Intelligent Perception and Situation Awareness for Automated vehicles
Christian Laugier, Julia Chartre

To cite this version:
Christian Laugier, Julia Chartre. Intelligent Perception and Situation Awareness for Automated vehicles. Conference GTC Europe 2016, Sep 2016, Amsterdam, Netherlands. hal-01428547

HAL Id: hal-01428547
https://inria.hal.science/hal-01428547
Submitted on 15 Jan 2017

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Copyright
Intelligent Perception and Situation Awareness for Automated vehicles

Christian LAUGIER
Research Director at Inria, Chroma team
christian.laugier@inria.fr

Julia CHARTRE
R&D Engineer at Inria, Chroma team
julia.chartre@inria.fr

Contributions from
Mathias Perrollaz, Procópio Silveira Stein, Christopher Tay Meng Keat, Stephanie Lefevre, Javier-Ibanez Guzman, Amaury Negre, Lukas Rummelhard, Nicolas Turro, Jean-Alix David, Jérôme Lussereau

ADAS & Autonomous Driving

GTC Europe 2016, Autonomous Vehicle track
Amsterdam, Sept. 28 – 29 2016
Main features

✓ Dynamic & Open Environments => *Real-time processing*
✓ Incompleteness & Uncertainty => *Appropriate Model & Algorithms*
✓ Human in the loop => *Interaction & Social Constraints (including traffic rules)*
✓ Hardware / Software integration => *Satisfying Embedded constraints*
Industrial State of the Art & Today’s Limitations

- **Perception** for Autonomous Vehicles: *New trend of automotive industry!*

  - Mercedes F015
  - Valeo’s Cruise4U
  - Audi A7

  CES 2015 & 2016 (Las Vegas) + Large media coverage

But perception is still a **bottleneck for Motion Autonomy**, ...
... in spite of significant improvements (sensors & algorithms) during the last decade

- **Robustness insufficient** & High computational capabilities are required
  *Still an obstacle to the full deployment!*

  - Inria / Toyota
  - Google Car
  - Audi A7

  Trunk full of electronics & computers & processor units

Lack of Robustness & Efficiency
Lack of Integration into Embedded Sw/Hw
Numerous real-life experiments...but Safety is still insufficient

=> Some benign & serious accidents in the past few months (Google, Tesla ..)

Autonomous Car: Next generation technology & Expected market of 500 B€ in 2035

Tesla Autopilot based on Radar & Mobileye

• Partnership with Mobileye uncertain
• Commercial option: 3400 € in France

Costly 3D Lidar & Dense 3D mapping

Drive Me trials

• 100 Test Vehicles in Göteborg, 80 km, 70km/h
• No pedestrians & Plenty of separations between lanes

Driverless Taxi testing in Pittsburgh (Uber) & Singapore (nuTonomy)

=> Numerous Sensors & Engineer in the car during testing
Improving robustness using Multi-modality sensing

Camera Image at Dusk (Pedestrians not detected)

Processed Lidar data (Pedestrians detected)

- Camera output depends on lighting conditions
  Cheap & Rich information & Good for classification

- Lidar more accurate & can work at night
  Good for fine detection of objects ... but still Expensive

- Develop Robust & Efficient Multi-Sensor Fusion approaches using probabilistic models

- Good news: A new generation of affordable “Solid State Lidars” will arrive soon on the market!
  => No mechanical component & Expected cost less than 1000 US$
  => Numerous announcements since Spring 2016
**Key Technology 1: Embedded Bayesian Perception**

- **Main challenges**
  - Noisy data, Incompleteness, Dynamicity, Discrete measurements
  - Strong Embedded & Real time constraints

- **Approach: Embedded Bayesian Perception**
  - Reasoning about Uncertainty & Time window (Past & Future events)
  - Improving robustness using Bayesian Sensors Fusion
  - Interpreting the dynamic scene using Contextual & Semantic information
  - Software & Hardware integration using GPU, Multicore, Microcontrollers...

---

**Embedded Multi-Sensors Perception**

⇒ Continuous monitoring of the dynamic environment

**Sensors Fusion**

⇒ Mapping & Detection

**Scene interpretation**

⇒ Using Context & Semantics

**Characterization of the local Safe navigable space & Collision risk**
Bayesian Perception : Basic idea

- Multi-Sensors Observations
  
  *Lidar, Radar, Stereo camera, IMU ...*

- Probabilistic Environment Model
  
  ✓ Sensor Fusion
  ✓ Occupancy grid integrating uncertainty
  ✓ Probabilistic representation of Velocities
  ✓ Prediction models

- Main philosophy
  
  *Reasoning at the grid level as far as possible for both :*
  
  - **Improving efficiency** (highly parallel processing)
  - **Avoiding traditional object level processing problems** (e.g. detection errors, wrong data association...*)
A new framework: Dynamic Probabilistic Grids

=> A clear distinction between Static & Dynamic & Free components

[Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]

Bayesian Filtering (Grid update at each time step)

Prediction

\[ P(O'_c A'_c) \]

Estimation

\[ P(O'_c A'_c | [Z' = z]) \]

Sensing (Observations)

\[ P(Z' | O'_c A'_c) \]

25 Hz

Bayesian Filtering

Joint Probability decomposition:

\[ P(OV|ZC) = \sum_{A'O'V'} P(C A O O^{-1} V V^{-1} Z) \]

Solving for each cell

\[ P(OV|ZC) = \lambda \sum_{A'O'V'} P(C A O O^{-1} V V^{-1} Z) \]

Sum over the possible antecedents \( A \) and their states \( (O^{-1} V^{-1}) \)

\[ P(C A O O^{-1} V V^{-1} Z) = P(A) P(O^{-1} V^{-1} | A) P(O V | O^{-1} V^{-1}) P(C | A V) P(Z | O C) \]

Bayesian Occupancy Filter (BOF)

=> Patented by Inria & Probayes

=> Commercialized by Probayes

=> Robust to sensing errors & occultation

Used by: Toyota, Denso, Probayes, IRT Nanoelec / CEA

Free academic license available

Industrial license conditions under negotiation with Toyota
Bayesian Occupancy Filter (BOF) – Main Features

• Estimate **Spatial occupancy for each cell of the grid** $P(O|Z)$
• **Grid update** is performed in each cell in parallel *(using BOF equations)*
• **Extract Motion Field** *(using Bayesian filtering & Fused Sensor data)*
• **Reason at the Grid level** *(i.e. no object segmentation at this reasoning level)*

**Bayesian Occupancy Filter (BOF)**

- **Occupancy Probability** ($P_{occ}$)
- **Velocity Probability** ($P_{velocity}$)

**Sensing**

**Grid update**

**Occupancy Grid** *(static part)*

**Motion field** *(Dynamic part)*

- **3 pedestrians**
- **Moving car**
- **2 pedestrians**

**Camera view (urban scene)**

**Free space**

**Static obstacles**

**Sensors data fusion + Bayesian Filtering**

**Exploiting Dynamic information !**
Recent implementations & Improvements

Several implementations (models & algorithms) more and more adapted to Embedded constraints & Scene complexity

- **Hybrid Sampling Bayesian Occupancy Filter (HSBOF, 2014)**
  
  $\Rightarrow$ Drastic memory size reduction (factor 100) + Increased efficiency (complex scenes) + More accurate Velocity estimation (using Particles & Motion data from ego-vehicle)

  [Negre et al 14] [Rummelhard et al 14]

- **Conditional Monte-Carlo Dense Occupancy Tracker (CMCDOT, 2015)**

  $\Rightarrow$ Increased efficiency using “state data” (Static, Dynamic, Empty, Unknown) + Integration of a “Dense Occupancy Tracker” (Object level, Using particles propagation & ID)

  [Rummelhard et al 15]

Jetson TK1

Grid & Pseudo-objects

Tracked Objects

Classification (using Deep Learning)

Tracking & Classification

$\Rightarrow$ See experimental results at the end of the talk (video)
Main challenges

Uncertainty, Partial Knowledge, World changes, Human in the loop + Real time

Approach: Prediction + Risk Assessment + Bayesian Decision-making

- Reason about Uncertainty & Contextual Knowledge (using History & Prediction)
- Estimate probabilistic Collision Risk at a given time horizon \( t+\delta \)
- Make Driving Decisions by taking into account the Predicted behavior of all the observed surrounding traffic participants (cars, cycles, pedestrians ...) & Social / Traffic rules
Short-term collision risk – Main features

=> Grid level & Conservative motion hypotheses (proximity perception)

Main Features

- Detect “Risky Situations” a few seconds ahead (0.5 to 3s)
- Risky situations are localized in Space & Time
  - Conservative Motion Prediction in the grid (Particles & Occupancy)
  - Collision checking with Car model (shape & velocity) for every future time steps (horizon h)
- Resulting information can be used for choosing Avoidance Maneuvers

System outputs

Proximity perception: $d < 100m$ and $t < 5s$
- $\delta = 0.5s \Rightarrow$ Precrash
- $\delta = 1s \Rightarrow$ Collision mitigation
- $\delta > 1.5s \Rightarrow$ Warning / Emergency Braking

Camera view
1s before the crash

Moving Dummy
Observed moving Car

Static
Dynamic
Risk / Alarm

No risk (White car) => safe motion direction
High risk (Pedestrian)
Objective: Detect all dangerous situations & Avoid most of false alarms

Urban street experiments
=> Almost no false alarm (car, pedestrians …)

Crash scenario on test tracks
=> Almost all collisions predicted before the crash (0.5 – 3 s before)

See video at the end of the talk
Generalized Risk Assessment (Object level)

Increasing time horizon & complexity using context & semantics

Decision-making in complex traffic situations

✓ Understand the current traffic situation & its likely evolution
✓ Evaluate the Risk of future collision by reasoning on traffic participants Behaviors
✓ Takes into account Context & Semantics

Highly structured environment + Traffic rules
=> Prediction more easy

Context & Semantics
History + Space geometry + Traffic rules
+ Behavior Prediction
For all surrounding traffic participants
+ Probabilistic Risk Assessment
Behavior-based Collision risk (Object level)

=> Increased time horizon & complexity + Reasoning on Behaviors

- Trajectory prediction & Collision Risk

  => Patent Inria - Toyota - Probayes 2010

- Intention & Expectation

  => Patents Inria - Renault 2012 & Inria - Berkeley 2013
Implementation & Experimental Results

Presented by Julia Chartre
Experimental Vehicles and Perception Units

- Toyota Lexus
- Renault Zoé
- 2 Lidars IBEO Lux
- Velodyne lidar
- cameras
- IBEO lidars

ROS

- Titan X
- Jetson TK1
- Jetson TX1

Perception Unit
Objectives & Achievements 2013 -17

Embedded Hardware (STHORM)

Experimental Platform

Fusion on many core architecture

Automotive Standard
Multicore. Dual cortex A9@ 800MHz

Microcontroller
STM 32 Cortex
M7@200 MHz

Nvidia Jetson Tk1

Nvidia Jetson TX1

BOF 2013

HSBOF 2014

CMCDOT 2015

CMCDOT Cuda Optimization on Tegra 2016 - 17

Risk assessment system

Experimental Scenario

Perception Unit

Distributed Perception

Zoe Autom. 1st Steps

GTC Europe 2016
Highly parallelizable framework, **27 kernels** over cells and particles. (Resampling, sorting, predict, occupancy, speed estimation)

**Real-time implementation** (processing 20 Hz sensor output), optimized using Nvidia profiling tools.

- 700 x 300 Grids
- 32768 velocity samples
- Configuration with **8 to 12 Lidar layers** (2x4 to 3 x 4),

Pushing the limits of the algorithm:

- 1400 x 600 Grids
- 65536 velocity samples

Jetson TK1: Grid Fusion 17ms, CMCDOT 70ms

Jetson TX1: Grid Fusion 0.7ms, CMCDOT 17ms
Experimental Platforms & Experiments

Embedded Perception

Distributed Perception

IRT Nanoelec Experimental Platform

Perception Unit

Connected Traffic Cone

Renault Twizy

Pedestrian Crossing Experiments
Experimental results in urban environment
Thank You

Any questions?

IEEE RAS Technical Committee on “AGV & ITS”
Numerous Workshops & Special issues since 2002
=> Membership open