DADA-2000: Can Driving Accident be Predicted by Driver Attention? Analyzed by A Benchmark

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Abstract—Driver attention prediction is currently becoming the focus in safe driving research community, such as the DR(eye)VE project and newly emerged Berkeley DeepDrive Attention (BDD-A) database in critical situations. In safe driving, an essential task is to predict the incoming accidents as early as possible. BDD-A was aware of this problem and collected the driver attention in laboratory because of the rarity of such scenes. Nevertheless, BDD-A focuses the critical situations which do not encounter actual accidents, and just faces the driver attention prediction task, without a close step for accident prediction. In contrast to this, we explore the view of drivers’ eyes for capturing multiple kinds of accidents, and construct a more diverse and larger video benchmark than ever before with the driver attention and the driving accident annotation simultaneously (named as DADA-2000), which has 2000 video clips owning about 658,476 frames on 54 kinds of accidents. These clips are crowd-sourced and captured in various occasions (highway, urban, rural, and tunnel), weather (sunny, rainy and snowy) and light conditions (daytime and nighttime). For the driver attention representation, we collect the maps of fixations, saccade scan path and focusing time. The accidents are annotated by their categories, the accident window in clips and spatial locations of the crash-objects. Based on the analysis, we obtain a quantitative and positive answer for the question in this paper.

I. INTRODUCTION

On the journey to truly safe driving, human-centric assistive driving systems are still the focus by exploring the agile, dexterous driving experience of human beings. Within the human knowledge exploitation, driver attention [1], [2] has the undeniable role to optimize the visual scene search (e.g., foveal vision [3]) with a saving of computational resources when driving in complex real-world [4]. In the meanwhile, driver attention is an important way to interact with the surroundings, and joint attention exploration [2], [5] between drivers and other road users can promote the intention prediction for safe-driving. In particular, because of the fast reaction of humans, the eye movement can respond immediately for critical driving situations. Therefore, in order to promote the development of truly safe-driving, we will study the relationship between driver attention prediction and actual accident prediction.

![Fig. 1. The attention process of five observers from a normal situation to critical situation.](image)

In complex driving scenes, the simulation of driver attention is rather challenging and highly subjective because of the various attributes of persons, such as driving habit, driving experience, age, gender, personal preference, culture, and so on. Therefore, the fixations of different drivers vary considerably on the same scene, as demonstrated in Fig. 1 with two typical pedestrian crossing situations. Over decades, simulation of driver attention has been emphasised on driving behavior understanding and is now formulated by computer vision techniques in the autonomous driving or intelligent assistive driving systems. The goal of this task is to seek the answers for the question “Where and what should we look when driving in different environments?”, and identify the regions of interest for further processing [6], [7].

Recently, some attempts are launched, and the most typical project is DR(eye)VE [1], which collected 555,000 video frames with driver attention maps in a practical driving car (we call it in-car collection). However, the eye fixation data in DR(eye)VE project focused on the sunny and unobstructed road scenes, where very few critical situations appeared, and the attention collection stood on one driver’s view. This setting cannot reflect the common sense in driving. Hence, Berkeley DeepDrive Laboratory recently launched a project to collect the driver attention for critical situations, where the dataset is called Berkeley DeepDrive Attention (BDD-A) [8] with 1232 videos. Because of the rarity of the critical situations in practical driving, BDD-A designed an in-lab collection protocol. BDD-A claimed that in-lab collection is actually better than in-car collection because observers in lab are more focused without 1) the disturbance of surroundings in open environment and 2) extra manoeuvres for car controlling inevitably introducing the attention distraction.

Although BDD-A realizes the importance of driver attention in critical situations, there are three major aspects that we think can be boosted for truly safe-driving. (1) For a convenience to build learning models, BDD-A treats the attention of multiple observers on buildings, trees, flowerbeds, and other unimportant objects as noise and wash it out with
eye movement average procedure. However, because of the highly subjectivity, these attention data maybe contextual for critical situation prediction. Seeing Fig. 1 as an example, the fixations of observers tend to be close together when seeing the crash-object. We call it as a “common focusing effect”. (2) The critical situations in BDD-A do not cause true accidents, where the attention simulation has not explored the dynamic process from critical situation to actual accidents (we call it as accident attention flow), which is needed for avoiding true accident. (3) BDD-A do not classify the braking events into different categories useful for fine-grained analysis.

In view of these aspects, this work contributes a new, larger and more diverse video benchmark with driver attention and driving accident annotation simultaneously, (we call it as DADA-2000). Because the accidents are rarer than the critical situations, we first collect crowd-sourced videos with 3 million frames. Then, we wash and divide them into 54 kinds of accidents with respect to the their participants, where 658,476 frames are selected out for further annotation. Second, the attention collection, similar to BDD-A, is conducted in lab with a carefully designed protocol. The driver attention data is collected by a RED250 eyetracker, which contains the information of fixations (fixation maps, fixation duration, start time, end time, positions, start positions, end positions, dispersions, and pupil size). Third, we carefully annotated the locations of crash-objects and their temporal occurrence intervals. Totally, DADA-2000 contains 2000 video clips, in which the scenes are fairly complex and diverse in weather conditions (sunny, snowy, and rainy), light conditions (daytime and nighttime), and occasions (highway, urban, rural, and tunnel).

With DADA-2000, we not only want to know “Where and what should we look when driving in different environments?”, but also we want to seek the answers for a new question “Can driving accident be predicted by driver attention?”. In addition, because we collected the attention flow from the normal situations to accidents, the more challenging question “What causes the occurrence of an accident that we can see?” can be explored in the future.

In a summary, this work has two contributions:

(1) We construct a new, larger and more diverse benchmark for driving accident prediction or detection, driver attention prediction problems than ever before, where each frame owns its corresponding attention data.

(2) We give an quantitative and positive answer for the question: Can driving accident by predicted by driver attention? This work not only provides a new solution for driving accident prediction or detection, but also pushes the driver attention one step further for safe-driving.

II. RELATED WORKS

Since this work concentrates on the driver attention mechanism understanding when encountering accidents, two main domains are involved, driver attention prediction and driving accident prediction with computer vision techniques.

Driving Accident Prediction. Since this work involves the accident situations, and wants to devote ourselves to give an analysis between driving accident prediction and driver attention, we also review the literatures on accident prediction. Accident is generally a special anomaly in driving scenes. Compared with extensively studied anomaly in surveillance systems [12], [13], accident has a more specific and clearer definition. Recent researches in computer vision have began to address the accident prediction or detection from different views. For instance, Kataoka et al. [14], [15] and Chan et al. [16] anticipated the traffic accident through adaptive loss and dynamic-spatial attention (DSA) recurrent neural network (RNN), respectively. Particularly, reference [14] contributed a large dashcam video dataset owning 6000 videos temporally labeled, but has not been released. Yuan et al. [17] addressed the driving anomaly by incremental motion consistency measurement. Yao et al. [18] newly proposed a first-person video benchmark for driving accident detection, which contains 1500 video clips with 208,166 frames. Generally, the accident prediction in previous studies concentrate on the temporal interval prediction/detection, without a spatial crash object localization. In the meantime, the accurate prediction/detection of participants needs the expensively computed optical flow. More importantly, these methods cannot immediately respond the sudden accident because there is no enough time window for computation.
After-AW

car
truck
road-centric
curb
70

Fig. 2. The ego-car involved and ego-car uninvolved accident category graph in driving, where each kind of accident category is explained.

Fig. 3. The sequence amount distribution w.r.t. accident categories in DADA-2020.

Fig. 4. The distributions of environment attributes of DADA-2000. From left to right, the attributes are light conditions, weather conditions and scene occasions, respectively. Note that the weather condition statistics are based on the daytime because of a clear distinction.

III. DADA-2000

In order to collect the accident videos as many as possible, we searched almost all the mainstream video websites, such as Youtube, Youku, Bilibili, iQiyi, Tencent, etc., and downloaded about 3 million frames of videos. However, these videos have many useless typing masks. Therefore, we have conducted a laborious work for washing them, and obtain 658,476 available frames contained in 2000 videos with the resolution of 1456 × 660 (=6.1 hours with 30 fps, over than DR(eye)VE). Different from the existing works with a strict trimming of frames [16], [8] (such as the last ten frames as the accident interval) for accident annotation, we advocate a free presentation without any trimming work. In this way, the attention collection maybe more natural. We further divide these videos into 54 kinds of categories based on the participants of accidents (pedestrian, vehicle, cyclist, motorbike, truck, bus, and other static obstacles, etc.). Among them, these 54 categories can be classified into two large sets, ego-car involved and ego-car uninvolved. Specifically, the accident categories and their amount distribution of our benchmark is illustrated in Fig. 2 and Fig. 3 respectively. Because the accidents are rather diverse, we consider the accident situations as complete as possible in driving scene. Therefore, we provide 62 categories denoted in Fig. 2 which is more than the collected 54 classes. From this distribution, the “ego-car hitting car” takes the largest proportion. In addition, we also present the scene diversity of DADA-2000 by Fig. 4. From Fig. 4 we can see that because of the more frequent and diverse transit trip in daytime and urban scene than nighttime and other occasions, they show the highest occurrence rate of accidents.

In DADA-2000, we annotated the spatial crash-objects, temporal window of the occurrence of accidents, and collected the attention map for each video frame. Therefore, we will elaborate the constructing process of DADA-2000 in detail. Specifically, Fig. 5 provides an illustration for

Fig. 5. Temporal partition of an accident video in this work.
temporal analysis of accident videos. For a video clip, we
partition it into three main clips: the frame interval before
the accident window (before-AW), accident window (AW)
and the frame interval after the AW (after-AW). What is more,
we further divide the AW into three sub-sections: start-section
with the length of \( \frac{1}{3} \text{AW} \), middle-section with the range from
\( \frac{1}{3} \text{AW} \) to \( \frac{2}{3} \text{AW} \) and the end-section with remaining \( \frac{1}{3} \text{AW} \).
Actually, in this work, AW not only contains the accident
frames, but the temporal window prior to the accident is also
contained. Therefore, this setting aims to explore whether
driver attention can capture the crash-object or not once it
appears in the start-section, i.e., driving accident prediction
by driver attention. In addition, by observation, most of the
actual accidents occur in the end section. Therefore, the
start-section and middle-section are the golden interval for
predicting accident. For AW determining, if half part of the
object that will occur accident (we define it as crash-object
in this paper) appears in the view plane, we set the frame as
the starting point, and set the frame as the ending point if
the scene returns a normal moving condition.

| Statistics | total | before-AW | AW | after-AW |
|------------|-------|-----------|----|---------|
| total frames | 650,000 | 315,154 | 131,679 | 211,643 |
| average frames | 325 | 157 | 66 | 106 |
| percent (%) | 100 | 48.3 | 20.3 | 32.6 |

A. Temporal and Spatial Statistics of DADA-2000

1) Temporal Statistics: In DADA-2000, the temporal
frame statistics of before-AW, AW, and after-AW are
presented in Table. I From these statistics, we find that the
before-AW contains about 5 seconds of time (30 fps) in
average and after-AW takes about 3.5 seconds of time. AW
takes a percent of 20.3% in each video averagely. Therefore,
the frames of abnormal driving are rather fewer than the ones
in normal driving.

2) Spatial Statistics: Beside the temporal statistics, we
also visualize the occurrence map of crash-object locations
for some typical categories denoted in Fig. II. These maps are
obtained by summarizing the crash-object locations in each
frame of certain accident category. For a clear demonstration,
we expand the location point of crash-object with a rectangle
neighborhood having the size of \( 14 \times 14 \), and set the value
within it as 1, and 0 for vice versa. Then, we normalize
the summarized occurrence maps to the range of [0,1] with
the min-max normalizer. From these maps, we can observe
that the crash-object locations tend to the middle of the field
of vision (FOV) for most of accident categories. However,
pedestrian crossing, motorbike crossing and car crossing are
dispersive, and converge to the sides of FOV. Particularly, the
cars with the larger velocity than motorbikes and pedestrians
has the larger convergence degree to the FOV sides. On
the contrary, locations of hitting behaviour converge to the
middle of FOV, and show a stronger degree of convergence
with the increasing of the target velocity. Therefore, although
the crash-object locations demonstrate a convergence of FOV,
different accident categories with differing participants have
diverse occurrence patterns of locations. This can be used
for model designing with spatial context cueing for accident
prediction or detection in future.

We also compare our DADA-2000 with the state-of-the-
art datasets for driving accident detection or prediction in
Table. II From Table. II we can observe that our DADA-
2000 has more diverse scenarios and is more complex for
driving accident analysis. This will provide a new and larger
platform for driving accident detection or prediction problem.

B. Attention Collection

1) Protocols: Because of the rarity of the accident in
practical driving, in our attention collection protocol, we
employed 20 volunteers with at least 3 years of driving
experience. The eye-tracking movement data were recorded
in a lab by a SMI RED250 desktop-mounted infrared eye
tracker with 250 Hz, in conjunction with an iView X script.
In order to approach the real driving scene, we weaken
the lighting of the lab to reduce the impact of surroundings,
by which only the computer screen is focused. In addition,
we asked the volunteers to be relaxed and imagine that they
are driving real cars. For avoiding the fatigue, we let each
volunteer watch 40 clips each time which are combined as
a single long sequence with about 7 minutes. Each clip was
viewed at least by 5 observers. It is worthy noting that, we
ensure that the 40 clips belong to the same category as much
as possible, so as to prevent chaotic attention.

For collecting the attention data, we launched the no-priori
and with-priori experiments. We ask each volunteer watch
the same video twice, where in the first time the volunteers
only know that they need to watch a video in driving scene
(no priori), whereas they are told that they need to find
the crash-object (with priori). By this experiment, we can
analyze the unconscious crash attention and conscious crash
attention, respectively. For our DADA-2000, we guarantee
that each video is watched by at least five observers. For the
attention map of a frame, there is a parameter determining
the temporal window which aggregates the attentions within
it to generate an attention map for a frame (1 second was
utilized in DR(eye)VE). This setting can reserve the dynamic
attention process in a small temporal window, but not be
conducive to the crash-object localization.

2) Statistics: In this work, we save the attention maps
as two types. 1) Type1: We recorded the common attention
maps, where an attention map contains five observers’ fixa-
tions without temporal aggregation. Note that, different from
the works [8], [1], we do not average the attention fixations
of observers and maintain them in the same frame because
of their subjectivity. We can observe that the fixations
get close to the appeared crash-object, and vice versa for
normal driving scenes. We call this phenomena as “common
focusing effect”. 2) Type2: We also recorded the attention
maps of all the observers individually, where one-second of
Fig. 6. The spatial occurrence maps of typical accident categories, as well as the occurrence map of DADA-2020, where the number in the bracket at the end of the accident class is the category index denoted in Fig. 2.

TABLE II

| Dataset             | videos | accidents | all frames | typical participants | annotation type     |
|---------------------|--------|-----------|------------|----------------------|---------------------|
| ShanghaiTech [19]   | 437    | 130       | 317,398    | bike, pedestrian     | temporal            |
| Street Accidents (SA) [16] | 994    | 165       | 99,400     | car, truck, bike     | temporal            |
| A3D** [18]         | 1500   | 1500      | 208,166    | car, truck, bike, pedestrian, animal | temporal |
| DADA-2000          | 2000   | 2000      | 658,476    | car, truck, bike, pedestrian, animal, motorbike, static obstacles | spatial and temporal |

TABLE III

| Dataset | rides | durations(hours) | drivers | gaze providers | event | gaze patterns for each frame |
|---------|-------|------------------|---------|----------------|-------|-----------------------------|
| DR(eye)VE [1] | 74    | 6                | 8       | 8              | 464 braking events | attention map of single person |
| BDD-A [8] | 1232  | 3.5              | 1232    | 45             | 1427 braking events | average attention map of multiple observers |
| DADA-2000 | 2000 | 6.1              | 2000    | 20             | 2000 accidents (54 categories) | raw attention maps of multiple observers |

temporal window is used to obtain an aggregated attention map like DR(eye)VE project, in which the dynamic attention process can be reserved and useful for dynamic attention flow analyzing. These two types are all recorded in 30 fps. We capture the attention data for all of the frames in our DADA-2000. The attribute comparison with other state-of-the-art driver attention datasets is presented in Table. III. From this comparison, our DADA-2000 is more diverse, and contributes a new benchmark for driver attention prediction. Note that, our DADA-2000 will be released in future.

IV. CAN DRIVING ACCIDENT BE PREDICTED BY DRIVER ATTENTION?

In this work, the most important purpose is to explore the question: Can driving accident be predicted by driver attention? The behind motivation is that, for the driving accident prediction or detection, current research paradigms often design and train complex models. However, the performance of previous works are still largely insufficient for safe-driving [18]. Hence, we want to seek new solution for this task. Inspired by previous attempts [2], driver attention is a powerful mechanism for object detection, especially for the sudden motion change. However, there is no promising studies with large-scale attention benchmark for driving accident analysis, where sudden motion changes are frequent.

A. Attended Object Categories

The crash objects in driving scene are usually the dynamic participants: such as the cars, pedestrians, motorbikes and other moveable objects. Therefore, these object categories should be attended more in abnormal driving situations. In addition, we also want to find the role of the priori for the crash-object localization when observing. As aforementioned, we conducted no-priori and with-priori experiments on all video clips. Hence, in Fig. 7 we exhibit their analysis in parallel. Note that, the semantic annotation for our DADA-2000 is rather laborious, we get the semantic map of each
frame by Deeplab-V3 model [20] pre-trained on ADE20 semantic segmentation dataset [21]. In ADE20K, they defined 150 object categories. In Fig. 7 we demonstrate the object categories with top fifteen proportions.

From the analysis, we can see that the road and cars are attended more positive than other object categories. However, person shows a manifest shift from the tenth one to the fifth, and cars shift to the first column in abnormal driving situations. In other words, drivers attend the vulnerable road users more largely in abnormal driving situations than the ones in normal driving situations. In addition, we find that the priori for attention collection has little influence on the attending of object. Actually, human eyes are sensitive for the sudden motion change whatever the priori exists or not. These shifts can give a positive answer for the helpfulness of driver attention when predicting driving accident to some extent. However, this conclusion still needs more evidence.

![Graph]

Fig. 8. The CLE distance distribution. y-axis denotes the frames with certain CLE range.

### B. Localization Error Analysis

Beside the attended object category analysis, we further analyze the center location error (CLE) between the crash-object center with the peak point with the largest saliency value in our Type-I attention maps. CLE represents the Euclidean distance between two points. Similarly, no-priori and with-priori are analysed. Differently, this analysis focuses on the abnormal situations (i.e., frames in AW).

1) **Overall Analysis:** We plot the histograms of CLE on all the frames in AW of our DADA-2000 dataset in Fig. 8, which again indicates that no-priori and with-priori have little influence on the crash-object localization. In addition, about 80% percent of abnormal frames (131,679 frames in total) with smaller CLEs than 300 pixels. Fig. 9 gives an example for demonstrating the physical meaning of 300 pixels. Actually, the size of the crash car is much larger than the circle with a radius of 300 pixels. These analysis indicates that driver attention can play a positive role for crash-object localization to a large extent. There are two important evidences that: 1) the accident category of ego-car hitting car takes the largest proportion in DADA-2000. When this kind of accidents occur, the radius of crash-object is prone to be larger than 300 pixels, and 2) from Fig. 3, ego-car involved accident categories almost take half size of DADA-2000. Therefore, the CLEs smaller than 300 pixels are acceptable. In addition, we also give an in-depth analysis for seeking the answer by checking the CLE evaluation in different sections in accident window.

2) **Analysis for Different Sections in AW:** Driver attention can localize the crash objects in accident to a large extent. Can it capture the crash-object when it just appears in the view? Following the temporal partition strategy of AW in Fig. 5 we plot the precision curves of different AW sections on all video clips in our DADA-2000. The precision curves contain two indicators: frame ratio and success rate, defined as follows:

- Frame ratio is obtained by counting the number of frames in each AW section with lower CLE value than certain threshold compared to total frames in the same AW section. In this work, we analyze the frame ratio for different sections of AW in each video.
- Success rate denotes the video clip ratio which is obtained by counting the number of clips that over a half of \( \left( \frac{1}{2} \right) \) whose frames generate a lower CLE than the certain threshold, corresponding to the total clips (i.e., 2000). Similarly, success rate is analyzed for different sections of AW in each video.

| DT | Star.wp | Mid.wp | End.wp | Star.jp | Mid.jp | End.jp |
|----|---------|-------|-------|--------|-------|-------|
| 60 | 10.8    | 10.7  | 5.1   | 9.2    | 10.1  | 6.8   |
| 100| 34.4    | 30.8  | 22.6  | 34.7   | 32.5  | 26.2  |
| 160| 59.0    | 57.2  | 49.1  | 61.1   | 59.0  | 52.1  |
| 200| 68.0    | 67.2  | 60.1  | 71.6   | 69.6  | 64.0  |
| 260| 76.6    | 76.6  | 71.5  | 80.0   | 79.5  | 73.3  |
| 300| 80.0    | 81.3  | 76.6  | 83.5   | 83.8  | 79.1  |

The results are shown in Fig. 10(a) and Fig. 10(b), respectively. From these figures, we can see that with or without priori have a tiny influence for different AW sections. For different sections in AW, the mean frame ratio can reach 80% when fixing the CLE threshold as 300 pixels. This result is also found by the success rate. For a clearer demonstration, we present the success rate of different AW sections when fixing the CLE threshold as 60, 100, 160, 200, 260, and 300 pixels in Table. From Table, we can see that when fixing the CLE threshold as 260 pixels, over 70% video clips can be successfully attended. From these results, we can observe that driver attention is positive for crash-object localization in the accident window, especially...
Fig. 10. The precision curves of driver attention localization for driving accident. x-axis specifies the CLE threshold. y-axis in (a) denotes the mean and its error bar (marked by the shadow area) of frame ratios of different AW sections. Instead, y-axis in (b) represents the success rate of all clips for different sections.

Fig. 11. Type1-attention maps (five observers) of some typical accidents in DADA-2020. (a) a person crosses ahead of ego-car, (b) a car hits a motorbike, (c) a car hits a person, and (c) a car crosses ahead of ego-car.

for the start section of AW. In other words, driver attention can capture the object that will occur accident very early. Fig. 11 demonstrates some typical accidents with the Type1-attention maps. We can see that for the person category, driver attention usually focuses the head or feet, but not the center of the body. However, almost observers can capture the pedestrians or cars when they will occur accident.

Highlights: From these analysis, we can conclude that driver attention can obtain a positive help for driving accident prediction. This will boost the future prediction model designing apparently. However, in complex scenes, the driver attention should be combined with more clues, such as the semantics and driving rules, to make a convincing prediction.

V. CONCLUSIONS

This work searched the answer for the question: can driving accident be predicted by driver attention? In order to answer this question, we construct a new and larger benchmark with 2000 video clips (containing over 650,000 frames) than the state-of-the-art related datasets. We named it as DADA-2000. For the construction of DADA-2000, we laboriously annotated the temporal accident window, spatial crash-object locations of all videos, and collect the driver attention data for each frame carefully. By quantitative analysis, we obtained a positive answer for this question.

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