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Laser-Based Feature Extraction and Pattern Recognition in Intersection Management Systems

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Pattern Recognition, 2014

Outline

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Context Problem Statement Aims and Conditions

Context

Master's Research Project:

Multisensor Architecture for a Vehicular Intersection Management System

Transportation Systems

Issues in traditional transportation systems

- Congestion
- Traffic rules violation
- Vehicle interaction

Transportation Systems

Issues in traditional transportation systems

- Congestion
- Traffic rules violation
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Intersections are critical places in transportation systems

Intelligent Transportation Systems

Objectives of ITS

- Increase safety
- Increase efficiency
- Reduce costs

Intersection Management Systems

Tasks

- Traffic Monitoring
- Traffic Management
- Warning Advertisement

Intersection Scenario

- Pedestrians, Vehicles (Cars, Two-wheeled vehicles, Big vehicles)
- Recognition, Classification, Tracking
- Incident detection, Intersection Management

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Context Problem Statement Aims and Conditions

Main Objective

- To develop a feature extraction and pattern recognition laser-based module for an intersection management system

- Review of laser-based feature extraction and pattern recognition in ITS and IMS

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- Evaluate pros and cons of the reviewed methods

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- Evaluate pros and cons of the reviewed methods
- Implement at least one method
- Evaluate implemented module and compare it with similar developments

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Context Problem Statement Aims and Conditions

Conditions

- The information source will be a dataset.

Conditions

- The information source will be a dataset.
- [New!] Just one laser.

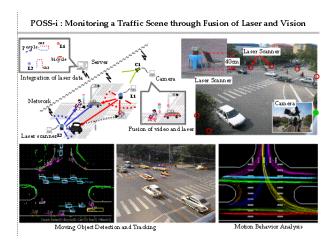
Research Groups

- PKU Omni Smart Sensing (POSS) Research group at Peking University (POSS-i project)
- Institute of Measurement, Control and Microtechnology at Ulm University (Ko-PER program)

PKU Omni Smart Sensing (POSS)

- POSS is leaded by Prof. Huijing Zhao, Ph.D.
- Focus on perception technologies using an intelligent vehicle, a network sensing system or a collaboration of them

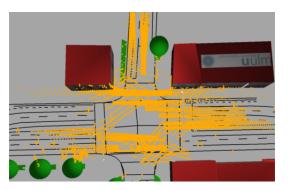
POSS-i



Ko-PER

- Ko-PER from Cooperative Perception
- Included in Forschungsinitiative Ko-FAS from Bundesministerium für wirtschaft und Technologie (Germany)
- Cooperative and collaborative sensors system for perception and preventive road safety.
- Daniel Meissen from Ulm University as leader researcher.

Projects



3D-recreated intersection scene with laser beams depicted [Meissner12, 13a, 13b, 13c, 14][Striegel13]

Applications, Methods and Techniques

Project	POSSi	Ko-PER		
Applications	Recognition, Classification and Tracking of Vehicles and Pedestrians			
Methods and Techniques	ClusteringKL TransformMarkov ChainsKalman FilteringAdaBoost	 DBSCAN Multi-object Bayes Filter Sequential Monte Carlo Methods Dempster-Shafer Theory Multiple-Model Probability Hypothesis Density Filter (in Gaussian Mixture representation) 		

POSSi and PKU projects comparison



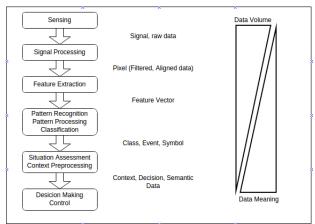
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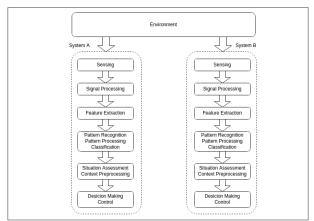


Typical System for one source of data



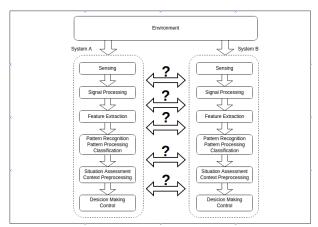
Single source system block diagram

Multisensor Data System



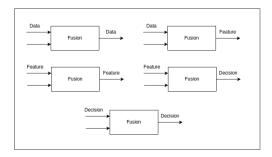
Multisensor system block diagram

How to fuse information?



Multisensor system block diagram

Fusion Levels



Fusion Levels [Luo11]

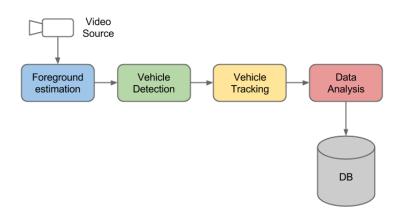
Block Diagrams Video Processing Laser Processing

Fusion Algorithms

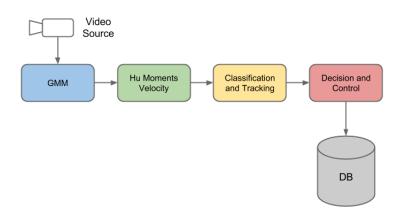
Low lev	rel fusion	Medium level fusion	High level fusion
Estimation methods		Classification methods	Inference methods
Recursive: • Kalman filter • Extended Kalman filter Non-recursive: • Weighted average • Least squares	Covariance-based: Cross covariance Covariance intersection Covariance union	Parametric templates Cluster analysis K-means clustering Learning vector quantization Kohonen feature map Artificial neural network Support vector machines	Bayesian inference Particle filters Dempster-Shafer theory Expert system Fuzzy logic

Classification of Fusion Algorithms [Luo11]

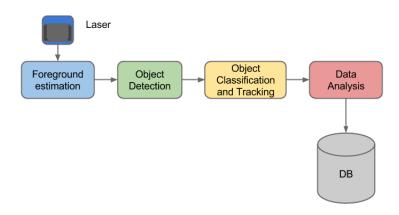
Video-Based System Block Diagram



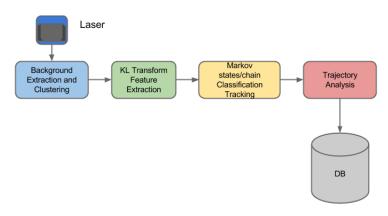
Video-Based System Block Diagram



Laser-Based System Block Diagram



Laser-Based System Block Diagram



Based on [Zhao06]



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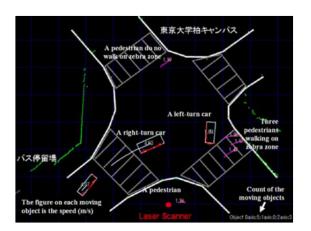
Dataset

- Although datasets for both projects are available, POSS-i dataset was choosen.
- It includes laser readings from 6 laser-scanner located in different corners in an intersection.
- The duration of scanning is approximately 10 minutes.

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Dataset



Capture of dataset viewer application [Zhao06]

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Background Extraction

- Histogram-based background extraction
- Done for each angle
- When a pick value is detected, tells that an object is detected

Datasets Overview Foreground Estimation Feature Extraction and Classification Next Steps

Background Extraction

- Histogram-based background extraction
- Done for each angle
- When a pick value is detected, tells that an object is detected
- Dataset already includes a background model for each laser scanner

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Clustering

In [Zhao06] it is not detailed how clustering was done, so
 DBSCAN is proposed to identify clusters in laser-data points

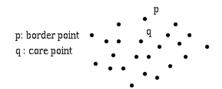
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DBSCAN - Introduction

- Density-Based Spatial Clustering for Applications with Noise
- Proposed by Ester et al in 1996 in KDD conference [Ester96].

DBSCAN - Explanation

- The algorithm needs two parameters: $Eps(\epsilon)$ and minPts
- Also are defined two types of points: Core points and border points
- p is a core point if in its *Eps-Neighborhood* are at least *minPts* points.



Types of points [Ester96]

DBSCAN - Algorithm

- DBSCAN starts at an arbitrary point p, then evaluate if point's Eps-Neighnorhood contains at least minPts points
- If *True*, *p* is a core point (Is in a cluster)
 - Assign *clusterId* to p and its neighbour, and neighbours of its neighbours and so on.
 - Increase clusterId.
- If False, p is labelled as Noise
- Continue with an unlabelled point, until all points in dataset are labelled.

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Clustering



Datasets Overview Foreground Estimation Feature Extraction and Classification Next Steps

Clustering



Datasets Overview Foreground Estimation Feature Extraction and Classification Next Steps

Clustering



Definitions

- Classes are proposed based on distribution of points in clusters
- Karhunen-Loeve Transform to detect number of axis

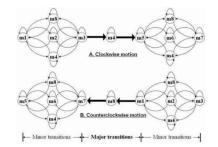
Objects in	Example of laser data					Class
cross road	t_1	t ₂	t ₃	t ₄	ts	definition
car	:			i	:	2-axis
bicycle						1-axis
pedestrian	٠.	٠.	٠.	٠.	٠.	0-axis

Datasets Overview Foreground Estimation Feature Extraction and Classification Next Steps

Markov States



There are 8 patterns that can happen



Possible transitions



Features

- Normal Vectors
- Number of axis
- Axis lengths
- Directional vector, Motion speed
- Markov States

Datasets Overview Foreground Estimation Feature Extraction and Classification Next Steps

Classification and Tracking

- Classification and tracking stages are under review

Datasets Overview Foreground Estimation Feature Extraction and Classification Next Steps

Next Steps

- Implement Dataset handler
- Implement Clustering and KL Transform to classify in 0, 1 or 2 axis object
- Get features from objects and obtain trajectory

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