerate}$. There are a few options for aggregating and interpreting the observations, all of which will be examined in the case study:

- Retain all observations by treating every moment in time equally or, alternatively, resample observations according to distance traveled. Because vehicles travel at different speeds, either way, some amount of sampling bias will be introduced as slower or faster road users will be given more importance over time or distance traveled, respectively.
- Retain one representative observation per vehicle, either a minimum or a percentile observation (e.g. the 85^{th} percentile).

- Retain one representative observation per interaction (or pair of vehicles), either a minimum or a percentile observation (e.g. the 85^{th} percentile).

In order to make the TTC measure useful in the context of road safety, it is important to understand its relationship with collision probability, if it reliably exists. Unfortunately, a formal relationship between the two still requires much research (both empirically and theoretically from the driver behaviour literature). However, it is generally accepted that spatial and temporal proximity increases collision risks, especially in the case of a collision course. Given that TTC is a measure of proximity which takes both space and time into account, it is proposed as a method of empirically measuring the probability of collision of an interaction, at time *t*, over a time step Δt, given a TTC and other unknown factors such as driver reaction time, visibility, vehicle performance, represented empirically by θ. Accordingly, the following relationship is formalised:

$$PC(t) = f(TTC(t), \theta) \tag{1}$$

Where $PC(t)$ is the probability of collision at any time *t* which depends on $TTC(t)$ and θ. By definition of time-to-collision, the probability of a collision for a TTC of 0 is 1:

$$PC(TTC(t) = 0, \theta) = 1 \tag{2}$$

The higher the TTC (that is, the closer the vehicles), the more likely that time-dependant collision mitigation factors—such as road user's reaction times or emergency breaking—alter the predicted collision outcome. For example, a collision point predicted with a TTC of 1 s seems vastly more probable than a collision predicted with a TTC of 20 s as there are many more opportunities for trajectories to be altered in the space of 20 s, especially at the human time scale. We can therefore hypothesize that:

$$\lim_{TTC \to +\infty} PC(TTC, \theta) = 0 \tag{3}$$

Because there are multiple factors at play, each operating at different time scales, we should not dismiss the relationship as linear. However, we may safely ignore very large time-to-collisions by assuming that their predictive power is improbably low. This paper picks a conservative threshold value of TTC of 50 s above which TTC measures are ignored. For the time being, a weighted collision density function is proposed for the purpose of mapping potential collision point density. It assumes an exponentially decaying function of TTC according to some empirical factor αwhich satisfies conditions (2) and (3) and the non-linear hypothesis:

$$WC(TTC(t)) = \frac{1}{e^{\alpha \times TTC(t)}} \tag{4}$$

where $WC(TTC(t))$ is the weighted collision density function used to compare weighted collision density maps. This type of collision probability weighing shares similarities with previous discussions of accident probability (e.g. (Saunier and Sayed, 2008)). Weighted collision density maps are a means of examining the spatial distribution of interactions. These maps are produced by plotting the 2-dimensional histogram of all observed $WC(TTC(t))$ according to position *CP(x,y)* using a Gaussian kernel size of 50 mm by 50 mm. Areas with a greater density of "low" TTC interactions are highlighted in this way.

Although, from a practical standpoint, $WC(TTC(t))$ does not influence density across lanes, as virtually all trajectories are parallel or near parallel with the highway, future work will attempt to turn this weighing function into a properly calibrated probability of collision function; until then weighted collision density maps are used primarily for cross-sectional and before-after comparisons with identical weighing only.

4. A CASE STUDY

4.1 Highway Ramps

The proposed methodology is illustrated with a study on a set of highway ramps with and without a lane-change ban marking (termed LCGV1) located between the middle and outside lanes in exit and entrance ramps of highways—see **Figure 3.** Analysis is attempted using both (i) a cross-sectional and (ii) a before-after comparison.

Figure 3
Example LCGV1. a) Exit ramp section diagram demonstrating an LCGV1 and a discouraged lane change. b) LCGV1 along autoroute 720 eastbound, entrance 3 (right), Montreal. Source: MTQ.

This marking treatment is particularly popular in urban multilane highways in Quebec, Canada. The treatment typically bans lane changing from the middle or inside lanes to the outside lane along the weaving zone, but allows lane changes from the outside lane to the inside lane. This marking was initially implemented on ramps that do not meet all required design standards. For instance, ramps treated with this type of marking were those with poor approaching visibility, short weaving zones, or close proximity to other ramps. However, this marking has proliferated to standard sites as well. Despite its popularity, this safety treatment has been a source of concern because the potential impact on highway safety has not been fully understood and the benefits are still debated.

The ramps involved in this case study are those for which video data was available. Video data was collected at eight sites of similar geometry, free-flow-speed, and average annual daily traffic on the Island of Montreal: two treated entrances, two untreated entrances, two treated exits, and two untreated exits. Video data was collected at one of the entrances before and after the installation of the treatment. Low-light and peak periods were avoided as they were problematic for data collection.

The traffic interactions analyzed stem primarily from the traffic movements on all lanes upstream of the pier-head in order to properly capture behaviour related to movement in anticipation of ramp approach (although exact dynamics still differ between entrances and exits). It is also theorized that the beginning of the lane-change ban is a critical point of conflict for drivers as is the pier-head of any exit.

Table 1 Video data inventory.

	Site	Treatment	Vehicles per hour	Mean Speed	Speed St. D.	Analysis length	Analysis time
Entrance	A20-E-E56-3	No (before)	2515	95 km/h	11 km/h	50 m	5 h
	A20-E-E56-3	Yes (after)	2598	105 km/h	12 km/h	50 m	10 h
	A20-W-E62	No	2946	88 km/h	16 km/h	80 m	3.6 h
	A20-E-E58	No	2497	111 km/h	15 km/h	100 m	5.3 h
	A720-E-E3	Yes	2193	60 km/h	10 km/h	75 m	6 h
Exit	A13-N-S3-1	No	2643	110 km/h	14 km/h	60 m	3.6 h
	A25-S-S5	No	3012	88 km/h	10 km/h	50 m	4 h
	A20-E-S58	Yes	2146	110 km/h	11 km/h	70 m	4.6h
	A25-N-S5	Yes	2388	90 km/h	9 km/h	50 m	3.2h

Table 1 summarises the site selection including the before/after treatment of site A20-E-E56-3. Care was taken to pick comparable sites yet some variation of number of vehicles and mean speed in the 5-20% range still exists, as finding identical urban environments proved to be challenging. Nevertheless, these variations are not found to be primary indicators of variation in

the results likely due to the fact that TTC is calculated from speed differential as opposed to absolute speed, and interactions are compared according to distributions instead of total numbers.

4.2 Data Collection and Video Pre-Processing

Data collection is done using i) permanent highway surveillance cameras where available in urban and suburban freeways in Montreal, and ii) a mobile video data collection unit (MVCU) for all other sites out of reach of permanent cameras (Jackson et al., 2013). For the design of this MVCU, many characteristics of the equipment had to be considered including: ease of installation, discretion (so as to not cause a distraction to drivers), height (a minimum of 7 metres is recommended), weatherproofness, remote operation (power for up to 24 hours and data storage of 8-16 hours of continuous recording per card), resolution, field of view, stability, etc. The MVCU was installed at various highway sites during the course of the summer of 2011. The choice of site was partially governed by accessibility and under supervision of the local transportation agency in order to meet road work safety codes and to avoid inconveniencing traffic. Video was collected at 25 frames per second. It is crucial for frame rate to be consistent so that evolution of speed is properly measured.

Some video data pre-processing needs to occur before it can be analysed: i) videos need to be stabilised and ii) videos need to be formatted appropriately while minimizing recompression so as to not lose quality. Video stability is generally an issue with mobile equipment due to its non-permanent nature. Camera shake can originate from wind or from road vehicle vibration forces which are mostly transmitted through the installation medium including superstructures. Camera shake manifests itself as tilting, panning, and rotation of the view. Small amounts of vibration are then corrected for by tracking the movement (local colour changes) of multiple pixels and calculating an overall movement pattern. By applying the inverse of the movement to the entire image, motion compensation is effectively achieved.

The positional analysis of vehicles requires accurate projection of the pixel coordinates in image space to real-world coordinates that lie on a reference surface with known model (pavement surface). When video data is collected by a third party, access to the camera is not possible and therefore all camera parameters must to be inferred from video observations and an orthographic (aerial) image of the section. This is done using a robust calibration method relying on various features such as the shape, position, and length of remarkable objects in both image and world spaces (Ismail et al., 2012). Additional issues are caused by slight camera orientation drift over time, which was dealt with automatically by tracking the stationary portion of the field of view. Time is measured in frames: a data point (position per object per frame) is collected for each new video frame. This high polling rate produces very large datasets of small increments (at highway speeds, typically on the order of 1 meter per frame).

This study makes use of a video analysis tool that relies on well-known feature-based tracking algorithms (Saunier and Sayed, 2006), now available in the open-source software project Traffic Intelligence[1] (Jackson et al., 2013).

A second phase of data filtering was developed specifically for this study to optimize the tracking reliability under the constraints of highway flow and for the type of camera angles used to record the video footage. This phase includes edge and warm-up truncation, expected trajectories coordinate transformation, noise reduction and tracking error filtering (such as duplicate objects, multiple vehicles per object, split objects, etc.). These filtering routines were reviewed manually in a semi-automated process.

Figure 4 shows sample trajectories overlaid on the camera's view. Vehicles were assigned a lane and a set of transformed coordinates for rear-end calculations according to geometry and lane clustering.

[1] https://bitbucket.org/Nicolas/trafficintelligence/

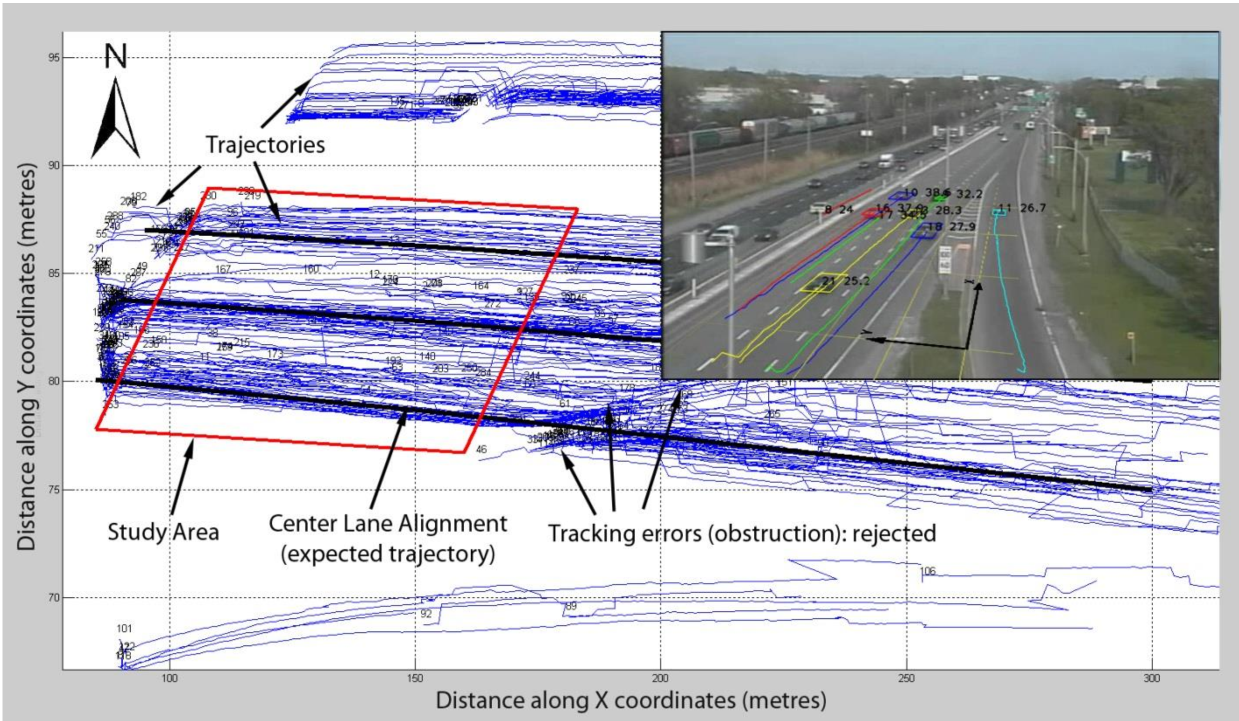

Figure 4
Sample X,Y data for spatial analysis of entrance 56 (Bouchard), autoroute 20 eastbound, Dorval, Montreal. Data points are filtered to include only the study area (50 m long by 10 m wide). Axes scales are not proportional in the interest of viewing long trajectories.

5. RESULTS

After generating TTC data for each particular site, different methods are proposed in this section to analyse TTC distributions and to investigate the treatment effect. The main results are presented in the following order: i) an exploratory analysis is first introduced to identify the TTC patterns between treated and non-treated sites, ii) the outcome of the multilevel regression approach is then presented to statistically test the effect of the treatment, iii) the before-after results using weighted interaction density maps are discussed.

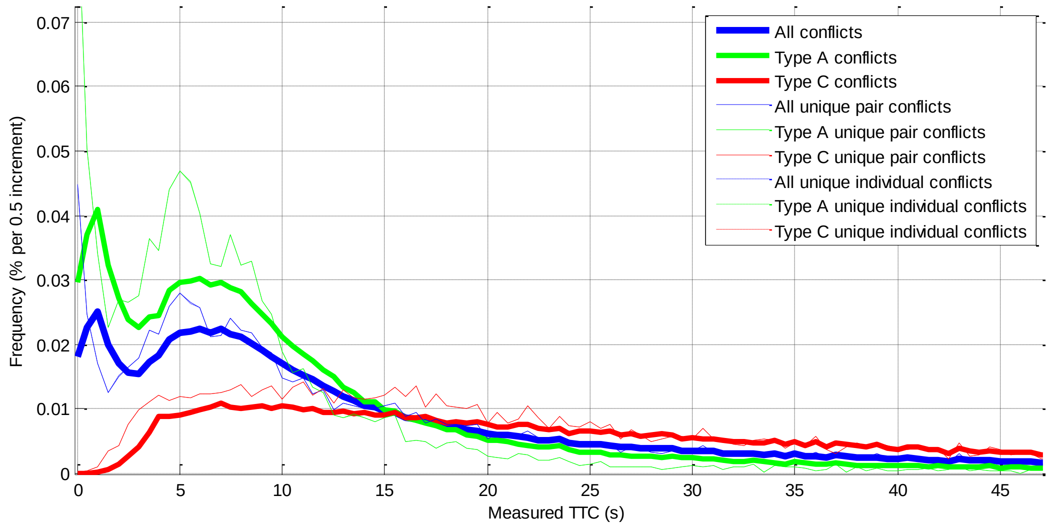

Figure 5
Sample distribution of TTC observations according to type and aggregation method (unique pair and unique individual distributions overlap each other)

Figure 5 presents the distribution of the measured TTC at one site as a probability density function according to the method of aggregation. Three methods of aggregation are presented: i) all observed TTCs, ii) the minimum TTC observed for every unique pair of vehicles over their co-existence, and iii) the minimum TTC observed for every unique vehicle. Aggregation by individual or pair appears to follow a similar trend as the distributions of all observations, albeit quite a bit noisier and oversampled by small values. There seems to be little difference between aggregating by pair or by individual (as both distributions overlap), likely because very few road users enter into low TTC interactions over a distance of 50-100 metres more than once. The remainder of the paper focuses on all TTC observations equally. A more thorough investigation of the benefits of different aggregation methods will be needed.

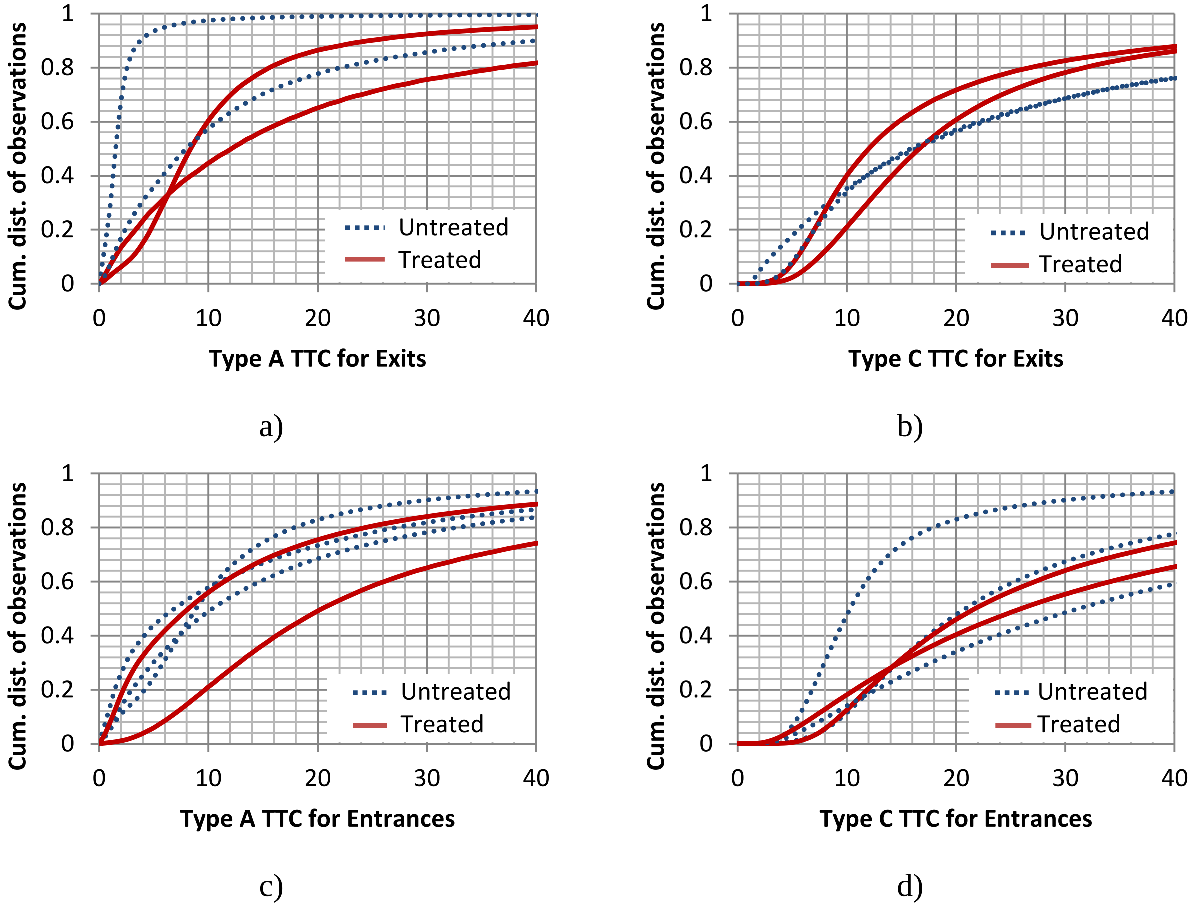

Figure 6
Cumulative distributions of TTC observations (no aggregation) according to interaction type and site type.

Figure 6 presents the cumulative distributions of all observed interactions according to ramp type and interaction type. Distributions are presented cumulatively so as to remove dependency with histogram bin width. From these figures, it is observed that, for both entrances and exits, Type A interactions are more concentrated in the lower TTC range than Type C, and as such have a higher weighted interaction density. This suggests that these types of interactions are theoretically more likely to result in collisions. Drivers following each other are traditionally more visible towards one another (as opposed to vehicles in adjacent lanes who may be traveling in a blind spot). Arguably, the increased visibility is a safety benefit, though the data clearly shows that this benefit is undermined by shorter TTCs. This effect might be explained as a response to higher perceived safety. Whether this increased collision risk is offset by a higher real gain in safety is something of an open question and ultimately at the heart of the relationship between TTC and accident probability. Interestingly, exits, on the other hand, seem to consistently have a greater proportion of interactions in the low TTC range (e.g., TTC < 5sec) without the lane-change ban, regardless of interaction type. Other than this last observation, few clear patterns emerge nor does there seem to be any correlation between interaction density and presence of the treatment in entrances.

In addition to the cumulative distributions, **Table 2** presents some statistics. From this table, again, there is no clear evidence about the treatment effectiveness. However, one can note again that the 5th and 10th percentiles are slightly greater for treated exits than for non-treated exits. This applies to both interaction types. For instance, looking at type C TTCs, the 5th percentiles for the two treated exits are 5.9s and 4.4s, while for non-treated exits these are 4.1s and 2.7s. Despite these slight difference for exits, no clear pattern is observed for entrances. For the only site with before-after data, the 5th and 10th percentiles in the after period become only slightly smaller after the treatment.

To further investigate the effect of the treatment, a multilevel regression analysis is implemented. This is to formally test whether or not the TTCs are significantly smaller for non-treated sites. To model TTC, different probability densities are tested given the positive-skewed (non-symmetric) distributions of this variable as shown in Figures 5 to 8. The following probability density functions were tested: Weibull, Gamma and Log-Normal. Since very similar results (in terms of goodness of fit) are obtained with these distributions, a Log-Normal multilevel regression model was used, which offers some computational advantages. This model is of the form:

$$ln\left(TTC_{ij}\right) = \gamma_0 + \gamma_1 T_j + \gamma_2 X_j + \gamma_{0j} + \varepsilon_{ij} \tag{5}$$

where $ln\left(TTC_{ij}\right)$ is the natural logarithm of measure i at site j ($j=0,..8$). T_j stands for treatment presence (as a dummy variable) with $T_j=0$ if site j is non-treated and 1 otherwise. Here, X_j represents whether the site is an exit or an entrance. γ_1 and γ_2 are regression parameters representing respectively the effects of the treatment and of the type of site (entrance or exit). Moreover, the random effect for each site j is specified and denoted by γ_{0j}. This is assumed to be normally distributed and represents unobserved heterogeneity at the site level. Finally, ε_{ij} is the model error term, following a normal distribution.

The outcome of our multilevel regression analysis is presented in Table 3. From the outcomes, we can see that the parameter γ_1 (treatment effect) is positive but not statistically different from zero with small *t* values. This applies to both types of interactions meaning that there is no sufficient evidence to conclude that the treatment is effective. Some regression analyses were also carried on for various geometry characteristics, showing in few cases a statistically significant impact. Also, the intra-site correlation coefficient shows an important correlation among observations coming from the same site. This suggests that the variations across sites can be more associated to the geometry characteristics than to the treatment. However, a larger sample of (treated and non-treated) sites would be needed to draw robust conclusions.

Table 2. Summary statistics of TTC by types

	Site	Treatment	No of instantaneous interaction observations	Mean	St.D.	Percentiles 5th	10th
TTC < 50, Type = A							
Entrances	A20-E-E56-3*	No (before)	247,143	10.7	9.3	0.8	1.5
	A20-E-E56-3*	Yes (after)	268,635	11.2	11.1	0.7	1.2
	A20-W-E62	No	70,246	13.0	11.9	0.7	1.4
	A20-E-E58	No	41,810	12.5	12.2	0.5	1.0
	A720-E-E3	Yes	169,520	18.8	11.5	4.3	6.0
Exits	A13-N-S3-1	No	72,896	10.3	10.2	0.8	1.2
	A25-S-S5	No	135,638	2.8	3.9	0.2	0.5
	A20-E-S58	Yes	13,779	13.8	12.2	0.8	1.5
	A25-N-S5	Yes	51,916	10.4	8.2	1.6	3.0
TTC < 50, Type = C							
Entrances	A20-E-E56-3*	No (before)	178,407	21.1	12.6	4.7	6.3
	A20-E-E56-3*	Yes (after)	299,546	20.8	12.5	4.6	6.1
	A20-W-E62	No	575,465	20.9	10.7	7.5	9.2
	A20-E-E58	No	465,731	12.8	8.3	4.8	5.7
	A720-E-E3	Yes	387,353	21.2	11.0	7.6	9.0
Exits	A13-N-S3-1	No	97,826	16.3	11.8	4.1	5.0
	A25-S-S5	No	16,808	17.5	12.4	2.7	4.1
	A20-E-S58	Yes	207,372	18.1	10.1	5.9	7.3
	A25-N-S5	Yes	80,150	14.3	9.8	4.4	5.4

Table 3 TTC multilevel regression outcomes

Model	Parameters	Estimate	Std. Error	t-value
Type A interactions	γ_0	1.314	0.678	1.938*
	γ_1	0.593	0.758	0.782
	γ_2	0.524	0.758	0.678
	γ_{0j}: (1.264, 1.124)+ ρ: 0.53 ++			
Type C interactions	γ_0	2.519	0.361	6.970*
	γ_1	0.108	0.404	0.267
	γ_2	0.209	0.400	0.518
	γ_{0j}: (0.359, 0.599) + ρ: 0.37 ++			

*statistically significant at the 5 % level
\+ variance and standard deviation in parenthesis
++ intra-site correlation coefficient

Figure 9 and **Figure 10** show weighted interaction density maps for the A20-E-E56-3 before and after application of the treatment respectively. Areas with the highest concentrations of weighted interaction are lighter in colour. These areas identify the most problematic areas of a given site. Note that the analysis area (bounded by the red box) is just upstream of the ramp where drivers should prepare to accommodate any possible merging traffic, and also where the start of the treatment occurs.

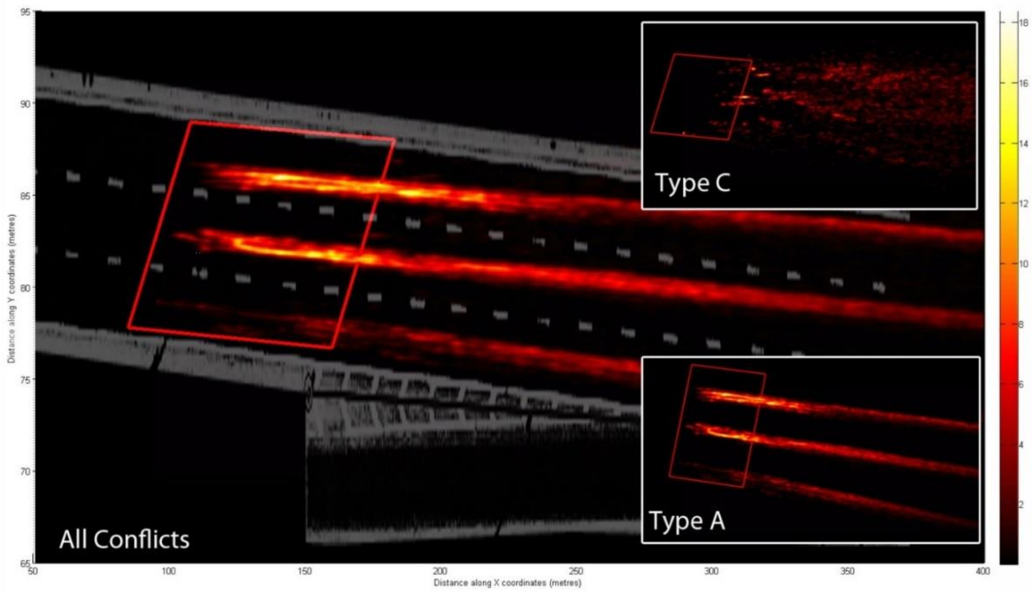

Figure 3
Weighted interaction density map for the A20-E-E56-3 site before treatment; map distances in metres, not to scale.

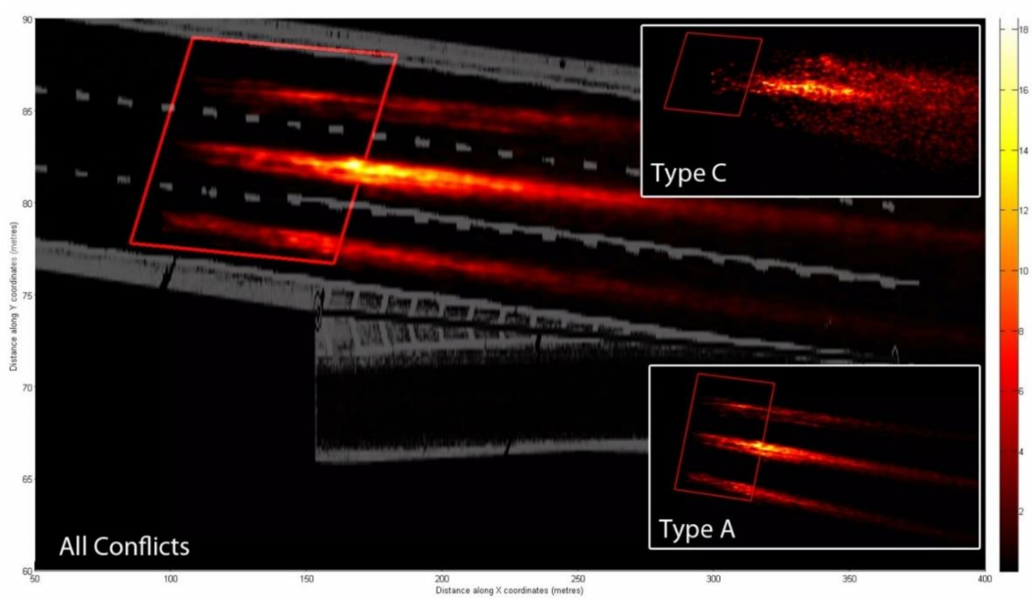

Figure 4
Weighted interaction density map for the A20-E-E56-3 site after treatment; map distances in metres, not to scale.

In both cases, the map of all interactions and Type A interactions are very similar, indicating that Type A interactions are the predominant type (according to weighting). In the case before the site was treated, weighted interaction density is greatest in the third and second lanes and is also more pronounced earlier. In the after treatment case, weighted interaction density is the greatest in the second lane, followed by the first lane, while interactions have become relatively less pronounced in the third lane, indicating a possible interaction migration effect from the treatment. Type C interactions are also included and show an equally interesting pattern: before treatment, Type C interactions are uniformly (albeit noisily) distributed, whereas after treatment, Type C interactions are heavily concentrated around the second lane in a funnel pattern, suggesting that the beginning of the treatment acts as a sort of critical or turbulent point in traffic flow.

Weighted interaction density maps were produced for each site but are not included in this paper for the sake of brevity. A great variety of patterns can be seen across all sites, often explained by peculiarities of the ramp (short or poor visibility, heavy merging activity, presence of auxiliary lane, narrow lane width, change of the posted speed limit, etc.).

6. CONCLUSION

This study introduces and applies an original approach for examining driver behaviour by analysing interactions produced from a rich vehicle trajectory data set. Overall, this represents an important first step in designing a large scale driver behaviour analysis framework for safety diagnosis. The methodology includes data collection, trajectory data extraction, interaction classification, basic path prediction, potential collision detection, and interaction measurement analysis. This methodology is illustrated using a sample of highway ramps (with and without a lane-change ban treatment) attempting both a cross-sectional and a before-after comparison. As part of the methodology, a mobile video data collection unit was used for supplemental data collection at sites out of sight of permanent highway video cameras and brings much needed flexibility for the proposed approach. The results show clear interaction patterns and practical knowledge has been gained in the application of the methodology. Conclusions about the case study are moderate as some analysis depth is missing and more sites are needed. Still, some evidence is found to suggest that rear-end interactions are the predominant behavioural problem, as opposed to lane changes, even at highway ramps; that the presence of the lane-change ban is not the primary factor in affecting interactions; and, finally, the treatment has a migration effect between lanes, particularly at the start of the treatment.

Some limitations need to be stated. Under particularly dense and turbulent flows, the presence of many more vehicles could increase the complexity and nature of the interaction, including multiple vehicle interactions (with more than 3 vehicles) as well as emergency breaking options. For this reason, the current methodology targets high-speed, low to medium-flow scenarios only. However, there is nothing to suggest that this could not be addressed in the future with larger data sets and more robust tracking systems: in fact, it would be very interesting to compare TTC for different driving periods, including peak-hour high-density traffic, and low-density, high-speed night-time driving, even if achieved semi-automatically.

This research can be extended in several directions. First and foremost, a more thorough understanding of the relationship between time-to-collision, reaction time, driver behaviour, and road collisions is needed to build a stronger case for the relationship between the time-to-collision measurements and the occurrence of collisions so that interactions can be used as robust collision predictors. Secondly, more video and trajectory data is required, over longer stretches of continuous highway using multiple cameras, longer times, and across more environmentally consistent sites. Finally there is still much room left for improvement in highway aerial video capture as well as video tracking algorithms in order to improve the quality of trajectory data.

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