Introduction

This research focuses on the perception and reasoning techniques using either an intelligent vehicle or a network sensing system or a collaboration of them.

We have a goal of developing an intelligent vehicle of Omni-directional eyes monitoring both static and dynamic objects when it cruises around a large dynamic environment; and a network sensing system that monitoring constantly the dynamic objects in a cluttered environment. Based on such platforms, we study methodologies on perception, modeling and reasoning of a dynamic procedure and a dynamic traffic scene, where the fundamental issues such as multi-modal sensor fusing, calibration, SLAM (simultaneous localization and mapping), moving object detection and tracking, behavior modeling and situation awareness, abnormal detection, semantic mapping, as well as potential applications are focused.

Research Objectives

- Sensing a dynamic environment
- Learning scene semantics
- Simulating a traffic scene

Q: Why always traffic jam or accidents?
A: We need to sense the data of both motion (e.g., people, cars) and motionless (e.g., building, tree, road, traffic sign) objects at the environment, analyze their relations, locate the problem, and find a possible solution.

Q: Where am I?
A: Locate “I” to the virtual space.

Monitoring a traffic scene through network sensing

Monitoring a dynamic procedure and scene using an intelligent vehicle

Intelligent vehicle and network sensing platforms
Omni-directional detection and tracking of on-road vehicles using multiple horizontal laser scanners

Huijing Zhao*, Chao Wang*, Wen Yao*, Franck Davoine**, Jinshi Cui*, Hongbin Zha*

Introduction
This research is motivated by two potential applications:

1) Detecting and tracking the moving objects at the ego-vehicle’s 360° local surroundings, so as to assist for safety driving;
2) Obtaining the motion trajectories of other traffic participants, so as to support for driving behavior modeling and reasoning.

This research studies at the on-road traffic environment, such as freeway, which is free of intersections, traffic signals, and pedestrians. So that the algorithm focuses on the detection and tracking of vehicles only.

Sensor Setting
In this paper, the Ladybug is for visualization only.

Contributions
In this research, a system of detecting and tracking on-road vehicles using multiple horizontal laser scanners on a vehicle platform is developed.

Algorithms are developed with focuses on solving data association of simultaneous measurements to single objects, and state estimation in case of partial observations in dense traffic situations.

Vehicle Model
1) \(y\) is distinct in each side of a vehicle;
2) \(y\) is equal in the measurements of different laser scanners.

Grouping overlapped measurements: by matching \(y\) with \(v\),
1) the overlapped measurements to the same vehicle side can be associated;
2) mis-grouping the data measurements can be avoided.

Accounting partial observations:
1) Reliability items are defined to denote whether the corresponding features are estimated on direct observations or inferred through the assumption on vehicle model.
2) Reliability items are accounted in data association and vehicle track estimation.

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Experimental Results

1) Laser sensing
2) Normal Traffic Speed
3) Slow Traffic Speed
4) Visualization
5) Accuracy Examination
Omni-directional detection and tracking of on-road vehicles using multiple horizontal laser scanners

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Introduction

Motivations: (1) Detecting and tracking the moving objects at the ego-vehicle’s 360° local surroundings, so as to assist for safety driving; (2) Obtaining the motion trajectories of other traffic participants, so as to support for driving behavior modeling and reasoning.

Scenario: on-road traffic environment, such as freeway, which is free of intersections, traffic signals, and pedestrians.

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Approach

Data integration

Labeling

Detection

Tracking

Validation

Vehicle trajectories

Online Flow

1) \( u \) is distinct in each side of a vehicle;
2) \( u \) is equal in the measurements of different laser scanners.

Grouping overlapped measurements:
by matching \( u \) with \( v \), the overlapped measurements to the same vehicle side can be associated.

Addressing partial observations:
1) Reliability items are defined to denote whether the corresponding features are estimated on direct observations or inferred through the assumption on vehicle model.
2) Reliability items are accounted in data association and vehicle track estimation.

Experimental Results

Accuracy Examination

Online vs Offline

Normal Traffic Speed

Slow Traffic Speed
Lane Change Trajectory Prediction by Using Recorded Human Driving Data

Wen Yao*, Huijing Zhao*, Philippe Bonnifait**, Hongbin Zha*

Introduction

Motivations: 1) Efficiently collect human driving data using an instrumented vehicle to build a human lane change database; 2) Predicting human driver’s potential lane change trajectory by referring to the database for risk assessment which helps the driver to decide whether to change lane.

Scenario: urban traffic scene, such as freeway. We mainly focused on lane change behavior on straight road currently, which is very common in daily driving.

Contributions: 1) A human driving database is generated through on-road data collection using an instrumented vehicle, which consists synchronized trajectories of ego vehicle and surrounding traffics during lane change maneuvers; 2) A lane change trajectory prediction is developed by referring to the human driving data of similar situations.

Work Flow

1.1 On-road Driving Data Acquisition
GPS/IMU Vehicle Parameters/ Lidar/ Video

1.2. Lane Change Data Extraction
Ego vehicle/Traffic participants/Road/Driver

Synchronized trajectories of ego and environmental vehicles in lane change

1. Human Driving Database Generation
human driving data acquisition using an instrumented vehicle

2. Lane Change Trajectory Prediction
lane change intention is detected as the trigger of this model

Trajectory Prediction

1) State Space Definition

S, S* = (sHV, sCF, sTF, sTR)

sHV,CF,TF,TR = (Pos, Spe., Acc.) at Fts,te

2) Trajectory Prediction Approach

Step1. Situation-based Neighborhood Trajectory Search

Step2. End State Interpolation from End States of Selected Samples

Step3. Trajectory Generation Using Polynomial Model (Werling, ICRA 10')

Database Generation

1) Synchronized motion trajectory collection of the ego and surrounding vehicles (Zhao, IV09)

2) Lane change samples
a) Manually record lane change start/end time
b) Steering wheel data
c) Video check

Experimental Results

Comparison of predicted and real trajectories in ego-frame

Contributions:

1) A human driving database is generated through on-road data collection using an instrumented vehicle, which consists synchronized trajectories of ego vehicle and surrounding traffics during lane change maneuvers; 2) A lane change trajectory prediction is developed by referring to the human driving data of similar situations.
A Probabilistic Framework for Occluded Vehicle Detection
Chao Wang¹, Huijing Zhao¹, Chunzhao Guo², Seiichi Mita³, Hongbin Zha¹

Abstract
In this research we propose a novel probabilistic framework for occluded vehicle detection on road scene. We build probabilistic vehicle’s viewpoint map on image with the road structure priority from GPS and road map. With different viewpoints, part-based vehicle detectors are trained to find vehicle part candidates, and a probabilistic model for parts’ locations relative to vehicle’s center is learnt to infer the vehicle’s viewpoint and occluded parts. The framework is evaluated on data from Nagoya downtown and Beijing freeway.

Probabilistic Viewpoint Map
Determine the viewpoint of vehicle in different place according to the map priority. The probability can be obtained by traffic rules and large real data statistic analysis. We divide the multi-view vehicles into 4 classes according to viewpoints. For each viewpoint class, probabilistic map is generated by considering the road structure. e.g. \( P\text{(view=viewpoint1, map=StraightRoad)} \)

Probabilistic Parts Location Model
Parts location distribution model across different viewpoints. In viewpoint \( k \), for each part \( i \), the distribution model is \( p(i|\theta^k) = G(\mu^k, \sigma^k, I^k, J^k, \rho^k) \)

Part Detectors
Train part detectors based on HoG features. Using unsupervised method, automatically select most representative parts for detectors, and record each part’s position for parts location distribution model learning. The part detectors are training in each viewpoint class.

Inference
Problem definition: infer the vehicle’s center and viewpoint \( r^k \),
\[ r^k = arg \max_{r^k} p(r^k|U^k, M^k, M_r) \]

Solution:
\[ p(r^k|U^k, M^k, M_r) = \prod_{i} p(i|\theta^k) m^k \prod_{i} p(i|\theta^k) m^k ) p(r^k|M_r) \]

Then infer the occluded parts, \( p(ocr) = p(\theta_{ocr}^k|r^k) \)

Experimental Results

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Monocular Visual Localization using Road Structural Features
Yufeng Yu*, Huijing Zhao*, Franck Davoine+, Jinshi Cui*, Hongbin Zha*

Motivations: 1) Precise localization is an essential issue for autonomous driving applications, while low-cost GPS can not meet such requirements; 2) General visual-based localization algorithms use point feature, which is highly affected by the moving objects in a normal traffic scenario; 3) Line segments with three perpendicular directions, which are road’s longitude, latitude and vertical directions, are stable in rotation estimation and those on environmental cars provide additional supports.

Scenario: Major roads in downtown Beijing, which are structured and with intense dynamic traffic.

Contributions: 1) We designed a novel feature named Road Structural Feature (RSF), which is robust dealing with moving objects, for on-road localization. 2) We proposed a real-time precise visual localization method based on RSF, and the experiment showed good performance.

Experimental Results
(a) Normal Traffic
(b) Straight Road Situation
(c) Complex Situation

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Objective

We aim to provide a map with high-level representations. This map enables a robot to have semantic knowledge of the environment which is large and dynamic, such as objects, their types and their spatial relationships.

System Flowchart

1. Range Image
2. Over-segmentation
3. Joint Merge with Classification
4. Objects with Semantic Label

Experimental Results

Joint Classifier

Line Classifier

Point Classifier

Joint Classifier

Manu Labeling

Building Road Tree Car People Bush Bus
Introduction

It becomes a well-known technology that a low level map of complex environment containing 3D laser points can be generated using a robot with laser scanners. Given a cloud of 3D laser points of an urban scene, this paper proposes a method for locating the objects of interest, e.g., traffic signs or road lamps, by computing object-based saliency. Our major contributions are: 1) a method for extracting simple geometric features from laser data is developed, where both range images and 3D laser points are analyzed; 2) an object is modeled as a graph used to describe the composition of geometric features; 3) a graph matching based method is developed to locate the objects of interest on laser data. Experimental results on real laser data depicting urban scenes are presented; efficiency as well as limitations of the method are discussed.

Approach

Learning-based Object Detection

Graph-based Object Detection

Introduction

For a multi-LIDAR system (Fig.1), calibration is essential for collaborative use of LIDAR data. In our research, we developed a 2D-LIDAR calibration method using 3D point-clouds alignment. In order to enable the calibration method work in urban outdoor scene, we proposed a alignment method based on multi-type geometry features extracted from 3D point-clouds of urban outdoor scene (Fig.2).

Method Overview

Suppose a LIDAR, called as the reference LIDAR, has been calibrated with mobile platform and would produce undistorted 3D point-cloud. Whenever a new LIDAR, called as the target LIDAR, is introduced to the on-board system, it could be calibrated by alignment of 3D point-clouds from reference and target LIDARs to find its geometric transformation to the mobile platform. [1, 2]

This research aims at an online self-calibration, therefore, an approach is proposed by using multi-types of geometric features (Eq.1) in urban outdoor scene to cope with the challenges such as small overlapped area, different viewpoints, occlusion and scene dynamics.

\[ G = \{ P, \{ \phi, f^\phi \}, \{ \mu, \sigma^2 \} \} \]  

\[ P : \text{3D point-set} \{ p_i \} \] 
\[ \phi : \text{Geometry type descriptor} \] 
\[ f^\phi : \text{Parametric equation} \] 
\[ \mu : \text{Confidence degree}, E(f^\phi(p_i)^2) \] 
\[ \sigma^2 : \text{Noise level}, \text{D}(f^\phi(p_i)^2) \]

Experiments

Experiments are conducted using the data sets of an intelligent vehicle platform POSS-V (Fig.1) through driving in the campus of Peking University (Fig.3).

Calibration Verification (Accuracy and Robustness)

<table>
<thead>
<tr>
<th>Feature Types</th>
<th>Geometric Features</th>
<th>( e_1 ) without noisy features</th>
<th>Accuracy Evaluation</th>
<th>( e_2 ) with noisy features</th>
<th>Error Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mono</td>
<td>Point (P)</td>
<td>0.03232</td>
<td>Bad</td>
<td>0.04615</td>
<td>1.427</td>
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<tr>
<td></td>
<td>Line (L)</td>
<td>0.07979</td>
<td>Bad</td>
<td>0.15548</td>
<td>1.994</td>
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<td></td>
<td>Plane (PL)</td>
<td>0.01939</td>
<td>Good</td>
<td>0.05878</td>
<td>3.031</td>
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<tr>
<td>Dual</td>
<td>P + L</td>
<td>0.01363</td>
<td>Good</td>
<td>0.01249</td>
<td>1.048</td>
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<td></td>
<td>P + PL</td>
<td>0.00980</td>
<td>Excellent</td>
<td>0.00993</td>
<td>1.013</td>
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<tr>
<td>Triple</td>
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<td>0.00981</td>
<td>Excellent</td>
<td>0.00989</td>
<td>1.008</td>
</tr>
</tbody>
</table>

References
