Flexible, efficient and robust Sensing with AI

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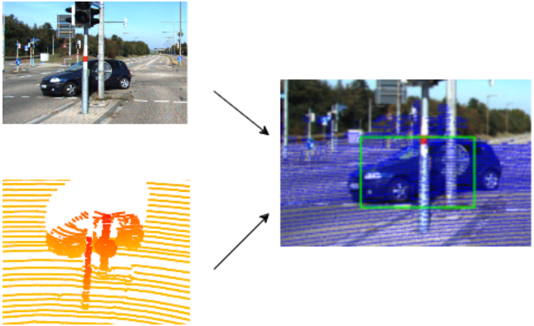
Sensor Fusion

- Combining data from multiple sensors
- Better accuracy, more information
- Often different types of sensors



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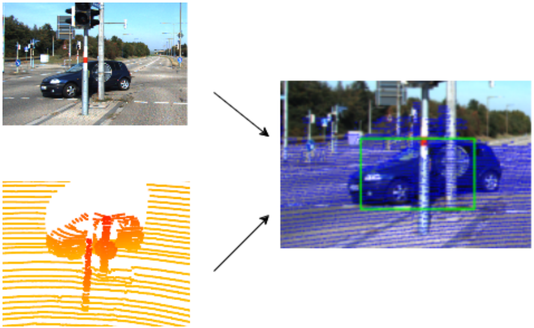

Some fusion examples:

- Detection using camera and LIDAR
- GPS and IMU for localization
- Health monitoring

‘ Multiple sensors $\Rightarrow$ likely sensor fusion

Challenges of Sensors

Nowadays:

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XenseAI

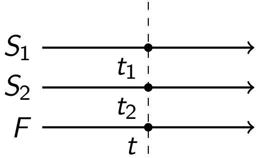
How can we use machine learning models to make sensors flexible and resilient with respect to changing environmental conditions while still being efficient?

Misaligned Fusion

Time T

Sensors $S_i : T \to X_i$

Fusion $F : X_1 \times \ldots \times X_n \to Y$



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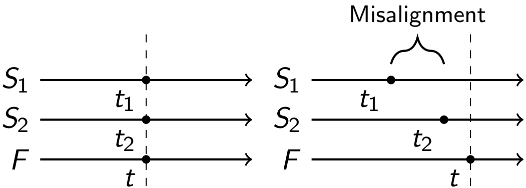

Sensor-Fusion-Robustness

One key aspect of fusion correctness – Robustness:
Ability to maintain performance under perturbations

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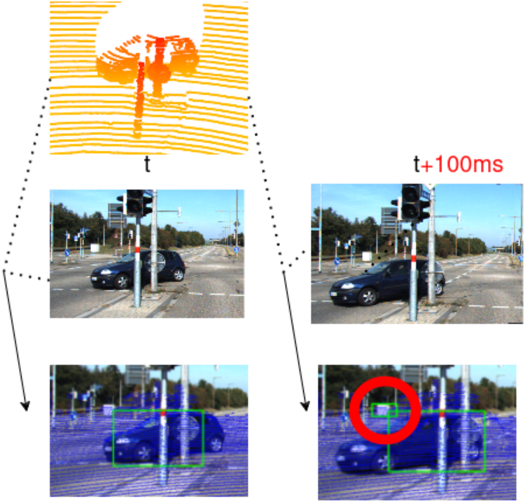
Our focus: **How much misalignment can a fusion function tolerate?**

Temporal Misalignment

Robustness for *temporal misalignment*

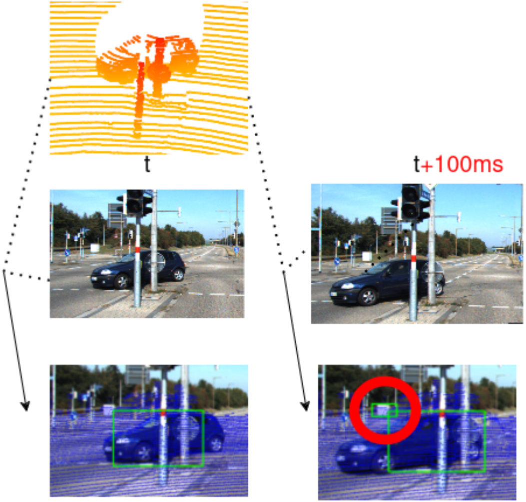


Temporal Misalignment

Robustness for *temporal misalignment*

Reasons for misalignment:

- Different sampling rates
- Network/Processing delays
- Clock drift
- Inaccurate calibration



Temporal Misalignment Mitigation

Temporal misalignment is generally acknowledged as a problem!

In practice, people do their best to

- reduce misalignment
- interpolate sensor results
- compensate in fusion

Synchronize clocks, triggered synchronization, filtering...

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Synchronize clocks, triggered synchronization, filtering...

Often rather ad-hoc - if we notice problems, fix them.

Robustness

Basic idea: temporal misalignment as perturbation

- misalignment threshold Δ
- loss L to measure fusion quality $L(y, \hat{y})$
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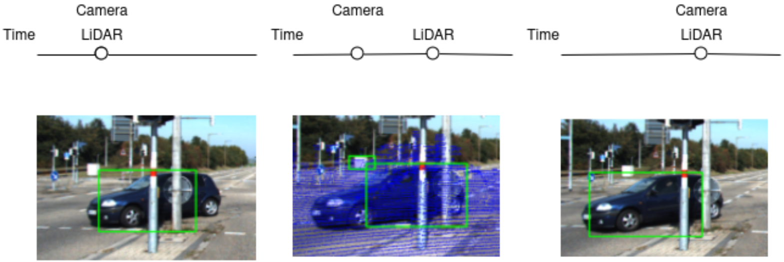
Problem: What is the ground truth?



Robustness

Not necessarily single ground truth, we call it reference point

Two ideas for robustness:

- reference point $\rightarrow$ add perturbation
- perturbed data $\rightarrow$ determine reference points

Reference-Point-Based Temporal Robustness

Given a reference point t and a misalignment threshold Δ, we say F exhibits *Reference-Point-Based* Temporal Robustness for t, if and only if

$$L(F(S_1(t), ..., S_n(t)), F(S_1(t_1), ..., S_n(t_n))) \leq \varepsilon \quad \forall |t - t_i| \leq \Delta$$

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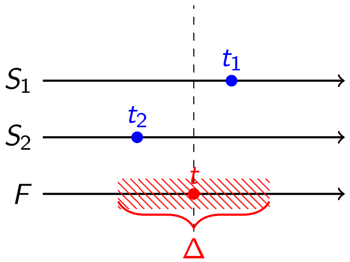

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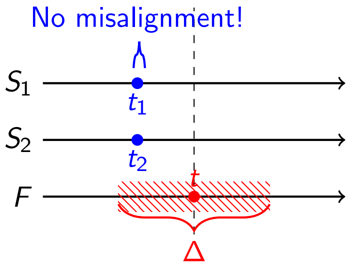
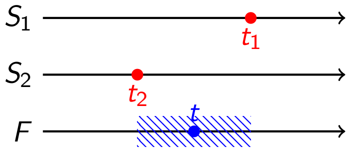


Sample-based robustness

Opposite of traditional approach:
Take a set of samples and use possible reference points in between them.



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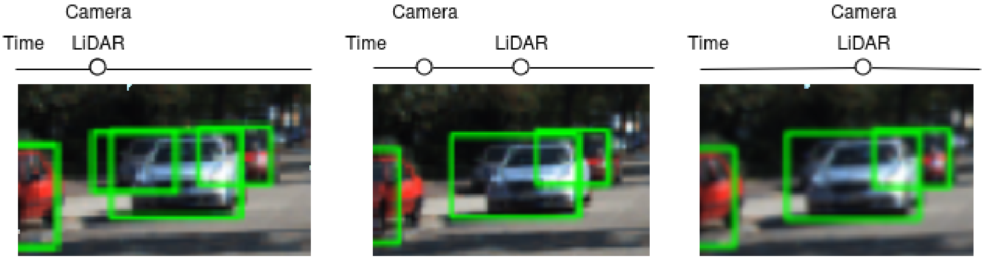

- Car moves behind middle one
- Now owrnly visible in image, not LiDAR
- Not detected in fusion, is this robust?

Sample-based robustness

Given a set of samples $T = \{t_1, ..., t_n\}$, we say

F exhibits *Strong Sample-Based* Temporal Robustness for T, if and only if

$$L(F(S_1(t), ..., S_n(t)), F(S_1(t_1), ..., S_n(t_n))) \leq \varepsilon \quad \forall t \in [\min t_i, \max t_i]$$

F exhibits *Weak Sample-Based* Temporal Robustness for T, if and only if

$$L(F(S_1(t), ..., S_n(t)), F(S_1(t_1), ..., S_n(t_n))) \leq \varepsilon \quad \exists t \in [\min t_i, \max t_i]$$

Objectives

1. Flexible online self-adaptation through re-training, transfer learning, and parameterization
2. Resilient operation in varied conditions through active sensing using reinforcement learning to decide which sensors to use and to which degree) and learning-based sensor fusion
3. Efficiency and correctness by leveraging domain knowledge in neuro-symbolic methods during training and as a basis for specified features