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Minimising Missed and False Alarms: A Vehicle Spacing based Approach to Conflict Detection

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***Abstract*— Safety is the cornerstone of L2+ autonomous driving and one of the fundamental tasks is forward collision warning that detects potential rear-end collisions. Potential collisions are also known as conflicts, which have long been indicated using Time-to-Collision with a critical threshold to distinguish safe and unsafe situations. Such indication, however, focuses on a single scenario and cannot cope with dynamic traffic environments. For example, TTC-based crash warning frequently misses potential collisions in congested traffic, and issues false alarms during lane-changing or parking. Aiming to minimise missed and false alarms in conflict detection, this study proposes a more reliable approach based on vehicle spacing patterns. To test this approach, we use both synthetic and real-world conflict data. Our experiments show that the proposed approach outperforms single-threshold TTC unless conflicts happened in the exact way that TTC is defined, which is rarely true. When conflicts are heterogeneous and when the information of conflict situation is incompletely known, as is the case with real-world conflicts, our approach can achieve less missed and false detection. This study offers a new perspective for conflict detection, and also a general framework allowing for further elaboration to minimise missed and false alarms. Less missed alarms will contribute to fewer accidents, meanwhile, fewer false alarms will promote people's trust in collision avoidance systems. We thus expect this study to contribute to safer and more trustworthy autonomous driving.**

***Index Terms*— Advanced Driving Assistance System, Forward Collision Warning, collision avoidance, conflict detection, vehicle spacing patterns**

I. INTRODUCTION

The common concern of driving safety is one of the imperative aspects in the development of Advanced Driving Assistance Systems (ADAS). To prevent accidents and mitigate crash severity, collision avoidance systems (CAS) play a critical role. In general, CAS encompasses two proactive components: forward collision warning (FCW) which alerts drivers to imminent collisions, and automatic emergency braking (AEB) which initiates corrective actions such as braking or steering when the driver fails to respond timely. The effectiveness of both FCW and AEB hinges on the accurate detection of conflicting vehicular interactions, which potentially entail collisions.

Conflict detection leverages data collected from various sensors such as radar, lidar, and cameras. In the past two decades, real-time road user detection and tracking have been the predominant challenge in CAS [1], and substantial research efforts have been devoted to this task [2–4]. Along with the rapidly evolving advances in computer vision, constant improvements have been made on object detection and tracking [5,6]. Nowadays, these techniques are extensively employed in current intelligent cars.

With increasingly accurate localisation of other road users, forward conflicts can be indicated using the surrogate safety measure, Time-to-Collision (TTC). TTC is one of the most effective and broadly used indicators for rear-end collisions [7–10]. It estimates how much time remains until a collision between two vehicles following each other [11,12]. As an continuous variable, TTC has been used to assess pedestrian-vehicle interaction risk [13,14], vehicular collision risk [15–17], and safe autonomous driving [18,19]. When applied to collision warning, TTC needs to be discretised with critical thresholds in order to distinguish un(safe) situations. More specifically, a TTC value shorter than the critical threshold indicates high enough risk of a collision. Such a threshold determines when CAS should issue emergency warnings and intervene if the driver does not take action [20].

While threshold-based detection is straightforward and computationally efficient, it often falls short in dealing with dynamic traffic environments and more complex driving interactions [21]. For example, when vehicles maintain similar speeds in relatively dense traffic, the TTC between them is very large and suggests a low risk of collision. There then may be missed alarms, as traffic fluctuations can propagate and pose unexpected hazards. For another example during lane-changes, vehicles may exhibit short TTC values that indicate a high risk of crash. However, such alarms can be false as the drivers of the interacting vehicles often anticipate each others' actions and would not perceive an imminent threat. As such, threshold-based conflict detection can yield inconsistent reliability across different driving conditions.

Reliable conflict detection requires minimising missed and false alarms, which remains a challenge. According to an analysis of the consumer complaints about safety-relevant ADAS failures [22], more than 30% of complaints are about AEB and FCW, and over 75% of these complaints are about missed and false alarms. Missed alarms overlook dangerous scenarios and can preclude intervention opportunities, while false alarms might trigger distracting or even disruptive driver responses [23,24]. In addition, many studies have found that false alarms may diminish drivers' trust and compliance with the assistance systems [25–27]. Frequent incorrect alarms violate drivers' expectations about system warnings, and hence undermine their behavioral adaptation to ADAS.

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We open source our code at https://github.com/Yiru-Jiao/Conflict-detection-MFaM

Therefore, there is an increasing need for a more reliable method to detect conflicts and prevent collisions. In this paper, we provide a new approach to minimising missed and false detection of conflicts. With preliminary experiments, we will demonstrate that this method is characteristic of

- data-driven detection based on vehicle spacing patterns;
- adjustable balance between missed and false alarms;
- adaptive-tuning to varying traffic scenarios and driver preferences.

II. Methods

A. Indication of conflicts

An interaction between two vehicles can be indicated as safe or unsafe based on the information gathered about this scenario. An unsafe interaction is a conflict[1]. For a scenario at time t with a vehicle i and another vehicle j, a set of variables can describe this scenario and be denoted by $X_{ij}^t = \{\boldsymbol{x}_i^t, \boldsymbol{x}_j^t, \boldsymbol{x}_E^t\}$. Here $\boldsymbol{x}_i^t$ and $\boldsymbol{x}_j^t$ respectively encapsulate the motion of vehicles i and j, and $\boldsymbol{x}_E^t$ is about the physical environment such as weather and road conditions. We can process the information X_{ij}^t as represented in Equation (1):

$$X_{ij}^t = \{s_{ij}^t, \theta_{ij}^t\}, \tag{1}$$

where s_{ij}^t is the spacing between vehicles i and j, and θ_{ij}^t encodes the conflict situation where this scenario occur. Generally, a smaller value of s_{ij}^t suggests a higher likelihood that vehicles i and j are in a conflict and a collision could happen. A critical spacing s^* is then required to determine whether vehicles i and j are close enough to be considered as a conflict. As formulated in Equation (2), $C(X_{ij}^t)$ indicates the scenario X_{ij}^t as a conflict (abbreviated as c) or a non-conflict (nc) by comparing s_{ij}^t and s^*, where s^* depends on the specific situation captured by θ_{ij}^t.

$$C(X_{ij}^t) = C(s_{ij}^t, s^*|\theta_{ij}^t) \begin{cases} \text{c}, & \text{if } s_{ij}^t \leq s^*(\theta_{ij}^t), \\ \text{nc}, & \text{otherwise.} \end{cases} \tag{2}$$

Existing conflict indicators (of which most are surrogate safety measures) can all fit in this expression. For example, TTC is typically calculated by assuming no change in movement of the interacting vehicles, i.e., the drivers are unable to react in time. This assumption considers the relative speed between vehicles as the only condition so that $\theta_{ij}^t = \Delta v_{ij}^t$. In this case, given a threshold TTC*, the critical spacing $s^* = \Delta v_{ij}^t \text{TTC}^*$. Time headway (THW) is another widely used conflict indicator [7]. Let vehicle j follow vehicle i, $\text{THW}_{ij}^t = s_{ij}^t / v_j^t$ thus $\theta_{ij}^t = v_j^t$. Then the speed of the following vehicle j becomes the condition considered. Given a threshold THW*, equivalently, the critical spacing is $v_j^t \text{THW}^*$.

[1]Here we consider car-following and thus one-to-one interaction. Multiple vehicles can be considered in other interaction scenarios

B. Probability of missed and false alarms

Under a specific interaction situation θ, conflict detection is a binary classification based on vehicle spacing s and a critical threshold s^*. The probability distributions of spacing s respectively of conflicts and non-conflicts may overlap, as illustrated in Fig. 1. Therefore, determining the critical spacing s^* involves a trade-off between missed and false alarms. *Missed alarms* misclassify unsafe scenarios as safe (false negatives) and *false alarms* misclassify safe scenarios as unsafe (false positives). Generally, smaller s^* leads to fewer false alarms and more missed alarms. In contrast, larger s^* reduces missed alarms but increases false alarms.

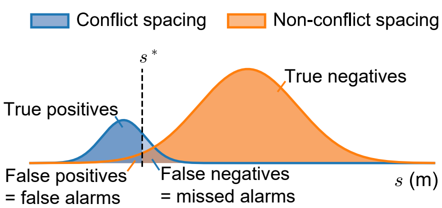

Fig. 1. Illustration of the trade-off between missed and false alarms.

Considering the spacing between two vehicles as a random variable S, we can estimate the probability of missed alarm and missed alarm when considering a spacing s as the critical threshold. As presented in Equations (3), PMA(s) denotes the conditional probability of missed alarms (false negatives) and PFA(s) denotes the conditional probability of false alarms (false positives). In this context of conflict indication, a positive means $S \leq s$ and a negative means $S > s$; a true event is a conflict (c) and a false event is a non-conflict (nc).

$$\begin{cases} \text{PMA}(s) = P(S > s|\text{c}) \\ \text{PFA}(s) = P(S \leq s|\text{nc}) \end{cases} \tag{3}$$

Given $p(A|B) = p(AB)/p(B)$ in Bayes' theorem and $p(A\bar{B}) = p(A) - p(AB)$ in set theory, we transform PMA(s) into Equation (4) and PFA(s) into Equation (5), where $s_{\max}$ is a large enough value of spacing and will be specified in Section II-D.

$$\text{PMA}(s) = P(S \leq s_{\max}|\text{c}) - P(S \leq s|\text{c}) \tag{4}$$

$$\begin{aligned} \text{PFA}(s) &= \frac{P(S \leq s, \text{nc})}{P(S \leq s_{\max}, \text{nc})} \\ &= \frac{P(S \leq s) - P(S \leq s|\text{c})p(\text{c})}{P(S \leq s_{\max}) - P(S \leq s_{\max}|\text{c})p(\text{c})} \end{aligned} \tag{5}$$

Equations (4) and (5) include two cumulative probabilities, which can be estimated from data. One is of S and we denote its probability density function as $f(x)$ in Equation 6. The other is of S in conflict, and we denote its probability density function as $g(x)$ in Equation 6.

$$\begin{cases} f(x) = \dfrac{\mathrm{d}}{\mathrm{d}x} P(S \leq x) \\ g(x) = \dfrac{\mathrm{d}}{\mathrm{d}x} P(S \leq x|\text{c}) \end{cases} \tag{6}$$

Summarising these derivations, when using s as the critical spacing to distinguish safe and unsafe scenarios, the probability of missed and false alarms are computed according to

Equation (7).

$$\begin{cases} \mathrm{PMA}(s) = \displaystyle\int_{s}^{s_{\max}} g(x)\mathrm{d}x, \\ \mathrm{PFA}(s) = \dfrac{\int_0^s f(x)\mathrm{d}x - k\int_0^s g(x)\mathrm{d}x}{\int_0^{s_{\max}} f(x)\mathrm{d}x - k\int_0^{s_{\max}} g(x)\mathrm{d}x}, \end{cases} \tag{7}$$

where $k = p(\mathrm{c})$ can be counted as the conflict frequency.

C. Spacing patterns between vehicles

Computing $\mathrm{PMA}(s)$ and $\mathrm{PFA}(s)$ needs the two spacing distributions $f(x)$ and $g(x)$. In this study, we use Gaussian kernel density estimation (KDE)[2] to give a preliminary demonstration.

For a certain interaction situation $\boldsymbol{\theta}$, let $\boldsymbol{s}$ be the set of s_{ij}^t, of which the corresponding $\theta_{ij}^t \in \boldsymbol{\theta}$; we then denote the subset of $\boldsymbol{s}$ in conflict by $\boldsymbol{s}_\mathrm{c}$. To estimate $f(x)$, we apply Gaussian KDE to the samples $s_1, s_2, \ldots, s_n$ in $\boldsymbol{s}$. Similarly, to estimate $g(x)$, we apply Gaussian KDE to $\boldsymbol{s}_\mathrm{c}$.

D. Minimising missed and false alarms

Based on the estimated probabilities of missed alarms and false alarms, we can optimise a critical spacing as in Equation (8). The parameter α is the weight on minimising missed alarms and $1-\alpha$ on false alarms. This makes the optimisation weigh between less missed alarms or less false alarms. As a result, a reliable critical spacing s^* should minimise the balanced probability of false negatives and false positives. We call this method missed and false alarm minimisation, which can be abbreviated as MFaM.

$$s^* = \underset{0 \le s \le s_{\max}}{\arg\min}\ \alpha\mathrm{PMA}(s) + (1-\alpha)\mathrm{PFA}(s) \tag{8}$$

Fig. 2 gives an example of applying MFaM, where $\mathrm{PMA}(s)$ and $\mathrm{PFA}(s)$ are estimated based on real spacing samples. As s increases, the probability of missed alarms decreases and the probability of false alarms increases. Then various $s^*(\theta)$ can be obtained by minimising the weighted sum of $\mathrm{PMA}(s)$ and $\mathrm{PFA}(s)$ given different α.

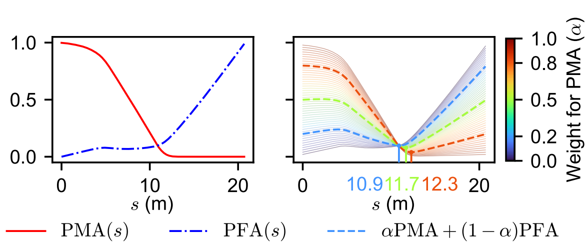

Fig. 2. An example of minimising missed and false alarm probability.

A proper value for $s_{\max}$ is necessary in the Equations (7) and (8). In Equation (7), $s_{\max}$ determines the range within which $\mathrm{PMA}(s)$ and $\mathrm{PFA}(s)$ are normalised to the interval [0,1]. In Equation (8), $s_{\max}$ sets the searching range for s^*. Although $s_{\max}$ approaches ∞ in theory, a range is important to facilitate computation in practice. In this study, we take the maximum between two values, as shown in Equation (9).

$$s_{\max} = \max\{\max \boldsymbol{s}_\mathrm{c}, \arg\max_{s} f(s)\} \tag{9}$$

The first value in Equation (9) is the maximum of conflict spacing $\boldsymbol{s}_c$. This ensures that all the occurred conflicts are considered. The second value is the most probable spacing in $\boldsymbol{s}$. The spacing maintained between vehicles is based on drivers' perception and preferences. Therefore, we assume that the most frequently maintained spacing is safe enough for most drivers.

III. Experiments

This study introduces a new approach, MFaM, aiming for more reliable conflict detection. To demonstrate this approach, we conduct experiments with both synthetic conflicts and real-world conflicts.

A. Synthetic conflicts

We used a subset called Freeway-B of the CitySim dataset [28] to generate synthetic conflicts. Freeway-B comprises trajectories collected on a 725-m segment of a 6-lane road (three lanes per direction). The movements of 6,555 vehicles in a duration of 0.57 hours were recorded at a frequency of 30 Hz. The average flow was approximately 1,917 veh/hour/lane. This is indicative of congested traffic that is more likely to yield conflicts than fee-following traffic. In total 3,082 car-following pairs were extracted from the dataset.

Existing studies in conflict detection often assume conflicts as when TTC values falling below a critical threshold, to name a few, see [29–31]. However, relying solely on relative speed (as assumed by TTC) to determine whether a conflict occurs is inadequate, especially when the absolute speed is slow. In this paper, we define three types of conflicts for a more comprehensive comparison to demonstrate our approach. As outlined in Table I, we let type I and type II conflicts be conditioned by relative speed only, but additionally consider the absolute speed of following vehicles for type III conflicts. For type I conflicts, we set a uniform threshold to distinguish unsafe scenarios homogeneously; while we use various thresholds for defining type II and type III conflicts heterogeneously.

B. Real-world conflicts

For real-world conflict data, we reconstructed trajectories[3] from the 100-Car Naturalistic Driving Study's time-series data [32]. The data was collected during an instrumented-vehicle study conducted in the Northern Virginia / Washington, D.C. area in early 2000s [33]. The instrumentation was designed to be unobtrusive, study participants were given no special instructions, and experimenters were not present.

From the data collection, an event database was compiled consisting of 68 crashes and 760 near-crashes which were manually reviewed and annotated. With the time-series profile for each event, containing radar and accelerometer data

[2] We applied the function "gaussian_kde" from the python library "scipy" with default arguments.

[3] We open source this reconstruction at https://github.com/Yiru-Jiao/Reconstruct100CarNDSData

TABLE I

CONFLICT DETERMINATION FOR TEST EXPERIMENTS

Conflict type	Conditions (θ)		Threshold (m)
	Relative speed (m/s)	Follower speed (m/s)	
I	$\Delta v > 0$		$s \leq 3\Delta v$
II	$\Delta v > 5$		$s \leq 2.5\Delta v$
	$2 < \Delta v \leq 5$		$s \leq 3\Delta v$
	$0 < \Delta v \leq 2$		$s \leq 3.5\Delta v$
III	$\Delta v > 5$		$s < 2.5\Delta v$
	$2 < \Delta v \leq 5$	$v > 25$	$s \leq 3.5\Delta v$
		$10 < v \leq 25$	$s \leq 3\Delta v$
		$v \leq 10$	$s \leq 2.5\Delta v$
	$0 < \Delta v \leq 2$	$v > 5$	$s \leq 0.5v$
		$2 < v \leq 5$	$s \leq 0.3v$
		$1 < v \leq 2$	$s \leq 0.6$

spanning 30s before the event and 10s after the event, we reconstructed bird's eye view trajectories for the vehicles involved in these events. Not all of the events can be reconstructed due to the missing values, inaccuracy of sensing, and the lack of a ground truth; matching the conflicting vehicle among the detected vehicles in each event is neither trivial. Eventually, we obtained 219 car-following near-crashes of which vehicle trajectories are properly reconstructed and conflicting vehicles are matched.

With the two conflict datasets, we apply MFaM under varying weights for missed and false alarms, and then compare the detection results with those obtained using TTC with a range of critical thresholds. The next section will present and discuss the results.

IV. RESULTS AND DISCUSSION

Our experiments assume that the only known information of conflict situation $\boldsymbol{\theta}$ is relative speed. This aligns with the assumption of TTC-based detection. By doing so, different synthetic conflict types allows for comparisons under different levels of information completeness and conflict heterogeneity. The detection of type I conflicts represents the detection of homogeneous conflicts with complete information of conflict situation; the detection of type II conflicts then represents that of heterogeneous conflicts with complete information of conflict situation; and the detection of type III conflicts represents the cases where incomplete information is known and the conflicts are heterogeneous. From type I to type III, these synthetic conflicts were designed to simulate more realistic and complex conflicts. At the end, we will demonstrate the detection of real-world conflicts.

A. Detection of synthetic conflicts

Fig. 3 shows the detection of type I conflicts using TTC and MFaM. A total number of 21,885 type I conflict moments are defined utilising a uniform TTC* (critical threshold of TTC) of 3 seconds. This criterion makes the conflict situation $\boldsymbol{\theta}$ include solely the relative speed between a vehicle and its preceding vehicle, which is completely considered in conflict detection. With increasing values of TTC* and the weight assigned for missed alarms (α), there are fewer missed alarms and more false alarms. Remarkably, both missed alarms and false alarms reach 0% when TTC* is precisely 3 seconds. In contrast, MFaM does not have such an optimal point. When the weight for missed alarms is larger than 0.2, there are very few missed alarms and the rate of false alarms is also low.

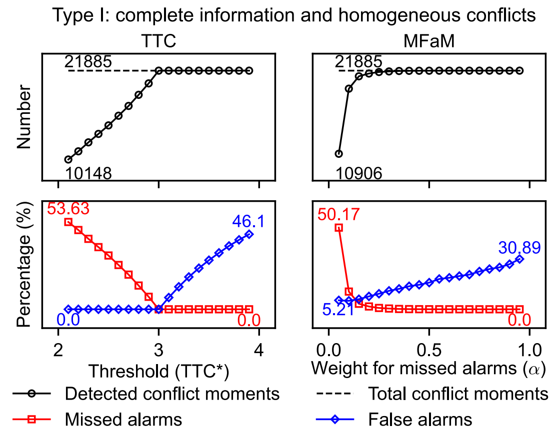

Fig. 3. Type I conflict detection using TTC and MFaM.

The detection of type II conflicts, as shown in Fig. 4, shows similar patterns as of detecting type I conflicts. The 26,912 conflict moments are also conditioned by relative speed only, however, are defined using varied critical thresholds. For these heterogeneous conflicts, implementing MFaM leads to a very similar tendency of increasing false alarms while reducing missed alarms as observed in type I conflict detection. In contrast, when using TTC, both trends of more false alarms and fewer missed alarms with increasing TTC* are slower than in type I conflict detection. Furthermore, there is no longer an optimal TTC* where both missed alarms and false alarms reach 0%.

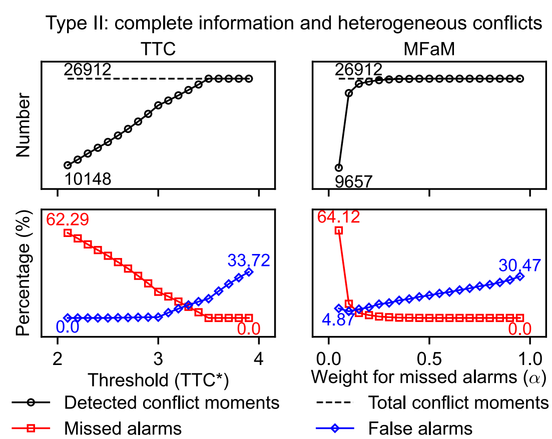

Fig. 4. Type II conflict detection using TTC and MFaM.

The challenge of reliable conflict detection is intensified with the 34,203 type III conflict moments, as displayed in Fig. 5. The detection is characterised by conflict heterogeneity and incomplete information on conflict situation. Regardless of the magnitude of TTC*, more than 69.36%

conflict moments are missed if using TTC. Conversely, MFaM manages to detect nearly all (99.69%) conflict moments, although this is at the expense of a heightened rate of false alarms.

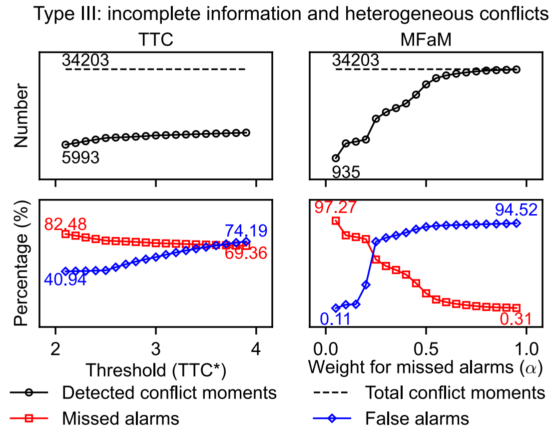

Fig. 5. Type III conflict detection using TTC and MFaM.

B. Trade-off between missed and false alarms

Observing the detection results of these three types of conflicts, there exists an inherent trade-off between missed alarms and false alarms. This trade-off is particularly significant when the conflict situation are incompletely known. Fig. 6 illustrates the trade-off curves for detecting the three types of synthetic conflicts, where optimal performance is indicated by the proximity to the origin $(0\%, 0\%)$. Next, we will first analyse the effectiveness of MFaM across homogeneous (type I) and heterogeneous (type II) conflicts. Then we will compare its performance when the information of conflict situation is completely known (type II) or only partially known (type III).

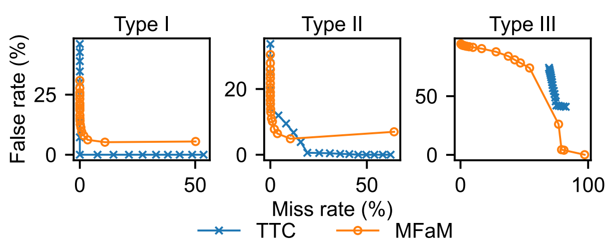

Fig. 6. Trade-off between miss rate and false rate in conflict detection.

1) Homogeneous vs. heterogeneous conflicts: Both the detection of type I and type II conflicts have complete information on conflict situation available. Comparing the subfigures of type I and type II in Fig. 6, it is evident that MFaM demonstrates robust effectiveness across homogeneous and heterogeneous conflicts, while TTC does not. For homogeneous conflicts (type I), TTC can ascertain the precise critical threshold, thereby achieving $(0, 0)$ rates of missed and false alarms. In contrast, heterogeneous conflicts (type II) preclude the identification of a single critical threshold applicable to TTC. Conflicts, in reality, are heterogeneous due to factors such as dynamic traffic environments and diverse human driving styles. For this reason, robust detection of conflicts requires managing the heterogeneity of conflicts.

2) Complete vs. incomplete information: While both type II and III conflicts are heterogeneous, the detection of type II conflicts considers complete information and the detection of type III conflicts operates with only partial information of conflict situation. In the sub-figure of detecting type II conflicts in Fig. 6, MFaM can reach a commendable balance of low missed and false alarms. This outperforms TTC, which has comparable performance to MFaM only when the miss rate is around 15%. In the sub-figure of type III conflict detection where the information is incompletely known, MFaM's curve consistently outperforms TTC. Nevertheless, neither TTC nor MFaM attains low rates of missed and false alarms due to information insufficiency.

C. Detection of real-world conflicts

As presented in Fig. 7, the detection results of the real-world conflicts in 100-Car data resembles the detection of type III synthetic conflicts. Around 41.28% conflict moments cannot be detected if using TTC. In contrast, MFaM can detect around 98.80% of them, but still, along with a high rate of false alarms. The trade-off curves of this real-world conflict detection, at the right of Fig. 7, also show similar trends as the detection of type III synthetic conflicts: MFaM consistently outperforms TTC.

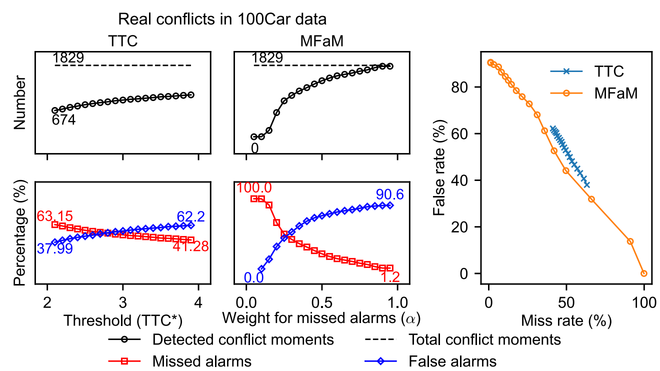

Fig. 7. Real-world conflict detection using TTC and MFaM.

Real-world conflicts are heterogeneous and the information on conflict situation in detection is always imperfect, which, however, significantly influences the detection effectiveness. Despite the lack of information, MFaM can detect the highest possible number of actual conflicts at the expense of an increased rate of false alarms. To reduce false alarms while preserving minimised missed alarms, it is important to include multi-source information for conflict detection in future studies.

V. Conclusion

This study presents a new approach to more reliable conflict detection, which minimises the estimated probabilities of missed and false detection based on vehicle spacing patterns. We abbreviate this method as MFaM representing Missed and False alarm Minimisation. Through comparative experiments of applying MFaM and TTC on both synthetic and real-world conflicts, hereby we summarise the main features:

- MFaM secures a better balance between missed and false alarms compared to TTC in detecting heterogeneous conflicts, both the synthetic and real-world ones;
- MFaM surpasses TTC in accurately identifying true conflicts, especially when the information of conflict situation is incomplete;
- MFaM is flexible to be extended given various vehicle spacing patterns. For example, it can be used to develop user-adaptive collision warning given that drivers perceive different levels of collision risk and react differently to automatic warnings.

Beyond the approach itself, the importance of the information considered in conflict detection is particularly notable. If given limited information of conflict situation, we argue that there is a trade-off curve between missed and false alarms that constrain any algorithms for conflict detection. Nevertheless, this requires further exploration. Our future research will include utilising more effective information of conflict situation and developing adaptive algorithms that can account for varying response patterns of drivers. These developments will enhance the reliability of ADAS collision warning, contributing to safer and more trustworthy autonomous driving.

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