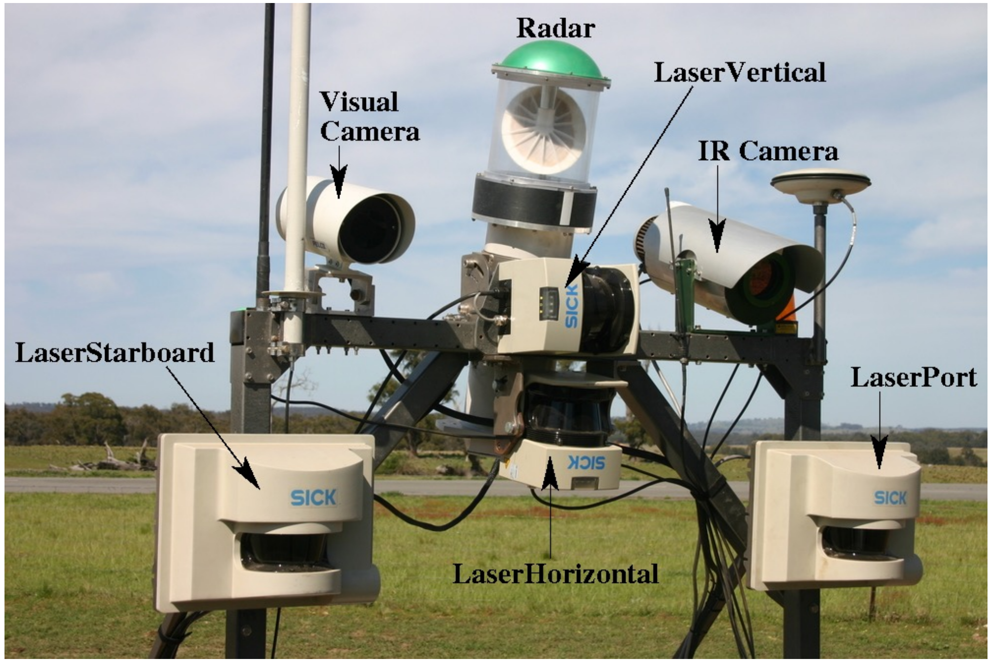
AuSRoS
Australian School of Robotic Systems

A3 - Sensor Data Fusion in Robotics

A/Prof. Thierry Peynot

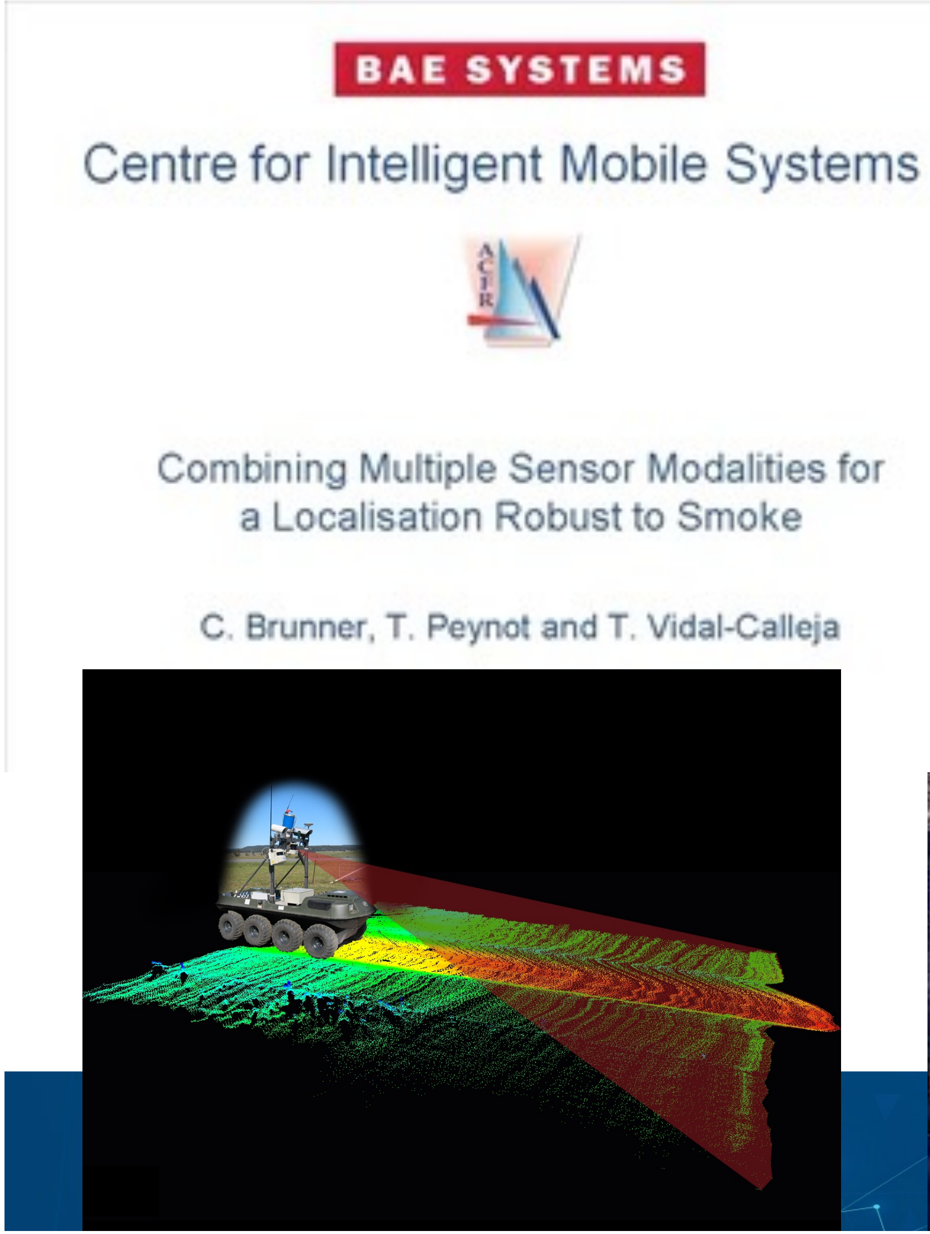
Sensors!

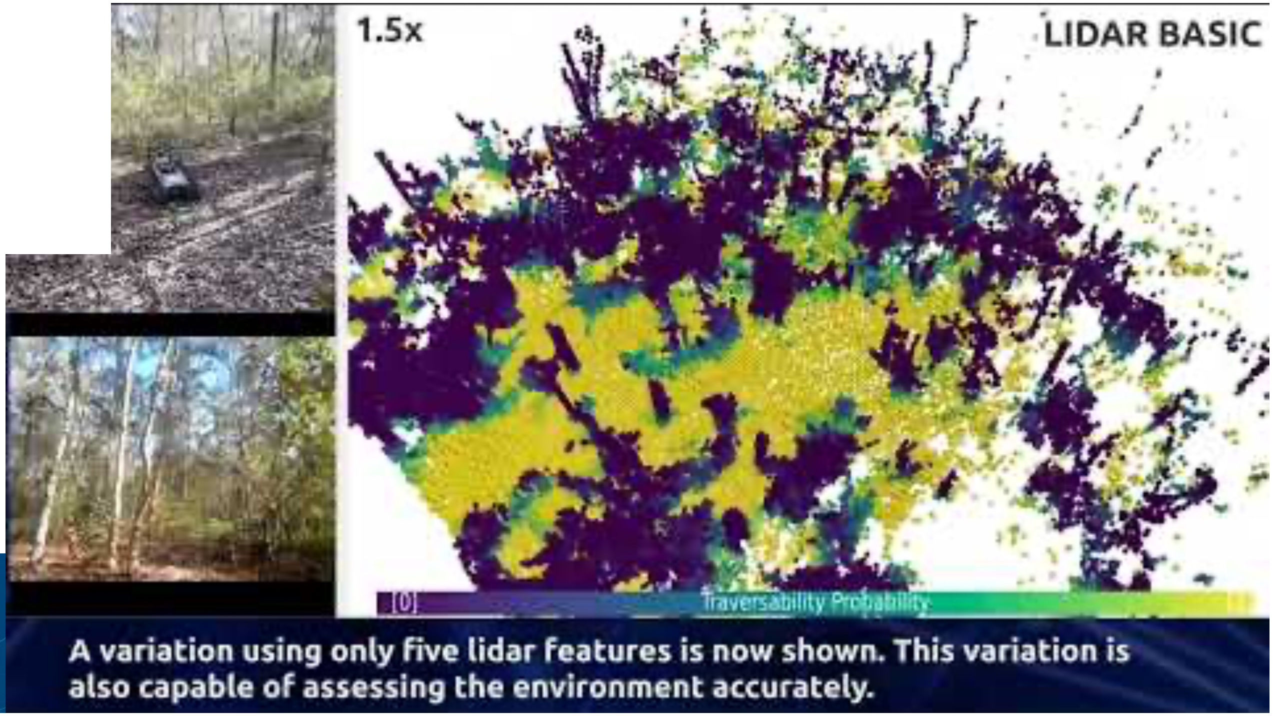


Radar
LaserVertical
Visual
Camera
IR Camera
LaserStarboard
LaserPort
LaserHorizontal
SICK
SICK
SICK
SICK

SHRIMP

Sensor Data Fusion





Outline

- Definitions and concepts
- Data Fusion Types/Categories
- 'Early' vs. 'Late' Fusion
- Use Cases in Robotics Research
  - Heterogenous sensing modalities

What is Sensor Data Fusion?

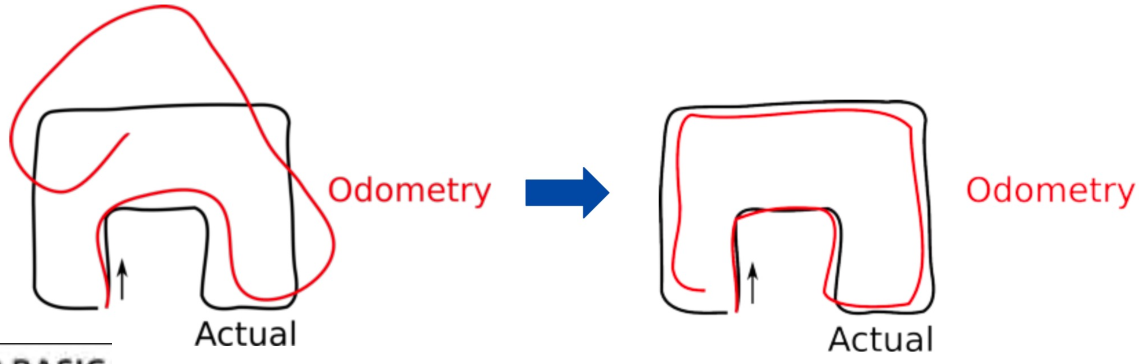
"**Sensible combination** of **multiple sources** of sensory data (of the same type or not), such that the **resulting information or model representation** is of **better quality** than it would be if these sensors were used separately"

Concept of **Synergy**

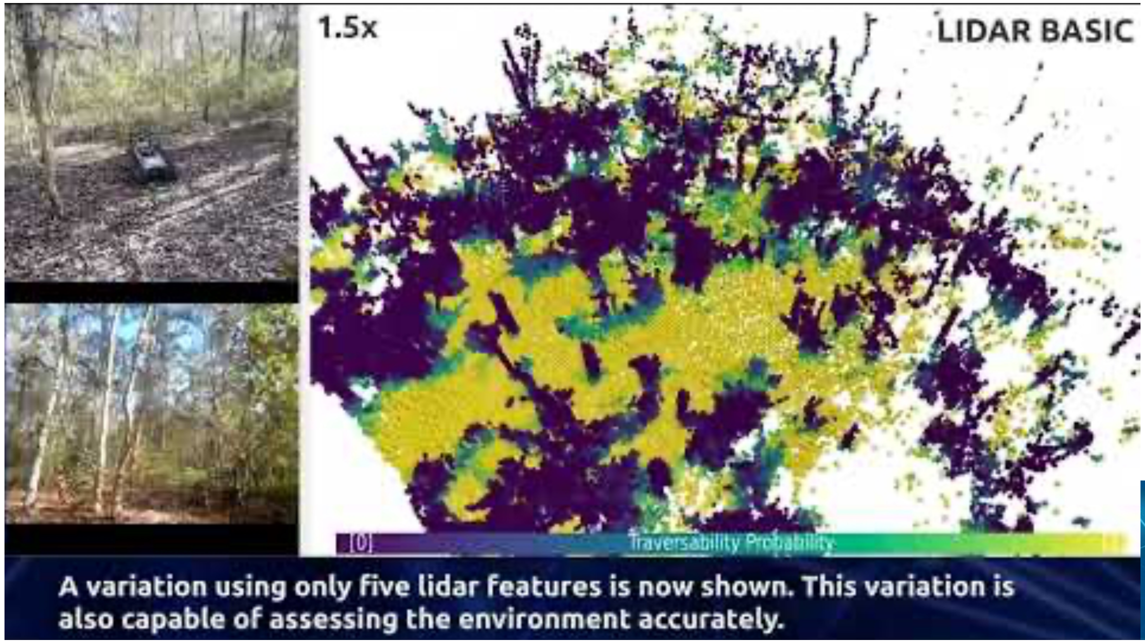
Raol, J. R. (2009). *Multi-Sensor Data Fusion with MATLAB®*. CRC Press.

Aspects of Quality

- Accuracy
- Completeness
- Certainty



From Lecture A1 by Don Dansereau



Benefits of Data Fusion

- operational performance of the perception system,
- extended spatial coverage,
- reduced ambiguity of inferences,
- improved detection of objects and representation of environment,
- enhanced spatial resolution,
- improved system reliability.

Hall, D. L. and McMullen, S. (2004). *Mathematical techniques in multisensor data fusion*. Artech House

Fusion Types

- **Fusion across sensors**: a number of sensors nominally measure the same property (e.g. a number of temperature sensors measuring the temperature of an object).
- **Fusion across attributes**: a number of sensors measure different quantities associated with the same experimental situation (e.g. in the measurement of air temperature, pressure and humidity to determine air refractive index).
- **Fusion across domains:** a number of sensors measure the same attribute over a number of different ranges or domains (for example, in the definition of a temperature scale)
- **Fusion across time**: current measurements are fused with historical information (e.g. from an earlier calibration).
  - Often the current information is not sufficient to determine the system accurately and historical information has to be incorporated to determine the system accurately.

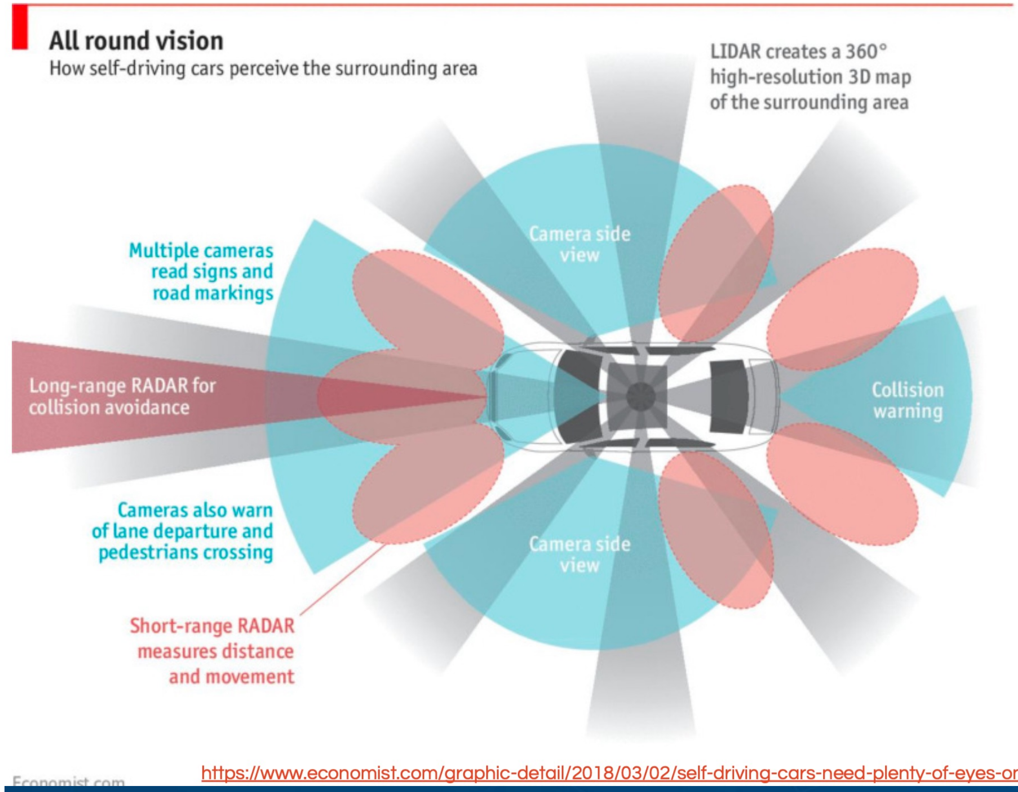
From Mitchell, H. B. (2012). Data Fusion: Concepts and Ideas. Springer

Sensor Configurations

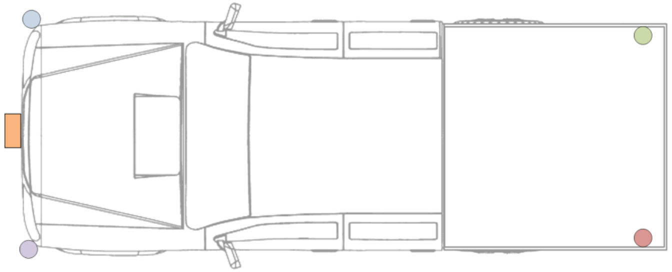
- **Complementary**: two or more sensors supply complementary information about the same observation. The sensor data **combination** result is a more complete image of the object or phenomenon under observation
  - the sensors do not directly depend on each other, but can be combined in order to give a more complete image of the phenomenom under observation
  - Aim: “completeness”
  - E.g. one sensor filling the gaps of the perception of another sensor

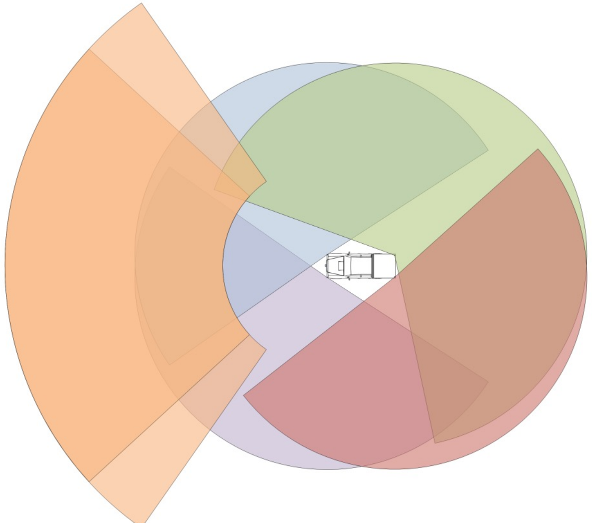
Durrant-Whyte, H. F. (1988). Sensor models and multisensor integration. The International Journal of Robotics Research, 7(6):97–113.

Complementary Fusion



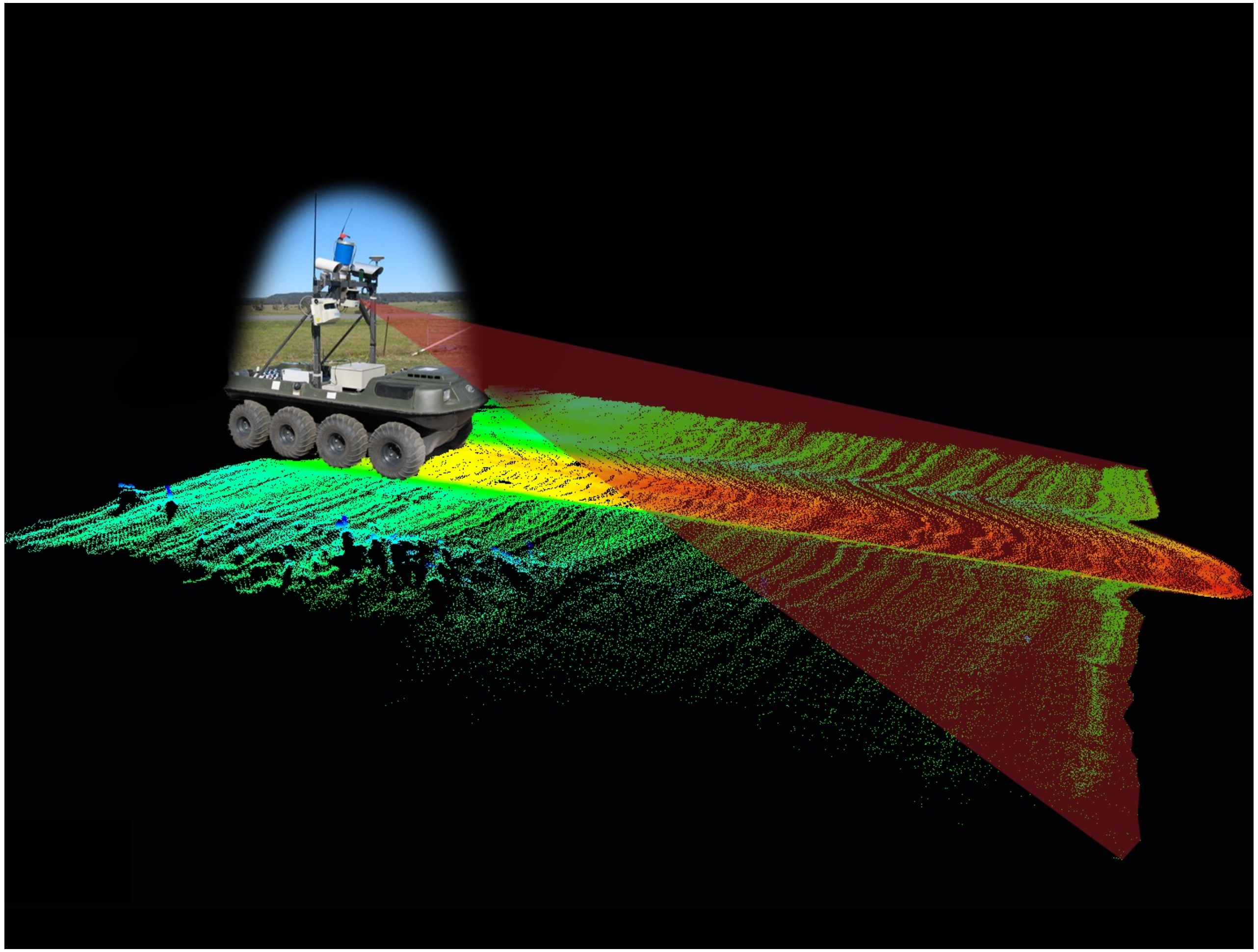
https://www.economist.com/graphic-detail/2018/03/02/self-driving-cars-need-plenty-of-eyes-on-the-road





Complementary Fusion

- Examples



Sensor Configurations

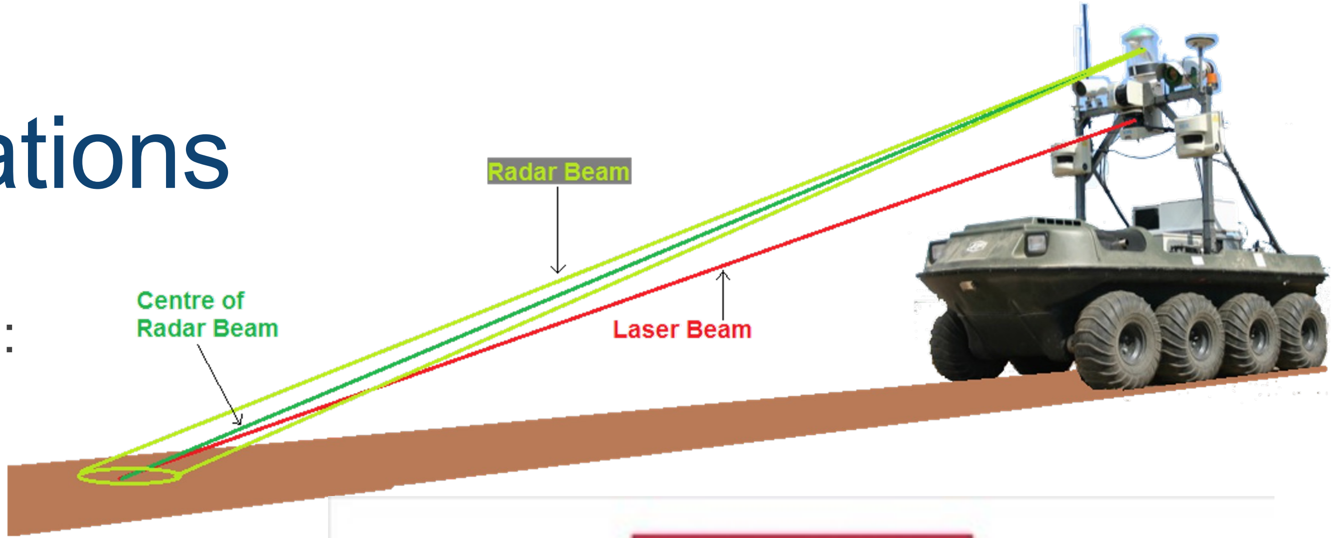
- **Competitive Fusion**: relevant when sensor observations refer to the same property or physical phenomena
  - Each sensor delivers an independent measurement of the same property
  - Aim: reduce the effects of *uncertain* and *erroneous* measurements.
  - In this case, the more overlap between the sensor's perception the better
  - also called **redundant configuration** or **analytical redundancy**.

Durrant-Whyte, H. F. (1988). Sensor models and multisensor integration. The International Journal of Robotics Research, 7(6):97–113.

Sensor Configurations

Competitive Fusion Examples:

- Aligned Laser+Radar (with "consistent" measurements)
- Multi-camera SLAM (with similar cameras and major FOV overlap)



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Combining Multiple Sensor Modalities for a Localisation Robust to Smoke

C. Brunner, T. Peynot and T. Vidal-Calleja

Data Fusion Categories

- **Cooperative Fusion**: used when independent sensors derive information that would not be available from single sensors.
  - Example 1: stereoscopic vision, where a three-dimensional image is obtained from two cameras observing a scene from slightly different viewpoints
  - Example 2: Super-resolution: cooperatively fuse together two or more images of the same scene and taken by the same sensor but from slightly different viewing angles. The result is a new image which has higher spatial resolution than any of the input image

Durrant-Whyte, H. F. (1988). Sensor models and multisensor integration. The International Journal of Robotics Research, 7(6):97–113.

Example:

Colouring a LIDAR point cloud

Faro Focus3D

Faris Azhari, *Automated crack detection and characterisation from 3D point clouds of unstructured surfaces.* PhD thesis, QUT, 2022

Sensor Observation

Sensor observation: $O = \langle E, x, t, y, \Delta y \rangle$

The output of a sensor is known as a sensor observation and includes the following terms:

- **Entity-Name *E***: includes the name of the physical property which was measured by the sensor and the units in which it is measured
- **Spatial Location *x***: position in space to which the measured physical property refers.
  - NB: In many cases the spatial location is not given explicitly and is instead defined implicitly as the position of the sensor element
- **Time Instant *t***: time when the physical property was measured.
- **Measurement *y***: value of the physical property as measured by the sensor element.
  - May have more than one dimension: vector y.
  - May be discrete or continuous.
- **Uncertainty *Δ y***: generic term, may include many different types of errors in y, including: measurement errors, calibration errors, loading errors and environmental errors

From Mitchell, H. B. (2012). Data Fusion: Concepts and Ideas. Springer

Types of Sensor Uncertainty

- **Random Errors**: characterized by a lack of repeatability in the output of the sensor. Caused by measurement noise.
  - For example: fluctuations in the capacity of the resistance of the electrical circuits in the sensor, or due to the limited resolution of the sensor.
- **Systematic Errors**: characterized by being consistent and repeatable. Types of systematic errors include:
  - Calibration errors: Result of error in the calibration process
  - Loading errors. These arise if the sensor is intrusive which, through its operation, alters the measurand.
  - Environmental Errors: arise from the sensor being affected by environ- mental factors which have not been taken into account.
  - Common Representation Format Errors: occur when transform from the original sensor space to a common representational format
- **Spurious Readings**: non-systematic measurement errors
  - Example: a sensor detects an obstacle at a location x when, in fact, there is no obstacle at x.

From Mitchell, H. B. (2012). Data Fusion: Concepts and Ideas. Springer

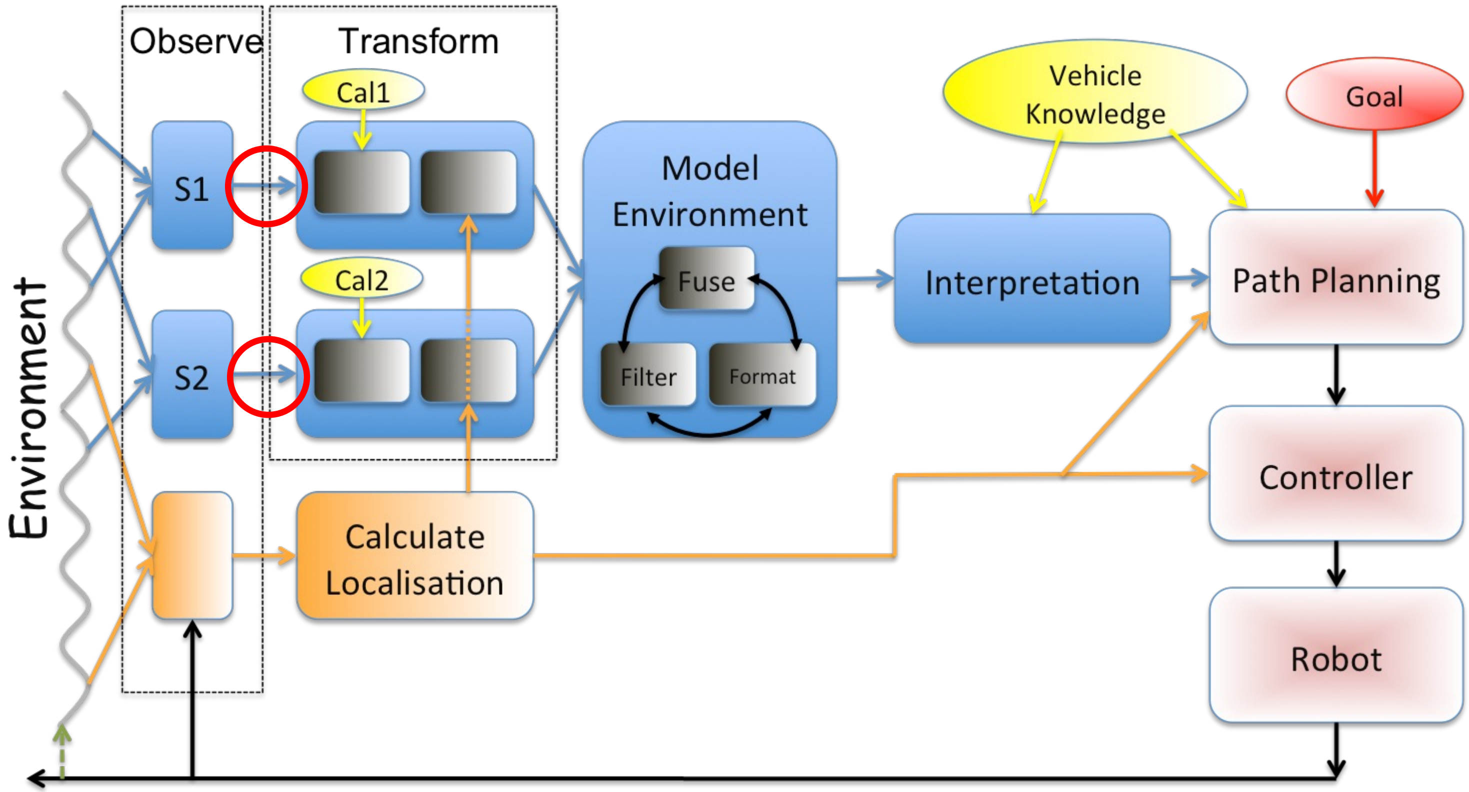
Common Representational Format

Major Requirement: convert all sensor observations to a common format

- **Spatial Alignment**: transforming or geo-referencing the data of each sensor from local spatial positions to a common reference frame.
- **Temporal Alignment**: Refers to the transformation of the data in each sensor to a common time frame.
- **Radiometric normalisation**: converting information of the sensor values to a common intensity scale, such as illumination, temperature or reflectivity
- **Semantic Alignment**: convert the data of each sensor so that they refer to the same objects or phenomena, where possible and relevant

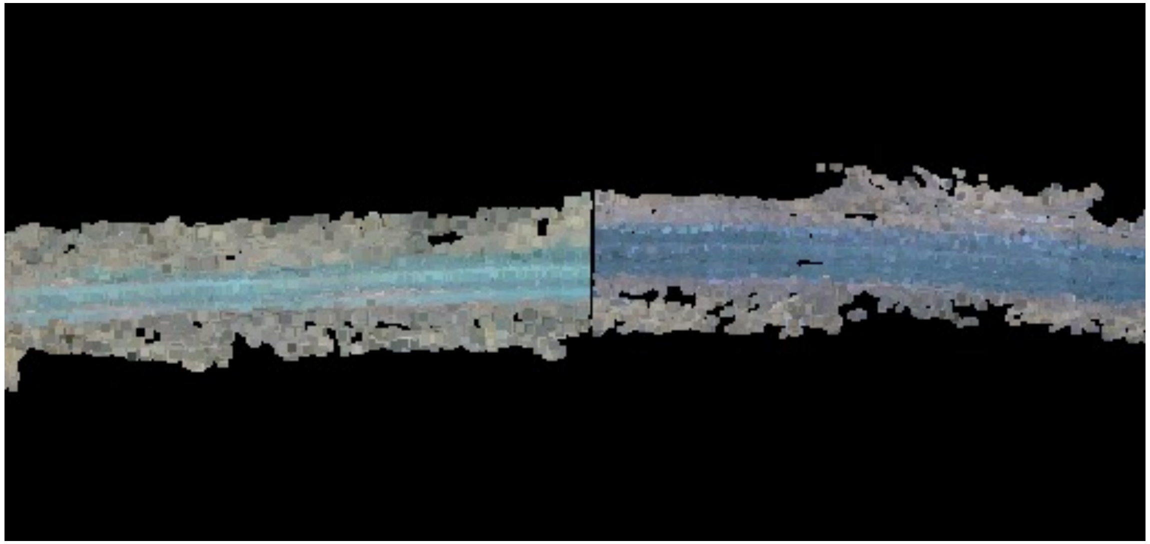
Mitchell, H. (2007). Multi-sensor data fusion: an introduction. Springer.

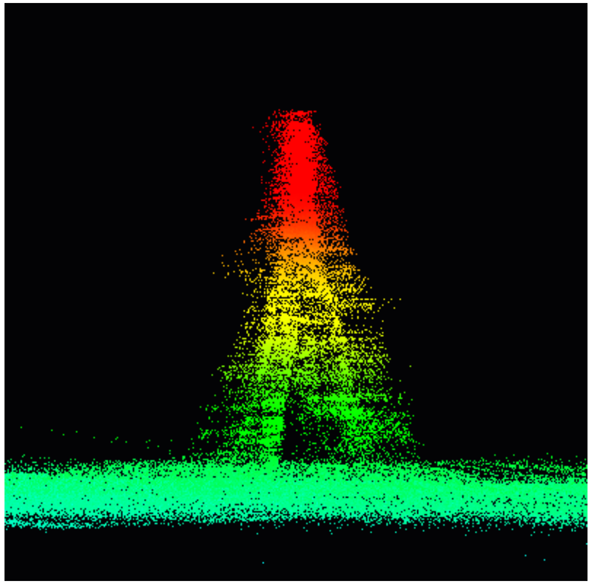
Spatial Alignment (a.k.a. Exteroceptive Calibration)



Extrinsic Calibration

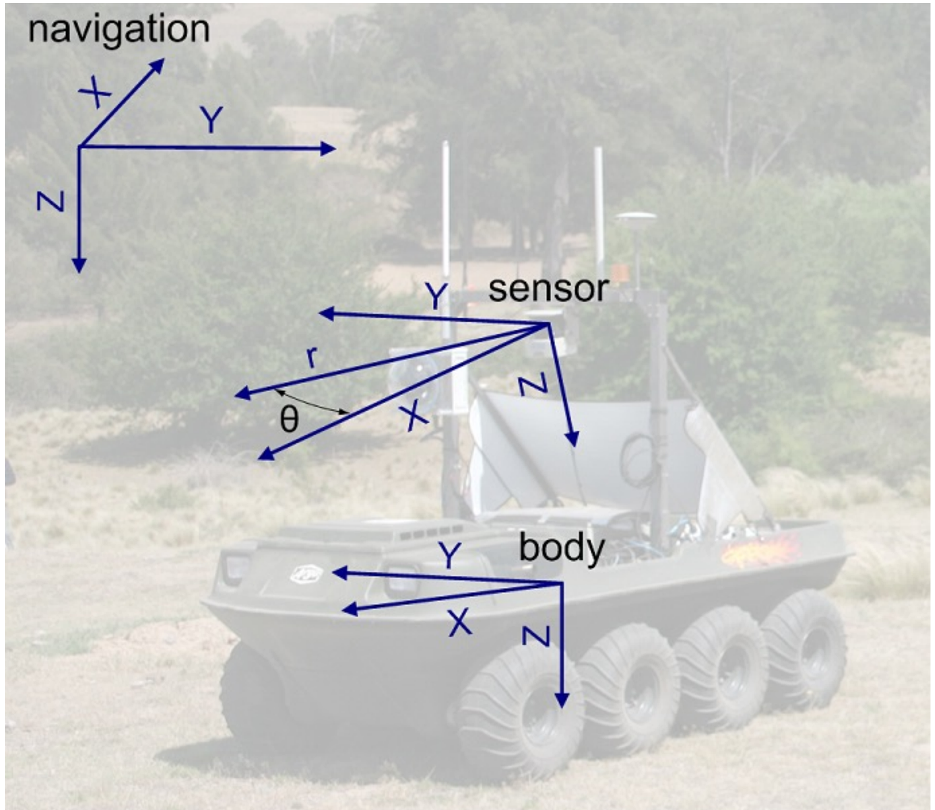
- Usually refers to the estimation of the relative pose of multiple sensors on a robot (for sensor data alignment)



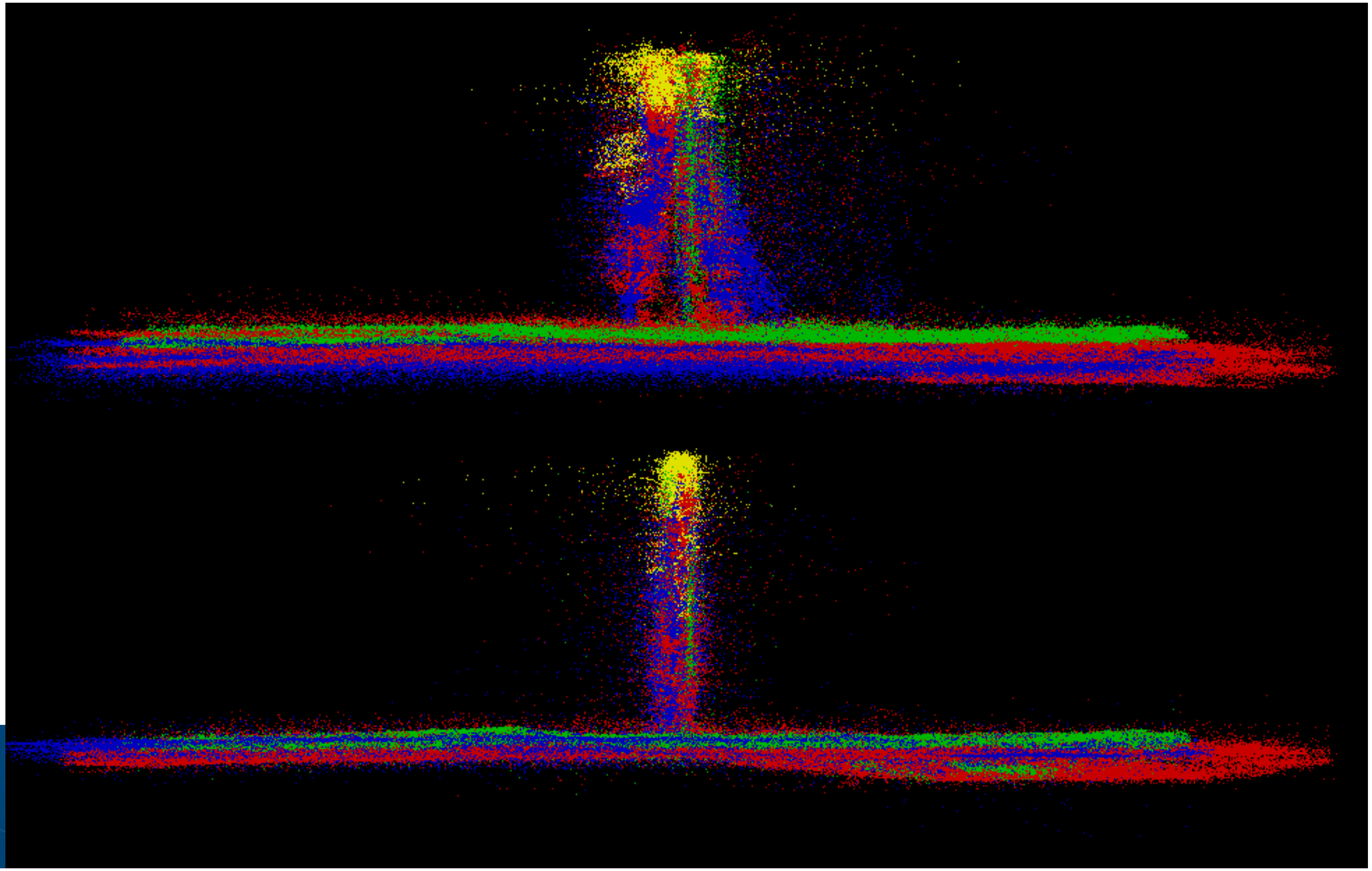


Extrinsic Calibration

- Objective: estimate (fixed) transformation between each sensor frame and the ‘robot body’ frame (sometimes ‘via’ the navigation frame)



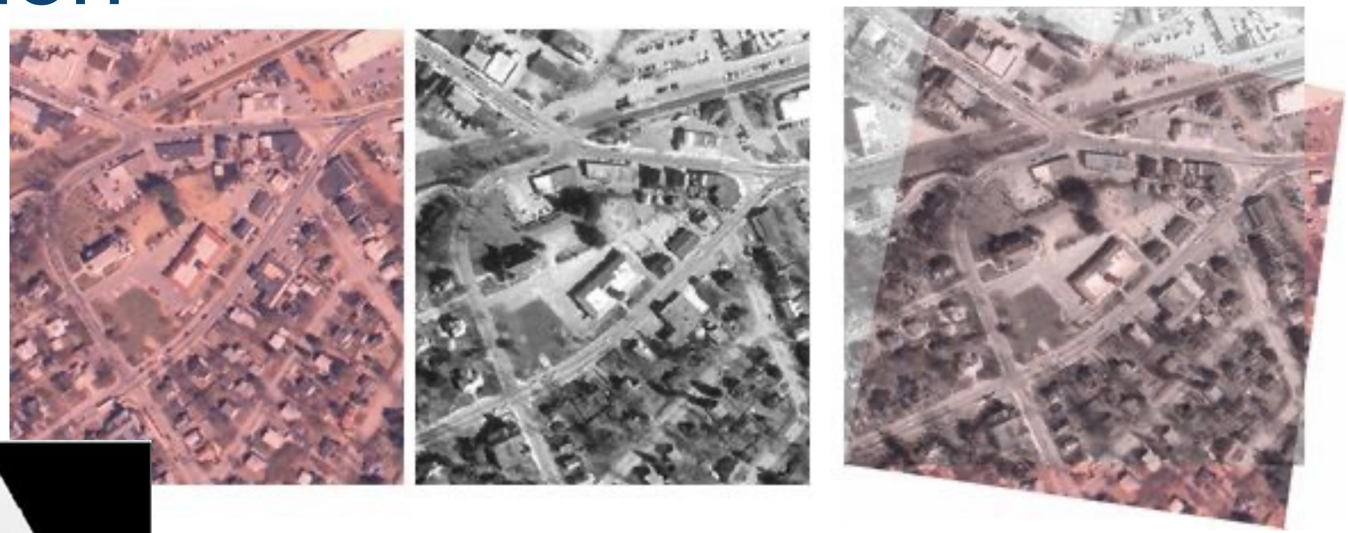
Extrinsic Calibration: Multiple LIDARs

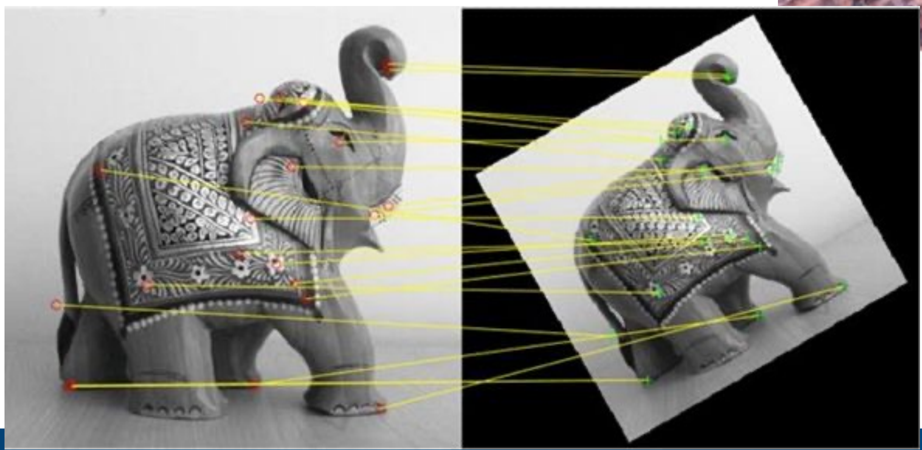


QUT the university for the real world

Image Registration

- Example:

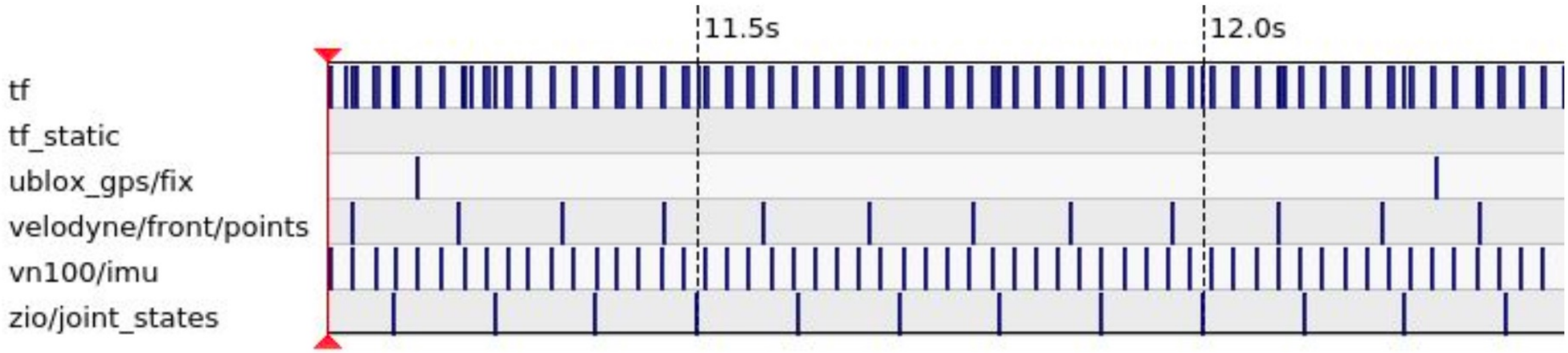




https://au.mathworks.com/discovery/image-registration.html

Temporal Alignment (Synchronisation)

- Example: Dynamic Time Warping (technique for performing temporal alignment between two time series)
- ROS Time Synchronizer



From Lecture A1 by Don Dansereau

Radiometric Normalisation (Calibration)

Conversion of all sensor values to a common scale

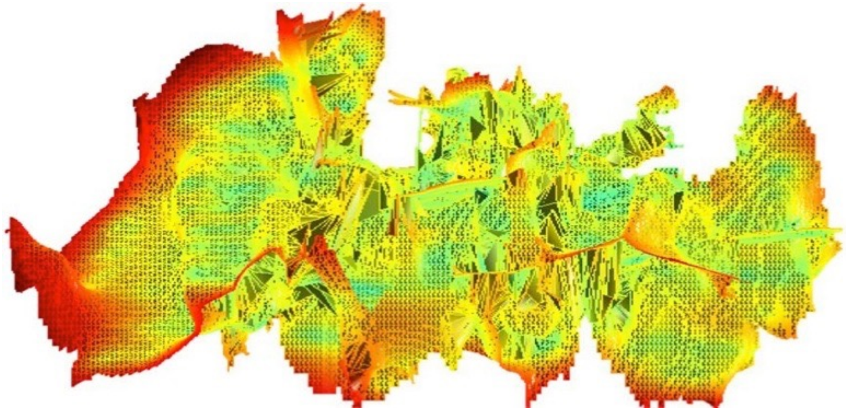
Scales of measurement:

- **Nominal Scale**. Variable values: **names** or **labels**
  - only operations that can be applied: “equality” and “inequality”
- **Ordinal Scale**. Variable values have all the features of a nominal scale and are **numerical**. Values represent the rank order (first, second, third, etc.) of the variables.
  - Operations: “greater” and “less” + “equality” and “inequality”
- **Interval Scale**. Variable values have all the features of ordinal scale and, additionally, are separated by the same interval.
  - Operations: e.g. “addition” and “subtraction”.
- **Ratio Scale**. Variable values have all the features of an interval scale and can also have meaningful ratios between arbitrary pairs of numbers.
  - Operations: e.g. “multiplication” and “division”.
  - Most physical quantities, such as mass, length, or energy are measured on ratio scales.

From Mitchell, H. B. (2012). Data Fusion: Concepts and Ideas. Springer

“Catastrophic” Fusion

- Occurs when the outcome of data fusion is actually of lower quality than the individual representations obtained using a single source of information (e.g. even if the spatial alignment between the sensors is well known).
- Particularly likely to occur when fusing data acquired by distinct sensing modalities (e.g. in the case of *inconsistent* or *conflicting* sensor data)


M. P. Gerardo Castro (2017), Robust Multiple-Sensing-Modality Data Fusion for Reliable Perception in Outdoor Scenarios, PhD Thesis, The University of Sydney

Handling Inconsistent/Conflicting Sensor Data

- Outlier Rejection
- Consistency checks/Tests
- Anomaly Detection
- Data Association

Methods

- **Probability Theory**
- Possibility Theory (based on fuzzy set theory)
- Evidence Theory (Dempster-Shafer)
- Random Set Theory (extending Bayes filter from single target to multiple targets

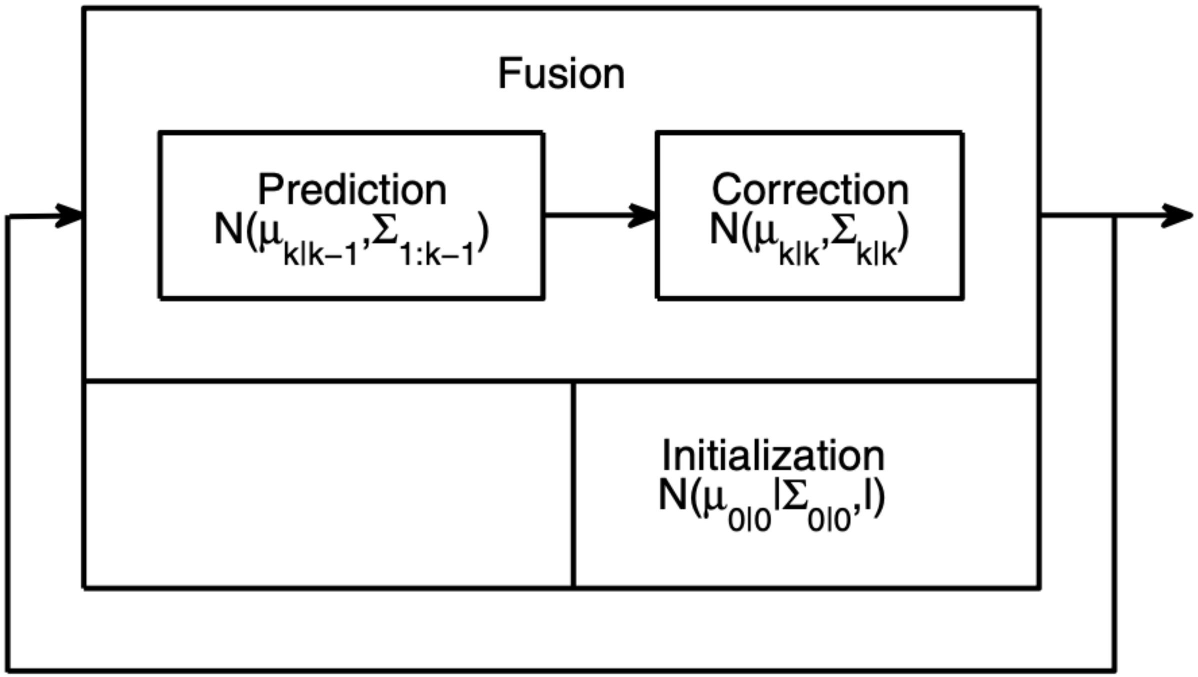
Probabilistic Methods

A Few Examples:

- Kalman Filter (e.g. GPS-IMU filter, or KF-SLAM)
- Complementary Filter
- Particle Filter
- Probabilistic Graphical Models (e.g. Bayersian Networks)

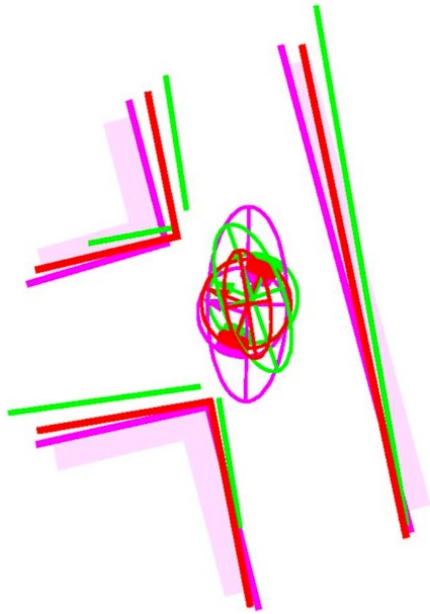
Kalman Filter (example of Recursive Filter)

- Fusion with Kalman filter



Fusion using Kalman Filter

Kalman Filter



- Prediction
- Measurement
- Kalman filter estimate

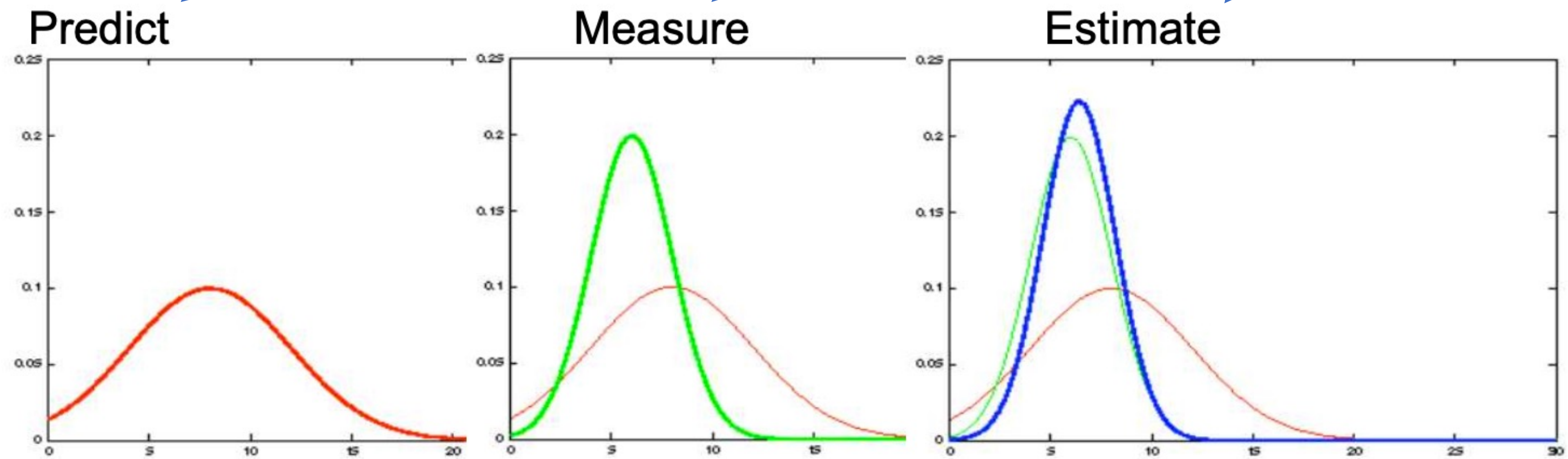
From: Will Browne, QUT ENN584 Lecture 5

Fusion using Kalman Filter

Dead-reckoning
(e.g. odometry)

Exteroceptive sensor
E.g. LIDAR or Vision

Result of Fusion

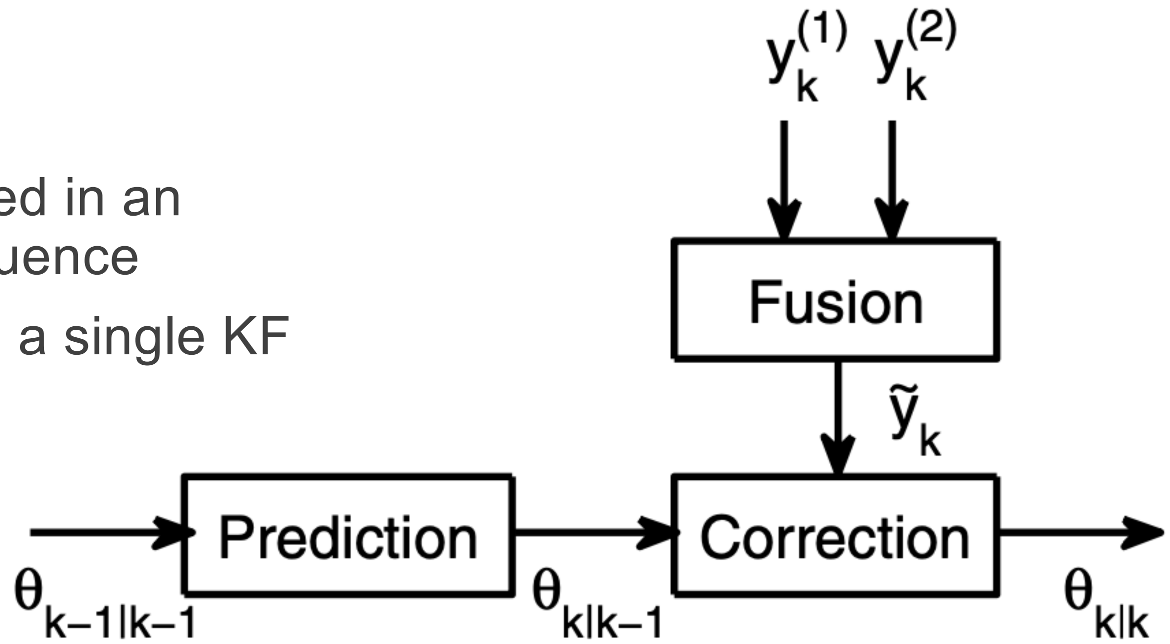


From: Will Browne, ENN584 Lecture 5

Multi-sensor Multi-temporal Data Fusion

- Measurement Fusion
- Example of “Early Fusion”

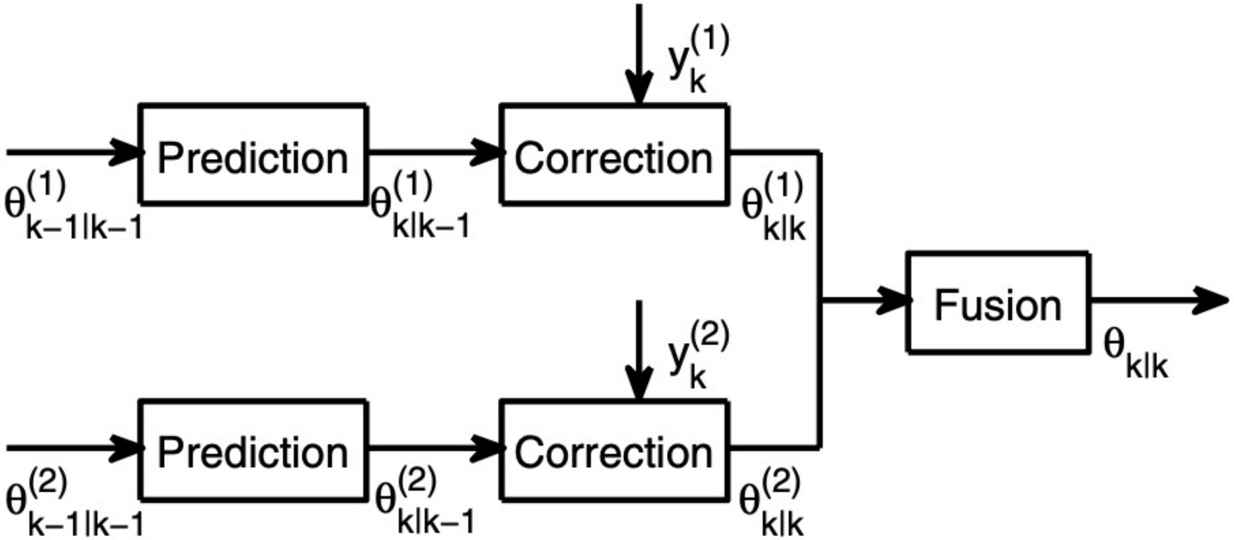
- Individual measurements placed in an augmented measurement sequence
- This vector is then fused using a single KF



Multi-sensor Multi-temporal Data Fusion

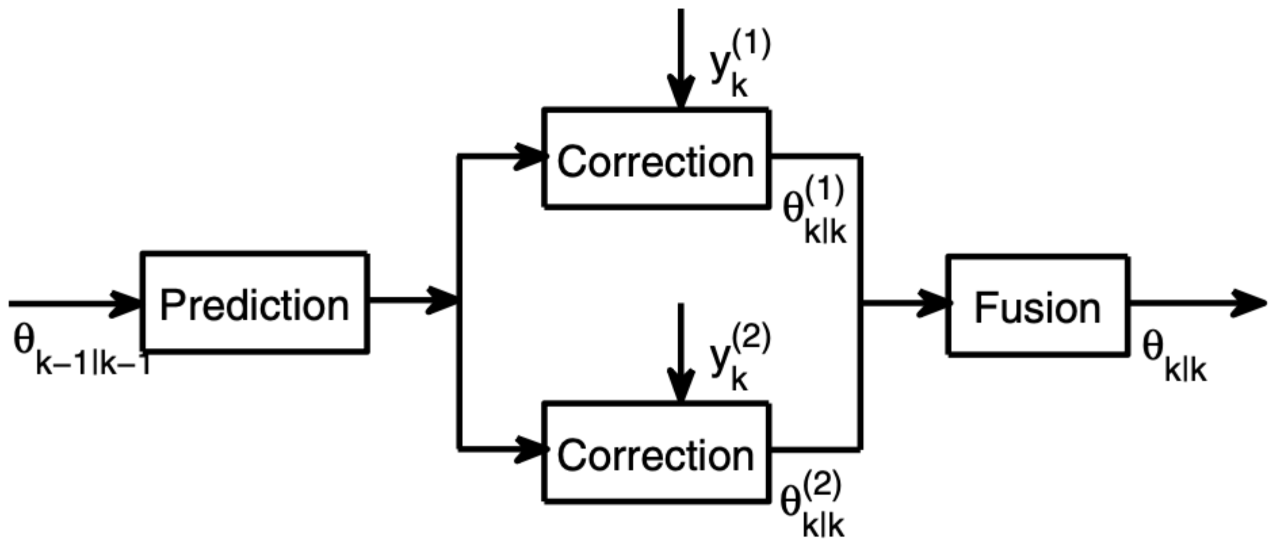
- Track-to-track Fusion (Example of “late fusion”)

- Two measurement vectors y1, y2 obtained from two sensors S1, S2.
- Each seq of measurements fused together using a KF
- Then outputs are fused together



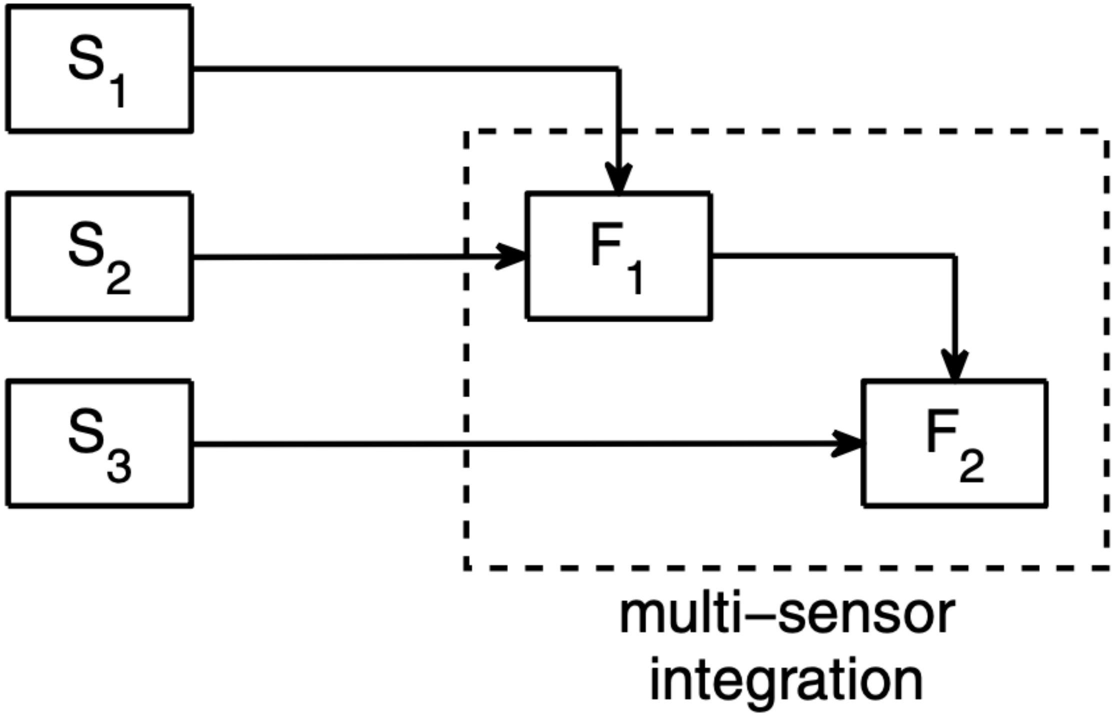
Multi-sensor Multi-temporal Data Fusion

- Modified Track-to-track Fusion



Multi-Sensor Integration

- Example



From Mitchell, H. B. (2012). Data Fusion: Concepts and Ideas. Springer

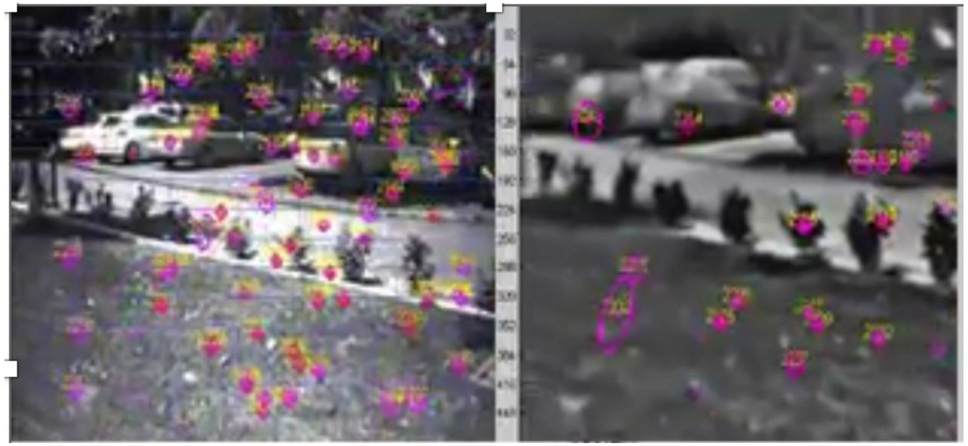
Sensor Data Fusion in Robotics

Use cases from robotics research

Use Case 1: Multi-Camera SLAM

Visual and IR SLAM

Example:
IR-Visual "Fusion"?



IR

(a)

Visual

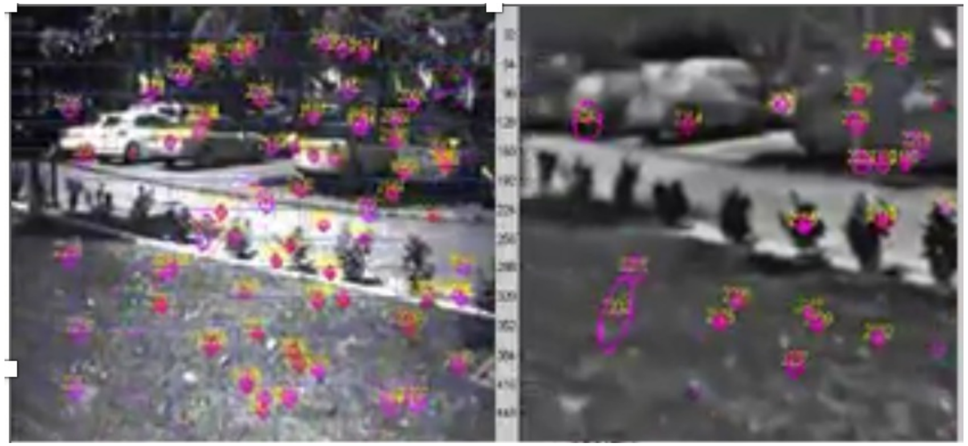
(b)

Fusion

An EM-CI Based Approach
to Fusion of IR and
Visual Images

[Chen & Leung - Fusion 2009]

Example:
IR-Visual “Fusion”?



An EM-CI Based Approach
to Fusion of IR and
Visual Images

[Chen & Leung - Fusion 2009]

(a)

IR

(a)

(b)

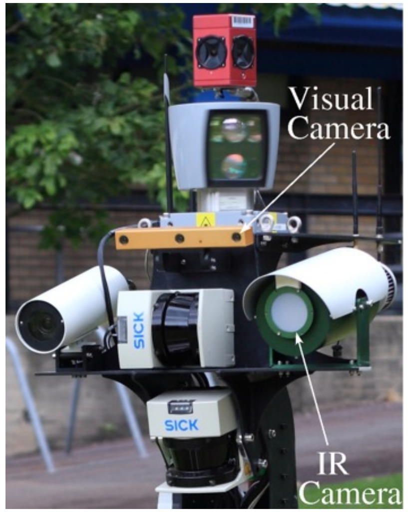
Visual

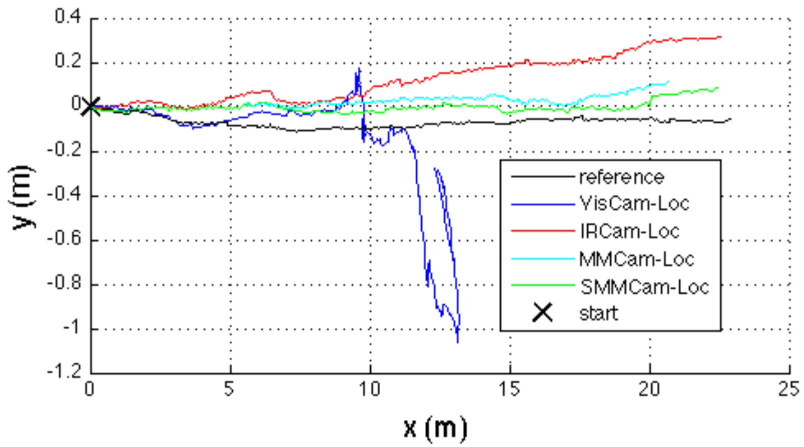
(b)

Fusion

Use-Case 1: Multi-camera SLAM

Combining Visual and Thermal Imaging for a Localisation Robust to Smoke





Use Case 1: IR-Visual Camera SLAM

- Multimodal-camera landmark-based EKF-SLAM

$$X^\top = \begin{bmatrix} \mathcal{R}^\top & \mathcal{L}_{vis_1}{}^\top & \ldots & \mathcal{L}_{vis_N}{}^\top & \mathcal{L}_{ir_1}{}^\top & \ldots & \mathcal{L}_{ir_M}{}^\top \end{bmatrix}, \quad (1)$$

Robot pose

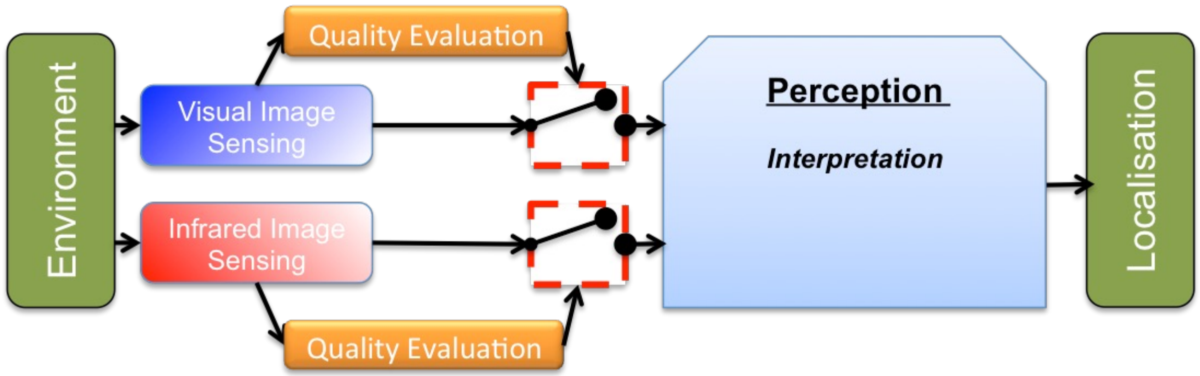
Visual Camera Landmarks

IR Camera Landmarks

- The cameras are intrinsically and extrinsically calibrated, therefore both independently update the robot pose
- Two cameras but no landmark in common/association => lack of scale
- SIFT points in each camera, but different appearance descriptors

C. Brunner, T. Peynot and T. Vidal-Calleja. "Combining Multiple Sensor Modalities for a Localisation Robust to Smoke". In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), San Francisco, CA, September 2011.

Selective Combination of Visual and Thermal Imaging for Resilient Localisation in Adverse Conditions: Day and Night, Smoke and Fire



Visual

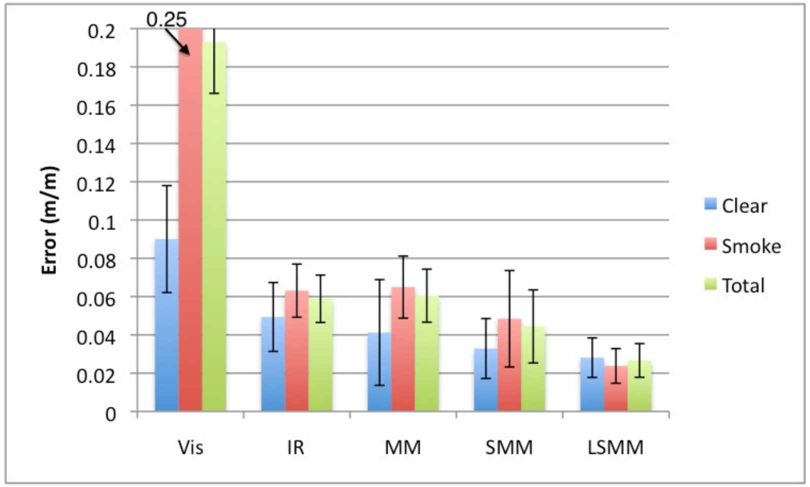
IR

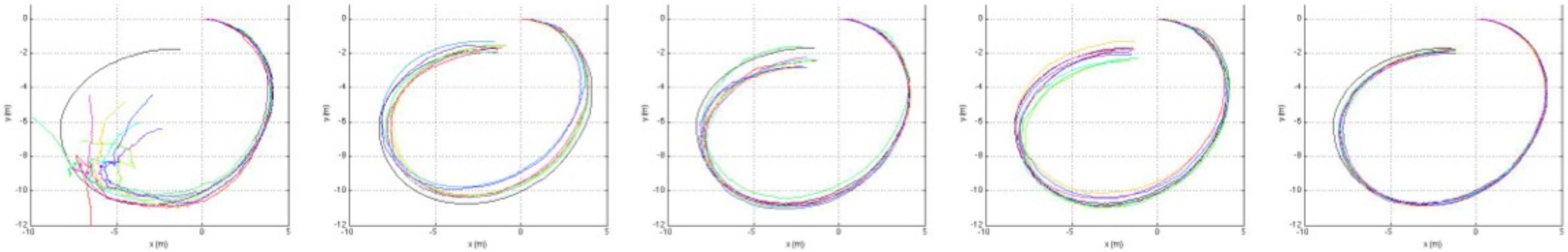
[Brunner et al. 2011-2013]

SMOKE

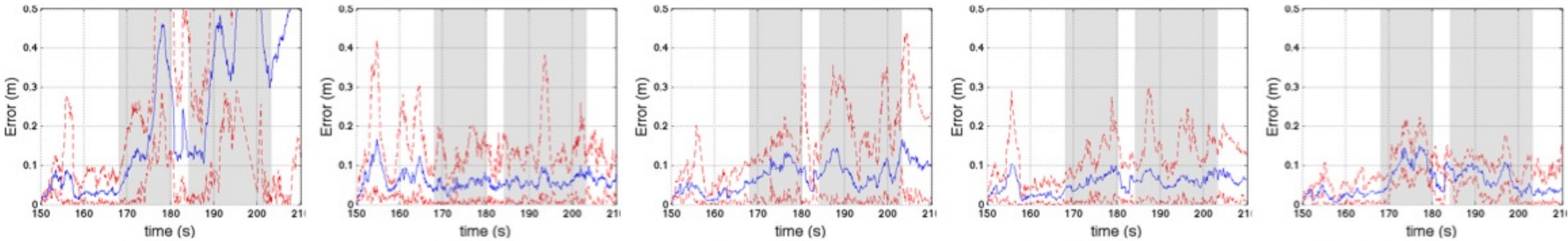
[Brunner-JFR-2013]

Localisation in Smoke





(a) Vis.Loc (b) IR.Loc (c) MM.Loc (d) SMM.Loc (e) LSMM.Loc

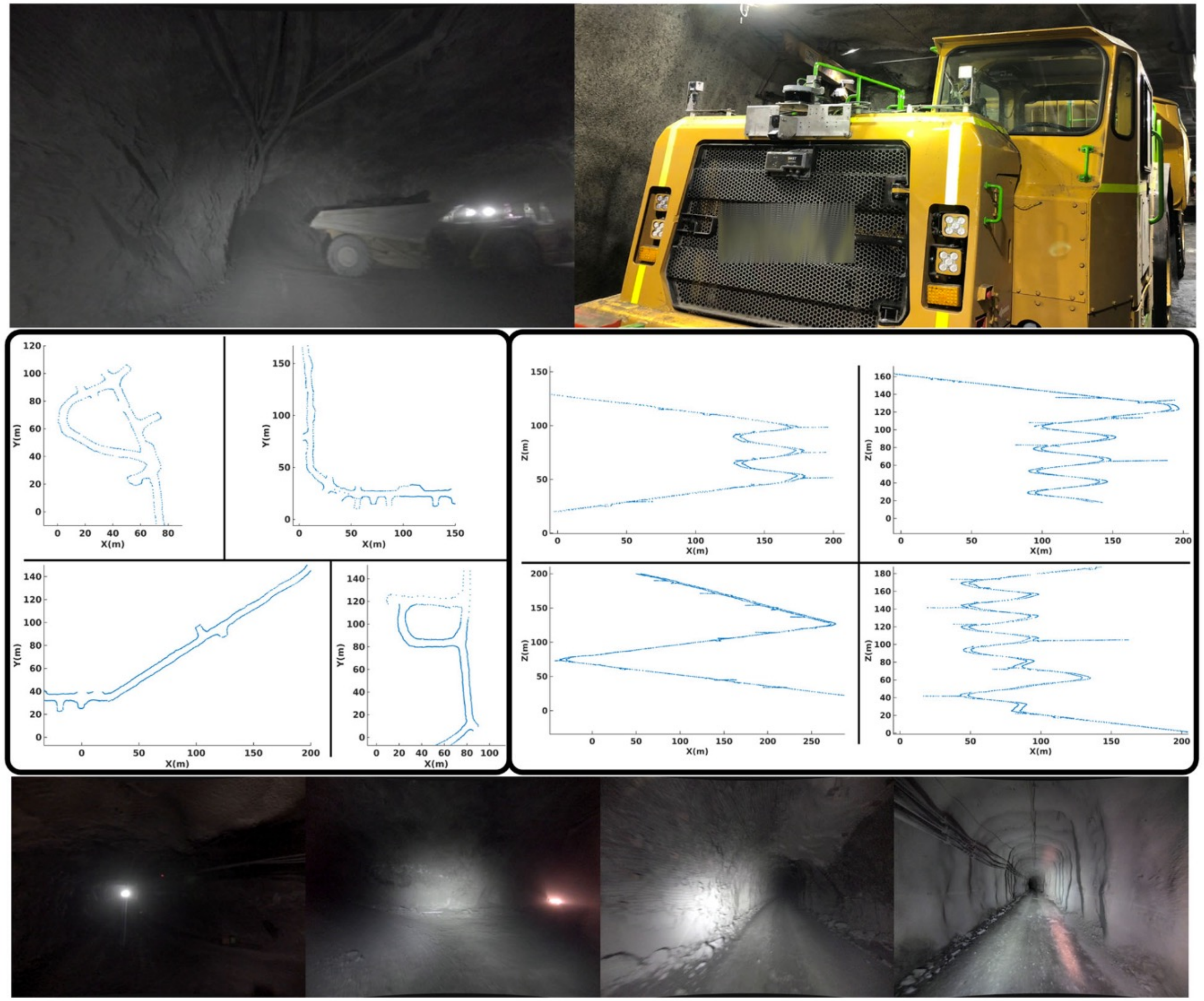


(f) Vis.Loc (g) IR.Loc (h) MM.Loc (i) SMM.Loc (j) LSMM.Loc

Use Case 2: Visual Camera – LIDAR Localisation in GPS-denied environment

Use case: Multi-sensor localization for underground mines

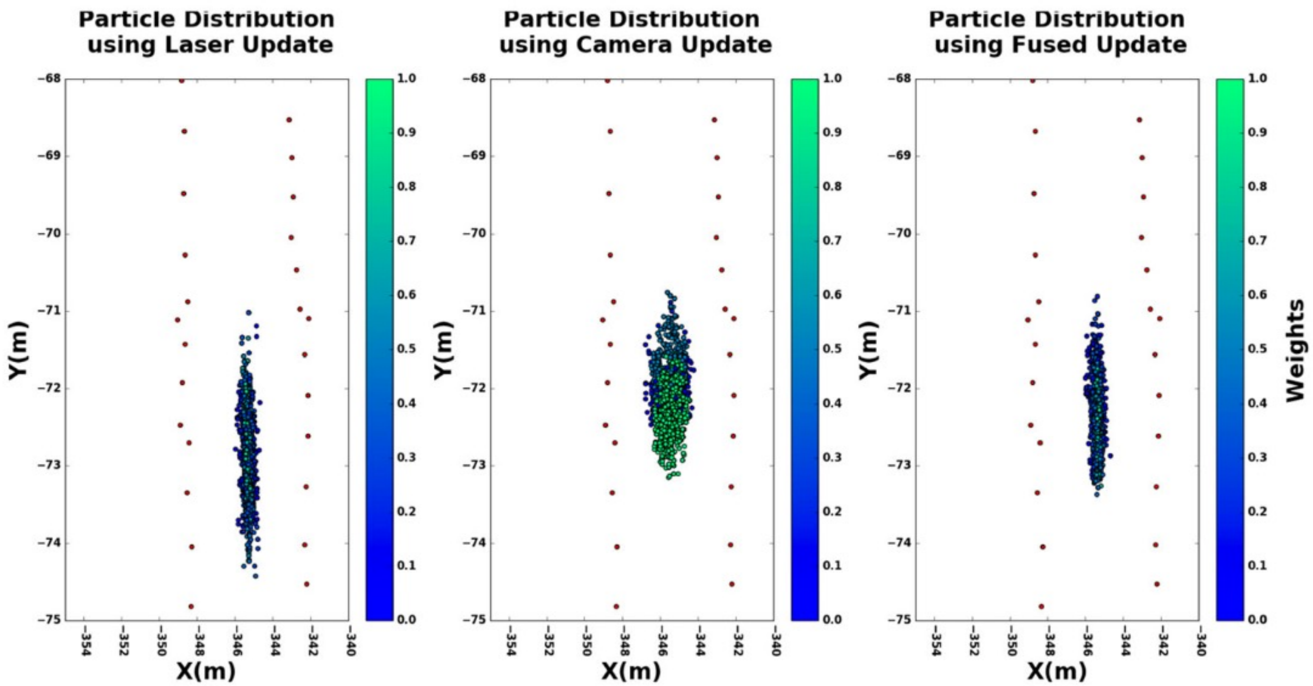
- Particle filter



A. Jacobson et al. “What Localizes Beneath: a Metric Multi-Sensor Localization and Mapping System for Autonomous Underground Mining Vehicles”.
In *Journal of Field Robotics*, Vol. 38, Issue 1, January 2021

Use case: Multi-sensor localization for underground mines

- Particle filter



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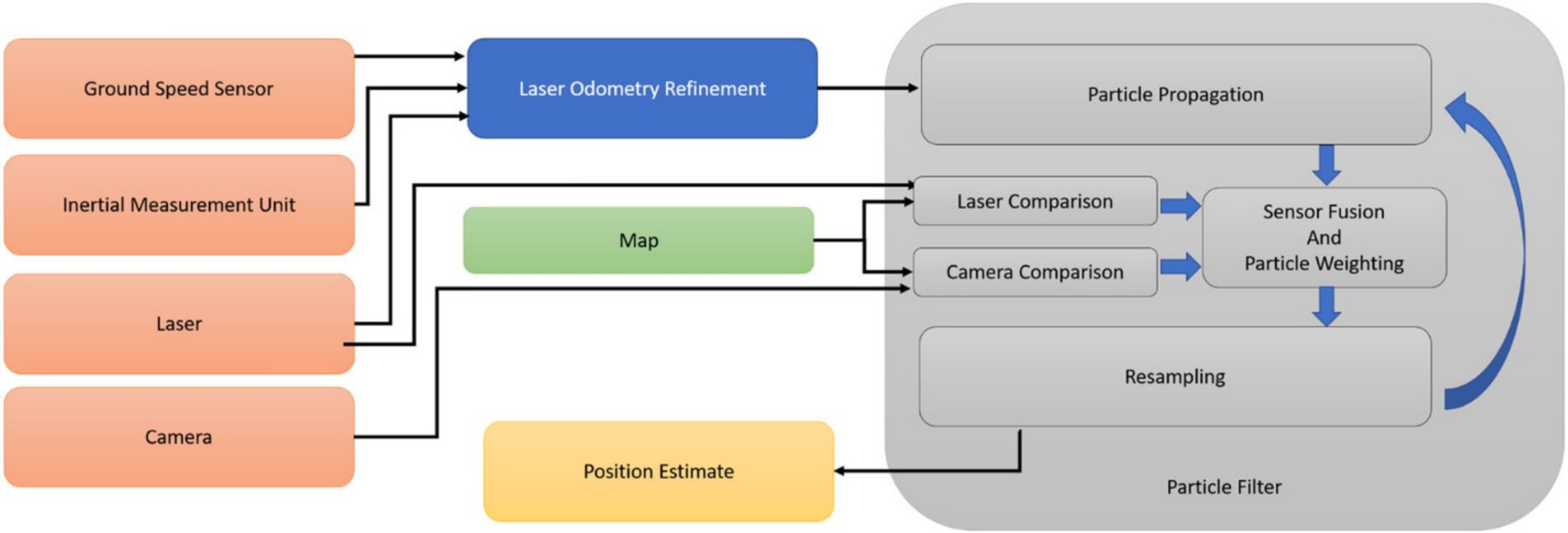
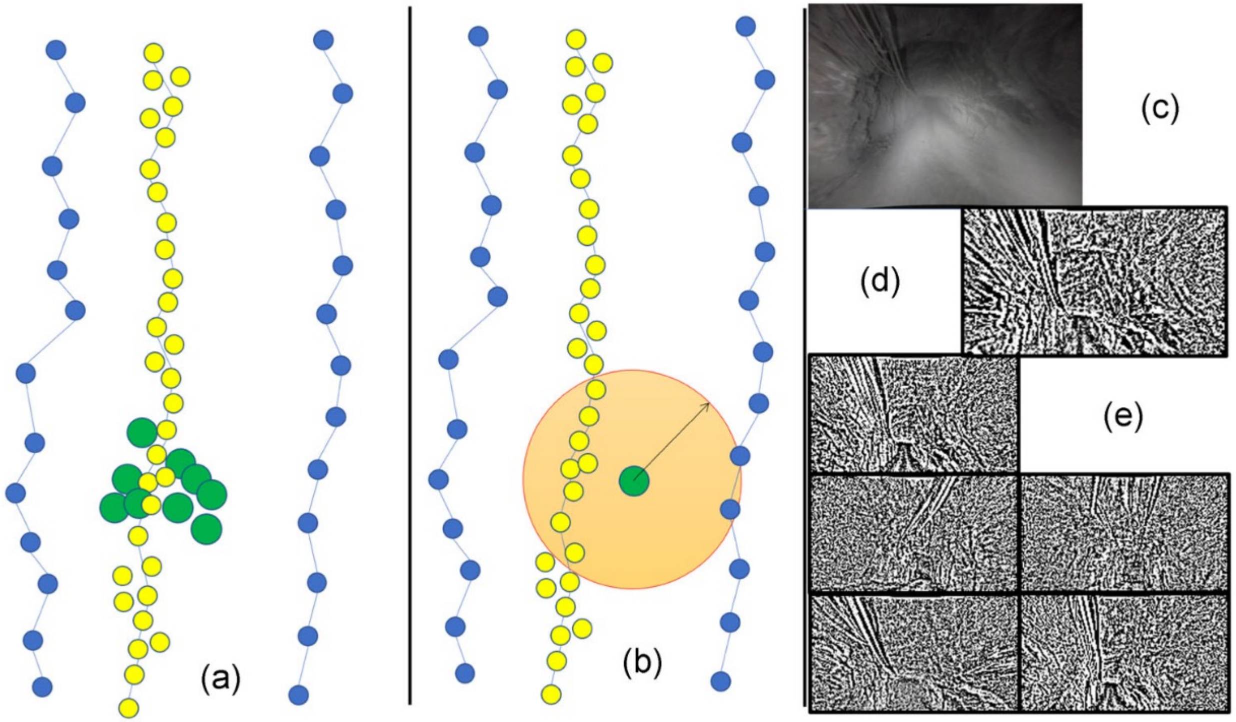
Use case: Multi-sensor localization for underground mines



A. Jacobson et al. "What Localizes Beneath: a Metric Multi-Sensor Localization and Mapping System for Autonomous Underground Mining Vehicles". In *Journal of Field Robotics*, Vol. 38, Issue 1, January 2021

Use case: Multi-sensor localization for underground mines

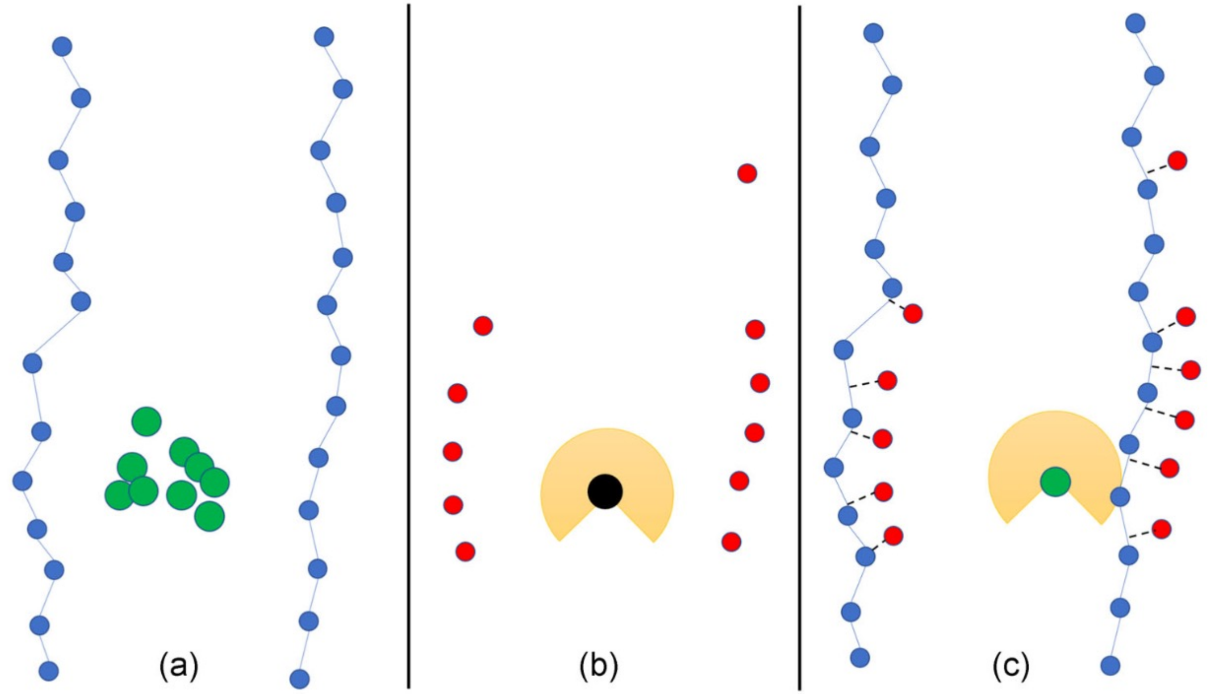
- Particles for Camera
- Blue: Mapped Tunnel
- Yellow: Map images loc.
- Green: Particle hypotheses



Use case: Multi-sensor localization for underground mines

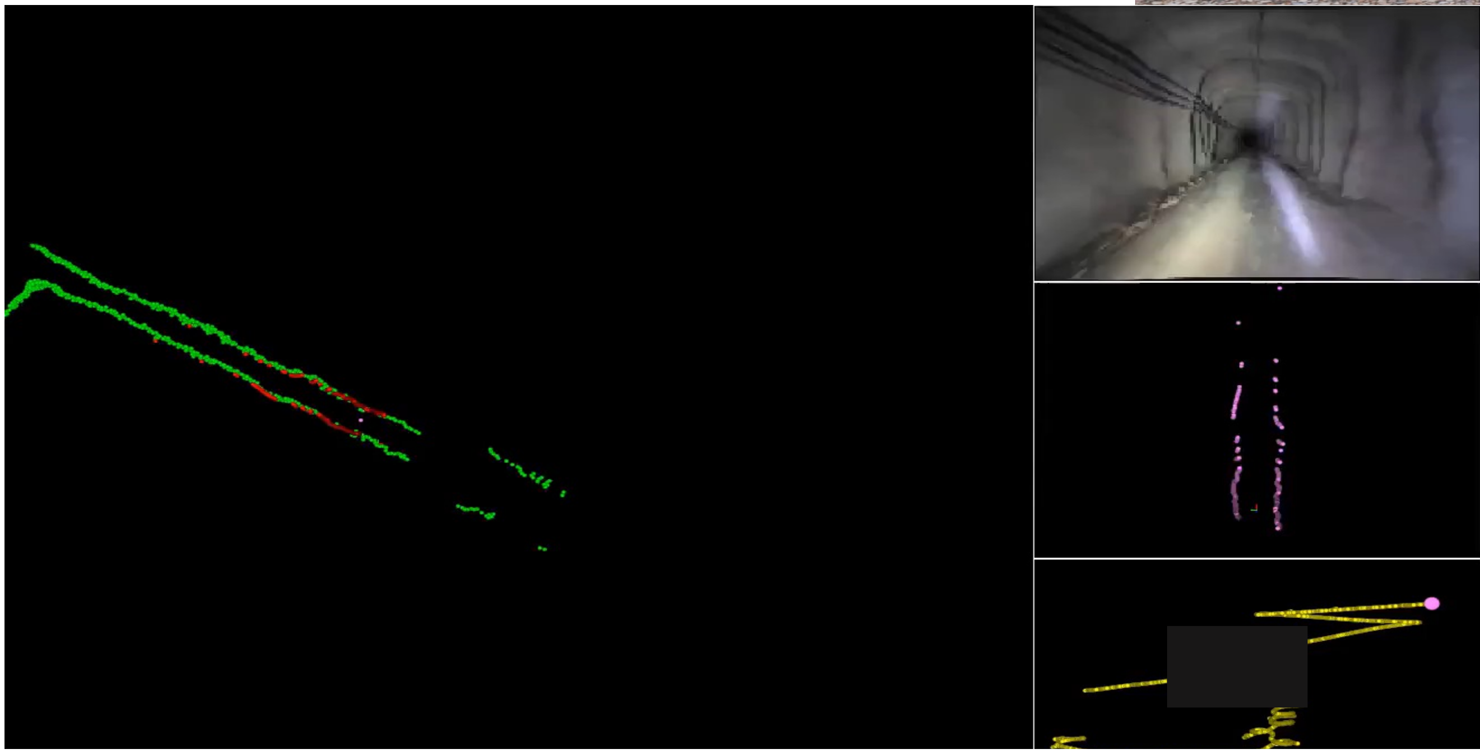
- Particles for LIDAR

- Blue: Mapped Tunnel
- Red: Current laser points
- Black: LIDAR
- Green: Particle hypotheses



Centre for Robotics

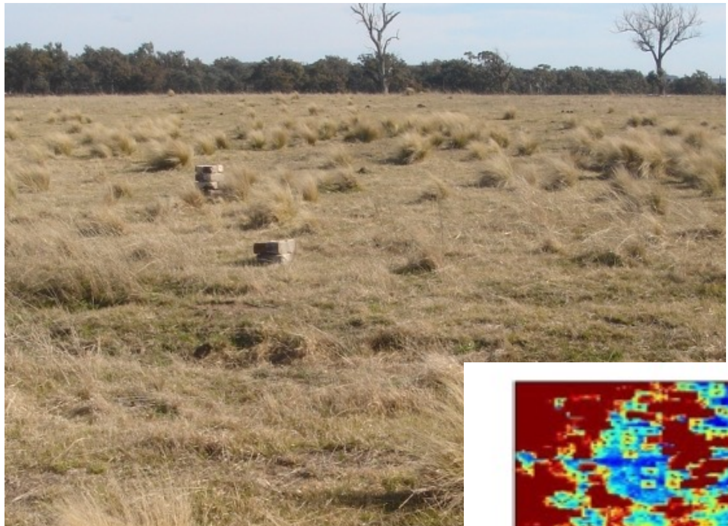
GPS-Denied Localisation & Mapping

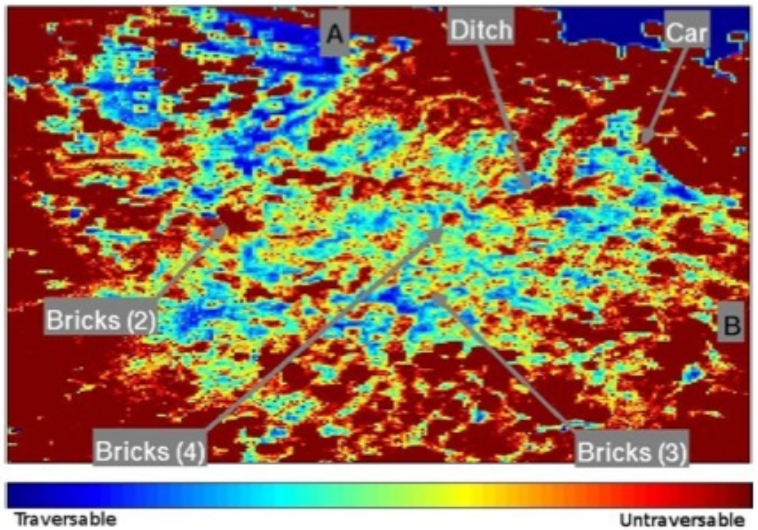


Use Case 3: LIDAR + UWB Radar Traversability Map

LIDAR Traversability Map ‘Augmented’ by UWB Radar data

Augmenting Traversability Maps with UWB Radar to Enhance Obstacle Detection in Vegetated Environments





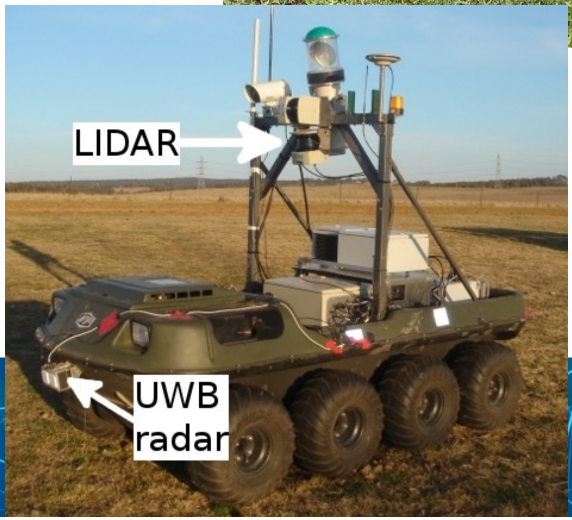
(a) LIDAR Traversability map (T_m)

[Ahtiainen-IROS-2013]

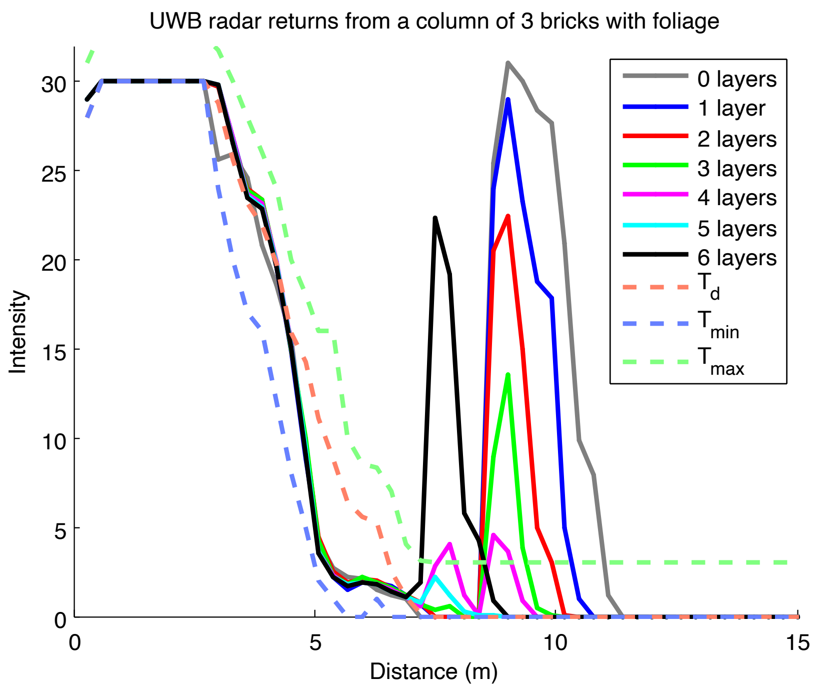
Obstacle Detection in Vegetated Environments

- LIDAR-based occupancy grids and traversability maps: good for geometry reasoning only
- Vegetation, e.g. grass tufts, seen as obstacle
- Can be classified with Visual/NIR but…
- UWB Radars can see through foliage

- Objective: clear areas seen as obstacles in LIDAR-based traversability maps (e.g. grass tufts)
  => Safe and "efficient" navigation of UGV in vegetated environments



Detection of Obstacle vs. Vegetation

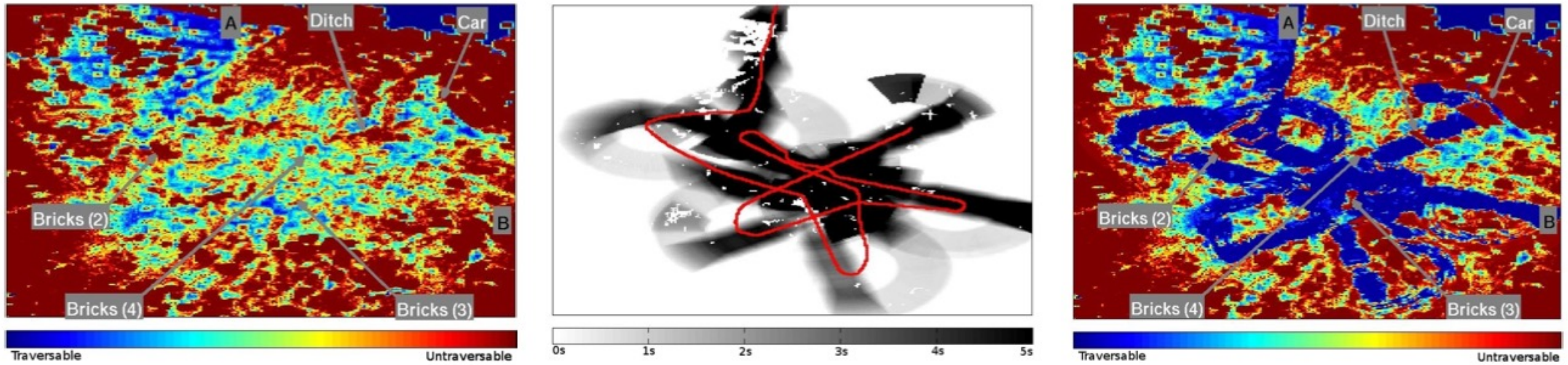


3 bricks

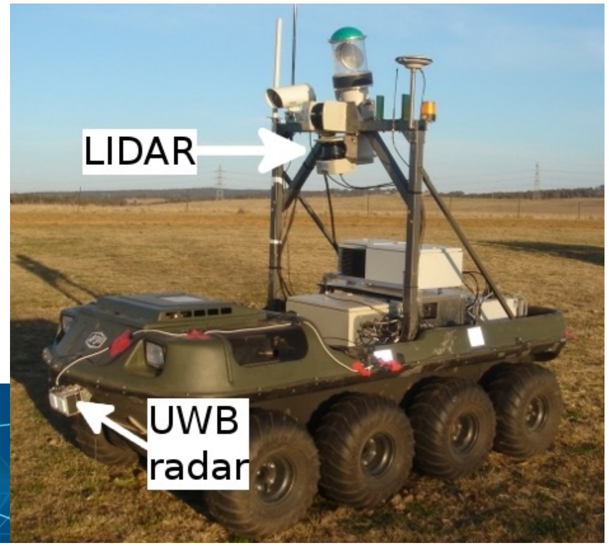
2 layers of vegetation

Amount of foliage	$P(z\|occ)$ of foliage ($8m$)	$P(z\|occ)$ of bricks ($9m$)
0 layers	0.3842	0.8000
1 layer	0.3842	0.8000
2 layers	0.3842	0.8000
3 layers	0.5129	0.8000
4 layers	0.7862	0.7914
5 layers	0.7188	0.4959
6 layers	0.8000	0.4959

Radar-Augmented Traversability Map



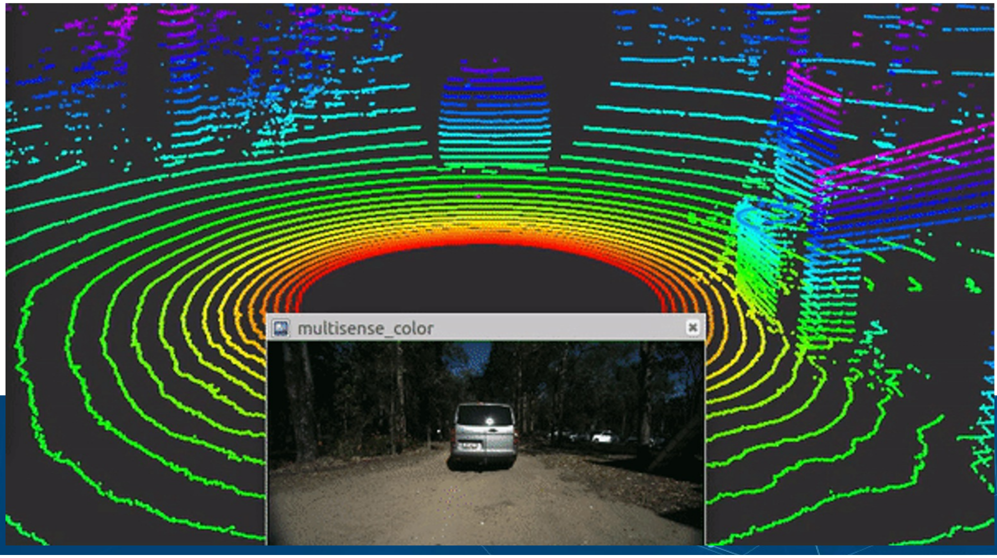
(a) LIDAR Traversability map (T_m)
(b) Updated cells in radar FOV
(c) Augmented traversability map (T_{ma})

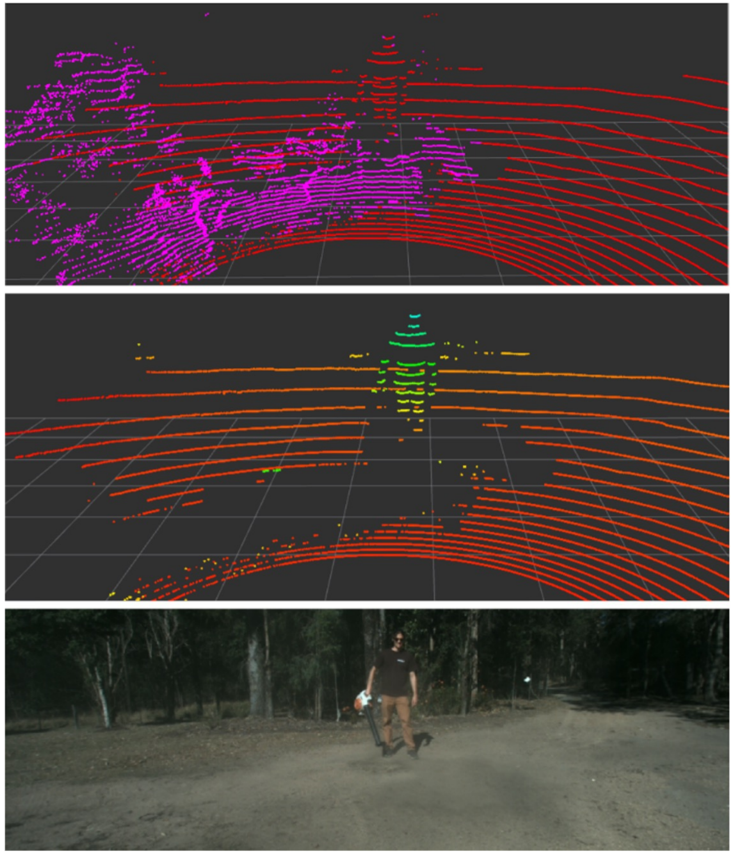


Use Case:
Detecting Airborne Particles in Sensor Data with Deep Learning

LIDAR + Stereo Point Clouds

LIDAR Scans in the presence of airbone dust





[Stanislas et al. 2018]

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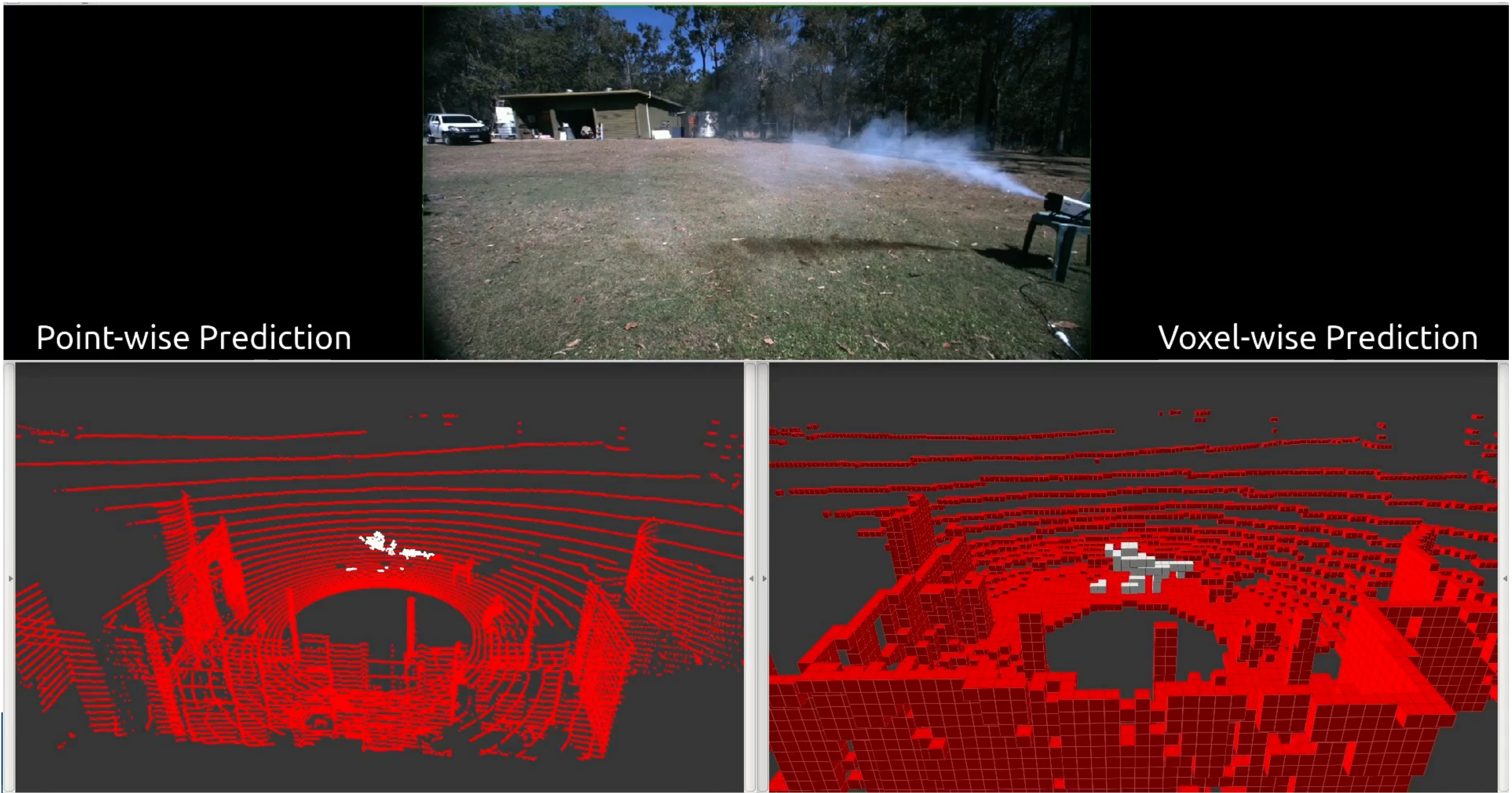
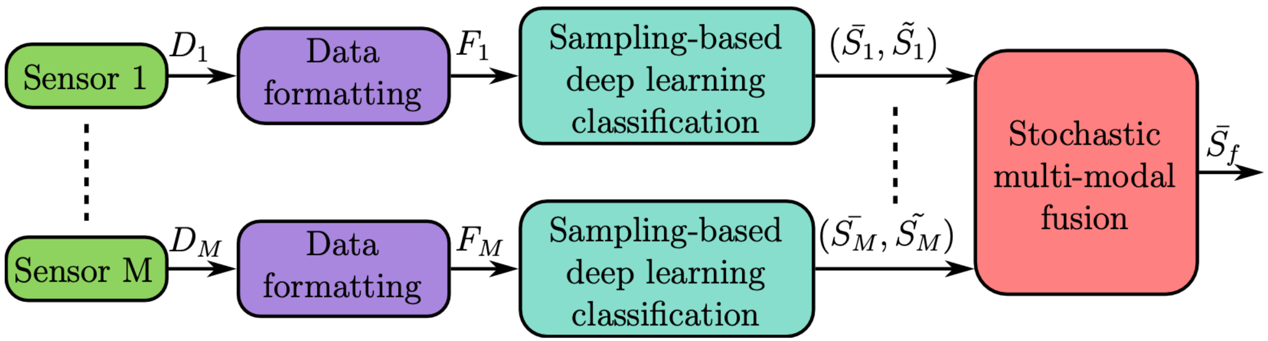
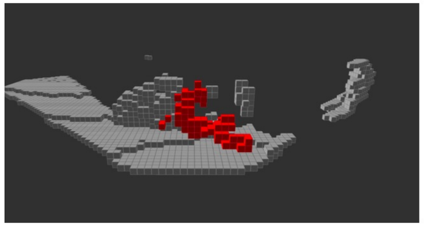

Point-wise Prediction
Voxel-wise Prediction

Airborne particle detection

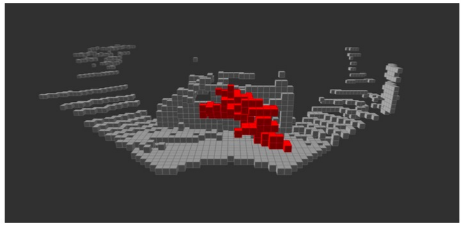
- LIDAR point cloud
- Stereovision point cloud



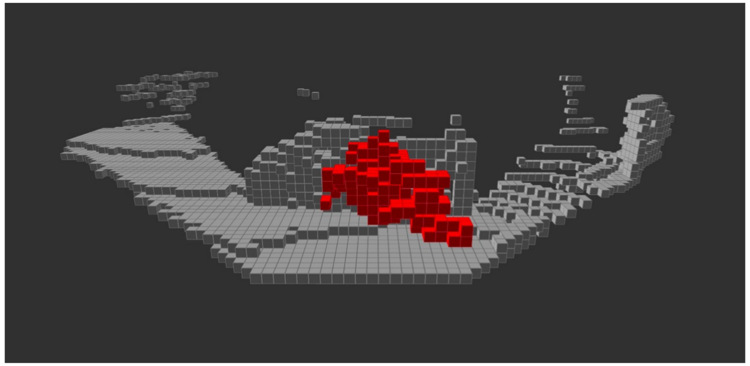
(a) Image of the scene.



(b) Stereo ground-truth.



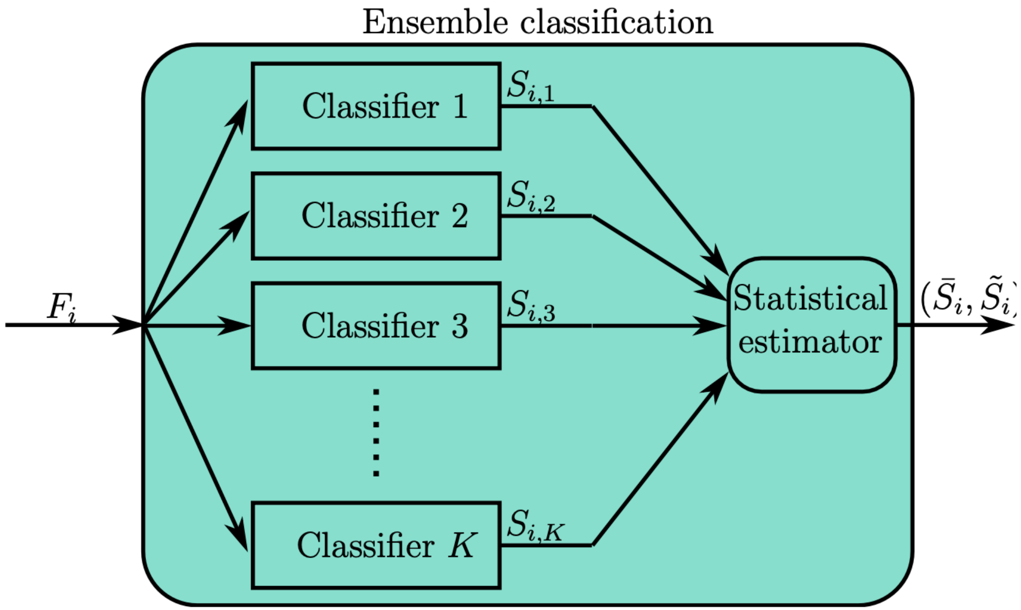
(c) LIDAR ground-truth.

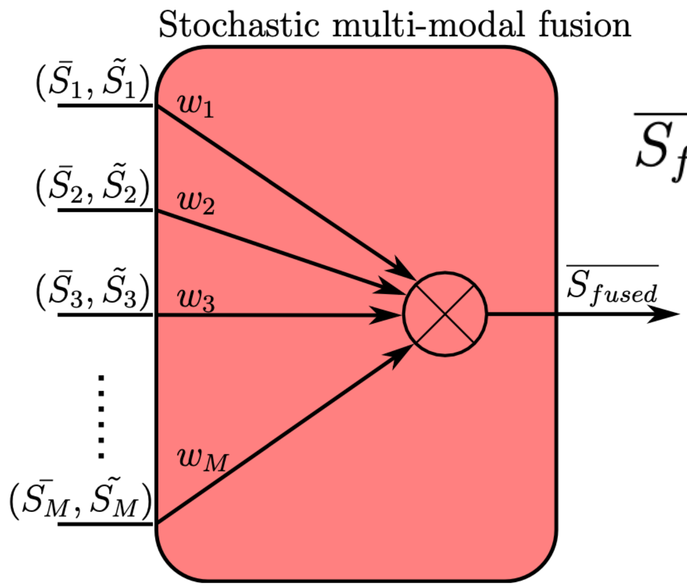


(d) Combined ground-truth.

Leo Stanislas. *Detecting Airborne Particles in Sensor Data with Deep Learning for Robust Robot Perception in Adverse Environments*. PhD Thesis, QUT, 2020

Ensemble Classification





$$\overline{S_{fused}} = \sum_{i=1}^{M} w_i \bar{S}_i$$

$$w_i = \eta \frac{1}{\tilde{S}_i}$$

$$\eta = \frac{1}{\sum_{i=1}^{M} \frac{1}{\tilde{S}_i}}$$

Early Fusion Deep Learning Architecture

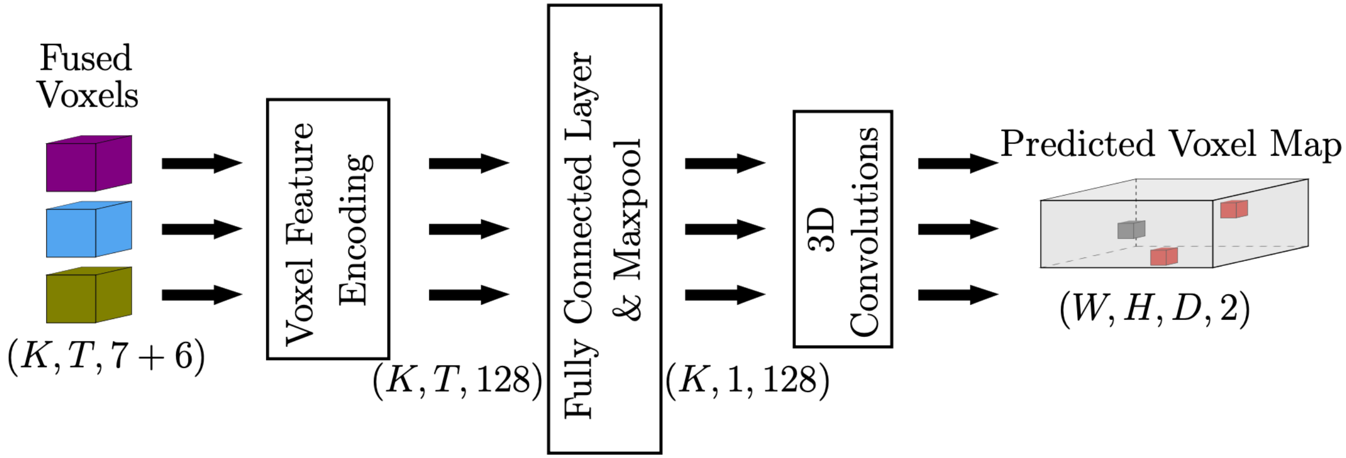


Figure 5.6: Early fusion architecture for LIDAR-Stereo voxel-based deep learning classification.

In the early fusion strategy, the sensor data for each modality is concatenated in a single input vector defined as

$$F_{early} = [F_{LIDAR-geometry}, F_{LIDAR-intensity}, F_{LIDAR-echo}, F_{stereo-geometry}, F_{stereo-colour}].$$

Late Fusion Deep Learning Architecture

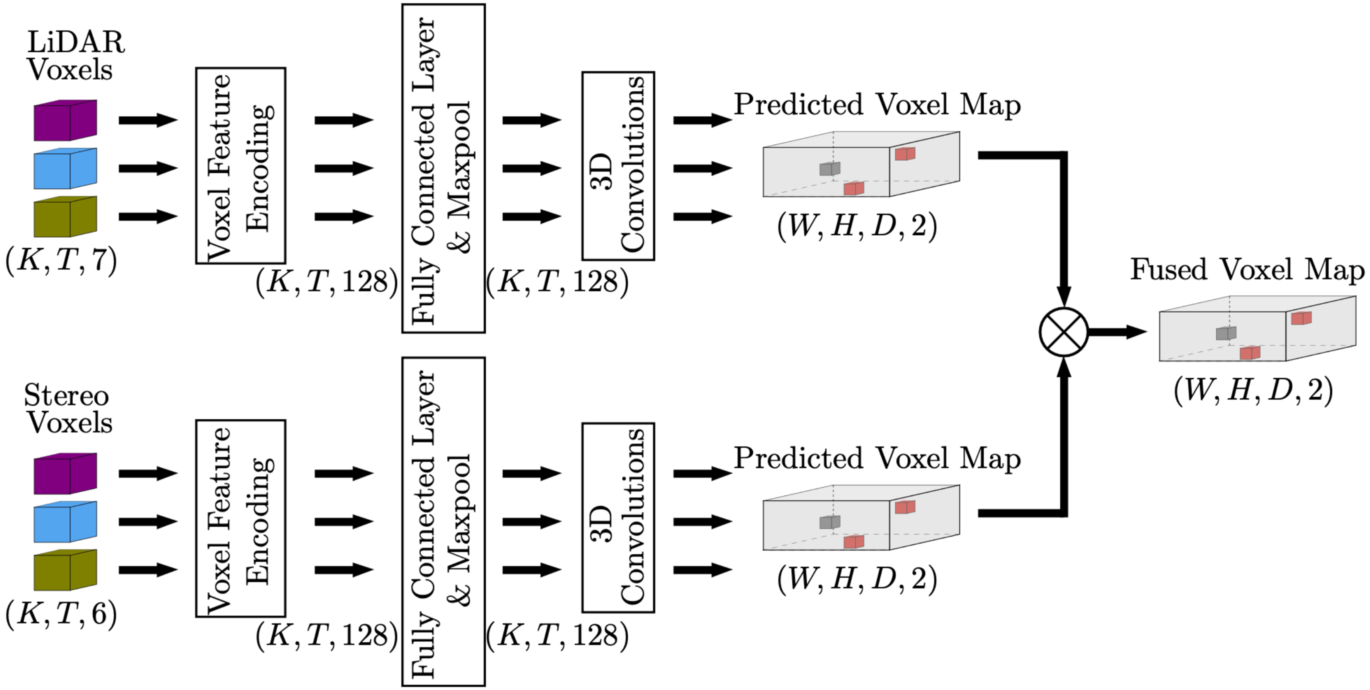
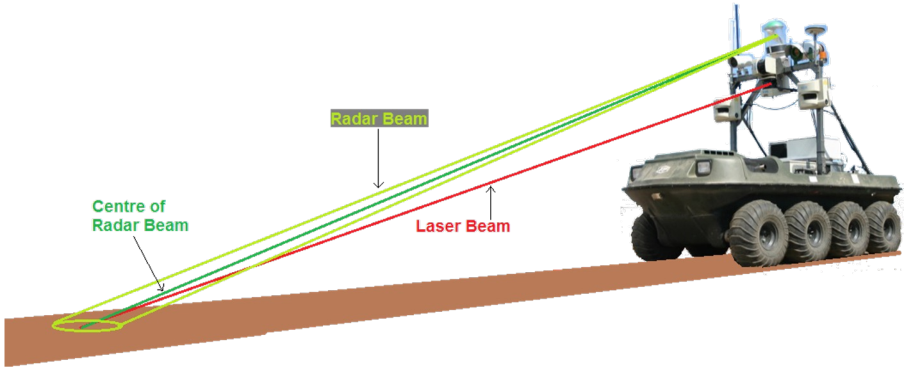


Figure 5.4: Late fusion architecture for LIDAR-Stereo voxel-based deep learning classification.

Use Case 4: LIDAR-RADAR Fusion for Object Reconstruction

Consistent case vs. inconsistent

LIDAR vs RADAR

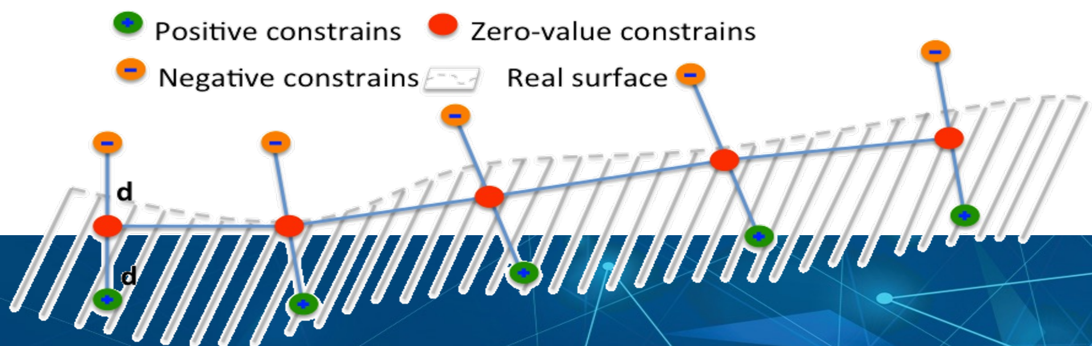


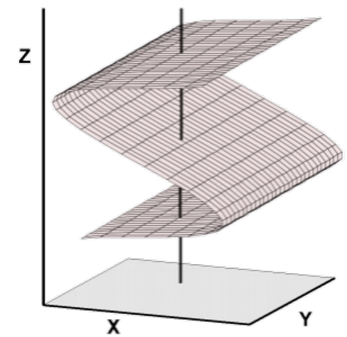
Sensor	Maximum range	Range resolution	FOV	Angular resolution
Laser (2D-Sick)	80 m	0.01 m	180º	0.25º
Radar (mm-wave)	40 m	0.20 m	360º	1.90º

Laser-Radar Data Fusion using Gaussian Process Implicit Surfaces (GPIS)

- Build **complete** and continuous representations of targets, with **uncertainties**, that can account for complex geometry
- Fuse data from multiple-sensing modalities, take the “best of both worlds”
- Experimental analysis of the performance of 3D reconstruction of objects from laser and radar data within the GPIS framework, in the context of field robotics
- Development of fusion techniques that can account for differences of perception
- GPIS estimate the function *f*, with the constraints:

$$f(x) = \begin{cases} = 0, & \text{if } x \text{ is on surface} \\ = -1, & \text{if } x \text{ is outside the surface} \\ = +1, & \text{if } x \text{ is inside the surface} \end{cases}$$





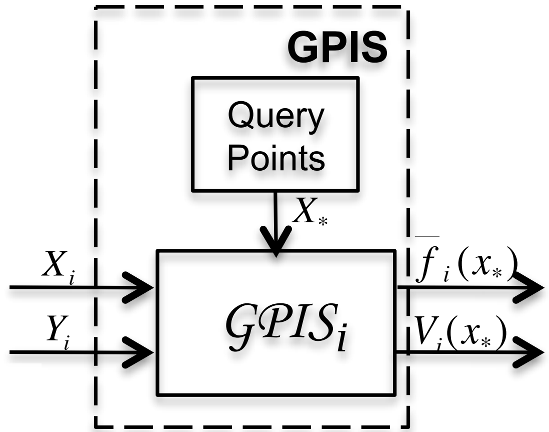
Gaussian Process Implicit Surfaces (GPIS)

- Conditional GP Regression

$$\mathbb{P}(f_*(x_*) \mid X, Y, \theta, x_*) = \mathcal{N}(\bar{f}_*, \mathbb{V}[f_*])$$

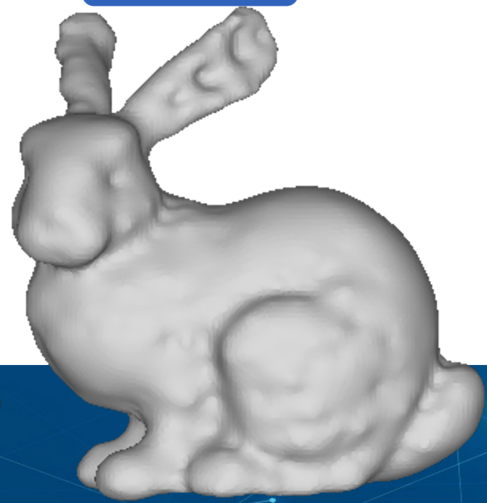
- Where mean and variance are:

$$\begin{aligned} \bar{f}_* &= k(x_*, X)^T (K + \sigma_n{}^2 I)^{-1} Y \\ \mathbb{V}[f_*] &= k(x_*, x_*) - k(x_*, X)^T (K + \sigma_n^2 I)^{-1} k(x_*, X) \end{aligned}$$

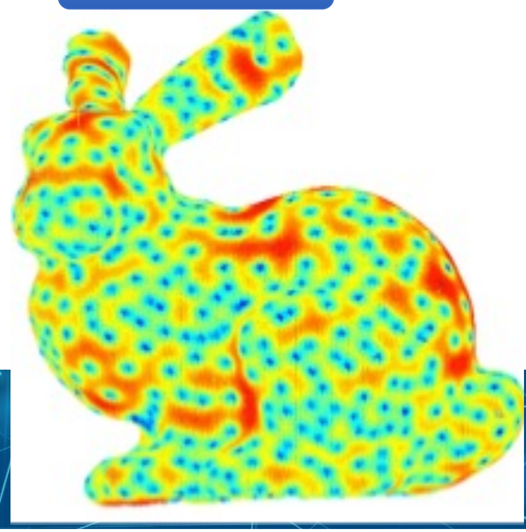


Raw data Stanford Bunny

Surface

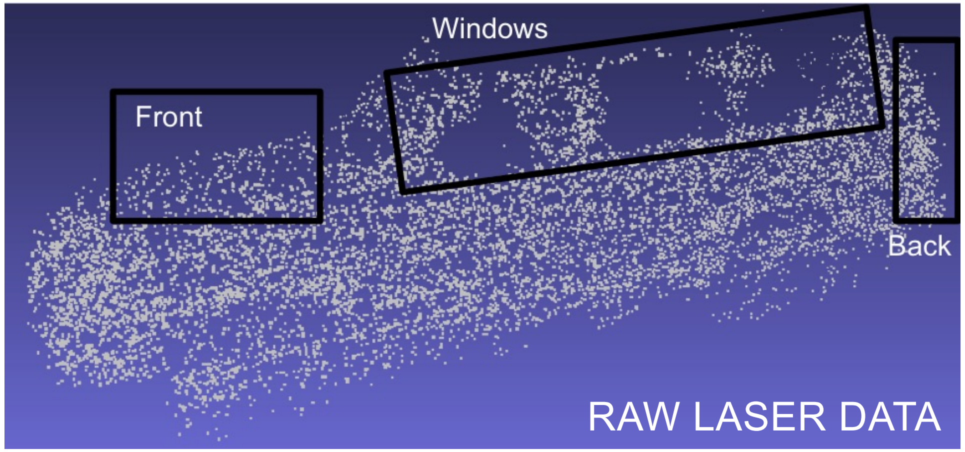


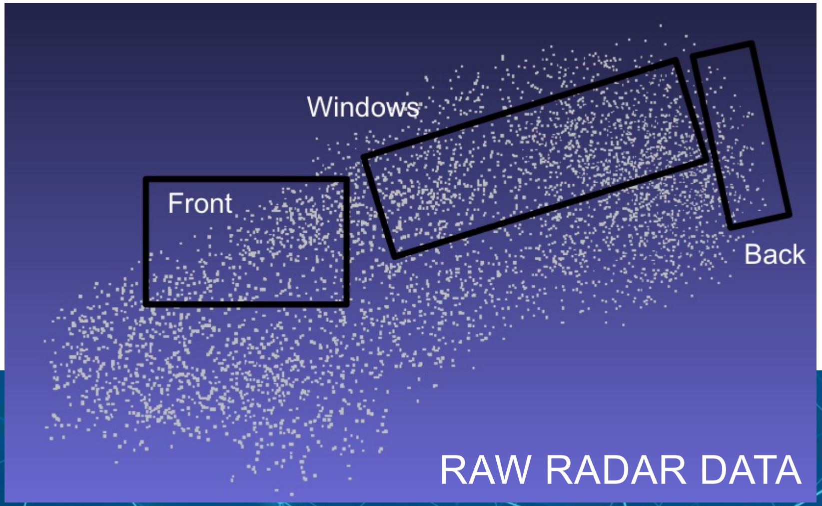
Uncertainty



Raw Laser and Radar Data

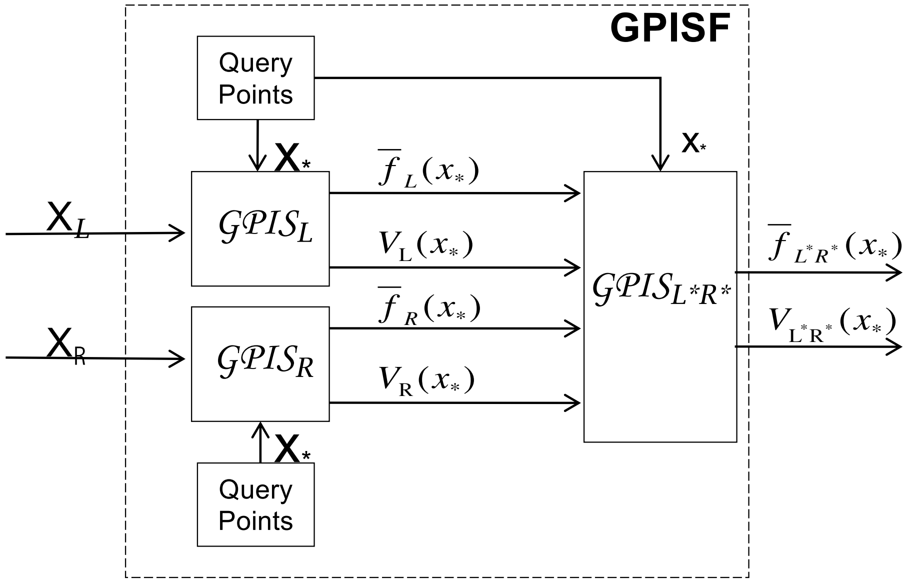
Full Res.: 22736 pts
Inputs to GPIS: 1500 pts



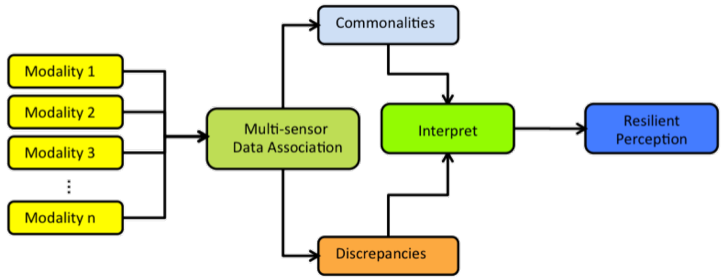


GPIS Fusion $\mathcal{GPIS}_{L*R*}$

- Fuse two estimates together using GPIS.



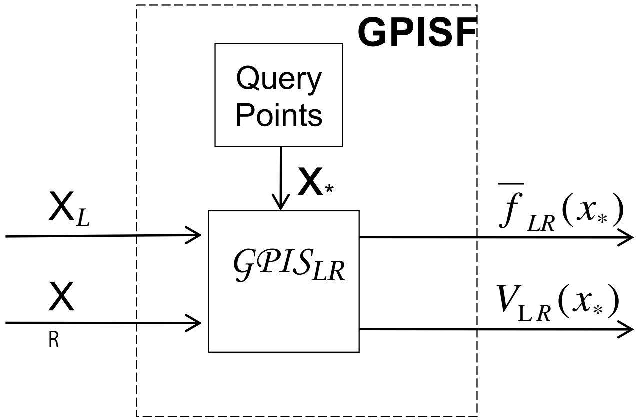
Possibility to compare laser-radar perception (incl. uncertainty) locally prior to fusion
=> separate discrepancies.



- Similar to $\mathcal{GPIS}_{L*R}$ predicted uncertainties V_{L*} and V_{R*} are included in $\mathcal{GPIS}_{L*R*}$

GPIS Fusion $\mathcal{GPIS}_{LR}$ (Early)

- Fusing two sets of raw data.



$\mathcal{GPIS}_{LR}$: Directly fuses raw laser and radar data.

Limited control on the process

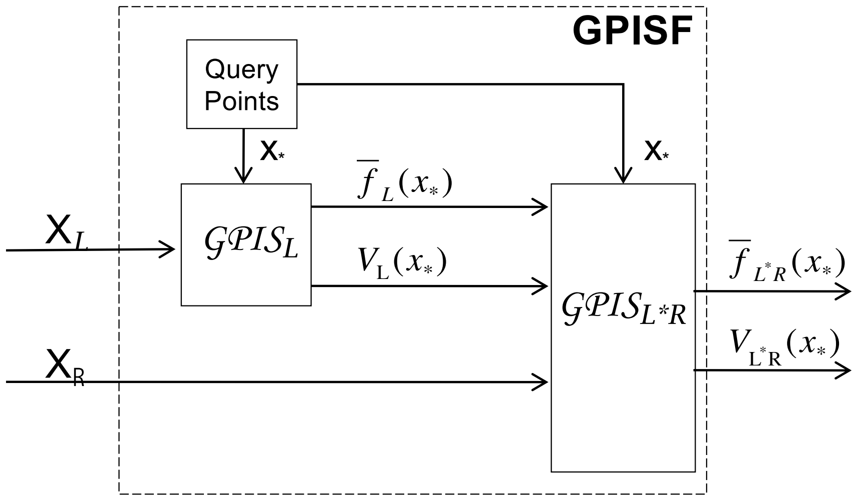
- Accounting for different noise parameters for data from each sensing modality.

$$
\begin{aligned}
\bar{f}_* &= {k_*}^T (K+H)^{-1} X \\
\mathbb{V}[f_*] &= k(x_*, x_*) - {k_*}^T (K+H)^{-1} k_* \\
H &= diag({\sigma_1}^2(X_1), {\sigma_2}^2(X_2) \ldots {\sigma_n}^2(X_n))
\end{aligned}
$$

GPIS Fusion $\mathcal{GPIS}_{L*R}$

To refine the surface estimate, we may choose to use more radar points in regions of higher uncertainty.

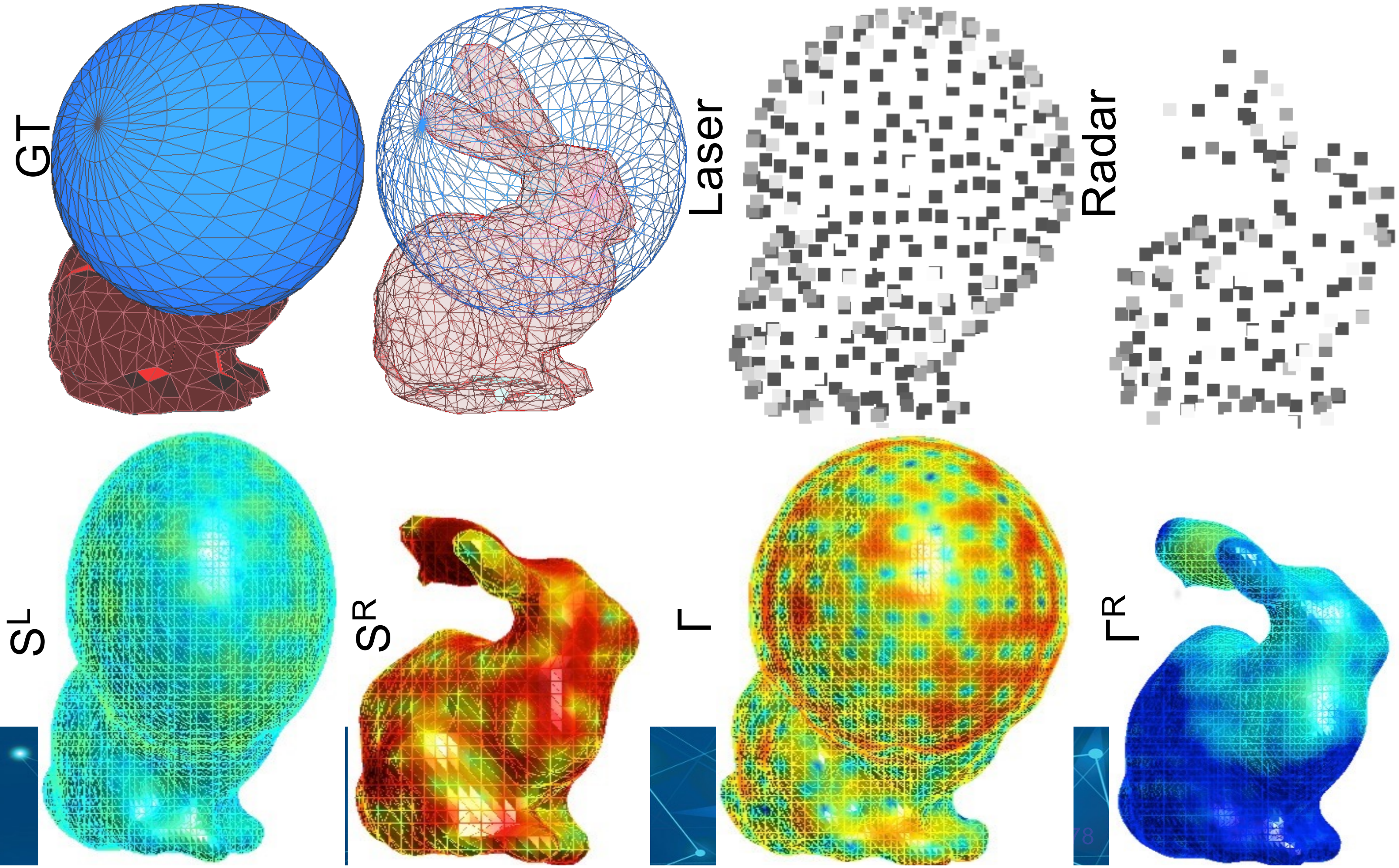
- Refining initial surface estimate from a single source of data with raw data from the other sensing modality.



- Incorporating predicted uncertainties V_{L*} in $\mathcal{GPIS}_{L*R}$

$$\bar{H} = diag(H_{L_*}, H_R)$$
$$H_R = diag(\sigma_r{}^2(X_{R_1}), \sigma_r{}^2(X_{R_2}) ... \sigma_r{}^2(X_{R_n}))$$
$$H_{L_*} = diag(\mathbb{V}_{L_{*1}}, \mathbb{V}_{L_{*2}} ... \mathbb{V}_{L_{*nl}})$$

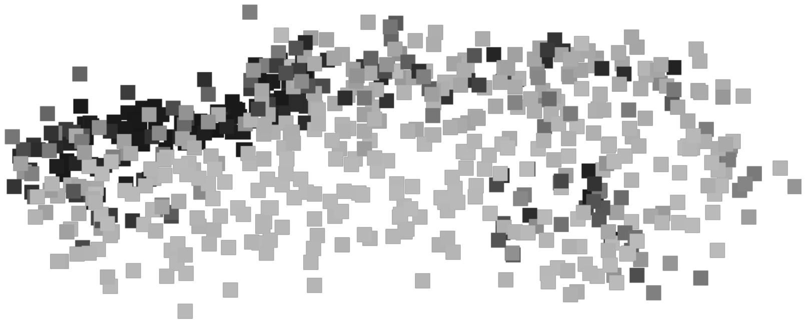
GPIS DF Synthetic Data Results



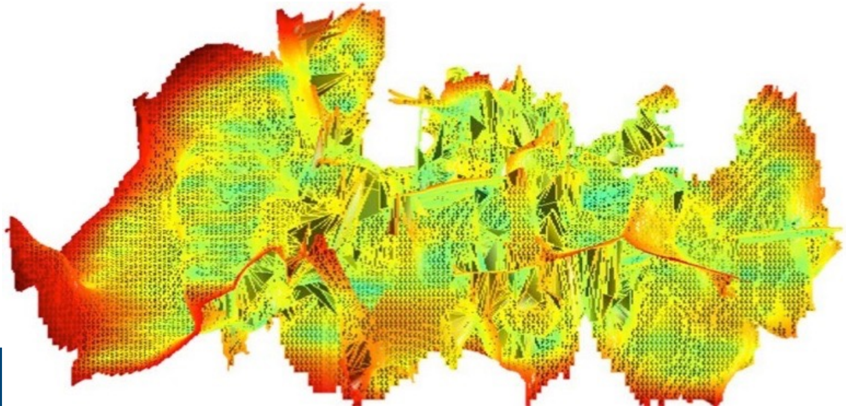
GPIS DF Field Results

Raw Laser Data

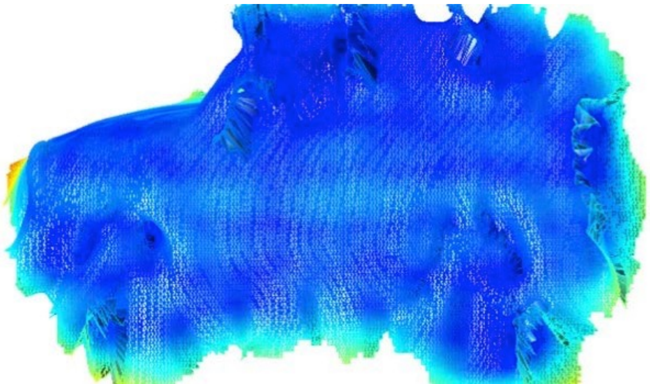
Raw Radar Data



GPIS DF



GPIS Consistent DF



Take-aways

- Sensor Data Fusion: "**Sensible combination** of multiple sources of sensory data (of the same type or not), such that the resulting information or model representation is of **better quality** than it would be if these sensors were used separately"
- Know your sensors (incl. heterogenous sensors) and your (inverse) sensor model
- Different types of Fusion call for different methods
- Early vs. Late Fusion (or in between)
- Beware of Catastrophic Fusion

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A3 - Sensor Data Fusion in Robotics

A/Prof. Thierry Peynot