Enhancing Safe Train Localization using Data Fusion from Heterogeneous Sensors

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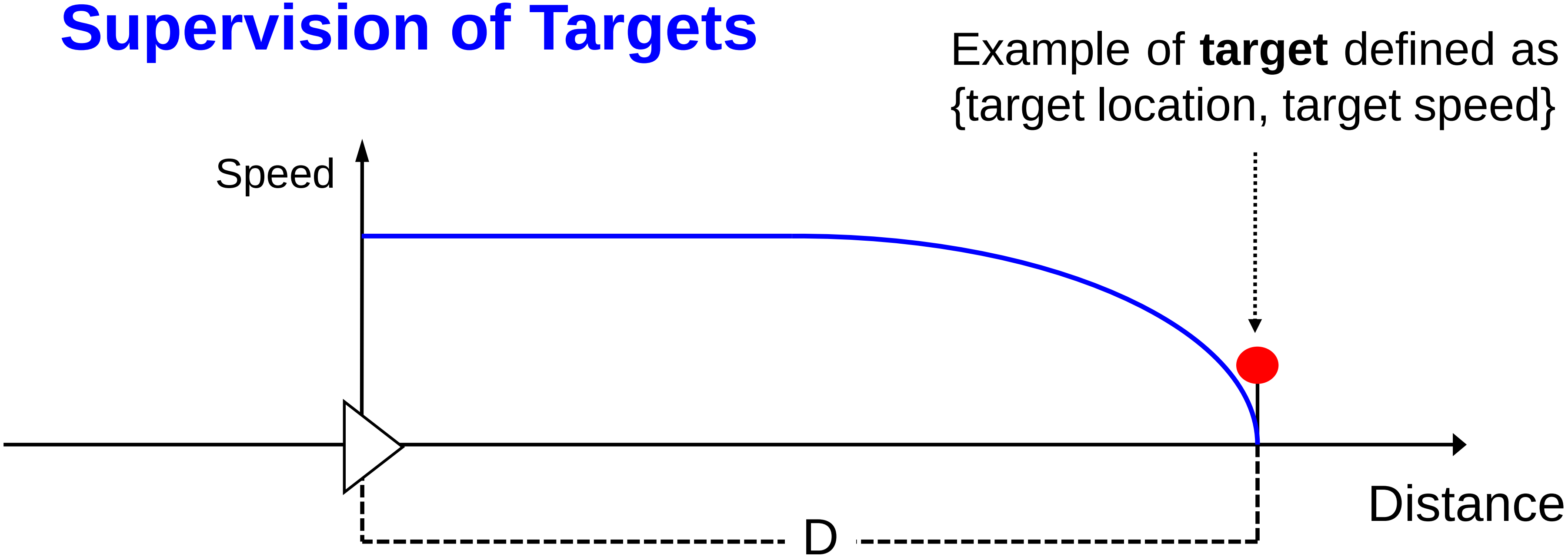
1. On-Board Railway Signalling Functions

1. On-Board Railway Signalling Functions

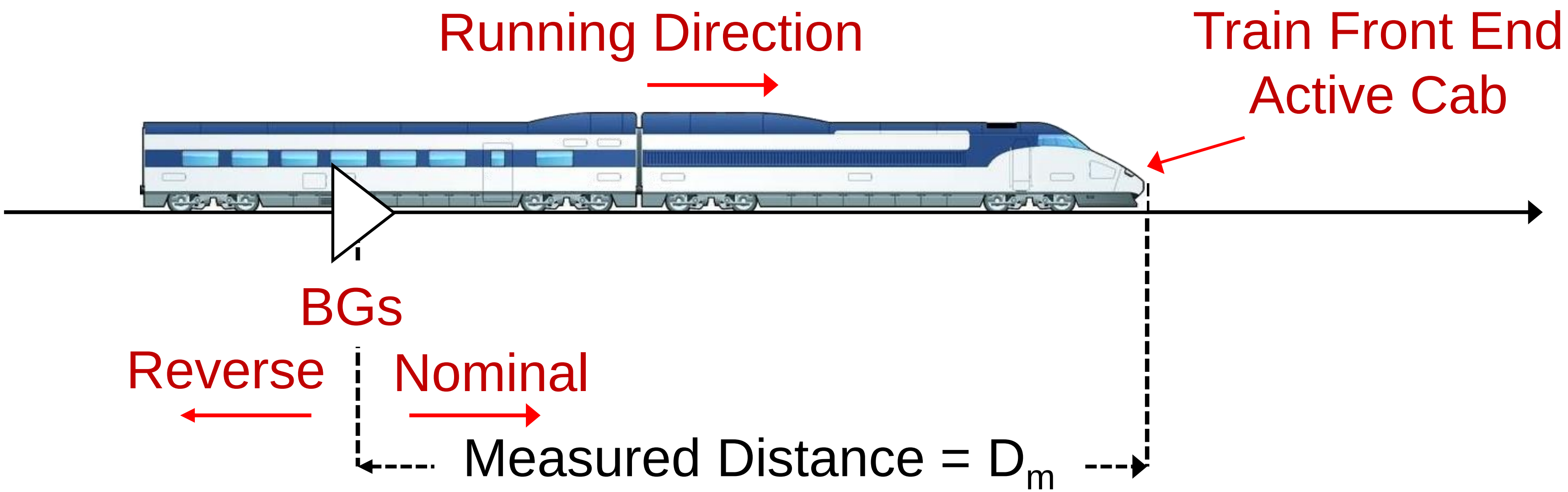
Supervision of Targets


Example of **target** defined as {target location, target speed}

The on-board has to **continuously** supervise a list of targets; for each target, it supervises the **current speed** of the train versus **its current position** to assure that the train remains within the given speed and distance limits.

Train Position

Position of the **train front end** with respect to a **position reference marker**, implemented by linked Balise Groups (BGs).



On-Board sends **Train Position Information** {D_m meters from LRBG, Nominal w.r.t. LRBG, running direction nominal, ...} to Trackside.

1. On-Board Railway Signalling Functions

Odometry

Main objective is the **periodic** (e.g. 100 ms) provision of the following information, computed at the current elaboration cycle:

- the **estimated cumulative distance** (D_Est) from the location associated with the on-board power on;
- the **estimated confidence interval** (D_Max – D_Min, respectively the maximum and minimum cumulative distances, with a specific probability);
- the **current movement direction (positive or negative)**;
- the **current estimated speed** along with the related **estimated speed confidence interval**;
- the **time** elapsed since the on-board power on; this time is the on-board platform time reference system used among on-board Master and Slave on-board platform nodes.

Odometry (cont.)

For any movement directions:

- the most probable (measured) distance (ΔD)
- the maximum (measured) distance (ΔD_Max) and
- the minimum (measured) distance (ΔD_Min) between **any two track locations** P and Q is defined as follows:

$$\Delta D = |D\_Est(Q) - D\_Est(P)|$$

$$\Delta D\_Max = |D\_Max(Q) - D\_Max(P)| + \text{max resolution distance error}$$

$$\Delta D\_Min = |D\_Min(Q) - D\_Min(P)| - \text{max resolution distance error}$$

In STS implementation, Odometry Task is a **Periodic HRT** with Period T = 100 ms, and the **odometry information** is periodically **transmitted** guaranteeing (a) predictable and bounded **jitter** and (b) predictable **delivery time**.

2. Challenges of the Odometry Function

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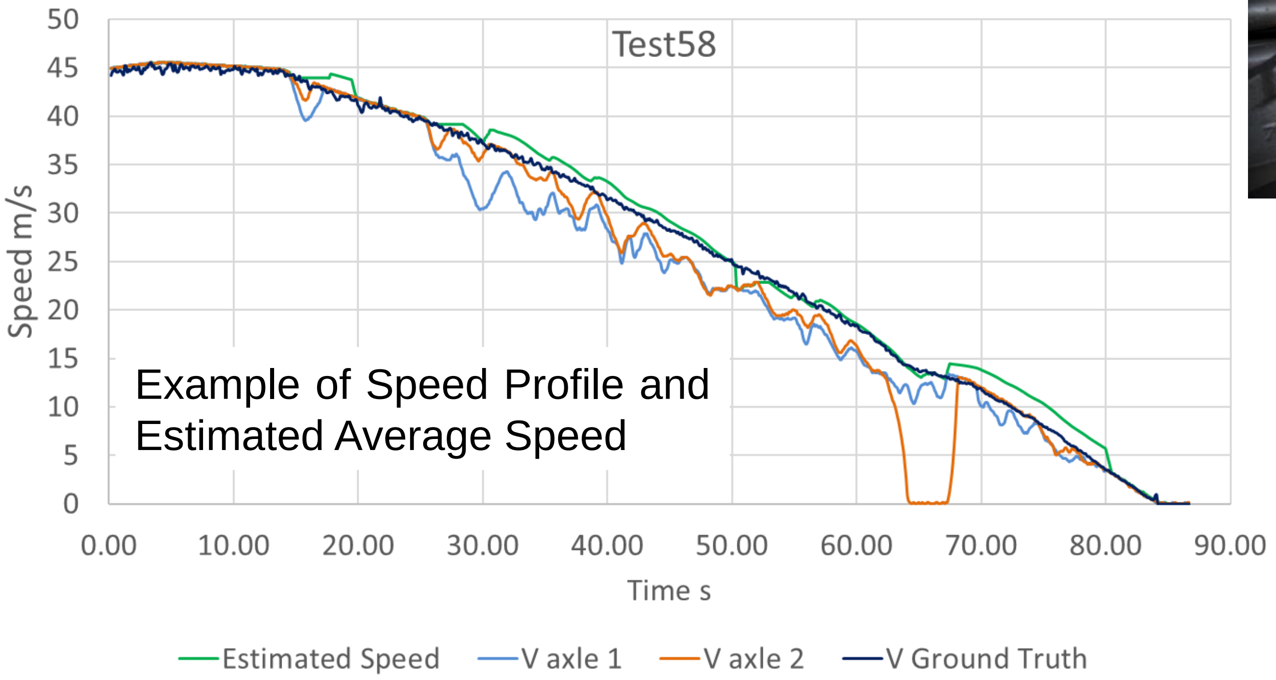
Current odometry algorithms use wheel sensors. Due to the adhesion coefficient between wheel and rail, **sliding** and **slipping** conditions have to be carefully managed to guarantee required **safe confidence intervals** on measured distances and speeds.



Example of Speed Profile and Estimated Average Speed

2. Challenges of the Odometry Function

The ERTMS Subset 041 requires that

“for **every measured distance s** the accuracy
shall be better or equal to ± (5m +**5% s**)”.

The standard also states “in case of **malfunctioning**, the on-board equipment shall evaluate a safe confidence interval”.

Infrastructure Managers and **Railway Undertaking** are now requesting a **better accuracy** for improving the line capacity and reducing the operational costs.

3. New Generations of Odometry and Train Position

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- The Innovation Department of Hitachi Rail STS (STS) has activated an internal R&D **multi-annual program** for exploring and developing Proof of Concepts on **innovative Odometry** and **Train Position solutions**.
- In the context of this program, STS has activated a **PhD** position and a **set of contracts** with the Scuola Superiore Sant'Anna (Prof. G. Buttazzo).

3. New Generations of Odometry and Train Position

Main current on-going activities with S. Anna:

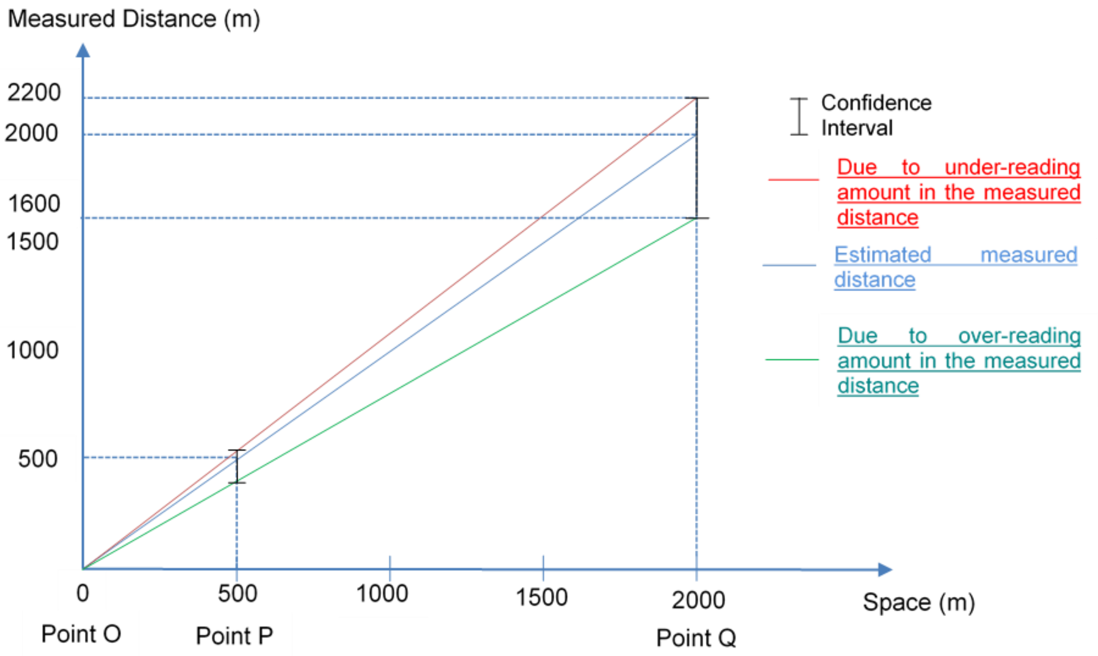
a) Improvement of Odometry Through the use of Inertial Data and Map Matching;

b) Odometry Improvement by using wheel sensors and IMU. No use of EGNSS;

c) Odometry and Train Position Improvements by using wheel sensors, IMU, EGNSS and LIDAR;

d) Simulation Environment for Verifying the New Solutions.

Improvement of Odometry Through the use of Inertial Data and Map Matching



To cope with the odometry error model, balises with known relative distances are used. Smaller distance between consecutive balises implies better performance.

This approach might require a large number of balises.

Improvement of Odometry Through the use of Inertial Data and Map Matching

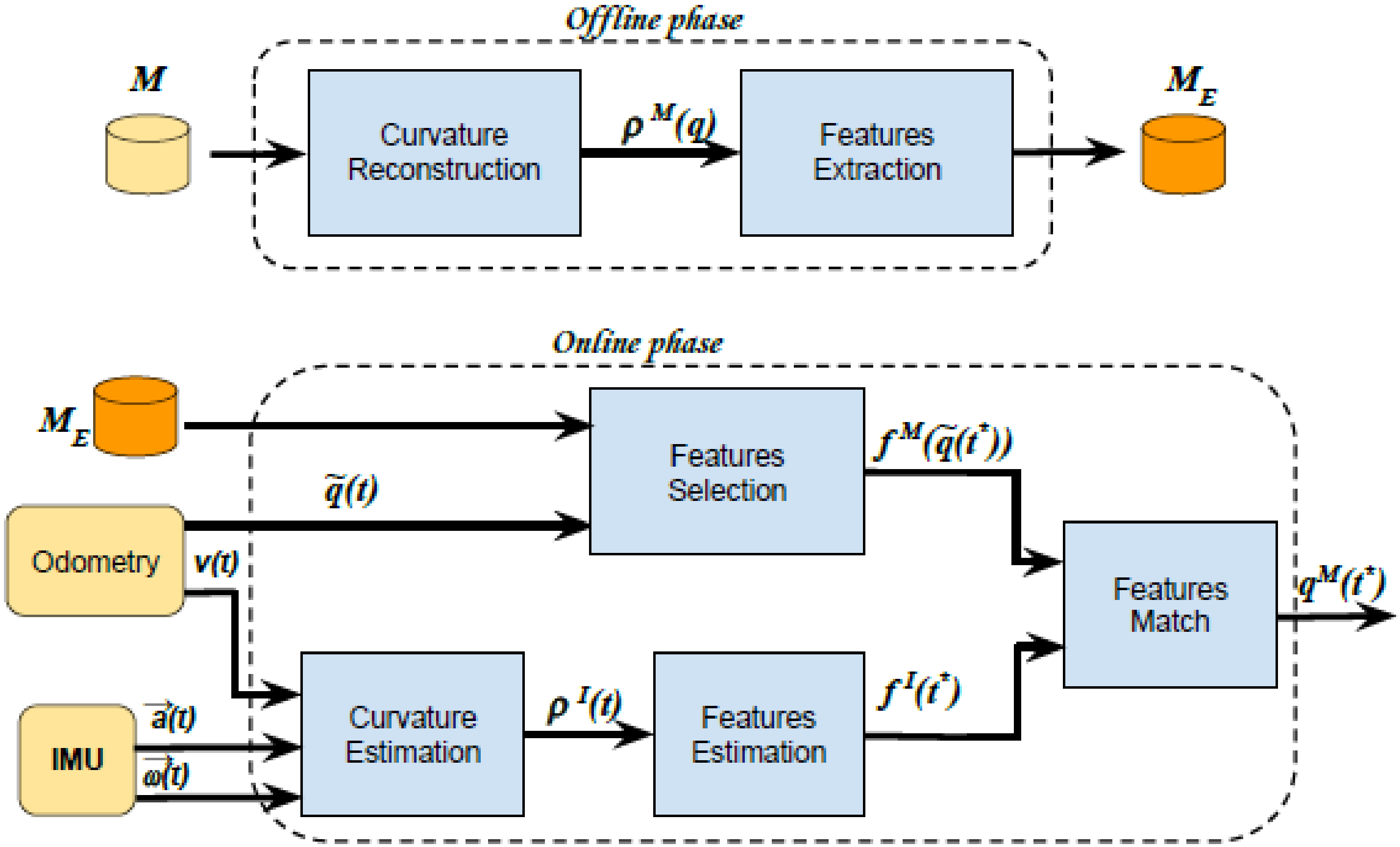
An approach has been defined for **extracting several cues** from the track layout (e.g., curvatures, slopes, cross switches) using **inertial data** and matching their location with the corresponding ones in a **Digital Map**.

Once the locations of these cues have been detected, these locations can be used both

a) as markers to **improve the odometry confidence intervals**; and

b) as a **monitoring technique for detecting unbounded GNSS position errors** (when GNSS is another sensor input for odometry).

Improvement of Odometry Through the use of Inertial Data and Map Matching (cont.)



$\rho = \frac{1}{r}$ with ρ and r respectively curvature and radiu

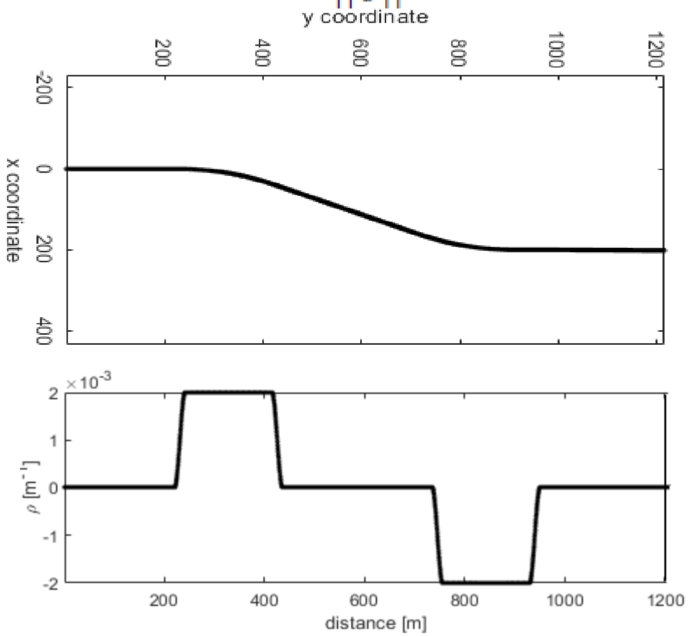
Improvement of Odometry Through the use of Inertial Data and Map Matching (cont.)

Curvature Estimation

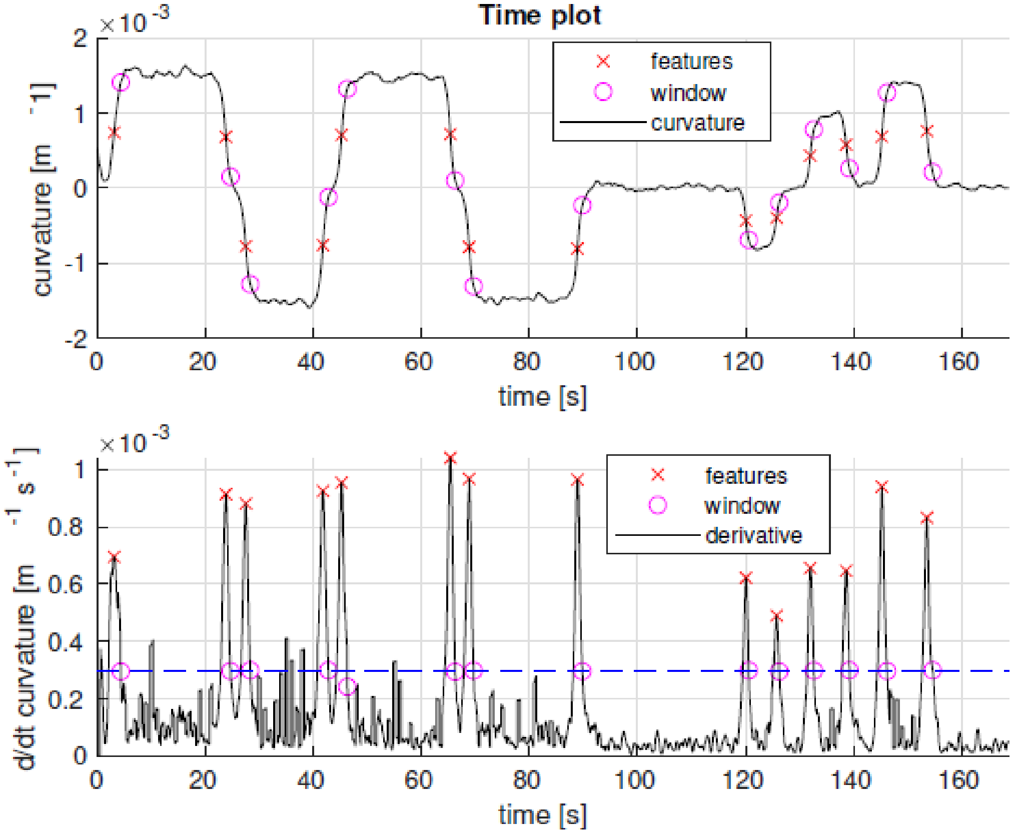
$$\rho^{(1)}(t) = \frac{\dot{\Psi}^2}{a_y} = \frac{w_z^2}{a_y},$$

$$\rho^{(2)}(t) = \frac{\dot{\Psi}}{||v||} = \frac{w_z}{||v||},$$

$$\rho^{(3)}(t) = \frac{a_y}{||v||^2}.$$



Feature Detection

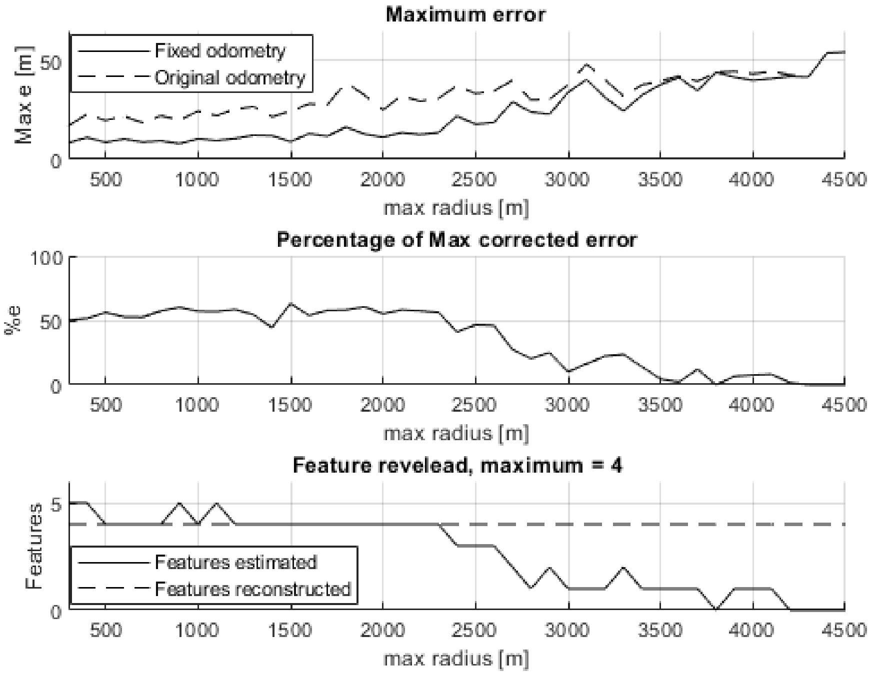


Improvement of Odometry Through the use of Inertial Data and Map Matching (cont.)

Sensitivity to the IMU Noise: Robust Algorithm

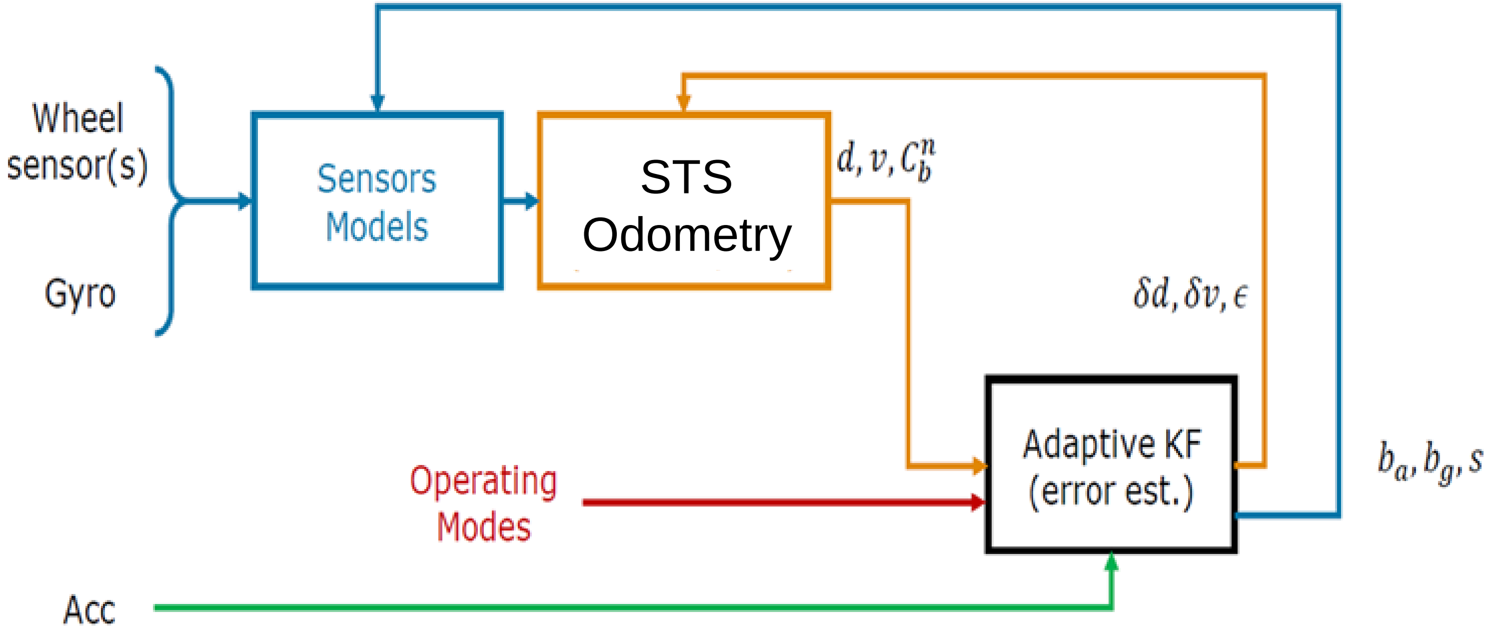
A white noise with a variable standard deviation has been injected on the yaw angular data of the virtual IMU (e.g. ARW with $0.08 < \sigma < 0.28\ deg/_{\sqrt{s}}$)

Sensitivity to Curvature's Radius



Improvement of Odometry Through the use of Measured Acceleration (IMU)

Preliminary Architecture

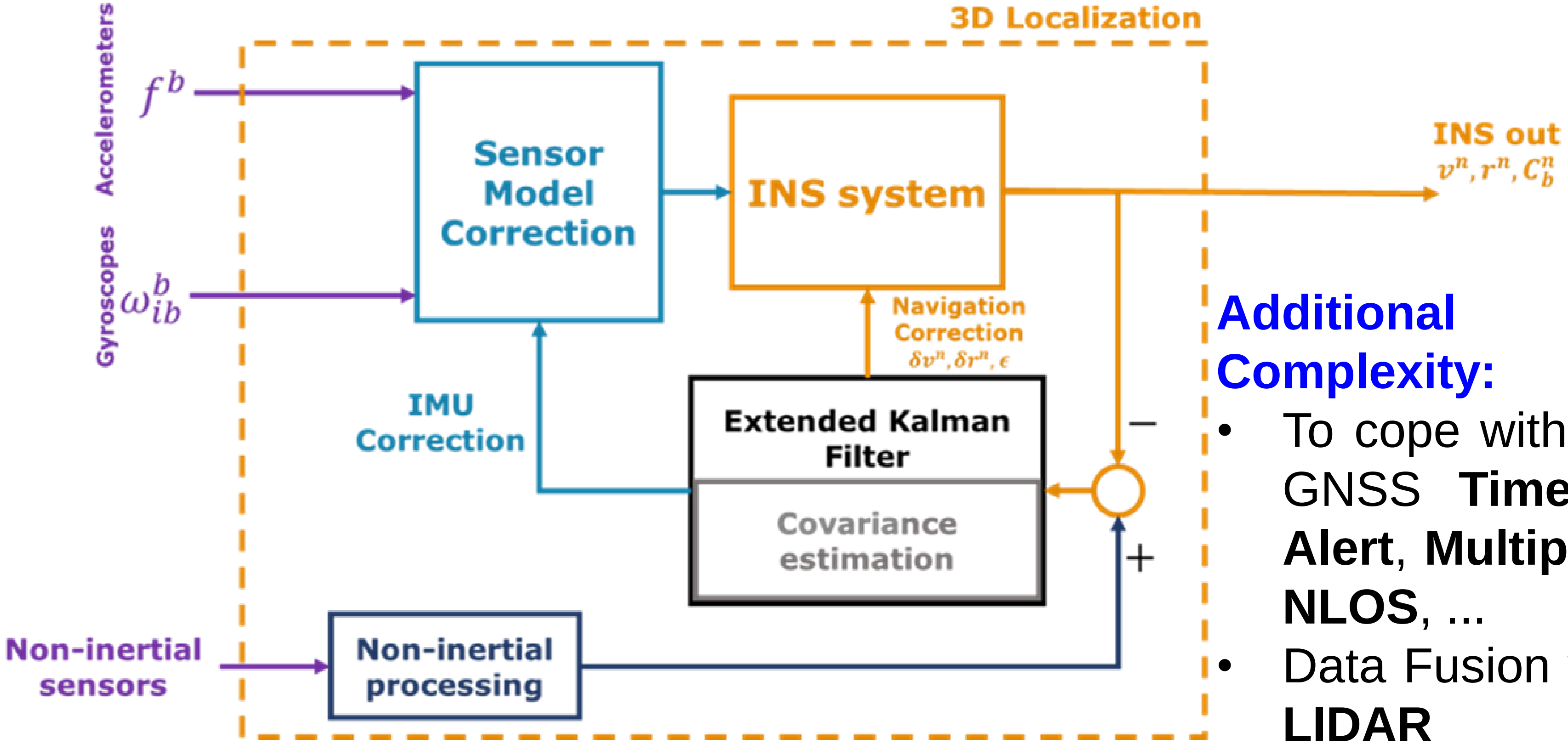


Complexity:

- **Overlap** to the existing STS Odometry Algorithm;
- Cope with **IMU Drift**;
- Define a Model that guarantees a **Trustable** and **Bounded Confidence Interval**.

3. New Generations of Odometry and Train Position

Improvement of Train Position Through the use of Measured Acceleration (IMU), EGNSS and LIDAR



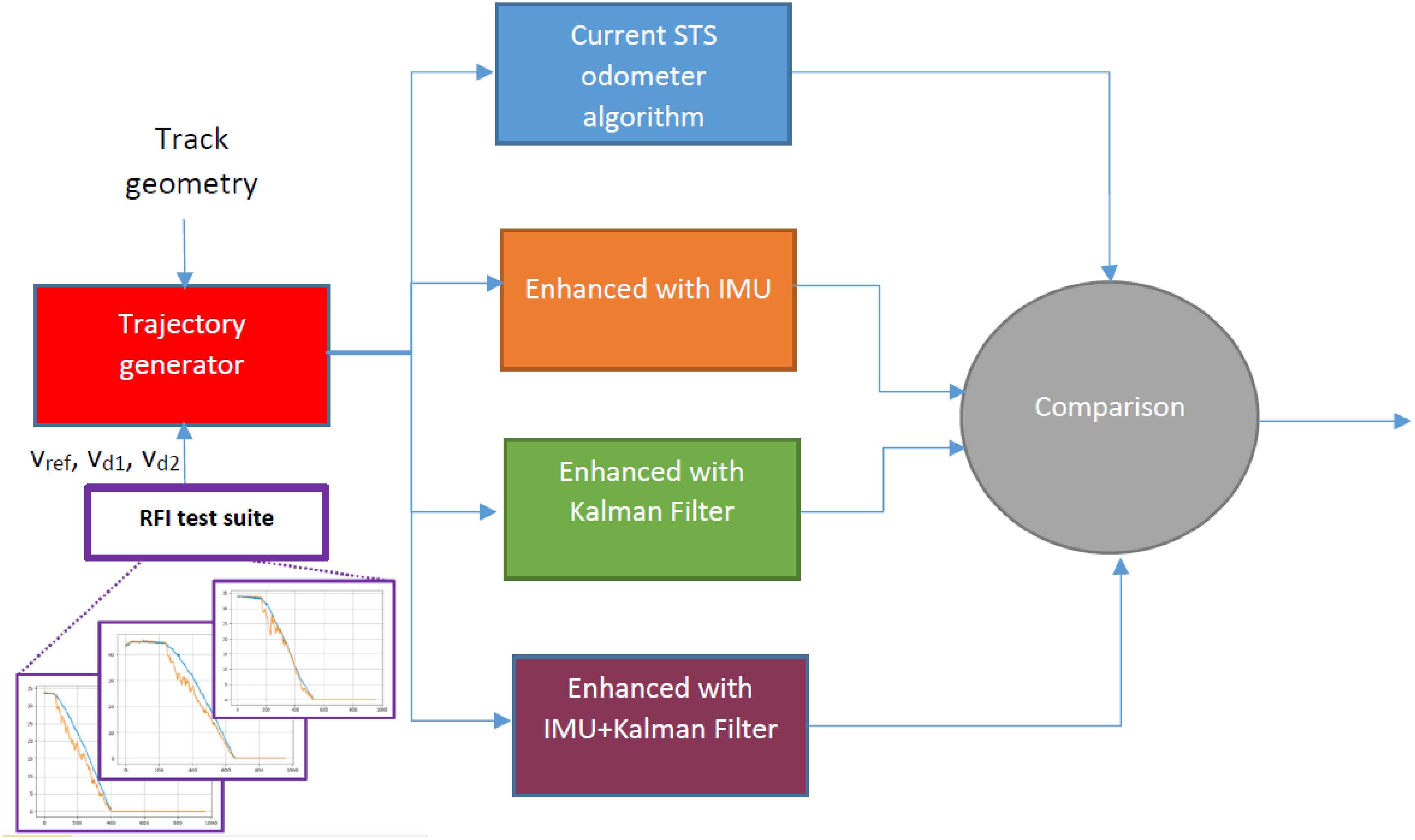
Preliminary Architecture

Additional Complexity:

- To cope with the GNSS **Time to Alert**, **Multipath**, **NLOS**, ...
- Data Fusion with **LIDAR**

3. New Generations of Odometry and Train Position

Simulation Environment for Verifying the New Solutions



Track geometry

Trajectory generator

V_{ref}, V_{d1}, V_{d2}

RFI test suite

Current STS odometer algorithm

Enhanced with IMU

Enhanced with Kalman Filter

Enhanced with IMU+Kalman Filter

Comparison

HITACHI

Inspire the Next

Hitachi Rail STS S.p.A.