<u>Motion Based Vehicle</u> <u>Identification in Car Video</u>

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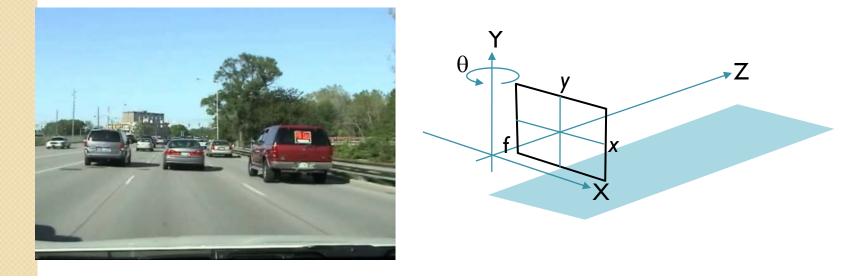


Outline

- Our goal is to track and identify moving vehicles ahead against static background in car video
- Under ego-motion, dynamic vehicles and background display different motion behaviors
- Profile features in car video and track motion for fast and robust processing
- Describe motion probability regarding image position and image velocity
- Use HMM to identify vehicles from their continuous movement

In-car Video: Assumptions

- Ego-motion (speed and steering) is controllable or readable from a vehicle
- All vehicles run on road, and are mostly moving in the same direction as the camera
- Horizontal image velocity change and vertical scaling happen in both background area and target vehicles
- We separate moving vehicles and static background including stopped vehicles





Challenges

- Variations of vehicles in shape, size, color, type, etc.
- Illumination changes in outdoor environments (day and night, shadow and highlight, etc.)
- Unpredictable occlusion between vehicles
- Cluttered background or no prior knowledge on changing background
- Real-time Performance

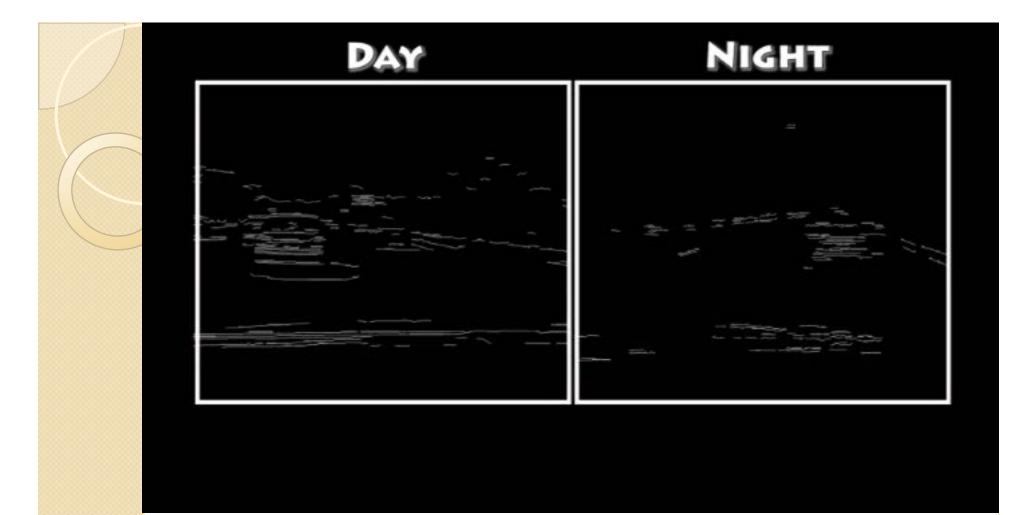
Related Works on Vehicle Detection Based on Shapes and Models

Employ priori knowledge to hypothesize vehicle locations in an image

- Intensity
 - Learning the characteristics of vehicle classes from a set of training images
- Shape cues
 - Symmetry, color, shadow, corners, vertical/horizontal edges, vehicle lights, and texture
- Model
 - Vehicle templates or models with varying degrees of deformability
- Optical flow or motion traces
 - Tracking vehicle

Our Approach Using Image Motion

- Ego-motion (forward translation + horizontal rotation) is general for all types of observer vehicle
- Ego-motion generated background motion is determinant in direction and scale
- The vehicle motion against background is invariant to the shape, color, and size of target vehicles



Motion alone tells something



Ego-motion

video frame

than at two sides

Background Motion

• Sky has zero flow

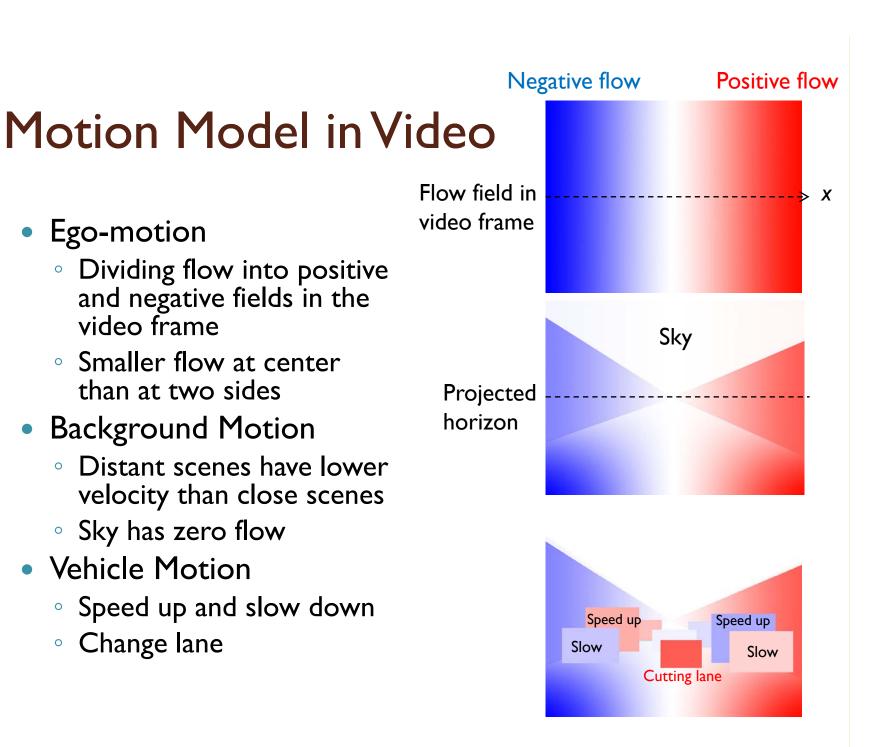
Vehicle Motion

Change lane

0

0

0

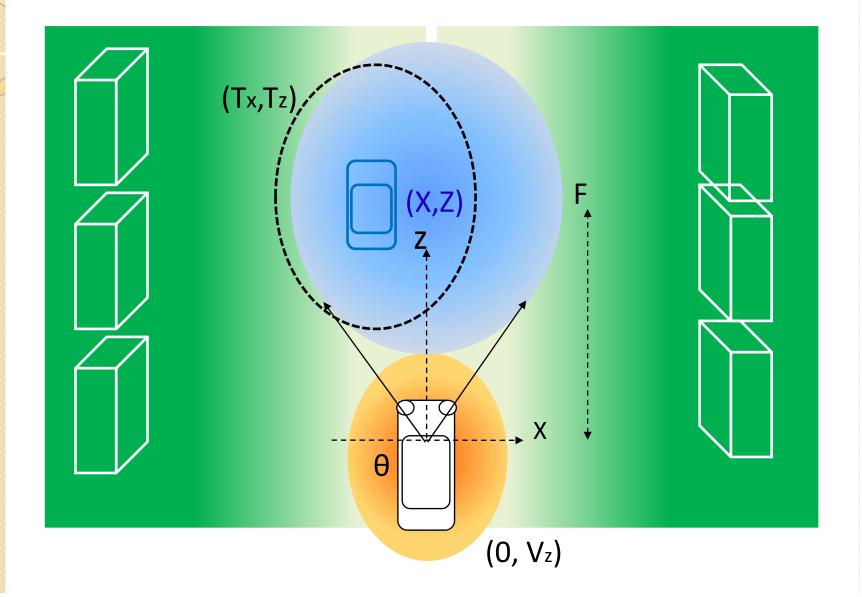


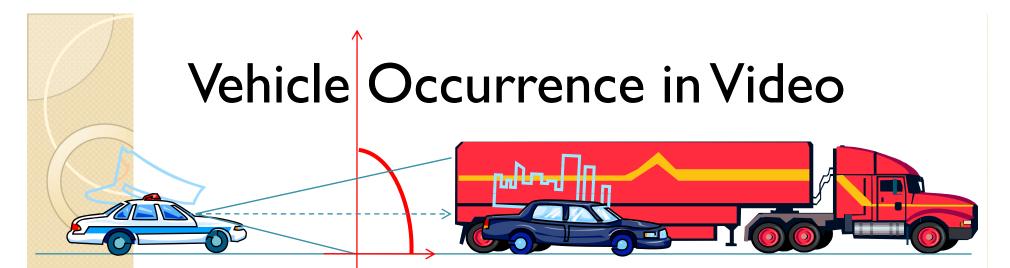


Method

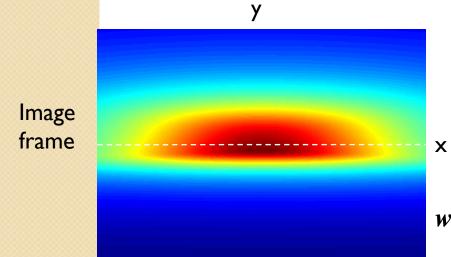
- Using horizontal image velocity only
 - Profiling video vertically and tracking the condensed image
 - This yields variables: (x,v)
 (Image position, Horizontal image velocity)
- Computing likelihood probability distribution P(x,v) for vehicles and background
- Detection using continuous motion behavior
 - Hidden Markov Model (HMM)
 - Results in identity with probability description

Background and Vehicle Distributions on Road





- Vehicles appear most frequently in the image across the projected horizon
- Taking I D profile from image using a mask to speed up tracking

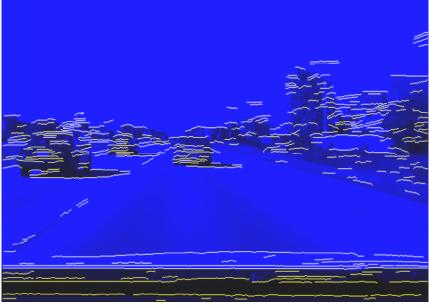


$$T(x) = \sum_{y=-h/2}^{h/2} w(x, y) I(x, y)$$

w(x,y)

Vehicle Feature Extraction

- Vehicles typically contain many horizontal edges formed by top and bottom boundaries of a car, license plate, and window edges.
- Other features include corners, intensity peaks, etc.



ID Profiles form a Condensed Image

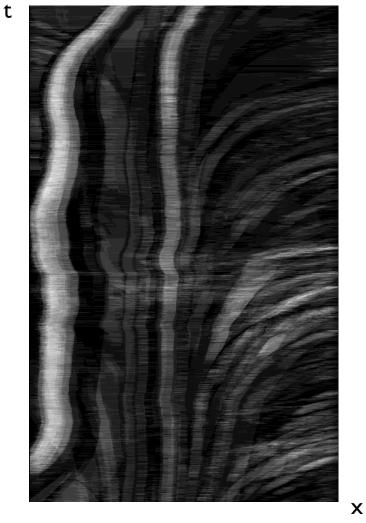
X

• Vertically profile features extracted in the video frames to generate traces of vehicles in the spatialtemporal image

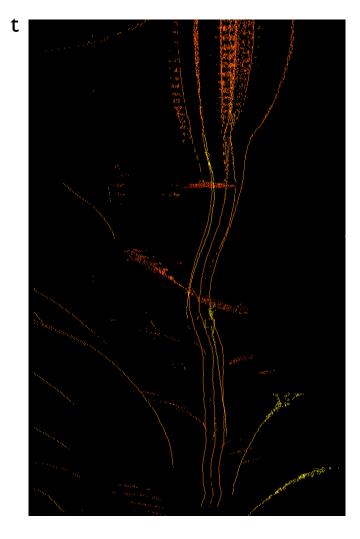
$$T(x,t) = \sum_{y=-h/2}^{h/2} w(x,y) I(x,y,t)$$

- The condensed image containing feature traces for detecting vehicles
- Reducing the influence of vehicle shaking in pitch and roll

Examples of Condensed Images



Horizontal Line Profile

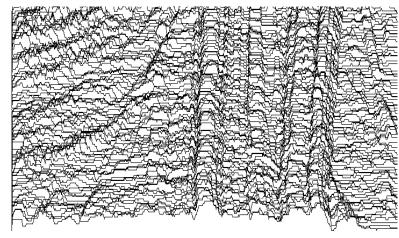


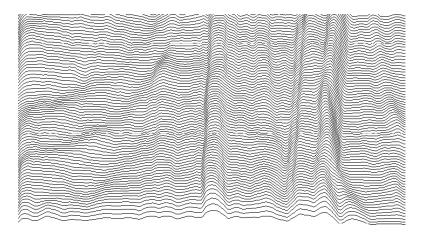
Intensity Peak Profile



I-D Profiles Processing

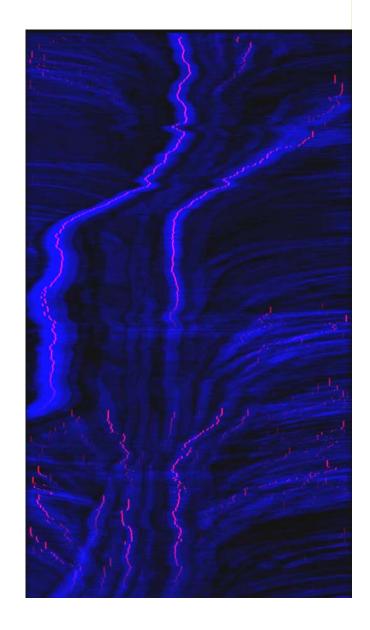
- Due to the presence of horizontal lines in the background scene, the original ID profile is very noisy
- Pyramid scaling operations are preformed on the profiles to eliminate the noise and extract major feature traces



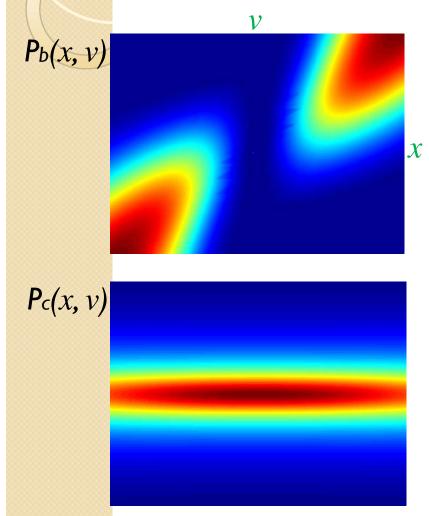


Tracking Traces in Condensed Image

- Tracking traces in the condensed image over time determines (x,v) sequences
- For unstable traces from line segments, we track the center part of each trace
- Track traces in the condensed image using Kalman filter during the vehicle motion
- Motion continuity is applied in tracking to avoid noise from instantaneous light changes



Likelihood Probability Distribution of Motion in Video

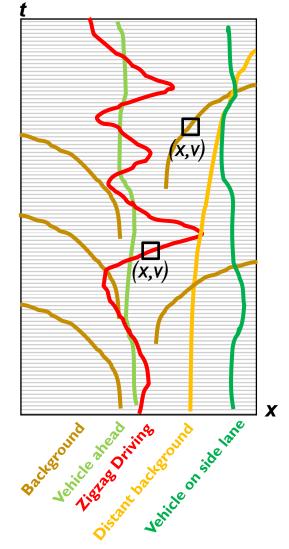


Red = high probability; Blue = low probability

- Joint probability P_b(x,v) for background
 - Including minor steering N(0,5°)
 - From uncertain positions at distance towards certain positions on left and right sides of observer's vehicle
- Joint probability P_c(x,v) for vehicle features
 - Relatively low image velocity when vehicles are confined in the road space

Motion Behaviors along Traces

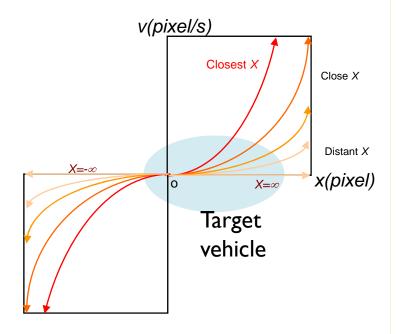
- Background objects pursue hyperbolic trajectories expanding from the Focus of Expansion.
- The curvature of a background trace is high if it is closer to road and is low if it is further from road.
- Their image velocity is higher on scenes passing by, and is lower at scenes down the street.
- On the other hand, vehicles tracked within the road may stay in the image frame even they drive irregularly in a zigzag way





Identifying Traces during Tracking

- Using a probabilistic formulation to model the motion to avoid using sensitive thresholds in classification
- Hidden Markov Model (HMM) is used to model the continuous process of vehicles and background motion
- Two hidden states describe every trace at any time *t*:
 - State C_t as vehicle
 - State B_t as background
- The observation is a sequence of (x(t),v(t)) obtained from tracking trace
 - Image position x(t)
 - Horizontal image velocity v(t)



 $v(t) = \frac{fXV}{Z^2(t)} = \frac{Vx^2(t)}{fY}$

Estimate Status of a Trace

Posterior probabilities P(C_t | x(t), v(t)) and P(B_t | x(t), v(t)) are updated by

 $P(C_{t}) = \max[P(B_{t-1})P(C_{t} | B_{t-1})p(x(t),v(t)|C_{t}), P(C_{t-1})P(C_{t} | C_{t-1})p(x(t),v(t) | C_{t})]$ $P(B_{t}) = \max[P(B_{t-1})P(B_{t} | B_{t-1})p(x(t),v(t)|B_{t}), P(C_{t-1})P(B_{t} | C_{t-1})p(x(t),v(t)|B_{t})]$

using Viterbi algorithm

- If P(C_t) > P(B_t), the trace is considered as a car at time t, or as background otherwise
- At any time t, $P(C_t)+P(B_t)=I$, for normalization

$$P(C_t) \leftarrow \frac{P(C_t)}{P(C_t) + P(B_t)} \qquad P(B_t) \leftarrow \frac{P(B_t)}{P(C_t) + P(B_t)}$$

• The identified trace is formally output after it is tracked over a certain duration. Otherwise, such a short trace is removed as noise



Vehicle Identification





Vehicle Detection Results

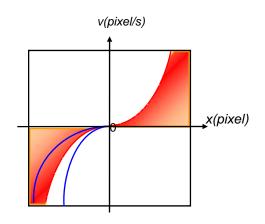
VEHICLE DETECTION AND TRACKING IN IN-CAR VIDEO USING TEMPORAL PROFILES



Vehicle Detection Results

- The longer the tracked duration, the more certain the identification becomes.
- If a detected vehicle moves too far from the observer car, it will be ignored
- Approaching vehicles on the opposite lane are classified as background
- Turning at a street corner needs another likelihood distribution, but not dealt with here

True-Positive	86.9
False-Negative	14.1
True-Negative	85.9
False-Positive	13.2



Opposite lane vehicle



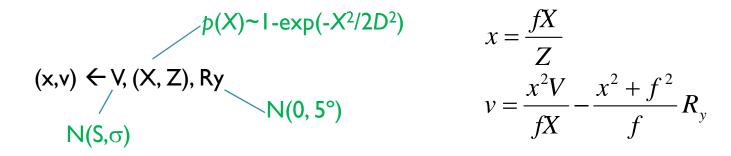
Conclusion

- Detected features and tracked their profiled trajectories in spatial-temporal condensed image
- Introduced a probability model of background and vehicles and computed the likelihood probability distribution of their motions
- Used HMM to estimate the process of location dependent motion for vehicle identification





Background PDF



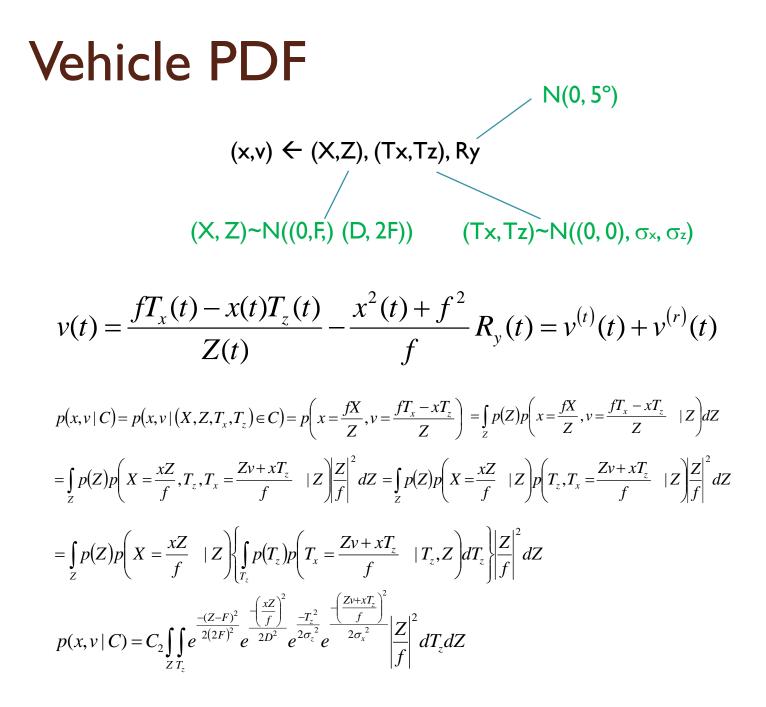
$$p(x,v \mid B) = \int_{R_y} p(R_y) p(x,v \mid R_y) dR_y = \int_{R_y} p(R_y) p(x,v \mid v = \frac{x^2 V}{fX} - \frac{x^2 + f^2}{f} R_y) dR_y$$

$$= \iint_{R_{y}X} p(R_{y}) p^{(d)}(X) p(X) p(X) p(Z, V \mid X) dX dR_{y} \qquad (Z(x, v, X), V(x, v, X))$$

$$= \iint_{R_{y}X} p(R_{y}) p^{(d)}(X) p(X) p\left(Z = \frac{fX}{x} \mid X\right) \times p\left(V = \left(v + \frac{x^{2} + f^{2}}{f} R_{y}\right) \frac{fX}{x^{2}} \mid X\right) dX dR_{y}$$

$$= C_{1r} \iint_{R_{y}X} e^{\frac{-R_{y}^{2}}{2\sigma_{r}^{2}}} \frac{1 - e^{\frac{-X^{2}}{2D^{2}}}}{|X| + 1} e^{\frac{-\left(\left(v + \frac{x^{2} + f^{2}}{f} R_{y}\right) \frac{fX}{x^{2}} - S\right)^{2}}{2\sigma^{2}}} \left|\frac{fX}{x^{2}}\right|^{2} dX dR_{y}$$





Parameter Selection in Probability Computation

D	Average road width	As wide as three lanes	6m		
F	Distance to target	Minimum safe distance	10m		
σ_{F}	Standard deviation of target distance		20m	20m	
σ_x	Standard deviation of relative horizontal speed T _x of target vehicle Maximum cutting of three lanes, tolerant for moving on curved path 6m/s				
σ	Standard deviation of relative translation speed T_z , T_z is zero if target is pursued 10m/s				
S	Average pursuing spe	eed of observer vehicle	50km/h 15	m/s	
σ	Standard deviation o	f the speed	10km/h 5m	/s	
f	Camera focal length	Through offline calibration	900 pixel		
∫ _z	Range for integration	From camera position to dist	ance close to infir	nity 0~200m	
∫ _x	Range for integration Wider than a road to include all backgrounds in video -50~50m				
∫ _{Tz}	Range for relative speed -40~40n		~40m/s		
∫ _{Ry}	Range of integration -10~10 d		~10 degree/s		
H	The maximum height	of vehicle, As high as a truck	, but mostly for ca	ars 4m	
σr	Standard deviation o	f steering angle of <i>R</i> _v			
	From the maximum tuning radius of a vehicle and road curvature.			5 degree/s	