Detecting Vehicle Interactions in Driving Videos via Motion Profiles

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***Abstract*— Identifying interactions of vehicles on the road is important for accident analysis and driving behavior assessment. Our interactions include those with passing/passed, cut-in, crossing, frontal, on-coming, parallel driving vehicles, and ego-vehicle actions to change lane, stop, turn, and speeding. We use visual motion recorded in driving video taken by a dashboard camera to identify such interaction. Motion profiles from videos are filtered at critical positions, which reduces the complexity from object detection, depth sensing, target tracking, and motion estimation. The results are obtained efficiently, and the accuracy is also acceptable. The results can be used in driving video mining, traffic analysis, driver behavior understanding, etc.**

I. Introduction

Finding interactions of vehicles on the road will be valuable for accident analysis and driving behavior assessment, because half of the accidents are collision with other vehicles, along with road departure [1]. Vehicle interactions include cut-in, merging, crossing, frontal approaching, etc. Vehicle interaction does not imply an accident, but a crash or near crash always starts from an interaction. In driving behavior analysis, aggressive drivers have more lane changes passing many vehicles and bumper-to-bumper chasing. A tired driver may drive slowly and be passed by most vehicles on multi-lanes. Major accidents are bumping into a frontal vehicle or with a cut-in vehicle to the same lane if ego-driver does not brake or avoid promptly. These interactions have been recorded in Naturalistic Driving Videos (NDV) [3] that yield clear visual motion footage.

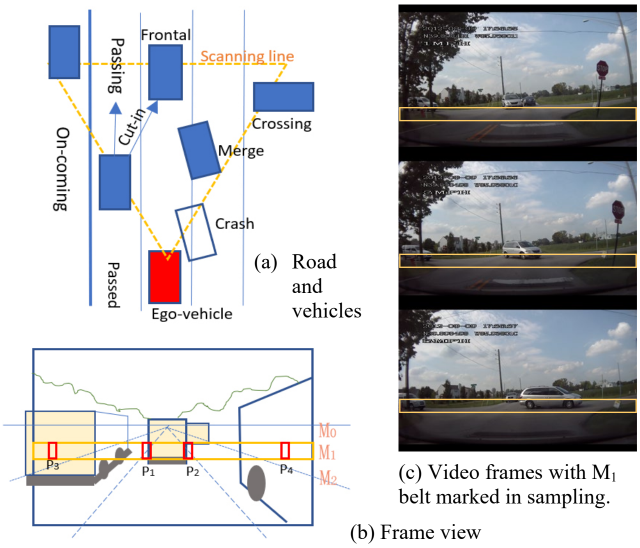
Driving video provides rich information to understand events between vehicles. We limit our sensing depth up to middle range in examining vehicle interactions. A horizontal zone reaching middle range in the frames can capture image velocity of surrounding vehicles. The range is determined from the relative speed and distance of vehicles with the camera. A motion profile [4] is sampled from such a zone such that surrounding scenes have their trajectories in the generated spatial-temporal image. We found that different events around camera correspond to unique trajectories. By filtering traces at special locations over time, we can classify trace types reflecting different events with surroundings.

Related works on vehicle interactions can be found in [2, 5, 6, 7, 13]. Traditional methods have spent much more efforts to achieve the goal. It starts from object recognition using detector [8], which requires more computing resources and time. Tracking bounding boxes is followed and motion trajectories have to be estimated and classified to interactions and events [10]. Our method skips object recognition of objects by focuses on vehicle motion observed at special locations in video. This reduced the complexity of the problems significantly because the shape recognition of vehicles suffers from the variations in vehicle shape, orientation, type, color, and illumination conditions. As preparation for motion understanding, the temporal profile has been proposed in [4] to directly reflect the relative motion of surrounding vehicles. The TTC computation has been carried out in the motion profiles [11]. Multiple motion profiles have been employed to sort the near crashing based on the motion trajectories in the field of view [12]. Traffic counting at opposite lane has used motion profile as well [9].

In the following, Section II introduces various interactions between vehicles, and their relative motion observable in the video. Section III introduces the motion profiles employed to capture the vehicle motion at surroundings. The motion traces are analyzed for different interactions. Section IV proposes an algorithm to detect motion traces and interaction type based on filtering at critical positions. Section V describes experiments and the results, followed with conclusion.

II. Vehicle Interactions on the Road

Vehicle interactions dealt with here are listed in Table I, and some cases are also depicted in Fig. 1. In the ego-vehicle centered space, a vehicle interaction happens at a depth up to middle range within, e.g., 20m. Further beyond, vehicle actions are not considered because they will not cause an immediate crash. Vehicle interactions affect safe driving and may cause near crash if they are not responded properly.



(a) Road and vehicles

(b) Frame view

(c) Video frames with M_1 belt marked in sampling.

Fig. 1 Different interactions between ego-vehicle and surrounding vehicles. (a) Interactions in a top view where ego-vehicle is moving upward. Many interactions are symmetric on left and right sides except for on-coming vehicles on left side. (b) Front view with a horizontal zone (M_1 in orange color) covering scenes up to a middle range of road for vehicle motion identification. In addition, M_0 and M_2 zones can also be obtained in the same way above and below M_1 for farther and closer vehicles, respectively. (c) Example frames of right turn of an opposite vehicle at an intersection.

We use a dashboard camera to observe vehicle

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Table I Major vehicle interactions happening on the road and their motion observable in video

	Interaction Types	Observable Positions in frames	Relative Motion in the Field of View
Frontal vehicle	*Following* it at the same lane	Front, middle depth range	Width keeps constant, enlarged and reduced
	Crossing vehicle: at intersection from either side including a left turn from opposite road	Side or center, across horizontally at least half field of view	Rightward or leftward across driving lane to one margin
	Front crash: to rear-end of front vehicle	Center, close depth range	Large expansion in width at center
Side vehicle	*Passing* (overtaking) vehicle goes ahead faster than ego-vehicle in the next lane	From either side, toward middle depth range	Centered (inward) motion ending at the next lane at middle depth
	Passed (overtaken) by ego-vehicle in the next lane	Toward either side, from middle depth range	Motion starting from the next lane at middle depth range outward to margin
	Cut-in vehicle or side-crash from the next lane into the driving lane of ego-vehicle quickly	Either side to center, at middle depth. Only partially visible in crash	Centered motion faster than *Passing* ending at the same driving lane of ego-vehicle
	Merging from crossing road or ramp slowly merging into the driving lane of ego-vehicle	From either side, toward center	Faster motion than *cut-in* from margin
	On-coming in the opposite lane	Starting from opposite lane at center, middle depth, fast speed leftward	Fast leftward motion due to fast relative speed between opposite vehicles and ego-vehicle.
Ego-vehicle	*Stopping* for signal or at stop sign	Most part of field of view are static except crossing vehicles	Scenes are static except crossing vehicles having motion, left-turning vehicle from opposite road moving rightward in the view.
	Turning at interaction	Scenes shift in entire field of view	Opposite to the turning direction
	Changing lane	Scenes shift in entire field of view	Short deviation of all scenes
	Speeding	Roadside scenes on two sides move outward	Roadside scene expending fast to margins from center
Traffic	High density vehicle flow	Many vehicles at middle depth	Stable motion near center in the field of view
	Leaving vehicles: turning away from road without interaction.	Two sides	Motion outward to a margin

interactions on the road. The camera orientation has been calibrated so that the planned moving space in front of ego-vehicle is known. Through mining of NDV, we found that lower parts of vehicles contain tire and shadow, which are relatively dark in almost all-weather conditions except night driving and strong raining on wet road (splash). Road is relatively brighter than lower vehicles. This constraint is common for all vehicles regardless of vehicle color, shape, and types. The vehicle motion on the road is projected as horizontal motion in the image with the vertical motion representing depth change. A vehicle appears in lower frame if its depth is close. Sky and high positions in the field of view can be omitted in monitoring. We therefore design an approach to find vehicle interactions through motion detection in driving videos.

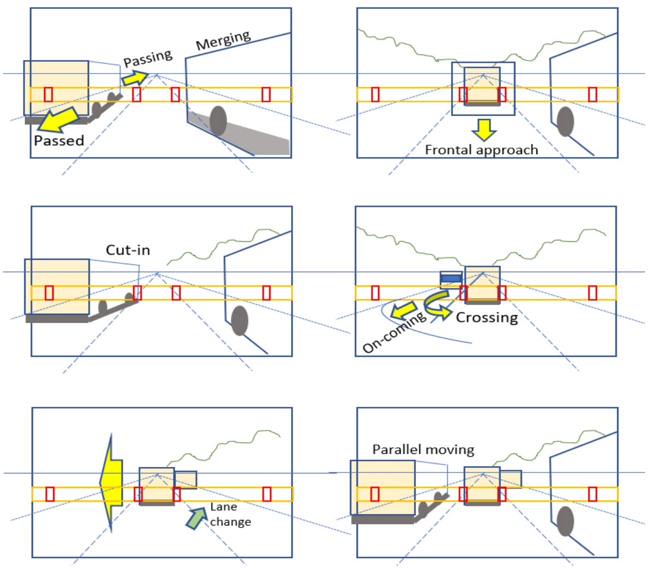


Fig. 2 Front views of driving video in different events. Yellow arrows indicate observable vehicle motion. Green arrow is for ego-vehicle.

Our goal is to sort all the major types of vehicle interaction off-line for data mining of driving behavior, rather than an early identification of vehicle's intention and responding to it in real time. We can thus refer to the entire process of vehicle motion to identify interactions. The constraints used in this work are: (1) Vehicles have almost the same width according to the design of road system, and thus lane widths are approximately similar. (2) Vehicle motion is from four-wheeled vehicles along smoothly curved path on road plane. (3) Ego-vehicle is on straight road locally, otherwise it is marked as turning or lane change in a short period. Figure 2 shows some scenarios in frames.

III. Motion Profiles Capturing Horizontal Motion

A. Data Reduction of Driving Videos to the Motion Profiles

To condense driving video for understanding interactions, the height of horizon in the video is first located for each camera. The frame is located with sampling regions or zones as well as sampling lines below the horizon. Top zone, M_0, is on the horizon to sense horizontal motion of all vehicles up to infinity (Fig. 1). A middle range zone, M_1, covers range 10-20m for understanding actions of surrounding vehicles and path planning. A close-range zone, M_2, located even lower in the image captures the sudden invasion of side vehicle and approaching front vehicle for urgent braking.

In each sampling zone, pixels are averaged vertically to produce a line of data. The lines from consecutive frames are further concatenated to form a long spatial-temporal image, $M_i(x,t)$, i=0, 1, 2, showing motion trajectories of scenes [4]. Because we average the pixels vertically in the zone, slanted road edges and lane marks in the image are blurred to a wide belt in the motion profile. Details in road area and grass at roadside are also blurred. Only vertical lines on vehicles remain high contrast after the pixel averaging, which further form distinct trajectories in the motion profile. Therefore, we can focus on trajectories for vehicles and ignore road edges and surface marks. As displayed in Fig. 3, a *motion profile* from zone M_1 and a *road profile* from a line in the zone show vehicles in both driving lane and next lane moving in parallel. The motion profile from closer range M_2 does not

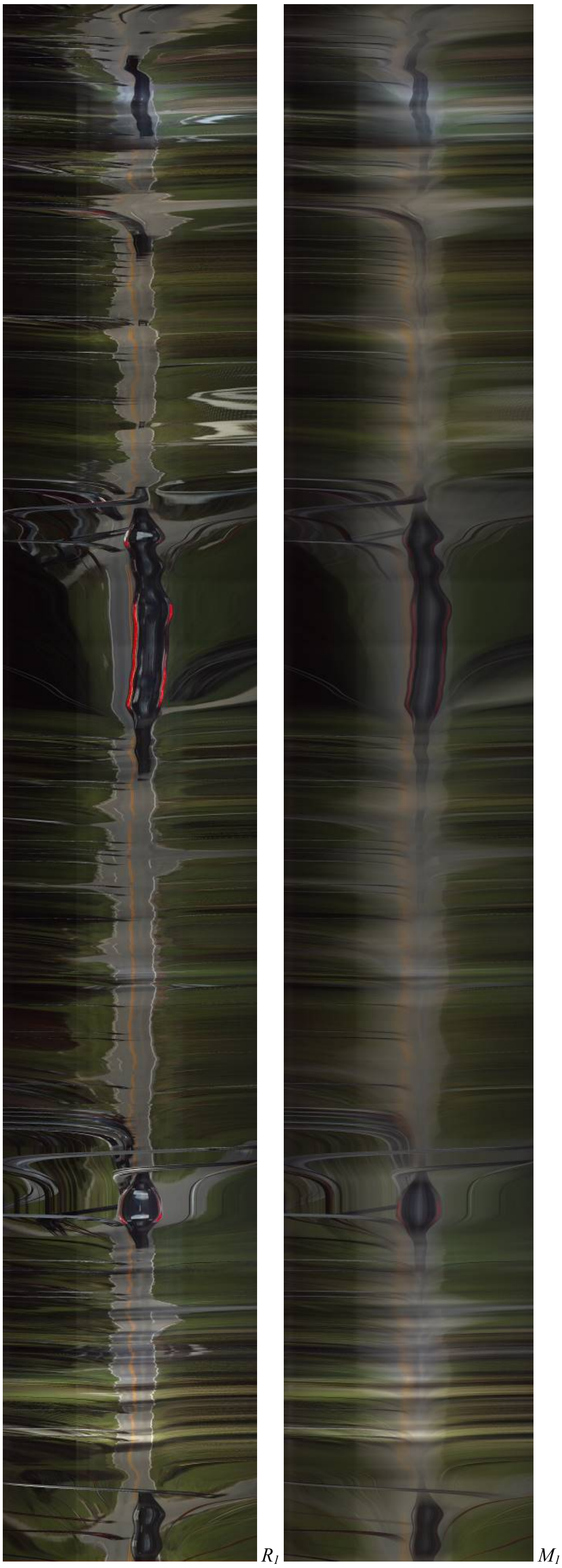


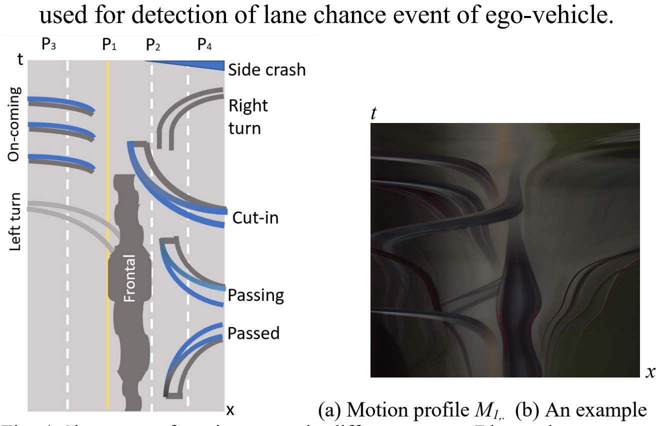
Fig. 3 Road profile (R_l) and motion profile M_l from middle range in the video of 5-min driving. The horizontal axis is the same as the image while the vertical axis upward is the time in pixel (frame number).

cover vehicle interaction but can be used for determining urgent braking if a vehicle trace is visible in it. On the other hand, the motion profile from far away, i.e., M_0, has dense traces of background, which makes it hard to identify vehicle traces against background. We will use them occasionally.

B. *Vehicle Trajectories from Different Events*

Through observing vehicle motion in Naturalistic Driving Videos as well as the traces in the generated motion profiles, we found phenomena of vehicle traces as in Fig. 4.

- A cut-in vehicle has an inward trace toward center and ends up at the same lane as the ego-vehicle.
- A passing vehicle faster than ego-vehicle on either side leaves an inward trace and it disappears at the next lane near the image center at middle range.
- A passed vehicle slower than ego-vehicle on either side has a trace toward margin.
- A frontal vehicle and side vehicle may keep parallel motion with ego-vehicle. Their traces maintain vertically and in the same widths approximately.
- A successful merging vehicle may have a fast trace toward center while its width may decrease; otherwise, if its trace has expansion at the same position, it may yield collision and need to brake [11].
- If a vehicle leaves away, its width is reducing. Inversely, if it is getting closer to camera because it slows down or ego-vehicle has a faster speed, the vehicle width is expending. The time-to-collision is computable [11].
- On-coming vehicles in the opposite lane appear near the image center and passing outward to the left margin in a very horizontal direction because of a high relative-speed. They are more observable from leftist lane on a road [9].
- Ego-vehicle turning, and lane change have all the traces in the profiles deviated in the opposite direction to the turning direction in a short period.
- A stop period of ego-vehicle produces pure vertical traces in the motion profile over the entire field except on some crossing vehicles.
- In the road profiles, lane marks and road edges are visible. When the vehicle changes its lane, lane marks are bended and pass through the center of profile. This is used for detection of lane chance event of ego-vehicle.

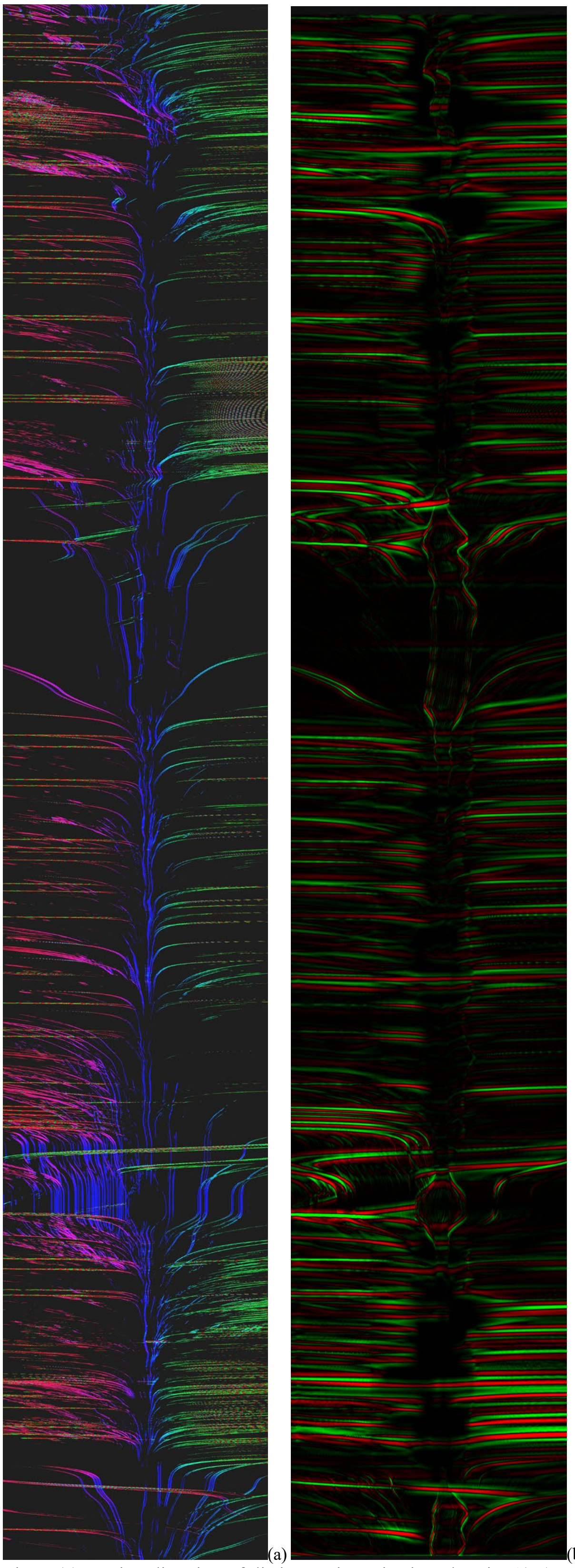


(a) Motion profile M_L. (b) An example

Fig. 4 Characters of motion traces in different events. Blue and gray traces indicate side and back of vehicles, respectively. The traces can be flipped to the other side horizontally except for on-coming vehicle traces.

C. Other Trajectories Observable in Motion Profiles

Roadside scenes such as vertical trees and buildings have traces in the motion profile fanning out from center [10].



(a) (b)

Fig. 5 (a) Motion direction of distinct trajectories in colors in $A(x,t)$, and (b) trace stripe image $L(x,t)$. (a) Vertical traces are marked in blue and horizontal traces are close to red or green according to their negative or positive direction. The intensigy of color is the gradient value at that point. (b) Positive and negative values in red and green after filtering L_T.

They are observed in far and middle motion profiles, particularly when ego-vehicle is in the rightmost lane. Scenes on the other roadside are blurred due to farther distance; their traces are less observable. The faster is the ego-vehicle speed, the more horizontal are those traces in the motion profile.

Other traces left in the motion profiles include instantaneous illumination changes, e.g., ego-vehicle runs into a shadow area or under a bridge. Such dark and instant trajectories are close to horizontal in the profiles over the entire field of view. Due to the average of pixels in the sampling zone, slanted road edges and patterns in the frames are blurred. However, some white and yellow lane marks at image center may still leave short but wide traces in the motion profile. They are weaker after blurring than vehicle traces from vertical boundaries and can be filtered out.

IV. Detecting Motion Events of Surroundings

A. Locating Traces by Filtering Motion Direction

Differential filters $D(x)$ and $D(t)$ are applied horizontally and vertically in the motion profile $M(x,t)$. The outputs of filters are combined to obtain gradient $G(x,t)$ of strong traces in the motion profile. Figure 5(a) displays such trace direction image in which pixel contrast is in intensity and the tangent direction of trajectories in colors. The trace orientation is converted to angle in (-90, +90) degree with the vertical (forward direction) as 0 degree. A vehicle trace is a bundle of edge traces with a coherent direction. Duo to the digitization errors and insufficient temporal resolution of motion profile for fast vehicles, close to horizontal traces may have angle values jumping between 90 and -90 degree after the local filtering of pixels. The trace angle is stored in an image $A(x,t)$ for identifying vehicle moving direction.

Along with the trace direction applied to the motion profile, another 1D Laplacian filter $L_T(t)$ is applied vertically at several horizontal locations p_1, p_2, p_3, p_4 in the motion profile (Fig. 4) to detect horizontal trace stripes bounded with two edges. The length of filter is T obtained from the average time of passing and passed vehicles in the driving video. The four horizontal positions for monitoring are indicated in Fig. 1 by small red boxes. Two outer positions, p_3, p_4, have a close distance from image margins, while two inner positions, p_1, p_2, are at edges of driving lane in a middle depth. They are set to sense the relative motion of vehicles in next lanes and check cut-in motion into driving lane. Figure 5(b) shows the entire motion profile filtered by this vertical filter resulting horizontal stripes in $L(x,t)$.

B. Locating Interaction Events from Traces

Locating an event trace is based on the trace position and direction in $L(x,t)$ and $A(x,t)$. Passing and passed actions are monitored at side positions p_3 and p_4 close to frame margins. On-coming vehicles are examined only at p_3 near left margin. The motion stripes are extracted from high values of $|L(x,t)|$ at side positions p_3 and p_4 with a narrow horizontal span. Then the stripe orientation are referred to in the direction image $A(x,t)$ with a median filter within the span. Passing, passed, and on-coming vehicle traces have their orientations inward, outward, and horizontal, respectively.

$$
\begin{array}{llll}
A(p_i,\ t)\ p_i < 0 & & \text{passing vehicle} & \\
\quad\quad\quad\quad > 0 & i=3, 4 \text{ for} & \text{passed vehicle} & \\
A(p_i,\ t)\ \cong -90 & & \text{on-coming vehicle} & (1)
\end{array}
$$

A cut-in can start as a passing vehicle from rear or a parallel moving in the next lane so far. To distinguish a cut-in with similar trace as passing vehicle, a further check at position p_1 or p_2 is carried out accordingly to see if the vehicle invades the driving lane of ego-vehicle at middle range. If a cut-in happens at close depth, i.e., a side crash, the front edge of cut-in vehicle generates an inward horizontal trace in a large span, while the back-side edge may have not appeared as illustrated in Fig. 4. Laplacian filter $L_T(t)$ also picks up such a strong edge from a close cut-in vehicle in M_1.

To monitor a front vehicle motion, the traces of vehicle edges are tracked overtime for the vehicle size change. This tracking starts from the moment when a front vehicle becomes visible in M_1 in the middle depth range. We allocate two horizontal windows around position p_1 and p_2 respectively with their distance adapted to the vehicle width. Major edge traces in $A(x,t)$ close to vertical (blue) are located by the windows. If two major traces are extracted from such windows, we denote their x positions as $x_1(t)$ and $x_2(t)$, the divergence/convergence rate of frontal vehicle is

$$S(t) = [tanA(x_2(t), t) - tanA(x_1(t), t)] / [x_2(t) - x_1(t)] \quad (2)$$

The front vehicle is approaching if $S(t)>0$ and is leaving away if $S(t)<0$. It has been derived in [11] that $S(t) = 1/\text{TTC}$. On the other hand, a trace of crossing vehicle is examined at positions p_1, p_2, p_3, and p_4 in $L(x,t)$. For left turn vehicles in opposite lane, p_1, p_2, and p_3 are checked.

Although ego-vehicle motion can be obtained from vehicle control parameters via CAN bus, we can also identify special moments of stopping, turning, and fast speeding by referring to the movement of surrounding scenes in the video and motion profiles. For a stopping period at an intersection or traffic jam, surrounding scenes are relatively static except some crossing traffic or vehicles passing on side lanes. This generates many pure vertical traces in the motion profile M_0 and M_1. Such vertical traces can be located at points $s(x, t)$ by limiting their angles $|A(x,t)|<\gamma$, where γ is a small threshold. By counting the number of such points, $\|s(x, t)\|$, at frame t, we can declare that ego-vehicle is stopping at time t if $\|s(x, t)\|$ exceeds a given number.

V. Experiments, Evaluation, and Discussion

The Naturalist Driving Videos [3] of 1280×720 pixels have been used and a subset generates motion profiles. The field of view covers 120 degree horizontally, and this covers about four lane width in the middle range depth. Three motion profiles are sampled at [0, 35], [35, 100], [100, 200] pixels below the horizon after it is picked in each video clips. Each five-minute of driving video yields 9000-pixel long motion and road profiles, notated as $M_i(x,t)$, i=0,1,2, and $R_k(x,t)$, k=1,2. The video set contains various types of road including rural, urban, highway, and local roads. Output events extracted are saved in labels as shown in Fig. 6. The data reduction from driving video to profiles make the computation much faster than the traditional methods using vehicle detection, tracking and motion estimation. The understanding of temporal process is turned to the identification of spatial relation of trajectories in profiles.

Ego-vehicle is driving in its own lane. The approaches of frontal vehicles are detected correctly in ego-vehicle's lane. If a pair of inward traces on left and right sides of ego-vehicle's driving lane, it means a front vehicle leaving away from to ego-vehicle. Oppositely, a pair of outward traces on both sides means a front vehicle approaching closer. The TTC can be computed from the traces in the colored areas by using (2). Crossing vehicles at intersections are detected by the traces through margins, i.e., p_3 and p_4. If a vehicle trace from left lane through center to right, the vehicle is turning (its) left from opposite lane at crossing, as shown in Fig. 6.

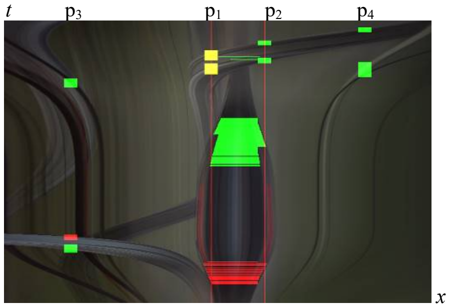


Fig. 6 Detected events of vehicle interactions in color labels. Vertical orange lines at p_1 and p_2 are the ego-vehicle driving lane. The red area at center means front vehicle approaching to ego-vehicle, and the green area means leaving of front vehicle. At p_1 and p_2 as well as p_3 and p_4, yellow and green boxes are inward are outward traces respectively. The crossing trace from left to right is a right turning vehicle from opposite lane.

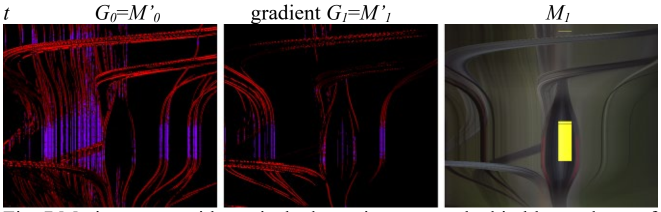
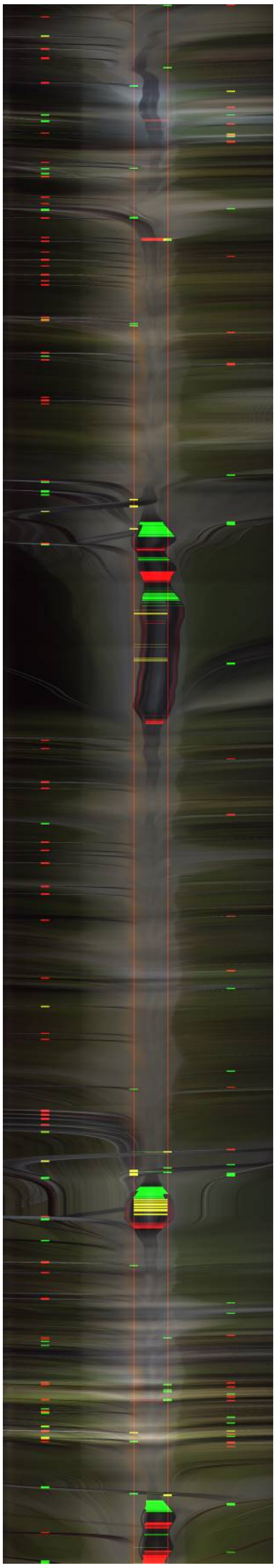


Fig. 7 Motion traces with vertical edge points are marked in blue and rest of traces in red from motion profiles M_0 and M_1. The resulting stopping period is marked with yellow lines at center.

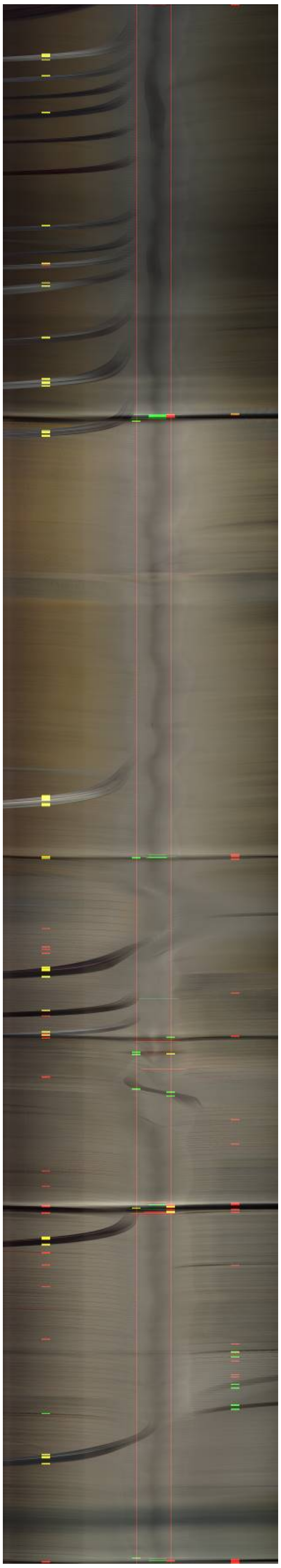
For stopping period detection of ego-vehicle, we refer to static scenes relative to the camera. Occasional cases of parallel driving of a nearby vehicle may generate vertical traces locally, but such traces only remain in short segments. Figure 7 shows a period of stopping with many vertical traces marked in the motion profiles, and the period is marked as stopping framewise when such traces exceed a given number.

As motion events detected by color in Fig. 8, green and red at center indicate a frontal vehicle at middle range moving away and getting closer respectively, computed from trace shrinking and expansion. Frequent shrinking and expansion mean a bumper-to-bumper traffic scenario. On the other hand, red color onside indicates on-coming vehicles, and some objects near driving lane due to their fast image velocity (traces are close to horizontal). Green and yellow further indicate outward and inward traces that are passed and passing vehicles on side lane, respectively.

For the overall evaluation, we select 47 clips of 5-min driving with rich vehicle traces in M_1. The interactions are labeled by humans and detected marks are compared with these labels. By counting events and periods, the accuracy is evaluated in Table II. Our method reduces the complexity of problem based on the camera setting and vehicle motion constrained by traffic rules and roads. The filtering at focused positions in a motion profile needs much lower computation cost than current deep learning methods in the recognition of vehicle and their motion. The motion profiles are obtained in video rate and all filtering takes at most 0.07s for 1s video on MAC with 2.2GHz Intel Core i7.



(a)



(b)

Fig. 8 Detected events of vehicle interactions in color labels. 5-mins of drivings with time axes upward. Orange lines at center indicate driveable width of ego-vehicle. Inward traces are detected in yellow, outward traces in green, and horiontal traces in red at sides. Green, red, and yellow at center indicate leaving, approach, and fixed distance between ego-vehicle and frontal vehicle. Yellow at center also indicates stop of ego-vehicle. (a) Result from Fig. 3 in rural driving. (b) Result on a highway with passing vehicles.

Our interaction classification is based on motion traces at critical locations. Some event detection has to wait for the entire process happened and is thus more suitable for batch processing of NDV than predicting vehicle behavior ahead. This work has not considered turning/braking lights on vehicles, traffic lights ahead of interactions, or future V2V communication during interactions. Recognizing different lights requires locating vehicles and then light blinking.

Table II Accuracy of interaction detection based on motion traces

Events	TP	FP	FN	Precision	Recall	F1
Passing (faster)	113	11	4	0.91	0.97	0.94
On-coming	260	27	51	0.90	0.84	0.87
Passed (slower)	104	13	7	0.89	0.94	0.91
Cut-in	38	7	2	0.84	0.95	0.89
Front approach	28	4	1	0.88	0.97	0.92
Front leaving	36	2	2	0.95	0.95	0.95

VI. Conclusion

This paper introduced a new method to capture vehicle interactions in driving video for driving behavior analysis. Our method captures the motion direction of vehicles at focused zones in driving videos without following the approach of recognition, tracking, classification, etc. We reduce the problem complexity by using filtering in the motion profile that is a compact representation of driving video. We will scan a large set of NDV and mine the frequency of different interactions from personal records for understanding driving behavior such as aggressive, fatigue, and normal.

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