

# CHARACTERIZATION OF SENSORS FOR SMART WALKER INDOOR LOCALIZATION

Marco Andreetto<sup>1</sup>, Paolo Bevilacqua<sup>1</sup>, Stefano Divan<sup>1</sup>, Daniele Fontanelli<sup>2</sup>, David Macii<sup>2</sup>,  
Valerio Magnago<sup>1</sup>, Luigi Palopoli<sup>1</sup>, Fabiano Zenatti<sup>1</sup>

<sup>1</sup>Department of Information Engineering and Computer Science, University of Trento  
Via Sommarive 9, 38123, Trento, Italy - [valerio.magnago@unitn.it](mailto:valerio.magnago@unitn.it)

<sup>2</sup>Department of Industrial Engineering, University of Trento  
Via Sommarive 9, 38123, Trento, Italy

## Introduction

Indoor localization and position tracking of people and robots are well-known measurement problems, which have recently attracted the attention of researchers both in industry and academia [1]. While many different localization techniques exist, the most effective solutions usually rely on the fusion of heterogeneous sensor data, and particularly *dead reckoning* systems (e.g. based on inertial measurement units) and wireless, ultrasonic or optical systems able to measure the absolute position and/or the orientation of the target within a given reference frame [2]. The key advantage of combining dead reckoning with absolute positioning techniques is the possibility to achieve excellent localization coverage and good scalability, while keeping positioning accuracy and costs within desired boundaries. Moreover, when wheeled robots are considered, dead reckoning can be effectively implemented through odometry, i.e. by installing incremental encoders on the wheels. Unfortunately, the path estimated through odometry is typically affected by growing uncertainty due to the accumulation of noise and systematic contributions perturbing encoder-based measurements. This problem can be mitigated if suitable landmarks (e.g. Quick Response (QR) codes associated with a given position and orientation in the chosen reference frame) are detected by a camera [3]. In this way, the drift of estimated position and orientation inherently due to dead-reckoning can be partially compensated thus keeping localization uncertainty bounded. In this paper, the results of the characterization of the sensors used to estimate the position of a smart robotic walker are briefly reported.

## Sensor characterization

The *Friwalk* (Fig. 1) is a smart walker developed within the H2020 project ACANTO - *A cyber-physical social networks using robots friend*, with the purpose of supporting the safe navigation of groups of elderly people in large, public and potentially crowded environments such as shopping malls, stations and airports. The rear wheels of the *Friwalk* are equipped with two incremental encoders AMT-102V. One tick of the encoders corresponds to about 0.08 mrad of wheel rotation. Sensor data are collected by a BeagleBone black board via a Controller Area Network (CAN) bus. Moreover, the *Friwalk* is equipped with a front RGB camera (i.e. a PLAYSTATION Eye) connected to a NUC mini PC (provided with an Intel core i7 5557 and 8 GB of DDR3 RAM) through a USB link. The NUC runs a program based on OpenCv 3.1.0 able to measure the relative pose of the camera with respect to an Aruco code detected in the camera field of view.

Since the encoders are used for odometry, the sensor accuracy was evaluated on the field by comparing the trajectories estimated by the *Friwalk* when it moves repeatedly over an eight-shaped path and the same trajectories measured by a reference localization system, namely an OptiTrack provided with 14 calibrated cameras, which is able to measure the position of ad-hoc reflective markers in a known reference frame with a standard uncertainty of about 1 mm. In different experiments, the *Friwalk* was driven at constant linear speeds ranging from 0.3 to 1.2 m/s. The linear and angular speeds of the *Friwalk* are given respectively by  $v=r/2(\Delta\phi_r+\Delta\phi_l)/T_s$  and  $\omega=d/r(\Delta\phi_r-\Delta\phi_l)/T_s$ , where  $r$  is the wheel's radius,  $d$  is the rear axle length,  $T_s$  is the sampling period and  $\Delta\phi_r$ ,  $\Delta\phi_l$  are the angular increments measured by the encoder of the right and left wheels, respectively. Such values of  $v$  and  $\omega$  have been aligned in time and compared with those

obtained from the derivative of the position values measured by the OptiTrack localization system, after filtering a few outliers due to some corrupted data.



Fig. 1 – Snapshot of the *Friwalk*.

The box-and-whiskers plots of the differences  $\epsilon_v$  and  $\epsilon_\omega$  between odometry-based and OptiTrack-based linear and angular speeds are shown in Fig. 2. Observe that both standard and maximum uncertainty increase monotonically with the speed of the robotic walker when it moves over the eight-shaped path. On the contrary, the mean values of  $\epsilon_v$  and  $\epsilon_\omega$  are about 1 mm/s and 10

$\mu\text{rad/s}$ , respectively. Such values, although apparently negligible, have a significant impact on odometry-based position tracking and should be properly compensated.

The OptiTrack reference localization system was also used to evaluate the accuracy of the distance and orientation measurements performed directly with the embedded vision system. Again, the *Friwalk* was driven repeatedly over eight-shaped till detecting one of the Aruco codes placed on the floor. The histograms of the differences  $\epsilon_x$  between the position and orientation values measured by the embedded vision system and those obtained with the OptiTrack are shown in Fig. 3. Observe that the mean values of variables  $\epsilon_x$ ,  $\epsilon_y$  and  $\epsilon_\theta$  are equal to -1.5 cm, -2.1 cm and 33 mrad, respectively, and can be easily compensated.

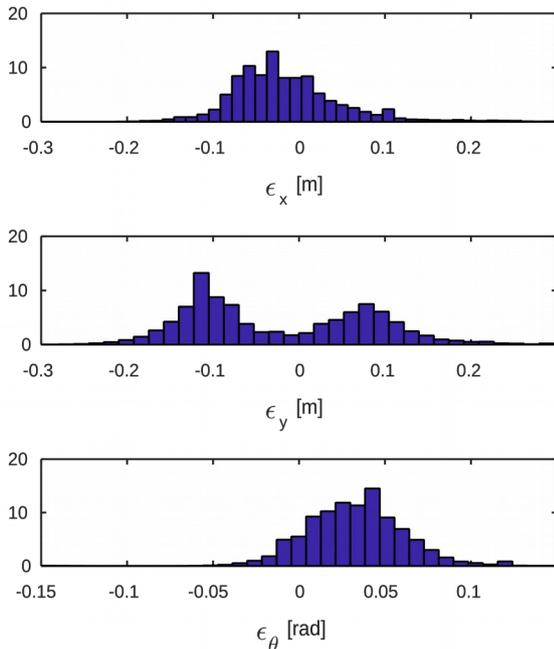


Fig. 3 – Histograms of the uncertainties in position and orientation measured by the embedded vision system installed on the *Friwalk*.

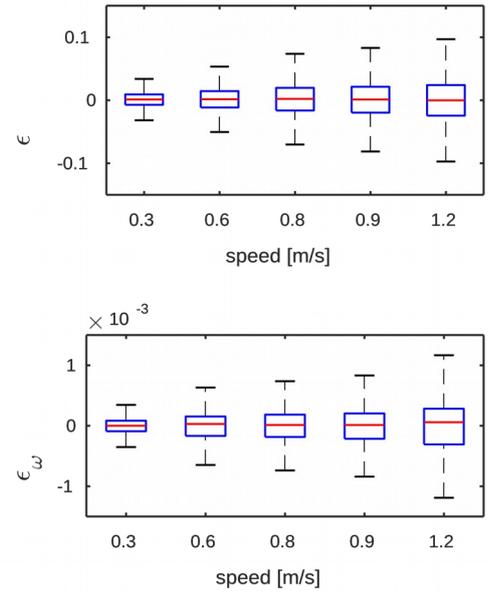


Fig. 2 – Box-and-whisker plots of the uncertainties in linear and angular speed measured by wheels encoders.

The corresponding standard uncertainty values (i.e. about 7 cm, 11 cm and 34 mrad) although not particularly small, are adequate for the intended application.

## References

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