Reliability of cooperative ADAS and the importance of the acceleration function for cycling safety

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1 INTRODUCTION

Cycling has become increasingly important on German roads over the past 20 years. However, the number of crashes involving cyclists, which may go along with severe injuries or fatalities, is increasing. Between 2010 and 2018 the number of killed cyclists increased from 381 to 445 (+16.8%) [1]. The interaction of right-turning motorists with passing cyclists is one of the most critical ones, particularly if the cyclist is relatively behind the motorist (i.e., in its blind spot). Advanced driver assistance systems (ADAS) are being developed in order to assist in potential critical situations before they evolve to crashes. Infrastructure-based, cooperative solutions could inform or warn road users before a potential collision via V2X or a roadside entity, such as a dedicated traffic light. The Bike Flash system is an example of such a solution [2]. Its drawback is that it warns if a cyclist is present without considering the possible outcome of the situation (e.g., dangerous or not), which can lead to acceptance problems. Thus, in [3] an algorithm was developed and successfully tested, capable of sending out warnings if a potential crash was predicted. For this purpose, a construction traffic light, called "amber light" (AL), was used to inform the right-turning motorists about potential collisions. This method is based on a decision tree (DT) considering the distances of the interacting cyclists and motorists to their collision/conflict point (CP), their speeds and the predicted post encroachment time (pPET), which continuously quantifies to what extent two interacting partners will miss each other. Interestingly, the acceleration functions of the road users are not part of the DT, although they are—except the change of direction—the only control parameters to realise evasive actions. Further, it is not clear, at what distance to the CP crash warnings are reliable and thus, where such an AL should be installed. We will address these open aspects by analysing the acceleration functions of cyclists and motorists in unaffected, uncritical and critical encounter situations in the time and frequency domains. We will emphasize the importance of acceleration functions distinguishing between critical and uncritical encounters in certain distances before the CP. Furthermore, we will show that critical encounters of cyclists and uncritical encounters of motorists show completely different characteristics, and we will try to measure surprise (or anticipation) by applying the entropy metric on the acceleration functions and conduct inference statistical tests. In terms of reliability and location of such a warning system before the CP we will compute pPET while considering kinematic patterns of the road users. These are examples of some of the essentially important aspects to establish well-accepted cooperative warning systems in the future.

2 THEORY

First, we reduced the whole data set (section 3) by computing and remaining interaction situations with PET<2.5s. The videos of the selected interactions were annotated by experts. For these situations we applied the DT according to [3] and computed the distance-dependent confusion rates sensitivity, specificity, over- and underestimation (Figure 1, top). Second, we computed kinematic patterns of unaffected, uncritical and critical encounters of cyclists and motorists including pPET in dependence on the distance to the CP (Figure 1, bottom left). Third, auto- (ACF) and cross-correlation functions (CCF) of the accelerations (eq. 1) and their auto- and cross-power density spectra (eq. 2) were computed and evaluated ($x(n)$: cyclist's and $y(n)$: motorist's discrete acceleration functions, τ: shift, $\omega = 2\pi f$: angular frequency, j: imaginary unit):

CCF
$$\varphi_{xy}(\tau) = E\{x(n) \cdot y(n-\tau)\} \quad (1)$$

Cross-power spectrum
$$R_{XY}(\omega) = \sum_{\forall\tau} \varphi_{xy}(\tau) \cdot \exp(-\mathrm{j}\varphi\tau) \quad (2)$$

Since the height of the maximum of the ACF reflects the signal energy and thus, allows to estimate the similarity to white noise, we applied this idea on the CCF, too. Based on the results, we computed the entropies on the acceleration functions. The entropy H is a measure of information content, which can be computed with symbols a_i, different binnings, their probabilities p_i and the dual logarithm $\log_2$:

$$H(a) = -\sum_{a_i \in |a|} p_i \log_2 p_i \quad (3)$$

Fourth, we applied inference statistical tests (i.e., Kruskal-Wallis-H, Mann-Whitney-U tests at confidence level α=0.05) to test for significance of the kinematic patterns, pPET, entropies and cross-power density spectra.

3 DATA AND EXPERIMENTS

The trajectory and video data of interacting cyclists and motorists as well as unaffected situations were recorded at 25 fps at the AIM research intersection in Braunschweig, Germany, in the years 2016 and 2018, which were annotated by experts. The trajectory data consist mainly of a GNSS-based time stamps, UTM positions, velocities and accelerations (derived by adequate dynamic motion models and Kalman filtering). 1.169 cyclist and 12.305 motorist trajectories were recorded, while 49 conflict and 273 uncritical encounter pairs resulted by filtering with PET<2.5s and expert annotation. 96 unaffected bicycle and 836 unaffected motorist trajectories were obtained. Due to poor data (e.g., broken trajectories, missing time stamps) not all of the data could be used. For computing pPET we extended those trajectories by 10 data points assuming the road users went on at same speed and direction as before. Then, 40 critical, 237 uncritical and 96 unaffected pairs remained. In case of computing the correlation functions, their spectra and entropies, the acceleration functions were cut at some distance before their CP, the parts from the cut to the CP remained. These limiting values were the result of the potential collision predictability in accordance with the outcomes of pPET, entropies and cross-power density spectra. For statistical evaluation we balanced the remaining data set yielding a 1:2 fraction of 40 critical, 80 uncritical and unaffected pairs, which were chosen randomly.

4 CONCLUSIONS & FUTURE PROSPECTS

Computing speeds and accelerations of road users interacting in critical and uncritical encounters as well and unaffected situations showed significant differences (see also [4]). Computing pPET (Figure 1, bottom left) showed significant differences between critical and uncritical encounters leading to an almost constant difference of approximately 1.3s (conflicts: pPET≈0.9s; encounters: pPET≈2.1s) beginning 12m before to the CP, which manifested the predictability of such situations. The confusion rates showed that sensitivity and specificity values appeared to exceed 50% after 16m (cyclists) and 13m (motorists) before the CP, respectively. The maxima of the cross-power density spectra and the entropies of the acceleration functions of critical, uncritical and unaffected situations (Figure 1, bottom right) turned out to be significant at 11m before the CP, but non-significant at larger distances. The following findings were robust against different binnings of the "acceleration alphabet", although the maximum entropies changed: The entropies of cyclists' critical situations were significantly larger than for all other remaining situations. However, the entropies of motorists' uncritical encounters were significantly larger than the remaining ones, which could reflect anticipation in terms of realising evasive actions. While approximately 70% of the cyclists were relatively behind motorists, cyclists disarmed conflicts by speed adaption while motorists behaved very similarly to unaffected situations. In case of uncritical encounters, motorists reduced their speeds reflecting to be aware of cyclists; anticipation/disarming the conflict was realised by the motorists. Thus, *H* can be a suitable measure to quantifying surprise and anticipation in road user interaction. As shown in [3] the DT worked well to predict conflicts, but was trained on 10 situations assessed by experts only. Further, situations with PET≥2.5s were not included, which might lead to biased data, particularly for uncritical encounters. A detailed investigation of crossing situations with larger PET values is necessary. Next, we will try to gain more insight in the importance of acceleration, particularly in terms of measuring anticipation or surprise in road user interaction. We think that considering solely accelerations might be only one side of the coin leading us to compute a joint entropy with speeds, pPET and distances to the CP.

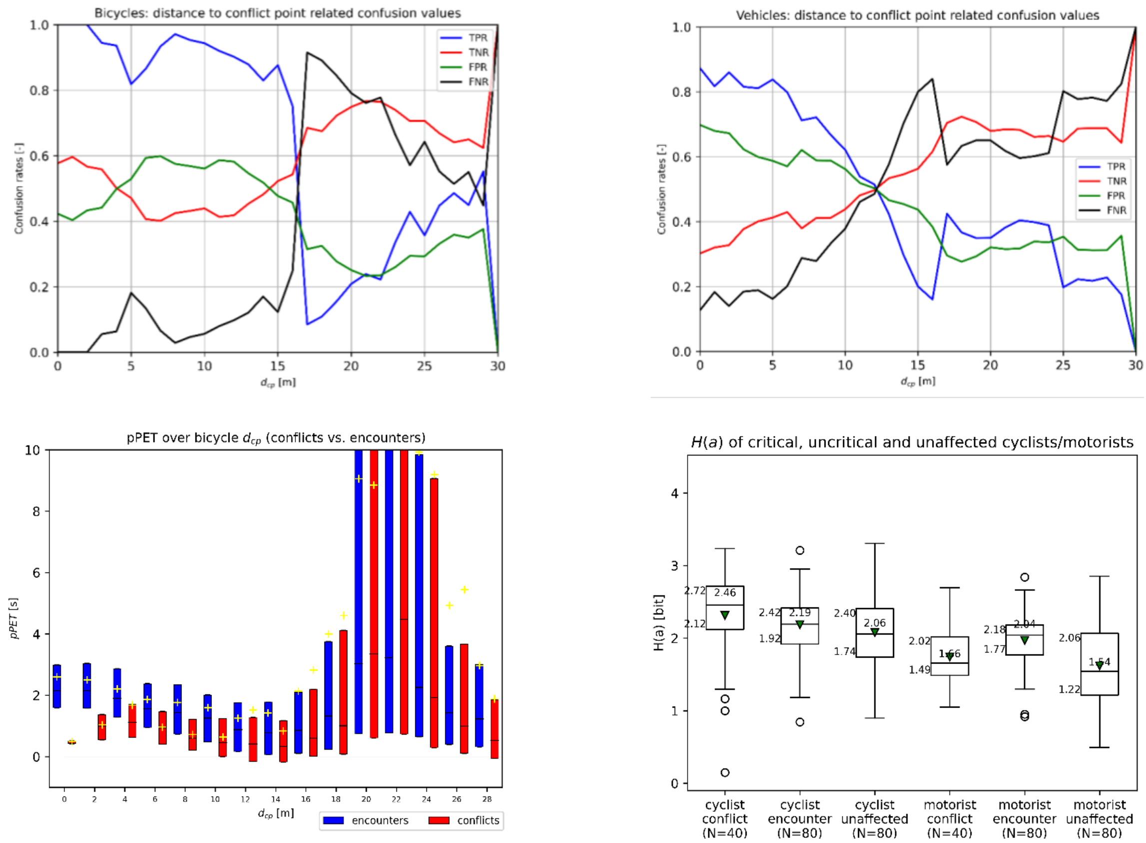

Figure 1. Confusion rates of cyclists (top left) and motorists (top right); pPET values for critical and uncritical encounters over distance to CP dc_p (bottom left, outliers and antennas are not shown for reasons of clarity); entropies for critical, uncritical and unaffected acceleration functions of cyclists and motorists (bottom right).

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