Chances for the evaluation of the traffic safety risk at intersections by novel methods

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1. Introduction

According to the European Road Safety Observatory (ERSO), road accidents were responsible for about 30,000 fatalities on EU roads in 2011 (ERSO 2013). If a number of fatalities equivalent to the population of a medium town were not bad enough, for every fatality there are eight serious injuries and fifty minor injuries. In Germany 3,600 people died in 2013 (approximately 10 per day); every second day dies someone in a left turn maneuver. In *Fig. 1* a three-year accident diagram of a black spot intersection, particularly for left turns, in Chemnitz, Germany, is shown.

Although road safety has improved in recent years, it is urgently required to better understand crashes and their causes. Further, it is important to utilize the current technical solutions, e.g. spatiotemporal sensors like cameras, radar and laser sensors, for the detection and analysis of accidents and traffic situations that lead to traffic conflicts or accidents, e.g. (Saunier et al. 2010). Consequently, the causes of accidents and conflicts as well as the chance to influence them can be identified. This will be the basis for developing targeted measures to bring traffic safety to a next level throughout Europe, e.g. "Vision Zero" (no fatalities at all), which has been aimed by the Swedish parliament since 1997 (DVR 2012), or, aimed by the EU, halving the number of fatalities until 2020 (EU 2010). Thus, the aim of traffic safety research within the EU is to protect our people and to reduce the number of fatalities and sever injuries drastically.

To achieve this goal, traffic safety must be

- measurable, quantifiable and assessable in every transport area,
- improved by tailored construction and traffic control measures,
- provided as information, warning message and assistance in case of potentially dangerous traffic situations to the traffic participants before and while traveling.

In the following chapters an approach will be introduced that explains how these four objectives can be achieved. Further, chances and limits will be discussed.

2. Methods and results

To make qualitative statements about traffic safety in considered traffic areas the following workflow is required, which is shown in the following subsections.

2.1 Classical approach

In the classical approach traffic safety is measured by accidents and their classification in conflict, accident type and accident severity. There are at least two essential drawbacks of this method:

- The concomitant circumstances, which lead to an accident, cannot be found out completely and sometimes even not at all.
- Accident analysis requires that accidents, particularly accidents with fatalities and sever injuries, have happened. In contrast it is assumed that the consideration of traffic conflicts instead of accidents can probably solely quantify traffic safety.

For that reason already in the 1950s the idea to measure traffic safety on the

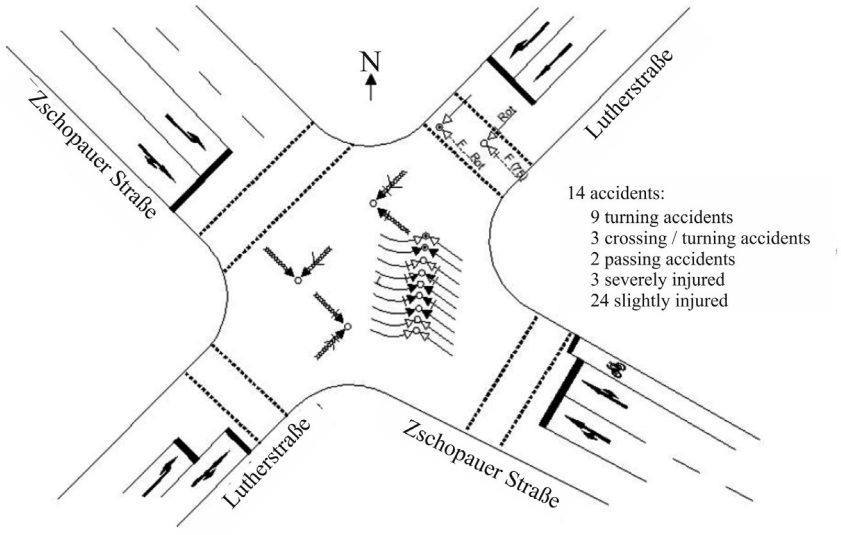


Fig. 1. Three-year accident diagram (2006–2008) for the intersection Zschopauer Straße/Lutherstraße, Chemnitz (modified from (Maier et al. 2013))

basis of traffic conflict measures before accidents happen, had risen, e.g. (FHWA 1989). Since then, there have been several trials by the traffic research community to identify functional correlations between accidents and near misses / traffic conflicts, but, however, there have been as many fails too, which is mentioned in some scientifically proven literature, e.g. (Carsten 2009, Glauz et al. 2009, Laureshyn 2010, Laureshyn et al. 2010). For instance, the empirical functional correlation found in (Gettmann et al. 2008) could not be found in (Souleyrette et al. 2012). However, recent research findings, e.g. (Sakshaug et al. 2010), indicate the hypothesis that there seems to be a correlation of accidents with traffic conflicts for specific conflict types. Nevertheless this study is based on a too small amount of data. As a consequence there might be conditional correlations between certain traffic conflicts and certain accident types, which emphasize, that there is an urgent need to intensify the efforts to transfer the "there might" into "there are (conditional) correlations between accidents and traffic conflicts". Clearly, this requires objective evidences by accurate, statistically verified long term measurements of traffic and performant methods to achieve the desired findings.

Due to the technical progress with regard to computer power, sensor systems, e.g. camera, radar and laser sensors, we now have the chance to measure and objectively assess the traffic situation with regard to traffic safety, see e.g. (Ismail et al. 2009, Saunier et al. 2010). Therefore it is necessary to realize an automated detection of traffic objects and an automated evaluation of the traffic situation. One possibility is to generate and analyze trajectories, i.e. spatiotemporal data, of traffic objects.

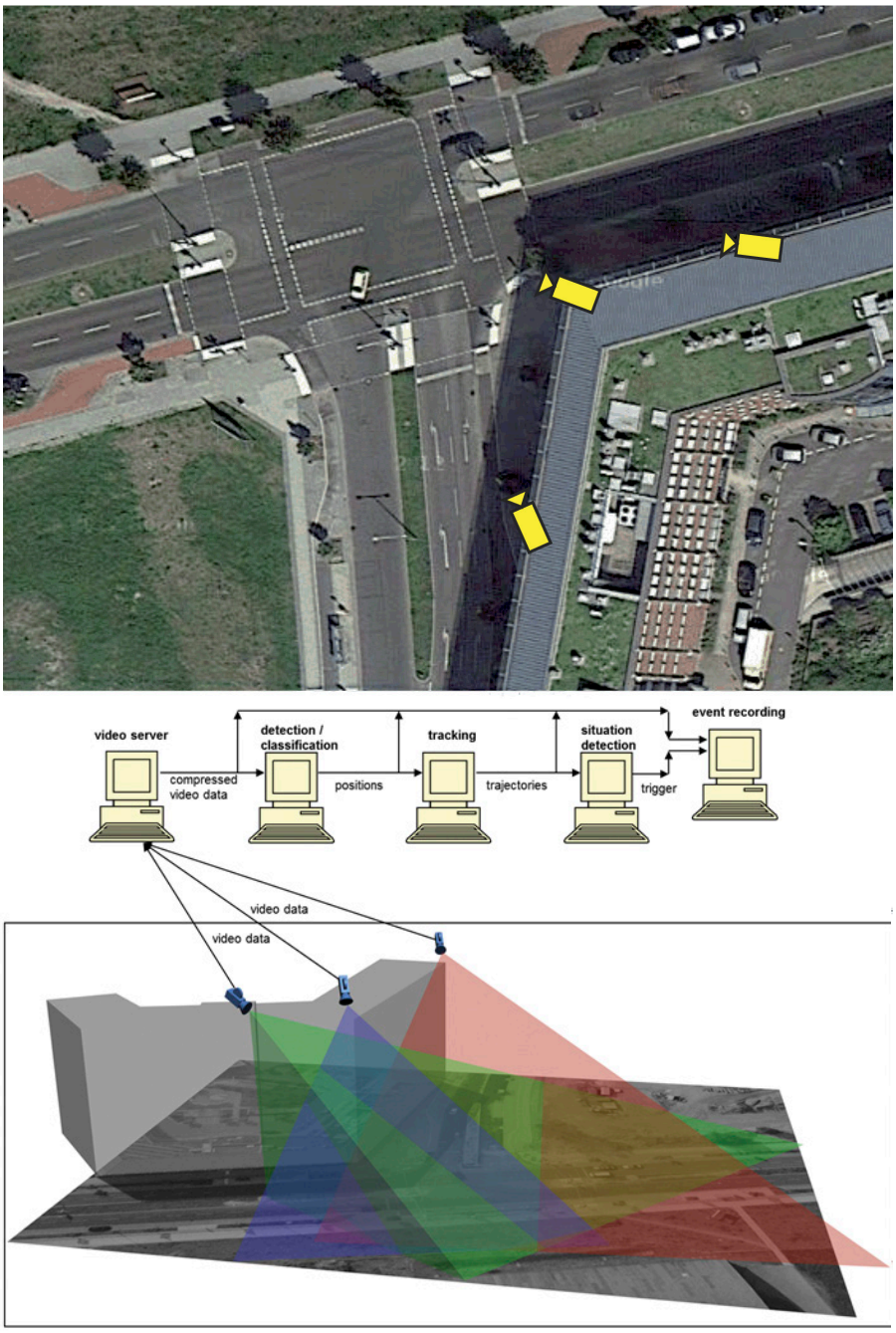


Fig. 2. Multi Camera System (MCS): Camera installation (top, ©googlemaps), Setup of the MCS (bottom)

2.2 Trajectory generation

To measure and quantify traffic safety it is necessary to detect the traffic participants in their interaction with other traffic participants and objects. Then, their upcoming behavior can be identified at an early stage. For that purpose selected urban intersections are equipped with performant sensors for traffic and environment detection. For instance the intersection Rudower Chaussee / Wegedornstraße, Berlin, Germany, is surveilled by a Multi Camera System (MCS), see *Fig. 2*, which is capable of detecting, classifying and tracking traffic objects. Tracking the traffic objects yields trajectories. By the superposition of the detected trajectories of each single traffic object crossing the intersection a spatiotemporal image of the traffic flow, which allows to assess traffic situations and eventually to quantify traffic safety.

For the generation of trajectories the following steps are required

• Object detection: There are several ways for object detection. One is to separate the moved foreground (traffic objects) from unmoved background, which can be obtained by background estimation, e.g. (Piccardi 2004). Another way is to place vehicle traps in the image, and use all pixels in the vehicle trap to compute some index value that indicates that an object is present, e.g. (Leich et al. 2015) in case of a vehicle trap based on a Histogram of Oriented Gradients Approach (HoG) (Dalal et al. 2005).

• Object classification: Classification of detected traffic objects in object and vehicle classes, e.g. car, truck, bicycle, etc.), which can be achieved by a particularly trained Support Vector Machine (SVM), e.g. (Chen et al. 2009).

• Object tracking: Generation of spatiotemporal curves of classified traffic objects to obtain trajectories by the application of adaptive filters (*Fig. 3*), for instance (Extended) Kalman Filter (e.g. Bar-Shalom 2001, Haykin 2001) or Particle Filter (e.g. Gordon et al. 1993, Ristic et al. 2004)

Fig. 3. Object detection by background estimation (top); object tracking (bottom)

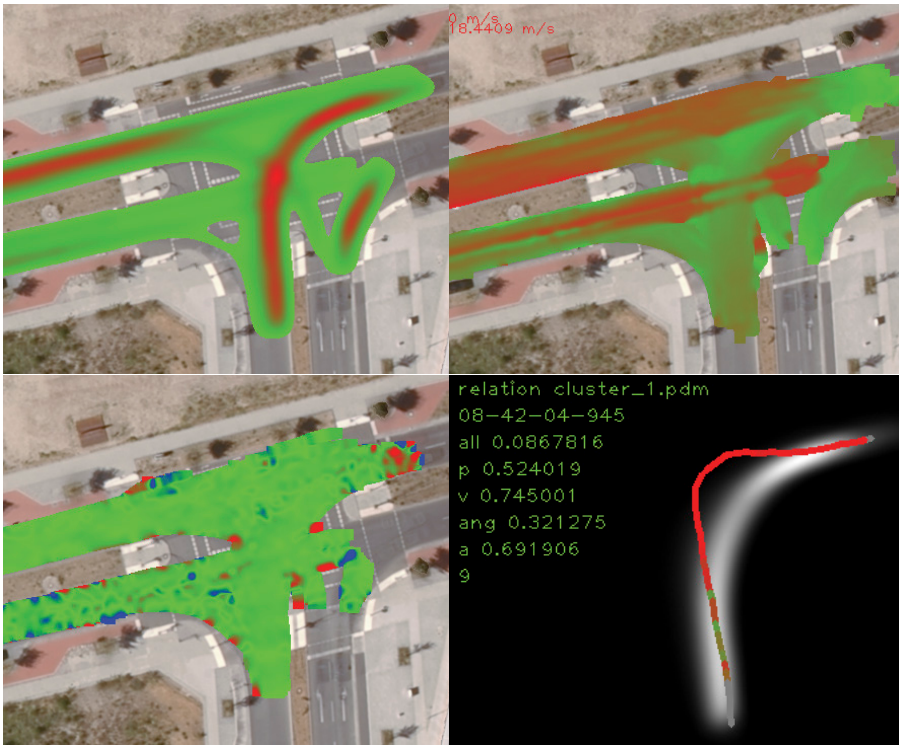


Fig. 4. Detection of atypical situations at an intersection: typical positions (top left), typical velocities (top right), typical accelerations (bottom left), atypical trajectory (bottom right) (Saul et al. 2014)

2.3 Analysis of traffic situations

Traffic situations imply traffic related and traffic safety related aspects:

- Traffic related: detection of traffic situations, particularly traffic break downs, i.e. the transition from free flow to synchronized traffic or the transition from synchronized flow to stop-and-go traffic, which are to be avoided by traffic and transportation management.
- Traffic safety related:
  - Detection of accidents
  - Detection and differentiation of atypical and dangerous situations.

In the following, the detection of atypical and dangerous situations is introduced.

Detection of atypical situations

As mentioned in (Detzer et al. 2014) "Atypical situations refer to incidents, which differ from the usual case, but most of all present a danger to road users." Examples are inadmissible U-turns, driving wiggling lines on less frequented roads, red light violations, etc. Atypical situations can evolve to dangerous situations.

For detecting atypical situations two approaches are applied:

(1) A Self Organizing Feature Map (SOFM) (Owens et al. 2000, Saul et al. 2014) is trained with measured trajectories. Its feature vector F consists of position (x, y), velocity (v_x, v_y) und acceleration (a_x, a_y) values. The functional s is a function with particular kernel size, which approximates these values:

$$F = \left(x, y, s(x), s(y), s(v_x), s(v_y), s(a_x), s(a_y)\right)^T$$

The training is finished as soon as a particular stop criterion is fulfilled. Afterwards, there occur feature vectors that describe normal situations very frequently. In contrast feature vectors for atypical situations occur rarely. Consequently, rare events can be surveilled directly by the SOFM.

(2) On the basis of normal trajectories a two dimensional probability density function (Probability Density Map, PDM) (Saul et al. 2014) is created. A „normal" trajectory fits in this PDM, while an atypical trajectory differs (see *Fig. 4*).

Detection of critical situations

Dangerous or critical situations are traffic situations, which may directly or indirectly lead to an accident, e.g. excessive speeds or speed differences in case of small headways to the vehicle driving in front, driving in the wrong direction, etc. For the determination of critical situations so called Safety Surrogate Measures (SSM) are measured, which may indicate an upcoming accident or conflict. Currently, several SSM are known, which can be categorized in time based, location based, kinematic based metrics that be found in several publications, e.g. (Allen et al. 1978, Hydén 1987, van der Horst 1990, Shelby 2011, Minderhoud et al. 2001, Kiefer 2005, Ozbay 2007, Cooper et al. 1976), which are more or less suitable for conflict and conflict severity estimation.

For instance, the time-to-collision (TTC) is the time that is needed to collide with a traffic participant, if no one changes his/her driving behavior. The TTC can be obtained by the ratio of the headway Δx between two traffic objects and their speed difference $\Delta v = v_0 - v_1$ (v_0: speed of the leading object, v_1: speed of the follower):

$$TTC = -\frac{\Delta x}{\Delta v}\Big|_{v_1 > v_0} \qquad \text{(Eq. 1)}$$

TTC values can be categorized as follows, which is in accordance to several empirical investigations, e.g. in the case of intersection conflicts see (Sayed 1998):

- TTC<2s: potential conflict, i.e. prepare for the upcoming situation
- TTC<1.5s: slight conflict, i.e. do something immediately to avoid the upcoming situation
- TTC<1s: serious conflict, i.e. an accident is almost unavoidable

Another SSM is for instance the deceleration rate to avoid the crash (DRAC), which can be computed as follows:

$$DRAC = \frac{\Delta v^2}{2\Delta x} = \frac{\Delta v}{2TTC} \qquad \text{(Eq. 2)}$$

By analogy to TTC critical DRAC values reach high braking acceleration. A critical situation occurs, for instance, if there is a DRAC > 4m/s², e.g. (Hydén 1998).

Fig. 5. Prediction of collision on the basis of measured positions

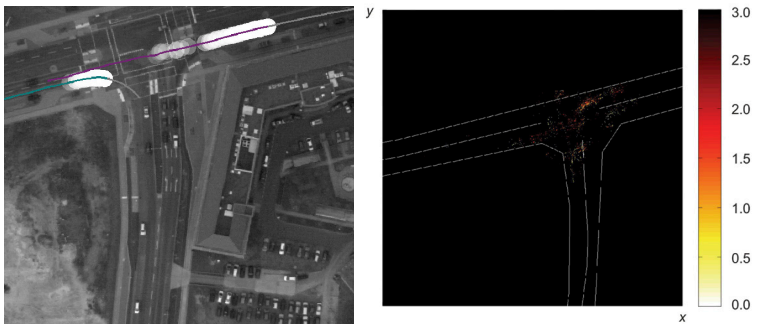


Fig. 6. Intersection area (left) and georeferencing of TTC values between 0 and 3s (right)

In *Fig. 5* the principle of an upcoming collision is shown. In the traffic scene (bottom right) the detected vehicles are masked and trajectories are determined and predicted (top left). In the case of interacting traffic objects, e.g. due to critical TTC or DRAC values, the colors of the predicted trajectories change from white (normal situation) to yellow (attention) and even red (upcoming accident).

By means of these and further SSM, critical situations and even their severity can be determined. By georeferencing these values, black spots can be determined (see *Fig. 6*) and dedicated measures to improve traffic safety can be launched.

3. Correlation analysis by probabilistic methods

3.1 Motivation

On the basis of traffic situations that are classified as atypical or dangerous, the next step is to make quantitative statements about traffic safety. For that purpose it seems reasonable not only to be restricted to accidental data (classical approach, see section 2.1), but also to integrate data about critical situations.

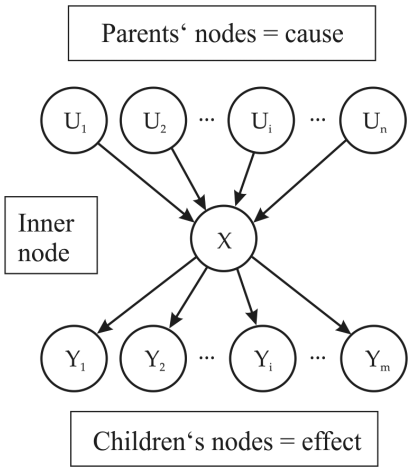
For decades the question about the functional correlation between accidents and critical situation has not sufficiently been answered yet. The common sense and some literature say: "yes", but if the tests are repeated or if the results are transferred to other intersections or tracks, it becomes evident, that this is not true, although a "no" seems to be wrong, too. Due to this, assumptions arise that conditional functional correlations probably exist, which are dependent on different conditions and circumstances, e.g. the conditional dependence on

- Time of day, time of year, season,
- Atmospheric conditions,
- Transport and traffic infrastructure and design,
- Traffic control and transportation management,
- Kinematics and driving dynamics (motion parameters, braking, steering, driving, etc.),
- Traffic state (e.g. free flow, synchronized flow, jam),
- Drivers and traffic participants and their mental and physical states,
- Vehicles and their states.

3.2 Probabilistic modelling as Bayesian Network (BN)

One possible way to a comprehensive analysis and assessment of recorded accident and near misses data is the concept of Bayesian Networks (BN). BN are a graphical formalism to process uncertain knowledge on the basis of causal relationships using probabilities. BN are directed acyclic graphs with nodes that represent random variables (e.g. events, situations) and arcs which describe the cause and effect relationships between the connected nodes (see *Fig. 7*). The nodes with "children" are called parents' nodes, the nodes that do not have "parents" are called root nodes. The nodes that do not have "children" are child nodes. All other nodes are inner nodes (Pearl 1991, Neapolitan 2004).

By the calculation of a BN a probabilistic model is created which quantifies the problem in question. For that purpose conditional probability tables are needed which form the joint probability distribution (JPD) by the application of the chain law, i.e. for an arbitrary BN with N nodes $X_1 \ldots, X_2$ and their N_i states $x_i = \{x_{i1}, \ldots, x_{iN_i}\}$, $\forall_i$ is:



BN allow causal reasoning (from cause to effect, i.e. downwards) and diagnostic reasoning (from effect to cause, i.e. upwards), which makes them very useful for diagnoses.

For the inner node X we can write according to Bayes' rule:

$$P(x|u_1, \ldots, u_n, y_1, \ldots, y_m) = \frac{P(x|u_1, \ldots, u_n)P(y_1, \ldots, y_m|x)}{P(y_1, \ldots, y_m|u_1, \ldots, u_n)}$$

with $Bel(x) = P(x|u_1, \ldots, u_n, y_1, \ldots, y_m)$,

the causal support $\pi(x) = P(x|u_1, \ldots, u_n)$

the diagnostic support $\lambda(x) = P(y_1, \ldots, y_m|x)$

and the normalization constant $\alpha = P(y_1, \ldots, y_m|u_1, \ldots, u_n)$

yielding

$$Bel(x) = \alpha \cdot \pi(x) \cdot \lambda(x) \qquad \text{(Eq. 3)}$$

Fig. 7. Generalized BN (left) and its calculation with causal and diagnostic supports (right)

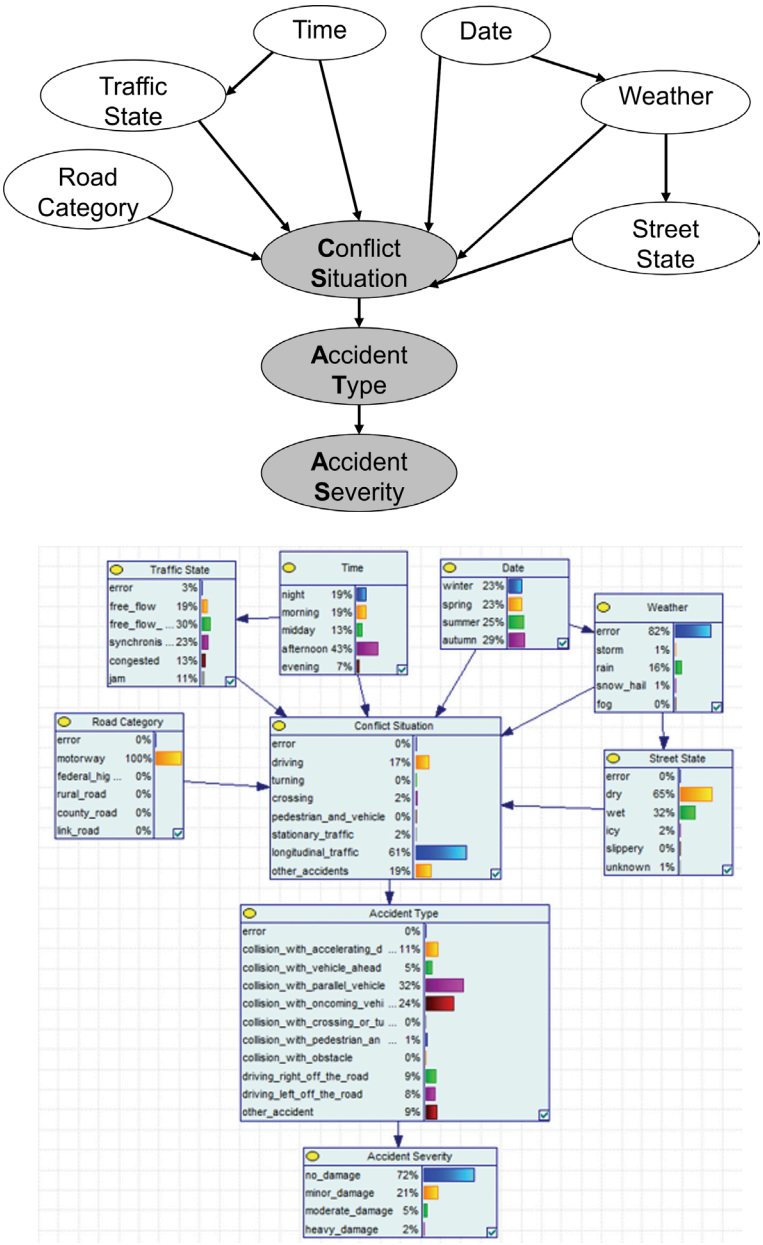


Fig. 8. Analysis of accident data of the motorway A2 with BN: causal graph (top), quantified BN (bottom)

$$P(x_1, x_2, \dots, x_n) = \prod_{x_i} P\left(x_i|\text{parents}(X_i)\right) \quad \text{(Eq. 4)}$$

Thus, for the BN in Figure 7 the JPD is:

$$P(x, u_1, \dots, u_n, y_1, \dots, y_m) = \\ = P(u_1, \dots, u_n)P(x|u_1, \dots, u_n)P(y_1, \dots, y_m|x) \quad \text{(Eq. 5)}$$

The quantification of the causal relationships by conditional probabilities enables the calculation of the JPD. That means, by means of BN it is not only possible to compute causal conclusion chains, but vice versa diagnostic conclusion chains by *Bel*(*x*) and the causal and diagnostic supports $\pi(x)$ and $\lambda(x)$. This process is called inference.

3.3 Example for accident data

An example for a BN, which can be created on the basis of the analysis of accident data of the German motorway A2 between Brunswick and Berlin in the years 2005 to 2008, considers as nodes accidents, time, traffic state, weather condition, road category and road state. Arranging these parameters and calculating the conditional probability tables yield one possible causal graph and a quantified BN as shown in *Figure 8* (Junghans et al. 2013).

In the BN in *Fig. 8* (top) the connections between different factors (root nodes) and the resulting traffic conflict / accidents are illustrated. It is evident that the different factors influence the upcoming accident. Here, it must be stated that each traffic conflict situation in the analyzed data used for learning the BN yielded an accident. Thus, the chain of causation starts with environmental and physical factors (weather, time, data, traffic state, street state, road category) that lead to a traffic conflict situation. This conflict leads to an accident type, which itself is characterized by a certain accident severity. The quantification of this causal graph with conditional probabilities yields the desired BN in *Fig. 8* (bottom), in which the transitions between the nodes are quantified with probabilities. Considering the BN for different traffic localities and furthermore, with regard to interesting parameters, e.g. weather or road state, it is possible to draw conclusions about traffic safety and to initiate measures to improve traffic safety.

If we consider the BN in *Fig. 8* in the opposite direction, i.e. diagnostically, statements about the causes of accidents on the basis of accident severity can be made for nodes of interest by the computation of Eq. 5. For instance, we can calculate the probability of a particular traffic state given the accident severity.

Having a look on the accident frequencies of the motorway A2 in *Fig. 9* (left) we can see that accidents at specific positions are more likely than at other positions. Taking *Fig. 9* (right) into consideration we can see the spatiotemporal context of all accidents within four years (days 1 to 1461), which shows areas that do not have so frequent accidents. It can be stated that there are accident clusters, e.g. at km 180, which is a motorway junction. Furthermore, it clearly indicates that the temporal analysis considering the accident causes is of essential need. For instance, it is noticeable that specific accident clusters occur only at particular times, which are marked with blue ellipses. This is particularly obvious in the case of the accident cluster between km 270 and 280 of the year 2007 (approximately the days 780 to 1000). In this area there is an inclined road, which was particularly dangerous in case of bad weather conditions (Schiessl et al. 2010). In the next year (2008) this part was redecorated, so that the number of accidents decreased.

In conclusion, BN are an adequate and powerful method to identify and quantify existing, but also unknown relationships between parameters of interest and influencing factors. The requirement to use BN is a sufficiently large data base with statistical significance. It is essentially important to analyze accidents spatiotemporally taking into account the environmental influences, e.g. road

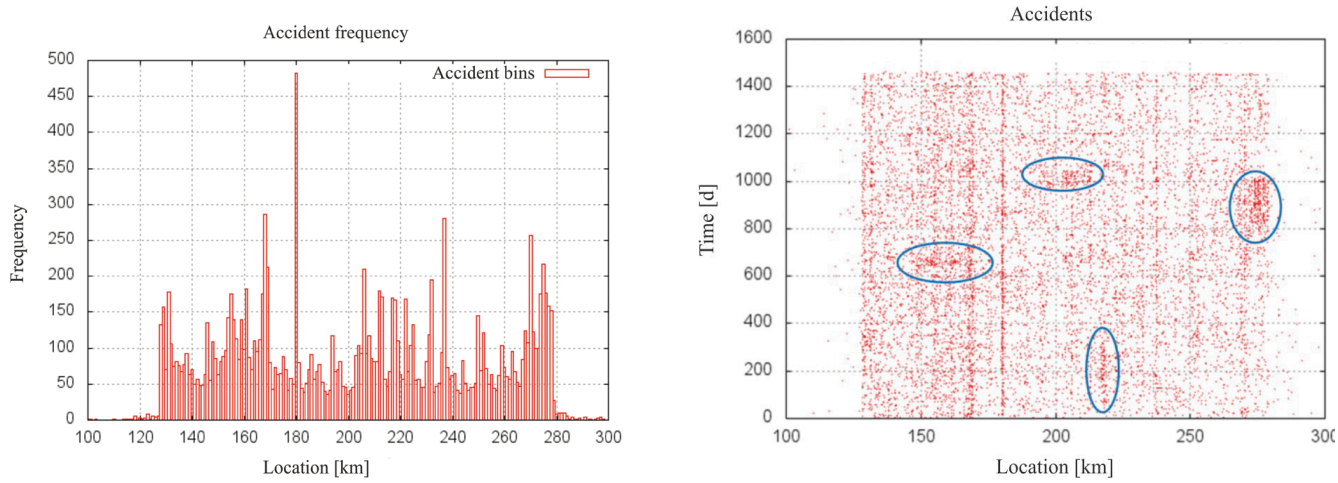


Fig. 9. Accident frequencies for the motorway A2 in different views: spatial (left); spatiotemporal view (right)

type, road state, weather conditions, traffic control measures. Further, it seems crucial, not only to restrict the traffic safety analysis only to accidents, but to consider other influencing factors, which describe critical traffic situations that may lead to accidents, or factors influence safety directly or indirectly. For instance: probability distributions of braking and steering maneuvers, ABS (Antilock Brake System) and ESP (Electronic Stability Program) activities of the vehicles, but also control phases of traffic lights, the states of the traffic infrastructure, etc. First promising analyses on the basis of BN were for instance made in (de Ona et al. 2011, Gregoriades et al. 2013).

3.4 Extension with safety related parameters

In this section the BN of section 3.2 (*Fig. 8*) will be extended by the results of section 3.3, which can be used for future research. For instance, it can be similar to the causal graph shown in *Fig. 10*, which presents the causal relationships between traffic conflict and influence parameters. These parameters are to be understood as collective terms that quantify all influences in one node. Clearly, for specifying a BN these nodes have to be disaggregated. For instance, the collective term node "Kinematics and driving dynamics" contains all nodes like braking intensity, steering intensity, ESP, ABS and other as well as all the relationships among these nodes. The collective term node "Traffic control" combines all nodes for the signaling, phases of the traffic lights, etc.

Furthermore, it can reasonably be assumed that there are dependencies between the illustrated influence nodes, which are omitted here due to reasons of simplicity. For instance, it is clear that particular brake and steering intensities (node "Kinematics and driving dynamics") are causally connected with the node "Driver behavior", since these are the results of the reaction of accident/traffic conflict participants on the upcoming critical situation.

In *Fig. 10* a further difference to *Fig. 8* can be mentioned, which shows that there can also be a direct causal relationship between the conflict situation and the accident severity in addition to the indirect relationship between conflict situation, accident type and accident severity. From a traffic safety point of view it is important to predict the accident severity that results from traffic conflicts.

4. Discussion

This article dealt with questions concerning the chances for the evaluation of the traffic safety risk by novel methods, whereas this question has not completely been answered. Instead, it can be seen as a basis for future analyses and evaluation of traffic safety and is derived from the current state of research, which has to be discussed further with scientists, local authorities, ministries, traffic safety institutions, etc.

At the beginning of the article it was shown, making no claim to be complete, which steps are necessary to objectively measure traffic safety, i.e. object detection, object classification, object tracking, trajectory generation and trajectory classification with regard to normal, atypical, critical situations and accidents. Furthermore, it was pointed out that the functional correlation between accidents and critical traffic situations is necessarily needed to utilize safety relevant parameters (also called as surrogate safety measures), but is still under current international state of research. In the case this correlation can be found, indeed, critical situations can be applied to measure and quantify traffic safety. For that purpose the concept of Bayesian Networks (BN) was introduced, which enables the identification and analysis of unknown functional correlations on

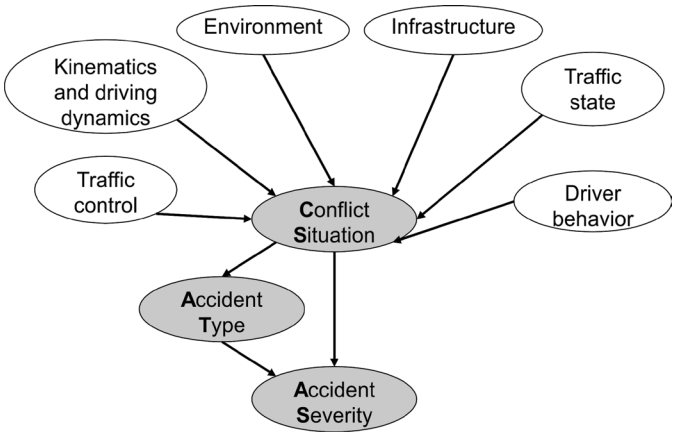


Fig. 10. Different influence parameters extend the causal graph of Fig. 8

a probabilistic and spatiotemporal level. Then, statements about the probability of accident types and accident severity can be made solely on the basis of traffic situations influenced by the parameters (factors) infrastructure, traffic state, driver behavior, road type and state, driving dynamics, etc. This would be an enormous advantage for the safety related evaluation and assessment of traffic areas. For that reason the promising chances can be seen as follows:

• Improvement of traffic safety research and establishment of powerful and tested methods of analysis

• Identification and quantification of the influence of risk factors (e.g. infrastructure, traffic control, driver, driving dynamics, etc.) on traffic safety in traffic areas

• Implementation of suitable measures to improve traffic safety and the minimization of the number of killed or severely injured people in traffic by the avoidance of accidents.

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