2014 IEEE Intelligent Vehicles Symposium (IV)
June 8-11, 2014. Dearborn, Michigan, USA

Visualizing Driving Video in Temporal Profile

Mehmet Kilicarslan, *Student Member*, *IEEE* and Jiang Yu Zheng, *Senior Member, IEEE*

***Abstract*— Nowadays, many vehicles are equipped with a vehicle borne camera system for monitoring drivers' behavior, accident investigation, road environment assessment, and vehicle safety design. Huge amount of video data is being recorded daily. Analyzing and interpreting these data in an efficient way has become a non-trivial task. As an index of video for quick browsing, this work maps the video into a temporal image of reduced dimension with as much intrinsic information as possible observed on the road. The perspective projection video is converted to a top-view temporal profile that has precise time, motion, and event information during the vehicle driving. Then, we attempt to interpret dynamic events and environment around the vehicle in such a continuous and compact temporal profile. The reduced dimension of the temporal profile allows us to browse the video intuitively and efficiently.**

I. Introduction

Current vehicles can be equipped with in-car video cameras to allow driving scene recording. The cameras record the dynamic changes of scenes on road, accidents, and the vehicle ego-motion. The data have been widely used in accident analysis, traffic pattern understanding, environment survey, driver behavior analysis, and vehicle safety design. However, the important issue raised is the effective access of huge video volumes; reaching a certain moment in the video is an infeasible process.

While key frames are still possible for showing what are in the video as an index, they are sparse in showing time and are difficult to visualize the continuous development of an event. In this work, a temporal profile image is generated from driving video according to the optical flow of scenes for visualizing events in the environments. This temporal profile is simply a 2D image whose one axis is the time and the other axis is the spatial layout of environments in orientation captured by a forward video camera. It is not showing every moment of all the objects, but reveals the footprints of most scenes in the temporal image for a brief search of objects. One can quickly browse the road environments and events in a scrollable and scalable temporal profile first, and then come to examine the details in the indexed frames.

The related works are mainly two approaches in dynamic image analysis. One is the *spatial-temporal analysis* for linear motion [1] that collects data on a pixel array along the optical flow direction such that the visual motion of spatial features is displayed as traces in the EPI image slice. This work extends the linear camera path to smooth curves on a plane to facilitate varied dynamic vehicle motion. Also, we employ the idea of condensed image given in [10] to compensate unstable vehicle shaking during driving periods. The second approach is the route panorama [6] that uses a line [2, 3, 4, 5] or variable strips [8, 9] of pixels to scan scenes along a road or railway [11]. Such works have been used for visualizing sideway scenes or street front for city navigation so far. We will modify the sampling lines to a U-type curve in order to capture more information on road surfaces. Our focus is more on visualizing dynamic motions of pedestrians and vehicles rather than automatic detection of those scenes. The advantages of observing such representation in addition to viewing key frames are (1) much more compact data size than video, (2) continuous trajectories for revealing vehicle motion and actions, and (3) fast counting of objects based on global view of long term motion.

For a front facing camera, we scan the video with a U-shape sampling curve to generate a temporal street profile including the road structure, surrounding vehicles and pedestrians. Also, we use another rectangular sampling belt near the horizon to acquire the long term motion information of moving objects. Proper combination of these profiles gives a complete and continues environmental representation along with the motion trajectories of dynamic objects. The vehicle ego-motion and surrounding vehicle actions can be observed in this temporal profile for efficient indexing and searching of events in large video database. In our study, we aim to identify events such as stopping, turning, and passed by or passing vehicles, pedestrians, and road signs in the temporal profile. Instead of recognizing shapes of objects in individual frames, this identification starts from motion trajectories, which is more effective than applying the optical flow computation in the video.

In the following section, the creation of temporal profile from video is explained. Section III categorizes the shape properties in the scanned road profile. Section IV will analyze the motion properties of dynamic vehicles and passing pedestrians. It also addresses the integration of road and motion into one temporal profile to categorize actions and behaviors of vehicles visible during the driving. Section V summarizes the experiments followed with conclusion.

II. Temporal Profile of Driving Video

A. U-Shape Curve Sampling for Road Profile

A view of in-car wide angle video is displayed in Figure 1. A camera centered coordinate system *O-XYZ* is set where *Z* is heading, *Y* is vertical, and *X* is the horizontal directions, respectively. As the optical flow expands from the *Focus of Expansion* (FOE), we scan the road scenes with a half ellipse sampling curve, and side scenes with two vertical lines

M. Kilicarslan is with the Department of Computer Science, Indiana University-Purdue University Indianapolis, Indianapolis, IN 46202, USA (phone: 812-391-4904; e-mail: mkilicar@iupui.edu).

J. Y. Zheng, is with the Transportation Active Safety Institute (TASI) and the Department of Computer Science, Indiana University-Purdue University Indianapolis, Indianapolis, IN 46202 USA (e-mail: jzheng@cs.iupui.edu).

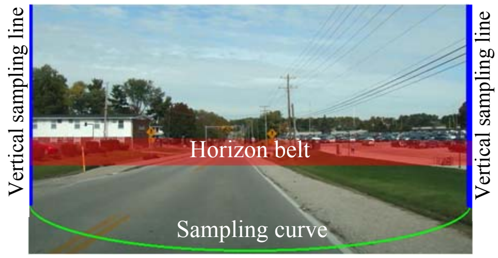


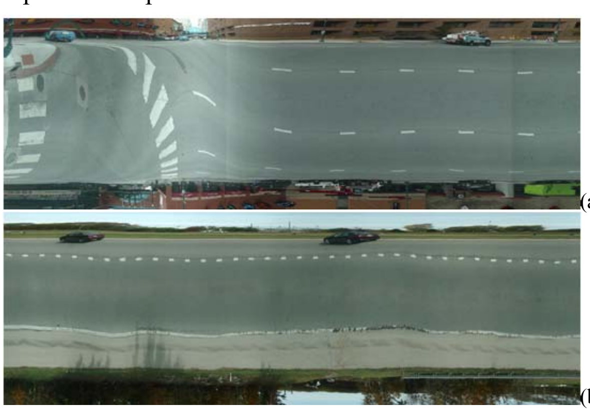
Figure 1. A camera view and the locations of sampling curve and vertical lines on side margins. The horizon belt is colored in red.

extended from both end of the ellipse curve. From consecutive frames, pixel values are copied from this sampling curve and straight lines, and are listed along the time axis to acquire an image, $P(x,t)$, named *environmental profile* or simply *road profile* (Figure 2). Compared to the scene tunnel [7, 11] using multiple sampling lines, a smooth curve with its vertically extended lines brings together the smooth results of shapes. This reduces non-smooth artifact caused by varied road width during the sampling with lines. In the 3D space, smooth lines or curves will be mapped to smooth features in the environmental profile, but linearity is not guaranteed. Vertical sampling lines will scan vertical structures such as buildings and poles in the video, whereas the sampling curve will scan horizontal structures such as pedestrian crossing marks on the road surface. In this way, we can preserve smooth lines and surfaces on temporal profile for shape visualization. Our curve is a half ellipse centered horizontally according to FOE (vehicle heading in the frame). The lowest part intersects the ground at about 3m ahead the vehicle so that we can capture a front vehicle if its distance gets close.

We sample 60 lines (frames) per second using the interlaced frame of video, which yields temporal resolution as precise as 0.017 second per pixel in representing time event. However, the shape shown in the temporal domain has a lower resolution than the spatial resolution in the image, unless a scene is at far away from the camera path. This causes under-sampling at road surface by the ellipse segment [18], and passing vehicles at next lane.

B. Resampling Profile Spatially for a Virtual View

Due to a low position of the camera and the ellipse segment close to the ground, the generated profile is dominated with the driving lane in a super-high resolution, which is not preferable for visualization of entire road. We warp the road profile such that the road surface is virtually



(a)

(b)

Figure 2. Environment profiles of (a) urban and (b) rural roads

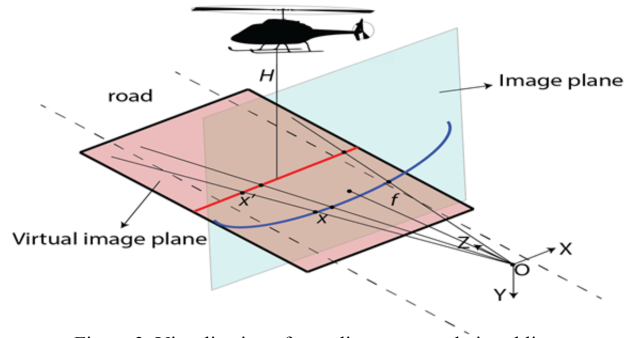


Figure 3. Visualization of sampling curve and virtual line.

viewed from a camera located at a high place (Fig.3). Denoting a pixel on ellipse by (*x, y*), the perspective projection transforms a 3D point (*X*, *Y*, *Z*) to (*x, y*) by,

$$x = \frac{fX}{Z}\ ,\ y = \frac{fY}{Z} \tag{1}$$

where *f* is the camera focal length. In (1), *x* and *y* are known on the ellipse and -*Y* is known as the ground point. We can thus determine depth *f*/*Z* for ground point. Hence, the real horizontal position *X* for a point on the sampling curve is given by

$$X = \frac{xY}{y} \tag{2}$$

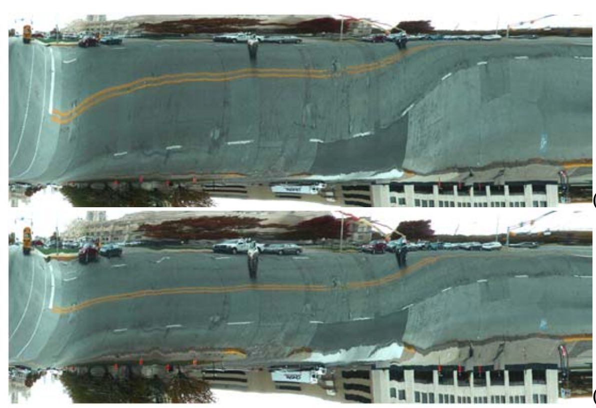
For consecutive pixels *i* and *i*+1 on the curve, we can find their corresponding positions at *X*(*i*) to *X*(*i*+1). The minimum width between two *X* positions is computed for all *i* as a standard width *W*. We map entire *x* to *x*' in a higher view by warping pixels locally such that resulting consecutive *x'* have standard *W* on the road surface, as described by

$$\Delta x' = \frac{fW}{H} \tag{3}$$

where *H* is a virtual camera height and $\Delta x' = x'(i+1) - x'(i)$. The new view $P(x',t)$ from the higher position thus is calculated such that *x*' is proportional to the road. Figure 4 shows such an implementation to transform the original road profile to such a profile of "helicopter" view.

C. Motion Profile of Dynamic Scenes

In the forward direction, the consecutive frames from the camera have pixel redundancy for road, background, vehicles, etc. Therefore, key frames can be used for indexing



(a)

(b)

Figure 4. Environmental (road) profiles. (a) Before resampling. Center lane is dominating in the image. (b) After resampling. Center lane is reduced in width, and side lanes and cars have better views.

video. In this work, however, we create a different temporal view from video to provide continuous motion trajectories of vehicles and pedestrians, in addition to the road profile. Mostly, vehicles and pedestrians are higher than the camera height (set at the in-car back mirror position), and they are projected to the video frame at least higher than the horizon in the frame. Our sampling line is then located at the horizon height to acquire their motion trajectories. In real computation, we place a rectangular belt (Fig. 1) on the horizon in order to tolerate the vehicle pitch on uneven roads. The pixels in the belt are vertically averaged to form a condensed array. This array is computed in each frame and consecutive arrays are stacked along the time axis to form the *motion profile*. Figure 5 shows vehicle, people, and environment motion trajectories in such a motion profile. The widths of those traces also tell the depths of vehicles from the camera. The trace color shows the average color of the objects. We can analyze the surrounding events by analyzing the trajectories, and measure the action time at a precision of 0.017 second.

D. *Integrating Environment and Motion Profiles*

Our final stage for visualization is to combine motion and road profiles with the same temporal resolution in a 2D image. The two sampling lines intersect at two known positions in the video frame. By aligning two profiles at intersection points, we can match an object in the road profile with its trace in the motion profile when the object is scanned by a vertical line and side part of the ellipse. The integration of two profiles is realized by blending their colors. A blending mask, $B(x)$, is designed in normal distribution $N(0,\sigma)$ with the highest opaque value to be 0.7.

$$T(x,t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} M(x,t) + \left(1 - \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) P(x,t) \quad (4)$$

where σ=350 and μ is the pre-computed horizontal position of FOE in the temporal profile. This will emphasize motion trajectories over the road surface, which has relatively uniformed color, and show passed roadside scenes and passing vehicles at sides. The final image is named temporal profile of video $T(x,t)$ as shown in Fig 6. Objects in road profile and traces in motion profile are aligned because the U-curve and sampling belt intersect at the projected horizon in the frame. Hence, we can understand specific objects in road profile with the attached motion trajectories. This display is particularly obvious in a stopping period where

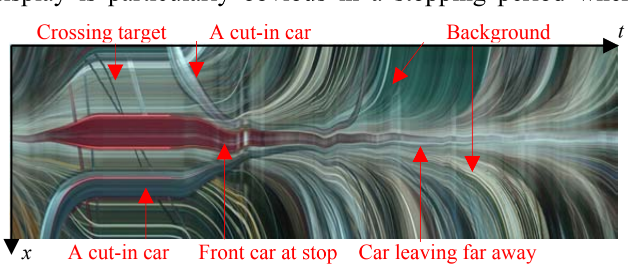


Figure 5. Motion profile during a stopping and moving forward action. A red vehicle in front with break light on has increasing size, when its depth becomes close before stopping. Passing vehicles are from side to center in the motion profile. Two pedestrians walked across the street slowly. Divergence traces of hyperbola are from background during the forward moving.

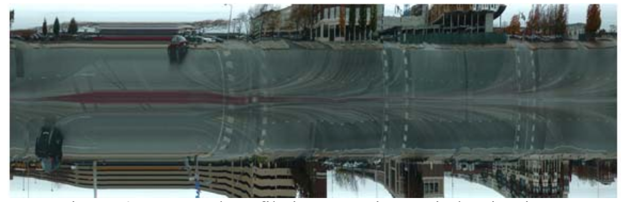


Figure 6. Temporal profile in a stopping period as in Fig. 5.

vehicles and pedestrians cross the street (Fig. 6). When visualizing the video, a place of interest can be identified in the temporal profile first and then the detailed frame can be displayed and examined when mouse is placed over the temporal profile.

III. Shapes in Road Profile for Identification

A. *Smoothness of Features Projected to Road Profile*

The camera motion can be described as a smooth path composed of changeable translation and rotation on the horizontal plane. Assuming the vehicle motion is $\boldsymbol{M} \in R^3$ and it also suffers from disturbance $\boldsymbol{s} \in R^3$ due to vehicle shaking on uneven road, the composite motion is

$$\boldsymbol{G}(t) = \boldsymbol{M}(t) + \boldsymbol{s}(t) \quad (5)$$

Through the smooth U-curve, a ray surface can be formed from the camera focus $O(\boldsymbol{M}(t))$ as smooth cone $R(X(t), Y(t), Z(t))=0$. If a smooth feature such as a line or curve in the 3D space is intersected by the ray surface, it is scanned during a relative motion of the camera. The intersection, $\boldsymbol{P}(X(t), Y(t), Z(t))$, is the solution of two equations as

$$\begin{cases} F:\ f(X,Y,Z) = 0 & \textit{feature in world system} \\ M: R(X(t),Y(t),Z(t)) = 0 & \textit{moving ray} \end{cases} \quad (6)$$

which is also smooth (differentiable with respect to t). Point $\boldsymbol{P}$ is mapped to the temporal profile at $P(t, x)$ via perspective projection so that the feature is smooth in the temporal profile, although the linearity is not preserved. The following resampling or warping is a continuous function to guarantee the smoothness in the results, which improves the feature visibility or readability in the temporal profile. Although vehicle shaking $\boldsymbol{s}$ adds zigzags to the projected features as shown in Fig. 7, the shaking is not extremely large so that features are still recognizable.

Two vertical lines extend from both ends of the ellipse to the top of frame. The two vertical ray planes scan buildings in parallel with their vertical structure. This preserves shapes of vertical structures in the temporal profile. We consider three sets of vectors in the space orthogonal to each other and parallel to the axes of camera system *O-XYZ*. They are along lanes, building rims, and crossing sections, respectively [7]. When the vehicle moves on a straight road,


Figure 7. Camera yaw and roll cause shape deformation due to vehicle shaking. In enlarged partial views, lines are vertically zigzagged.

the lanes are parallel to the time axis. The crossing lines on the road such as pedestrian paths form curves. Vertical lines on buildings stay vertical in the temporal profile. Further deformation is from the vehicle shaking and deviation. Figure 7 shows an example of urban profile with zigzagged appearance on buildings due to the change of vehicle roll. Also, lane marks may be curved because of the vehicle yaw change (Fig. 8b). However, structure persists and the scene is recognizable.

B. *Order and Deformation of Dynamic Scenes*

Two vertical lines also sample dynamic objects passing by such as vehicles and pedestrians. Entering or exiting the field of view, objects leave their shapes in the road profile once. A passing vehicle always has a shape in head-first order (head facing left), whereas a passed vehicle has shape in back-first order (head facing right) in the road profile (Fig 9a). Also, if a passing vehicle slows down, it will leave a front-back and back-front shape in the profile. The vehicle moving in parallel with the camera will drag its shape longer. Although it is not visually pleasant to observe this, it is a unique case that needs to identify (Fig 9b).

The length of dynamic object in the temporal profile is inversely proportional to the relative speed with respect to the vehicle. Oncoming vehicles on the opposite lane thus have short appearances in the road profile (Fig. 9c). Whereas, passed and passing vehicles moving in the same direction as the camera are usually longer than static objects on road sides in the temporal profile. Though objects are not accurate as compared to their real shapes, they are distinguishable.

IV. TEMPORAL CHARACTERISTICS OF VIDEO

The state of art pattern recognition algorithms for in-car video identify different types of scenes such as lane marks [14], vehicles [15] and pedestrians [16, 17], and then perform tracking algorithms for motion information. For indexing the volumes of driving video, we generate the compact temporal profile for fast event searching using motion information directly. We categorize motion events into two sets caused by ego-motion and relative motion.

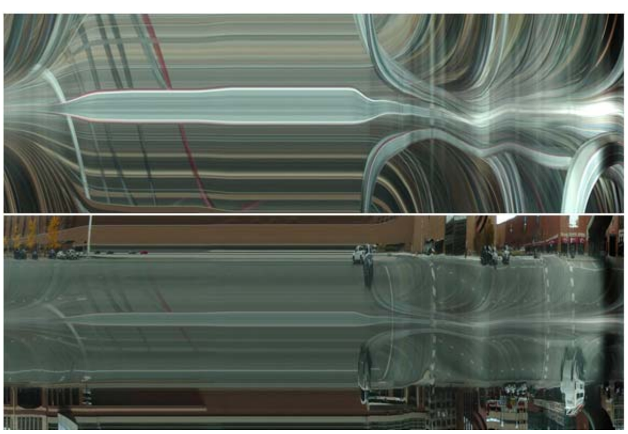


Figure 8. (Top) Motion profile in urban area. Front vehicle stops and its motion trace is enlarged. Multiple vehicles cross the street. Then, two vehicles are passing and their traces converge to FOE. (Bottom) Temporal profile with road and motion merged.

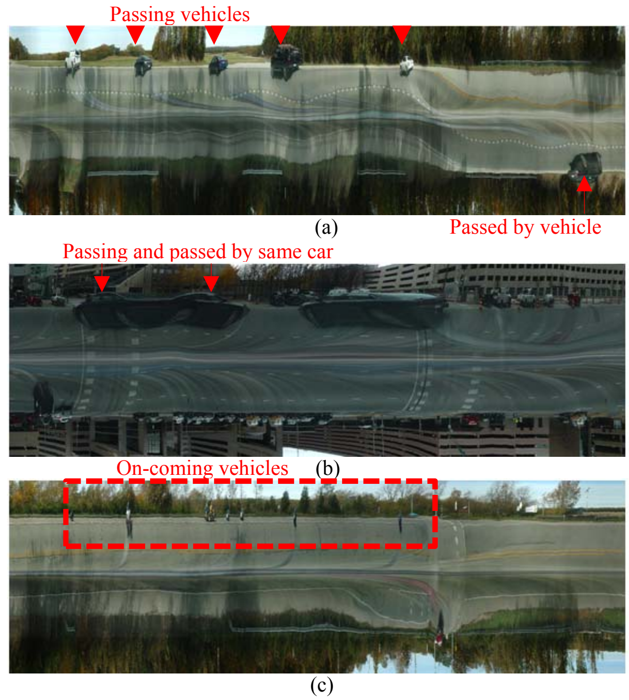


Figure 9. Temporal distortion of dynamic objects in the road profile. (a) Five passing vehicles on left and one passed vehicle after change to the left lane on a rural road. (b) Passing and passed vehicle shapes moving along with the camera. (c) Size of on-coming vehicles are small due to high relative speeds with respect to the camera.

Ego-motion can be obtained from other sensors such as GPS and inertial sensor as well. However, the temproal profile provides higher temporal resolution (60Hz). The phenomena visualized in the temporal profile are addressed here to help reading of these events.

A. *Vehicle Action based on Ego-motion*

1) *Forward Translation*

With the vehicle ego-motion, we can categorize static background and dynamic foreground according to their traces in the motion profile. For example, background motion expands from FOE and forms divergent traces (Fig. 8). A front vehicle trace is located at the center and its width either shrinks or expands based on its changing depth. The vehicles' traces occlude the background. The probability distribution of position and velocity of vehicle trace can be used to distinguish background and vehicle traces [12].

2) *Stopping*

If the vehicle stops, static background generates straight traces along the time axis in the temporal profile. Other dynamic objects such as crossing vehicles and pedestrians leave traces non-parallel to the time axis (Fig.10a). The motion can be identified with crossing traces in the motion profile, and their types can be confirmed in the road profile (Fig.10b).

3) *Turning at Street Corner*

When a turning event happens at a street corner, the motion vectors are obviously in one direction in parallel to each other in the motion profile (Fig.11a). Figure 11(b) shows a turning event in the road profile where surface marks are slanted.

Figure 10. One minute stopping event waiting for signal. Long horizontal lines both in motion and road profiles are visible. Vertically orientated traces in the motion profile are crossing traffic. The vehicle types that the traces connect can be confirmed in the road profile.

4) Lane Changing

In the temporal profile, lane marks deviate largely when a lane change action happens (Fig.12). However, the horizon positions on both sides do not change in the road profile. In more general case, a takeover action shows a big wave of lane marks with certain passed vehicles in the road profile.

B. Motion of Other Vehicles

1) Crossing Street Vehicles

While stopping at an intersection, crossing vehicles leave their shapes and whole motion traces in temporal profile. In such a stopping case, all background has horizontal traces. On the other hand, crossing vehicles have almost vertical motion traces in motion profile depending on their actual

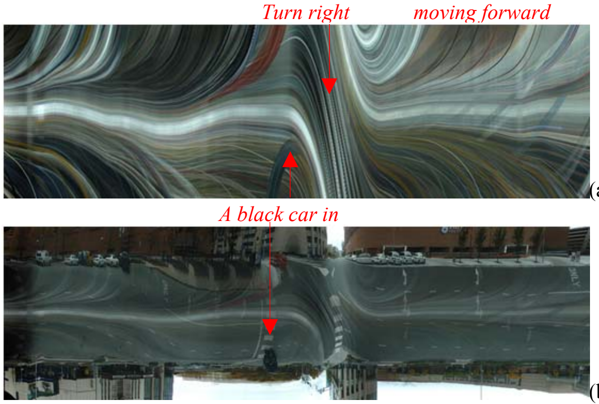


Figure 11. Turning to left. Parallel traces in one direction are distinct.

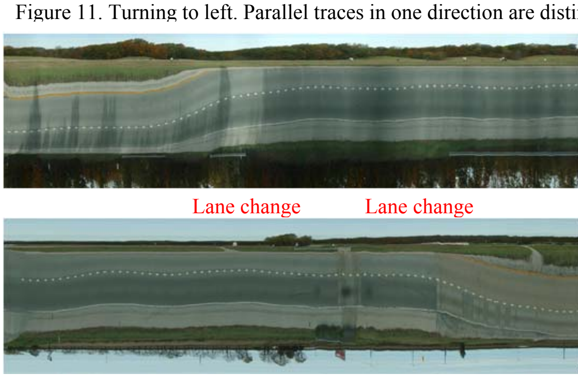


Figure 12. Lane changes. (a) Left to right (b) Right to left lane change.

Fig 13. A passed vehicle's motion trajectory from center to right margin on the temporal profile.

speeds. For pedestrians and bicyclists, their motion traces can be uniquely determined from their width narrower than vehicle traces. Left-turn and right-turn traffic into the current road can also be observed from their traces (Fig. 10).

2) Passing and Passed Vehicles

In the motion profile, passing vehicles (faster than the observing vehicle) have their trajectories starting from sides to center as the time goes on. The same trace direction can be observed for cut in vehicles. A passed vehicle (slower than the observing vehicle) has a trajectory from center to left or right margin depending on the location of vehicle (Fig 13). Passing vehicles leave their shapes in head-first order, while passed vehicles have back-first order in the road profile. Cutting-in vehicles have the similar traces as passing vehicles but in sharp traces.

3) Front Vehicles

In forward motion video recording, a front vehicle is not visible in road profile unless the vehicle is close to bumper-to-bumper situation. A front vehicle is visible by following the motion trace to the road profile (Fig. 14). The vehicle back including break lights become visible as the distance gets close, which is easy to be identified.

4) Pedestrians in Temporal Profile

In the motion profile, pedestrians usually have slower motion than the vehicle motion, which can be distinguished from the orientation and width of the traces. Figure 15 shows several examples of pedestrians in the temporal profiles.

V. Experiments and Discussion

We have driven vehicles in the city and suburban areas including local roads and highways. The vehicle heading direction described by FOE and horizon are estimated only once for each camera. It is calculated in advance from the optical flow by using several sampled frames taken when the

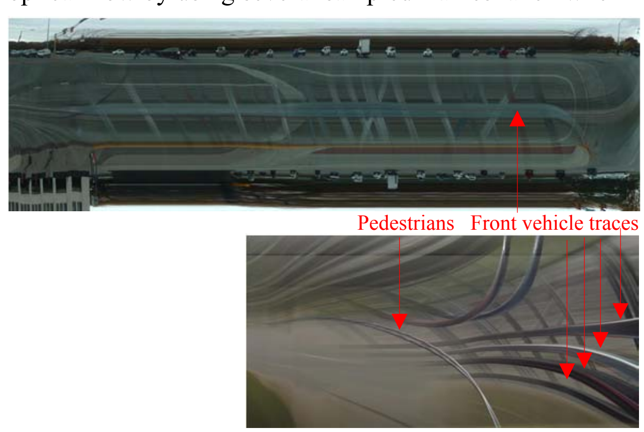


Figure 14. Front vehicle can be seen with its trace in the motion profile.

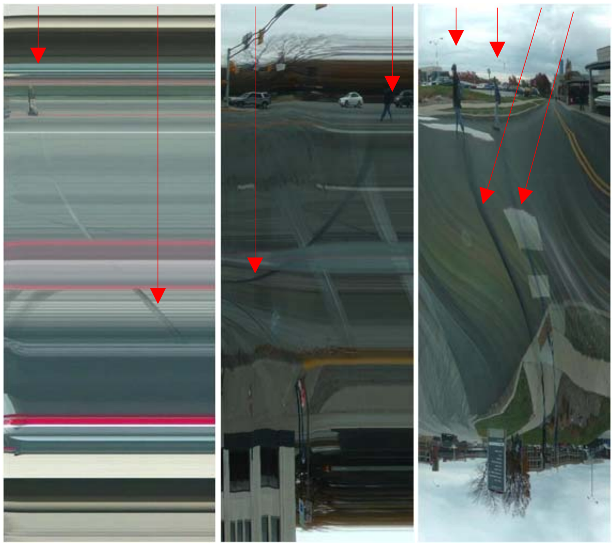


Figure 15. Finding pedestrians crossing streets from their traces in temporal profiles. Pedestrians also leave their shapes in road profile.

vehicle is moving on flat ground. Then the fixed sampling curve/lines are located in the frame accordingly for scanning the entire video. We analyze 12 hours driving video and every 5 min video is transformed to a temporal profile of 18000 pixels in JPG. Various weather conditions and illuminations are recorded for driving database construction. The spatial resolution of the profile is 1221 pixels. The data reduction rate is 1/500 from video without compression. The long temporal profile can be scrolled and scaled for browsing. Figure 16 shows a profile without size reduction. Many details can be observed even if the shape deformation exists. It is sufficient to count vehicles and pedestrians with their visualized traces. Figure 17 is a long temporal profile of 8 minutes in urban area.

Figure 18 shows a night driving profile and we confirmed that the reliable feature is the lane mark reflected under the illumination of vehicle head lights. For the night driving, our U-curve sampling has a constant depth in obtaining the road profile, which acquires the light reflectance from road surfaces. The illumination on the road thus becomes measurable. The total light intensity on the sampling line is the sum of vehicle head lighting and ambient illumination. This avoids direct measuring of other light sources such as head lights of opposite cars, pole lights, and ambient lights on buildings in the original video. We can approximately calculate illumination value at any given time by subtracting the biased component of vehicle headlight.

The temporal profile collects scenes at different places with the same time stamp. It is thus particularly useful for finding dynamic behavior of the driver/vehicle, as well as the interaction with other vehicles and pedestrians. They can be easily counted in the temporal profile as compared to counting frames. Driving video is scanned and the temporal profile is generated with the temporal coordinate mapped from the frame number.

The proposed temporal profile is a reduced-dimension

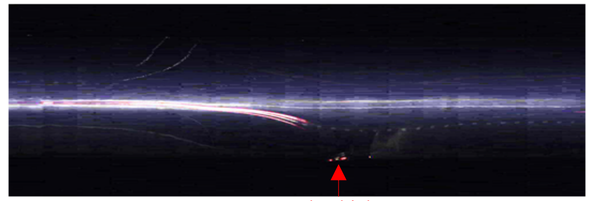


Figure 18 Night view. Lane change and passed vehicle are visible.

data set. Its continuity is suitable for fast scanning and counting of objects and events by human operators. Although it is not as intuitive as video frame, the readability can be improved after understanding the phenomena described above. It can be combined with the key frames for video browsing as shown in Fig. 19. We will use it in surveying naturalistic driving data with various traffic patterns in order to rank the top scenarios for vehicle testing.

The automatic video identification of objects and events is not necessary to be based on the temporal profile for its small data size. The extracted shape with fast and shaking camera motion usually is noisier in the profile than in the video frame. However, for some events characterized by long-term motion, the temporal profile has a great advantage in following the objects as compared to key frames. There is no need to combine temporal and road profiles to a single image in such a circumstance.

VI. Conclusion

This paper introduced a 2D temporal profile image created from driving video for understanding road environment and dynamic traffic. A method is proposed to acquire the profile to include rich scenes and precise time. The 2D temporal image is small in data size for fast video browsing and search, and the recorded continuous motion traces directly reflect the actions of observing vehicle and the events of surrounding traffic. The temporal profile can be scrolled and scaled in visualization for human operators to further examine individual video frames. Future work will be (1) the automatic event detection based on the motion traces in the temporal profile and traffic counting along

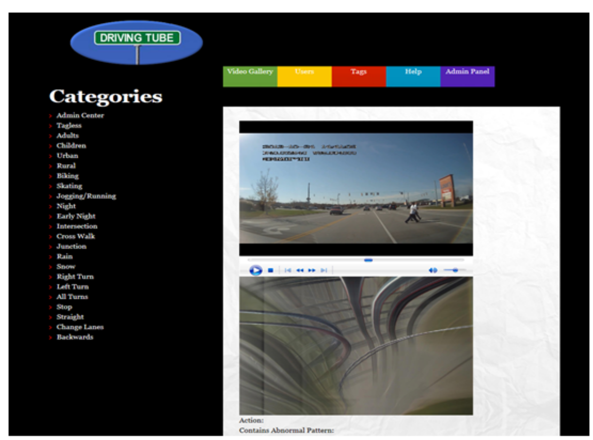


Figure 19. An interface developed for accessing a terabyte-database of driving video with temporal profiles. Motion profile shows the traces of the pedestrians, opposite cars, and front cars waiting for signals. Crossing cars also appear as traces partially occluded by front cars. Categories are listed for searching various video clips.

Figure 16. Urban driving in temporal profile. The caps and lane marks on the road surface are clearly recorded. The vehicle has a left turn from a one-way street to a two-way street, after changing from middle lane to left lane. The vehicle shifts to right lane after turning.

routes for terabyte database of driving video. (2) The road environment assessment on the pavement and illumination will be tackled as well by using the temporal profile. (3) Adding another scanning line segment at top part of the video frame to capture traffic light at a fixed distance ahead the vehicle.

ACKNOWLEDGMENT

This work is partially supported by TASI. The authors thank Christian Dodds, Alexnader Goodman, and Rui Chen for their contribution in website construction.

REFERENCES

[1] R. Bolles, H. Baker, D. Marimoto, Epipolar-plane image analysis: an approach to determine structure from motion, International Journal of Computer Vision (IJCV), 1(7-55), 1987.

[2] J. Y. Zheng, S. Tsuji, Panoramic representation for route recognition by a mobile robot, Int. Journal Computer Vision, 9, 55-76, 1992

[3] S. Peleg, J. Herman, Panorama mosaics by manifold projection, IEEE Comp. Vision Pattern Recognition, 338-343, 1997

[4] J. Y. Zheng, S. Tsuji, Generating dynamic projection images for scene representation and understanding, Computer Vision and Image Understanding, 72(3), 237-256, 1998

[5] S. Peleg, B. Rousso, A. Rav-Acha, A. Zomet, Mosaicing on adaptive manifolds, IEEE Trans. Pattern Analysis Machine Intelligence, 22(10), 1144-1154, 2000.

[6] J. Y. Zheng, Digital route panoramas, IEEE Multimedia, 10(3), 57-67, 2003

[7] J. Y. Zheng, Y. Zhou, P. Mili, Scanning scene tunnel for city traversing, IEEE Trans. Visualization and Computer Graphics, 12(2), 155-167, 2006.

[8] Z. Zhu, A. R. Hanson, E. M. Riseman, Generalized parallel-perspective stereo mosaics from airborne video, IEEE Trans. Pattern Analysis and Machine Intelligence, 26(2), 226-237, 2004.

[9] J. Kopf, B. Chen, R. Szeliski, M. Cohen, Street slide: browsing street level imagery, ACM Graphics 29(4), 96: 1-8, 2010.

[10] H. Cai, J. Y. Zheng, H. Tanaka, Acquiring shaking free route panorama by stationary blurring, IEEE Int. Conf. Image Processing, 2010, 921-924.

[11] S. Wang, S. Luo, Y. Huang, J. Y. Zheng, P. Dai, Q. Han, Railroad online: acquiring and visualizing route panoramas of rail scenes, The Visual Computer, 2013, 1-13.

[12] A. Jazayeri, H. Cai, J. Y. Zheng, M. Tuceryan, Vehicle detection and tracking in car video based on motion model, IEEE Trans. Intelligent Transportation System, 12(2) 583-595, 2011.

[13] M. Kilicarslan, J. Y. Zheng, Towards collision alarming based on visual motion, IEEE Int. Conf. Intelligent Transportation System, 654-659, 2012.

[14] N. Apostoloff, A. Zelinsky, Robust vision based lane tracking using multiple cues and particle filtering, IEEE Intelligent Vehicles Symposium, 558-563, 2003.

[15] H. Schneiderman, T. Kanade, A statistical method for 3D object detection applied to faces and cars, IEEE Computer Vision Pattern Recognition 2000, 749-751.

[16] D. Geronimo, A. M. Lopez, A. D. Sappa, T. Graf, Survey of pedestrian detection for advanced driver assistance systems, IEEE Trans. Pattern Analysis Machine Intelligence, 32, 1239-1258, 2010.

[17] P. Dollar, C. Wojek, B. Schiele, P. Perona, Pedestrian detection: an evaluation of the state of the art, IEEE Trans. Pattern Analysis Machine Intelligence, 34, 743-761, 2012.

[18] J. Y. Zheng, M. Shi, Scanning Depth of Route Panorama based on Stationary blur, Int. Journal Computer Vision, 78(2-3), 169-186, 2008.

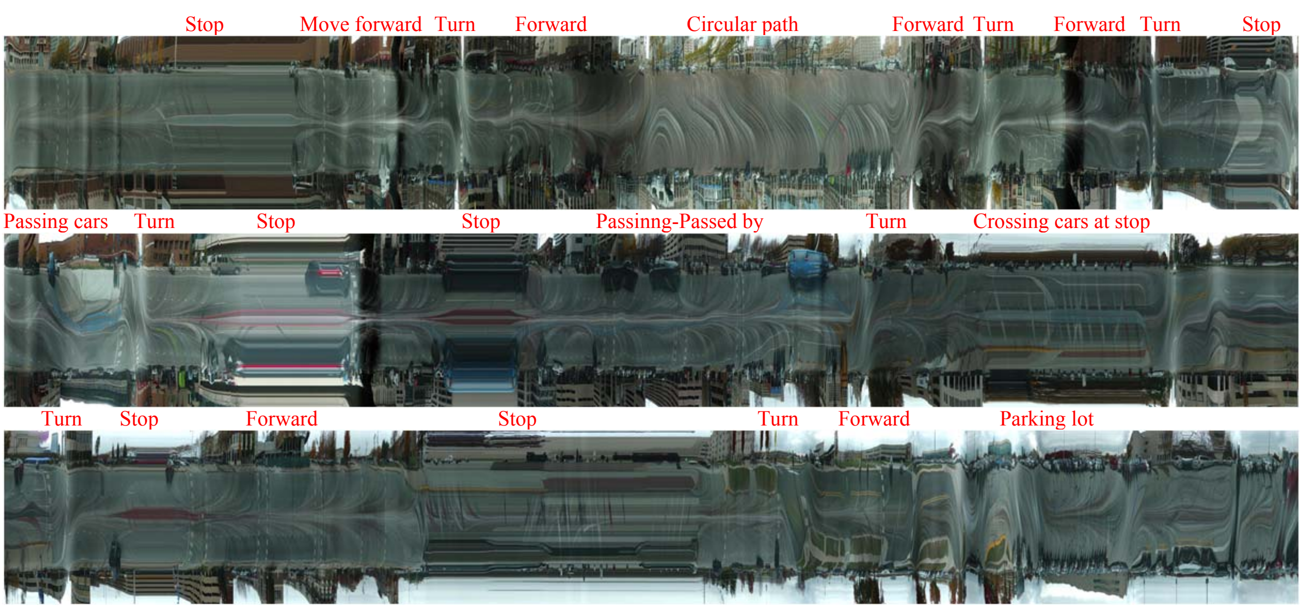


Figure 17. Eight minute long temporal profile from urban area for a global view of driving experience.