An Experiment of a 3D Real-Time Robust Visual Odometry for Intelligent Vehicles

Sergio A. Rodríguez F./Vincent Frémont / Philippe Bonnifait
(speaker)

Université de Technologie de Compiègne, UTC

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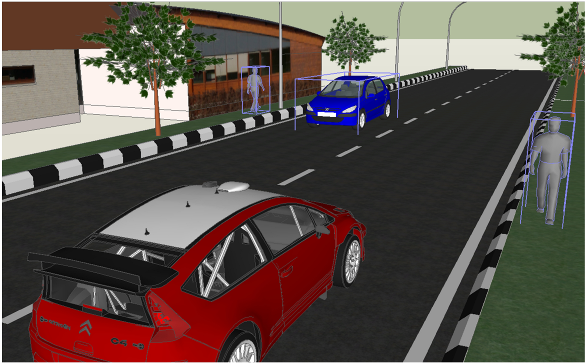
Motivation

On-board cameras widely use for:

- Detection and Recognition tasks (pedestrian, obstacles, speed limit road signs, road plane)
- but can also provide a 3D motion estimation (ego-motion)



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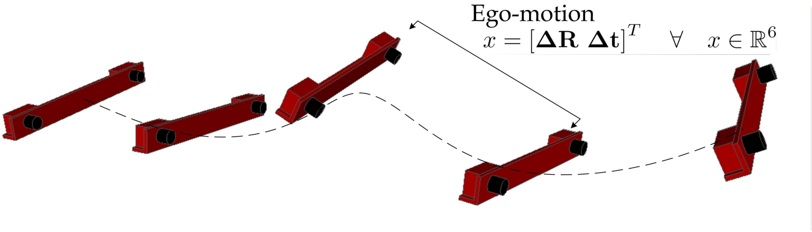
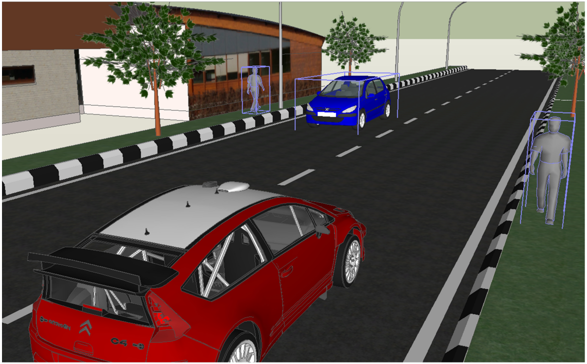


Motivation

In a multi-sensor context, ego-motion can be complementary:

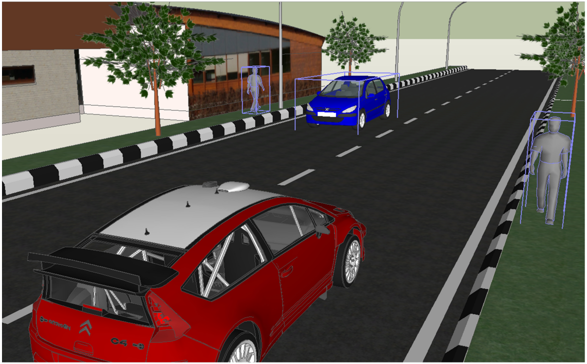
- Dead-Reckoning systems, IMU-WSS (2D trajectory)
- Global localization systems, GPS (latitude, longitude and altitude)



Motivation

Performance comparison of a real-time stereo visual odometric system under quasi-urban road conditions w.r.t classical techniques

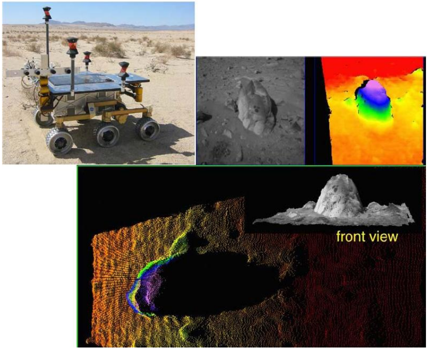
- Dynamic conditions of the environment
- Real time implementation issues



Outline

Some Applications of the Visual Odometry

Visual odometry on mars [L. Matthies et al. 2007]

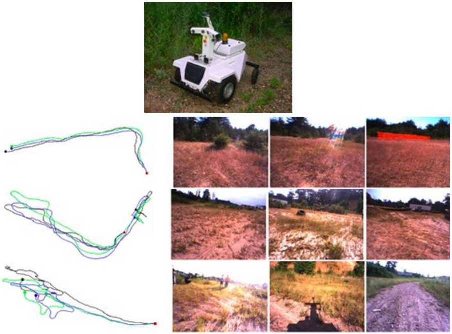


Conditions:

- There is not global positioning system (GPS)
- There are not visual landmarks available
- Wheel-coders odometry is vulnerable to wheel slip

Some Applications of the Visual Odometry

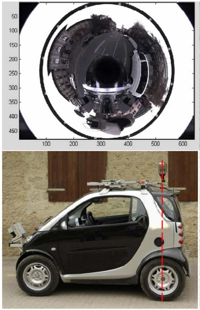
Real-time Localization in Outdoor Environments [M. Agrawal and K. Konolige 2006]

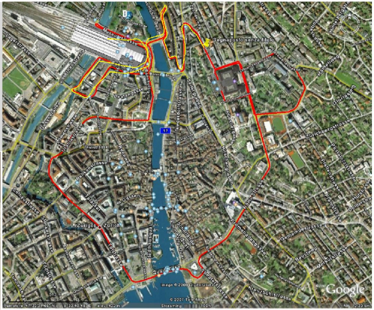


- Kalman filter: GPS + Vision
- IMU measurements to fill in motion estimates when visual odometry fails

Some Applications of the Visual Odometry

Monocular-Vision based Ego-Motion Estimation [Scaramuzza, D., Fraundorfer, F., and Siegwart, R.]

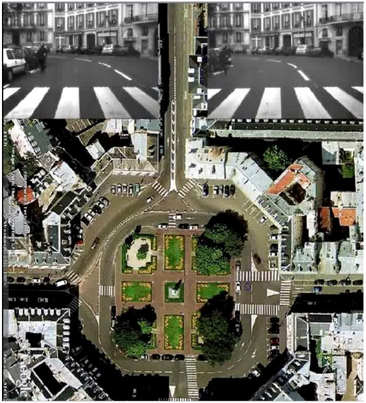


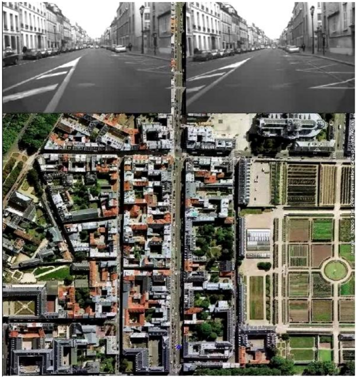


- Omnidirectional camera
- Non-holonomic Constraints
- 1 feature point is necessary for the ego-motion estimation
- Computation frequency: 400 Hz

Some Applications of the Visual Odometry

Off-line Dense visual odometry in urban conditions [A. Comport et al. 2007]

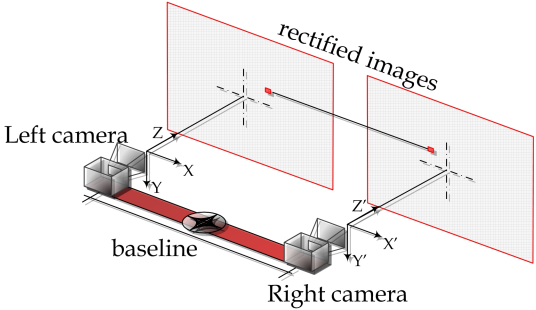




- Quadrifocal constraints

Stereo Vision System

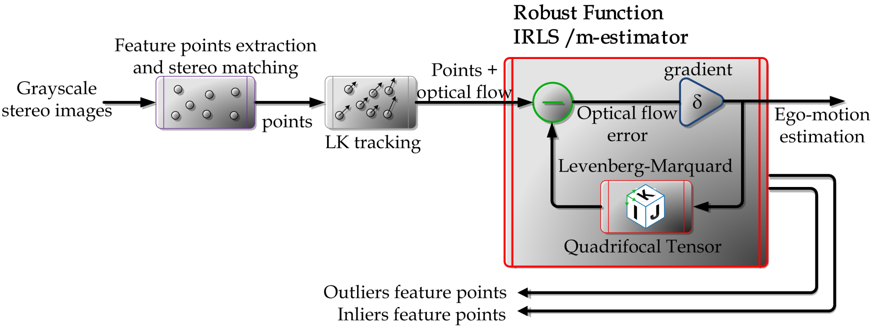
Projective Model and Initial Conditions



- Stereo vision system: 2 projective cameras rigidly joined
- The reference frame is placed at the stereo-rig center
- The intrinsic and extrinsic camera parameters are considered known
- Classical pinhole camera model $\mathbf{K} = \begin{pmatrix} f & 0 & u_0 \\ 0 & f & v_0 \\ 0 & 0 & 1 \end{pmatrix}$

Robust 3D Visual Odometry Method

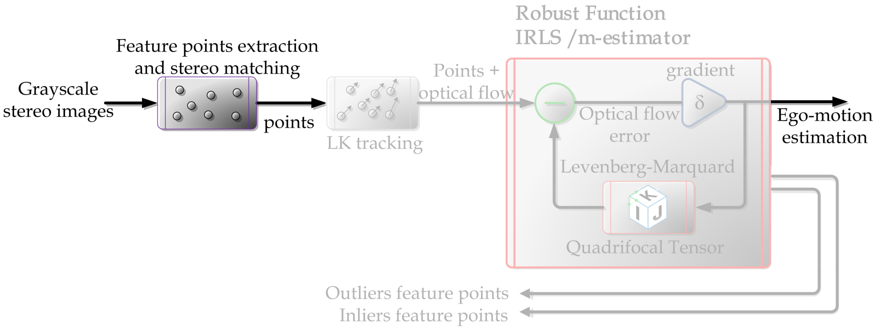
Algorithm



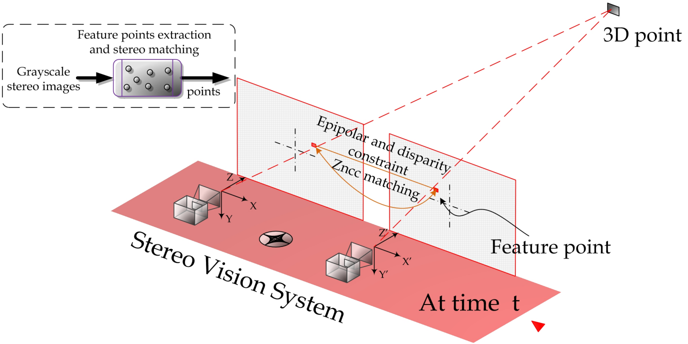
- Input: Gray-scale stereo images
- Output: Ego-motion parameters (Axe-angle rotation + translation)

Robust 3D Visual Odometry Method

Feature Extraction and Stereo Matching



Feature Extraction and Stereo Matching

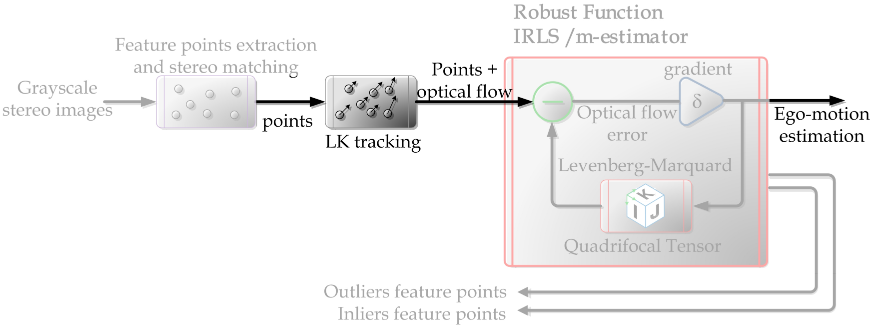


- Feature Points : SURF[1] (Speeded Up Robust Features)
- Stereo matching using ZNCC on 11×11 windows
- Sparse stereo crossed association

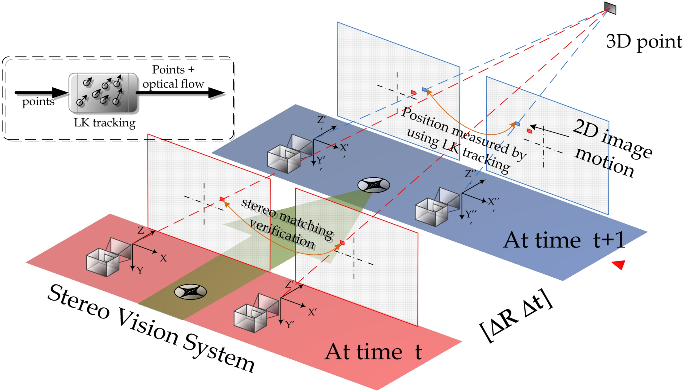
[1] H. Bay, A. Ess, T. Tuytelaars, , and L. V. Gool, *Speeded-up robust features (surf)*, 2008

Robust 3D Visual Odometry Method

Feature Tracking



Feature Tracking

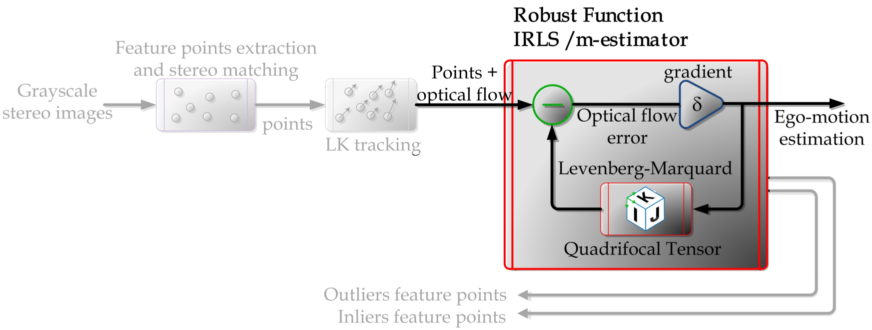


- Monocular image tracking using Lucas-Kanade approach [2]
- Stereo matching verification along the time

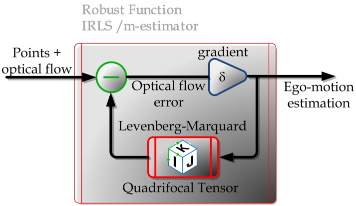
[2] B. D. Lucas and T. Kanade, *An iterative image registration technique with an application to stereo vision*, 1981

Robust 3D Visual Odometry Method

Quadrifocal Parametrization and Robust Function



Quadrifocal Parametrization



Warping function[3]

$$\begin{bmatrix} \hat{p} \\ \hat{p}' \end{bmatrix} = \begin{bmatrix} p^* l'_j{}^l \mathcal{T}_i^{jk} \\ p'^* l_j{}^r \mathcal{T}_i^{jk} \end{bmatrix}$$

$$\mathcal{T}_i^{jk} = a_i^j b_4^k - a_4^j b_i^k$$

$$P = [I|0],\ P' = [a_j^i] \text{ and } P'' = [b_j^i]$$

- Measure : tracked stereo features
- Estimation : warped stereo features

Optical flow error

$$\epsilon = \sum_{i=1}^{k} \left[||p_i - \hat{p}_i|| + ||p'_i - \hat{p}'_i|| \right]$$

LM Algorithm : Iterative warping of the stereo features at time t in order to minimize the error w.r.t the position of the tracked features.
It works only in static environments!! ... so what to do under dynamic conditions?

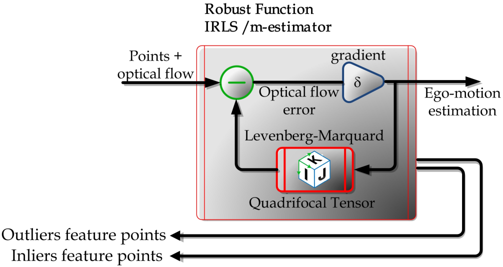
[3] A. Comport, E. Malis, and P. Rives, *Accurate quadrifocal tracking for robust 3d visual odometry*, 2007

Robust Function

In dynamic environments,

Optical flow error

$$\epsilon = \sum_{i=1}^{k} \mathbf{W} \left[||p_i - \hat{p}_i|| + ||p'_i - \hat{p'}_i|| \right]$$



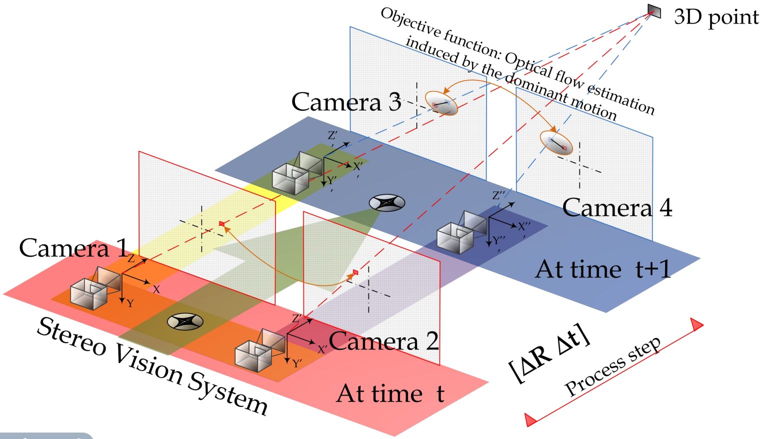
W is estimated iteratively on a IRLS algorithm using the Beaton-Tukey weighting function[4]

Assumption : At least 50% of features lying on static objects.

- Outliers rejection: Dynamic objects, stereo matching errors, tracking drifted points and artefacts.
- Inliers: Dominant motion estimated w.r.t the static scene

[4] C. Stewart, *Robust Parameter Estimation in Computer Vision*, 1999

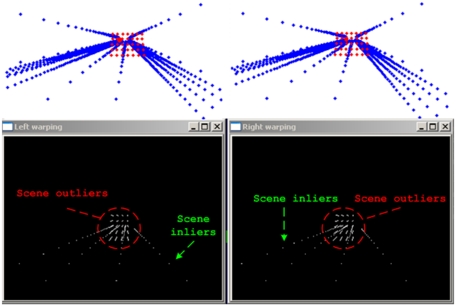
Quadrifocal Parametrization and Robust Function



▸ not clear yet?

Experimental Results

Synthetic data

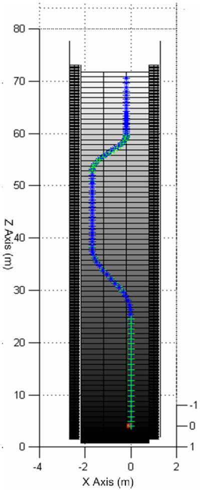


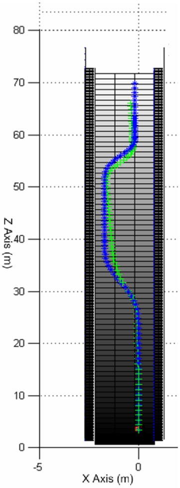
Simulation conditions

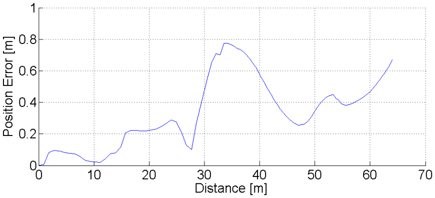
- 320 × 240 image resolution at 15 fps
- 3D Ego-Motion range: 0.92 m - 0.27 m simulating speeds of 50 Km/h and 15 Km/h respectively
- 20% of the features coming from moving objects

Experimental Results

Synthetic data



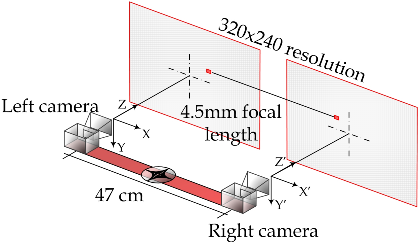




- Drift evolution: 1.04% (66 cm after 65 m travelled)
- Convergence of the algorithm into the environment feature points

Experimental Results

Real data

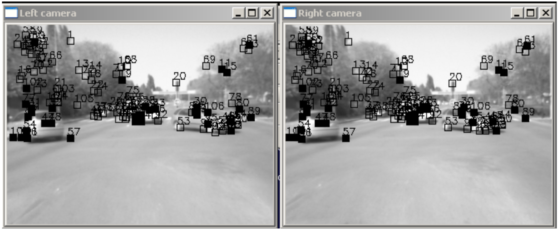


Experimental conditions

- 47cm-baseline Videre SVS. (CMOS cameras) installed at the top.
- 4.5mm focal length. 320×240 px. resolution
- Acquisition frequency: 15fps
- Vehicle max speed: 60 Km/h in a quasi-urban environment

Experimental Results

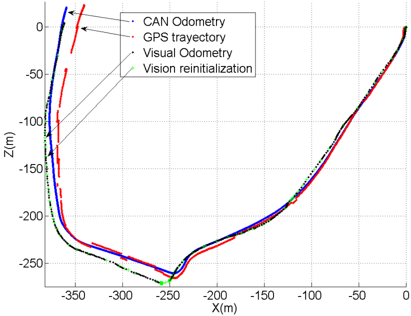
Real data

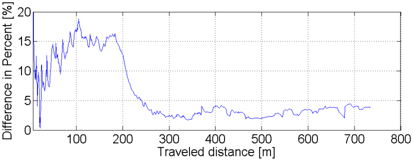


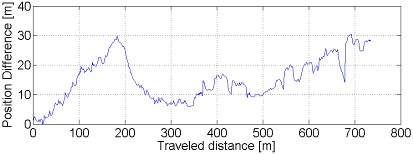
- Stereo images illustrate the outlier detection process
- Most of them are lying on moving objects

Experimental Results

Real data



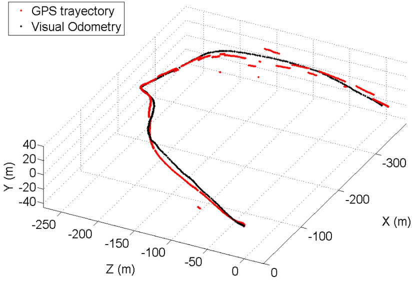


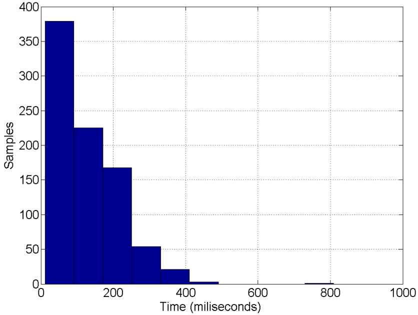


- Comparison w.r.t a Septentrio PolaRx2c GPS Receiver (differential SBAS mode) and proprioceptive sensors (IMU-WSS)
- In a 790 m long trajectory, 3.9% 2D Odometry and 0.25% vertical drift were obtained using visual odometry

Experimental Results

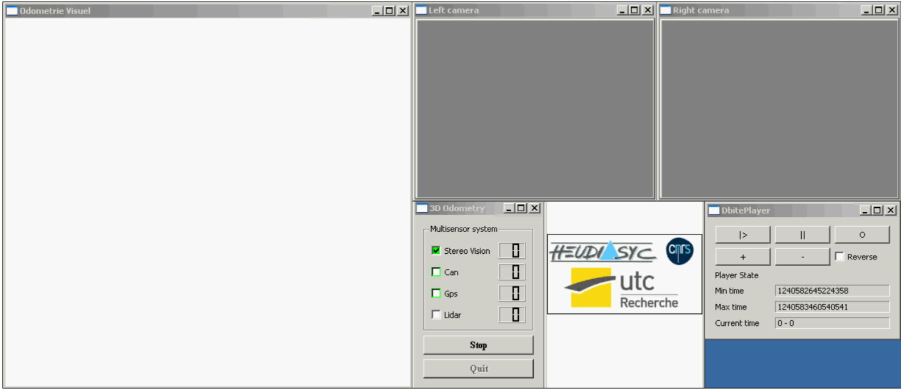
Real data





- The GPS jumps are mainly due to the satellites changes.
- Smooth 3D trajectory obtained by using the visual odometry
- Computation time depends on motion and scene complexity

Demonstration Video



▸ GE Video

Conclusions

- A real-time visual odometry approach was studied and experimentally validated.
- It combines in one non linear criterion the ego-motion estimation based on sparse optical flow and quadrifocal tensor warping
- The obtained real-time results show a good trade-off between precision and execution time thanks to a sparse feature approach.
- The Smooth 3D trajectory obtained by using the visual odometry is an interesting feature for GPS integrity monitoring
- An important degradation of the visual odometry performance is due to high rotational speed movements like 90° turns and roundabouts
- Error confidence propagation and multi-sensor fusion constitutes a perspective of this work.

Thank you for your attention