Seamless Development of Robotic Applications using Middleware and Advanced Simulator

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Abstract: This paper addresses the issue of efficient transition from robotic simulation to field experiments and validation. The idea to ease this transition is to proceed step by step with small increments in complexity. A user begins with a simple and not so realistic simulation and evolve slowly to a complex and realistic one. We identified two axis to be tackled to achieve this steps by step complexity. The first axis is about the communication with the sensors: each sensors have a specific protocol. A simple simulation can by-pass this protocol by proposing a (universal) middleware connection while a complex one will emulate the real protocol to ensure a realistic data exchange between the processing unit and the sensor. The second axis is the opportunity to emulate a large spectrum of simulation complexity for a given sensor/environment. To increase the realism, similarly to the communication protocol, the realism of the sensor and its interactions with the environment can be increased from simple to the most realistic. These concepts are tested with a real use-case: the development of an indoor real-time localization system. The main development is done with a simulator compliant with our requirements. Afterward, the code designed with simulation is tested with a real robot for final validation.

1 INTRODUCTION

The use of simulation for robotics applications validation is a very actual topic with the rise of autonomous cars and their authorization to roam free on our roads. Using a simulator is an interesting option to reduce the number of kilometers traveled with the real vehicle. Before an autonomous car or robot hits the market, several steps has to be overcome. While everything begins with problems and ideas to solve them, it appears that simulation is an interesting tool for this matter. Indeed, researchers and companies need tools to efficiently try out and prove ideas/theories to be converted to industrial goods (Ivaldi et al., 2014). Usually, both make use of simulator to reduce simultaneously duration and development costs. The use of simulation can sound like a simple and easy improvement but several issues arise when using simulation to address a problem. Technological locks are blocking the smooth transition between simulated and real world. The main locks are: seamless re-use of the developed source code, complexity of the simulated scenarios and pertinence of the simulation compared to real-world.

First of all, we will define proposed features needed for an advanced robotic simulator. Then we will present a robotic related issue we solved using simulator (Burtin et al., 2016) compliant with those features. In the end, we will show and comment the results obtained both in simulated and real environments with robots equipped with sensors. Finally, we will conclude on the effectiveness of the presented features for the developments of this robotic application.

2 APPROACH

To develop a suitable simulation tool aiming at validating a specific scientific concept, we previously need to identify the steps involved in the development of the concept. As seen in the figure 1, the loop is the most time consuming step: we have to do an unknown number of loops to improve incrementally the solution and every loop needs experiments. This experiment step can be done using simulation during the early loops, and possibly until second to last be-

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fore the real world experiment (last loop). During these loops, the goal is to increase the complexity and solve issues alongside for an interesting conclusion and possibly innovation.

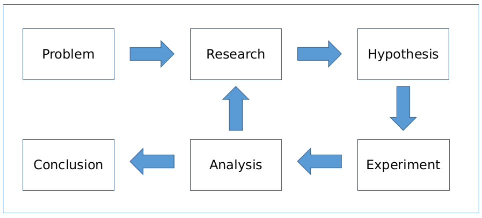


Figure 1: Steps involved in the scientific method.

2.1 Universal Interface

The first time related issue with innovation is the duration needed to perform the adaptation of the source code between different simulation platforms (Staranowicz and Mariottini, 2011). This transition usually implies a radical change in programming language and communication protocols with the simulated sensors resulting in a new driver to implement. Sometimes, the source code has to be entirely re-written to change the programming language (for example matlab toward C/C++). ROS (Robotic Operating System), a robotic designed middleware allowed a much more homogeneous format in data transfer and communications: every data can be sent on the network whatever is the original sensor and received by a ROS node. Gazebo (Koenig and Howard, 2004) is an open-source simulator developed within the ROS community, it has a fully ROS compatible interface. However it still needs nevertheless somebody to develop the ROS driver for the real sensor's driver to be compatible with ROS when doing the transition to real sensors. The researcher is prone to change its simulation platform to increase the complexity of the experiment because all simulators have specific ranges of realism. By making sure it has a full compatibility with every middleware (Ardiyanto and Miura, 2012), a simulator may not force the user to change its code if he changes between middleware compatibles simulation platforms. For example, V-REP (Rohmer et al., 2013) is another ROS compatible simulator that allows a ROS program to be tested with, even if it was previously tested with Gazebo. During the final tests of the code, developers has to take into account the real sensor and the computation platform on which the code will run. They will need to be able to get rid of any middleware and take into account the reality of the sensor and interface with it through the private communication protocol. An advanced simulation platform has to be able to emulate this crucial last step, vital to be connected to the real sensor during the real world experiment. In order to perform such task, the simulator needs to be able to emulate the data frame produced by the sensor and its firmware and transmit it with the same physical support (Serial, Ethernet, CAN bus). By doing so, the simulator propose an identical virtual twin for the algorithm to connect to: if the driver is correctly implemented, he can receive data from the real and virtual sensor without being able to tell the difference and with no modification of the source code.

2.2 Modular Complexity

Obviously, before testing a robot system in a full complex environment, we proceed by incremental steps. First of all, simple scenarios and if there are any successes, the complexity can grow toward the final full scale test. With the same idea, when starting with a simulation platform, we need to start with a simple simulation and increase the complexity before the transition to the real world experiments. Two choices are available: every time we need higher complexity, we change the simulation platform to have better realism, or we use a simulator able to emulate a wide range of complexities by itself. The second option is preferable because in the case of the first one, the time lost to transfer the code from a simulator to another may be important, but the time lost to learn how to use the new simulator and create the scenarios is greater. Considering the second solution, the simulation platform has to be able to produce sensor data with adjustable realism which means that a single sensors can be declined into several versions of increasing complexity. For example, the most basic sensor produces perfect measurement without noise/bias. A more complex version includes a white noise and/or a bias. The highest and most complex version would mimic the measurement method of the real sensor, producing a noise consistent with the environment and the sensor. This way of thinking can also be applied to the environment itself to determine the scenario complexity. For example, a basic scenery (motionless, simple shapes and monochromatic) won't produce the same results than a complex one (animated pedestrians, moving vehicles, realistic shapes and photo-realistic textures). Besides the geometric aspect, climate (snow, rain, shadows) can also prove critical for the behaving of the application and its final result.

3 ALGORITHM IMPLEMENTED

In order to test the impact of the simulation, we have developed a localization method from scratch for man-made indoor robot navigation.

An important hypothesis in our use-case is the fact that the robot is evolving in a man-made environment, comparable to an industry (factory) or office/hospital type. We state that the robot will encounter numerous structured elements with strong vertical and horizontal lines. Considering a flat floor, we also assume that the movement is only 2D. With this new assumption and the previous one, we can narrow features to propose a sparse localization method using specific landmarks. The most invariant observable elements in the image, as explained before, are going to be the vertical lines. 3D horizontal and other more random lines would have an incidence angle due to the point of view of the camera and wouldn't be invariant in the image, thus inducing more computation to detect and track them.

Using segments to perform SLAM (Simultaneous Localisation And Mapping) processing have been explored either with a lone lidar (Choi et al., 2008) or camera alone (Zuo et al., 2017). SLAMs are generally split between sparse and dense vision algorithms. Sparse SLAMs are using only a few salient features in the image to compute the localization, for example the ORB-SLAM (Mur-Artal et al., 2015). Each feature is represented and stored specifically in the map to be used later as reference in the localization algorithm. These types of process only need a small percentage of the pixels from the entire image to be tracked, while dense methods use almost all the pixels. Because dense methods such as DTAM (Dense Tracking And Mapping)(Newcombe et al., 2011) use every pixels from the image, users need a powerful hardware to perform all the operations in real-time. Most of the time, GPU processing is used to improve the computation speed. RGB-D (Kinect, Xtion) and depth camera sensors brought new SLAMs systems (Schramm et al., 2018), with new approaches. They avoid the issue of initialization from unknown range for the features. Monocular cameras have the weakness to be unable, using only one frame, to obtain the distance between an object and the camera for its given pixel in the image (scale factor). LSD (Von Gioi et al., 2012) is massively used by monocular and stereo-vision SLAMs systems (Engel et al., 2014) or (Pumarola et al., 2017) but this line segment detector is too generic and extracts all segments available while processing only B&W images: the process is not optimized enough. Moreover, the RGB to B&W conversion is a potential danger of missing gradients because of the gray level conversion method. The idea to use both lidar and monocular camera has been more usually applied to mobile objects detection and tracking (Asvadi et al., 2016) but more rarely to localization itself. In our case, we will focus on the detection of vertical lines in the camera because they are commonly found and invariant regarding our environment. The common slam, using these types of features are commonly referred as "bearing" only slam (Bekris et al., 2006), they are proven effective in minimalist set-ups with simple environments (Zuo et al., 2017).

In order to extract these vertical segments in the image (which are supposed to be the projection of 3D vertical structures of the scene: doors, angles of corridors), we are looking for classical edge segmentation composed of well known steps (Nachar et al., 2014): gradient computation, thinning, closing, linking, and polygonal approximation.

The localization process is an optimized parallel pipeline able to cross data from the lidar and camera sensors (Figure: 2). Each data process is split, but synchronous to use both extracted data at the same moment during the feature extraction stage. The objective is to detect a feature and determine its 3D position in the camera frame. The camera process extracts vertical lines in the image while the lidar process does a segmentation and a time-forward prediction to match the camera's data time-stamp.

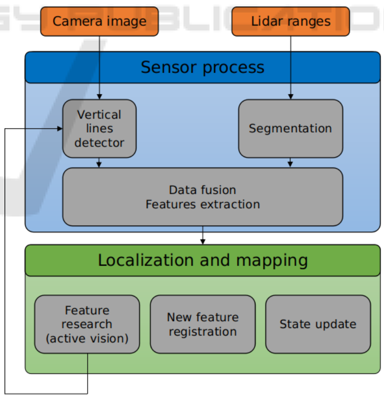


Figure 2: System overview.

The lidar, placed horizontally on the robot, produces an horizontal plane with the successive distances measurements. Our lidar process produces, through the lidar segmentation algorithm, a set of lines representing the environment around our robot. The camera, located above the lidar, through the lines detection algorithm, extracts a set of vertical lines in the focal plane of the image. The fusion of both of these data gives us a set of 3D points in the camera frame (Figure: 3).

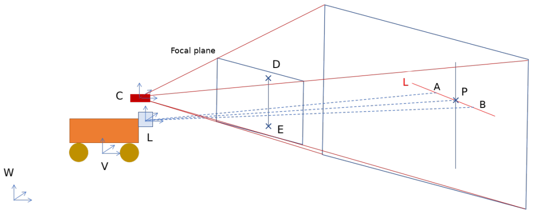


Figure 3: Feature (P) detected in the focal and lidar plane.

First we will see the optimized vertical lines detection algorithm for images processing. Then we will develop the 3D points extraction process using the camera vertical features and the horizontal lines from the lidar process. In the end, we will propose a SLAM implementation using the extracted features from the previous processes.

3.1 Lidar Process and Fusion

In this section, we will quickly explain the lines extraction from lidar's data and their fusion with features previously extracted from the image.

In a former work, we applied Wall-Danielsson to the lidar pointcloud (Burtin et al., 2018). This method, originally used in the vision field, was found to be efficient at segmenting lidar data very fast and accurately.

Those lines computed previously in the polygonal approximation exist in the 2D plane defined by the lidar's lasers. Therefore, we can compute the coordinates of these lines in the camera frame with the extrinsic parameters (homogeneous transformation matrix between lidar and camera frames).

The image process provides us vertical lines in the focal plane of the camera. We can compute from each line a 3D plane (CDE) (cf. Figure: 3) composed of the line segment (DE) and the focal point of the camera (C).

The objective is to compute the intersection between a 3D plane and a 3D line extracted from the camera and lidar data. This solution is assured to be unique and existing because (AB) is not coplanar nor collinear with (CDE) plane.

It's important to note that points A and B are projected in the camera frame at the exact moment the image is taken. Because the lidar and camera have different frame rates, data aren't synchronized and are generated at different moments.

To tackle this issue, we apply a rigid transformation, composed of two :

1. The prediction of the would-be lidar's measure, considering the current velocities and the time step between the lidar and the camera data;
2. The rigid transformation between lidar and camera frame;

3.2 Localization using a SLAM Method

The extracted features are 3D points, but with our hypothesis of planar environment we can make a 2D assumption. 3D features become 2D and we can define them in the camera frame with cartesian (x_i, y_i) or polar coordinates.

We decided to implement a SLAM system using an extended Kalman filter (Kalman, 1960) with the observations from both the camera and lidar using the cartesian coordinates. The estimation of the state vector, including the 2D pose (x_k, y_k, α_k) and the "n" features is $3+2\times n$ long:

$$\mathbf{X}_k = [x_k, y_k, \alpha_k, x_{1_k}, y_{1_k}, \cdots, x_{n_k}, y_{n_k}] \quad (1)$$

and the measurement vector, issued by the features in polar coordinates:

$$\mathbf{z}_{i_k} = \begin{cases} \rho_{i_k} = \sqrt{(x_{i_k}-x_k)^2+(y_{i_k}-y_k)^2} \\ \theta_{i_k} = \arctan(\dfrac{y_{i_k}-y_k}{x_{i_k}-x_k}) - \alpha_k \end{cases} \quad (2)$$

Our evolution model estimates the pose of the robot at the next step with the evolution function $\mathbf{f}$ taking $\hat{\mathbf{X}}_k$, the state vector, and $\hat{\mathbf{u}}_k$, the command applied to the robot, as parameters:

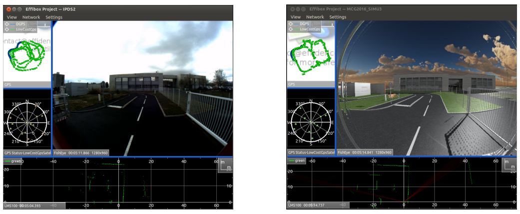
$$\mathbf{X}_{k+1} = \mathbf{f}(\mathbf{X}_k, \mathbf{u}_k) + \mathbf{q}_k \quad (3)$$

$\mathbf{q}_k$ is a Gaussian, white noise with zero-mean, representative of the evolution noise.

The four steps of the Kalman algorithm are: Prediction, Observation, Innovation and Update.

4 VIRTUAL ENVIRONMENT

One of the sides objectives in developing this localization method was the development, use and validation of an advanced robotic simulator. The concerned simulator is 4DV-Sim, developed by the company 4D-Virtualiz. Its development was initiated by two robotic PhD students (perception and command fields), that needed a powerful and capable simulator to speed up their work. At the end of their thesis, they patented the simulator and created a company. It has become a professional tool dedicated to real-time robots simulation in an HIL (Hardware In the Loop) manner. The aim of this simulator is to replicate very accurately real environments, sensors and robots into the virtual world, including shadows, textures, georeferencing, communication protocols, disturbances, etc (Figure: 4).



(a) Real sensors (b) Virtual sensors

Figure 4: Comparison of Camera, GPS ans LIDAR sensors between real data and data produced with the 4DV-Sim simulator.

4.0.1 Universal Interface and Modular Complexity

The simulator is designed to be able to connect independently to a middleware (ROS, RT-Maps, etc) or the proprietary interface. In figure 5, we can see on the left two configurations: on top, the Velodyne system connected to a ROS interface, on the bottom, it is connected to the proprietary interface. The results of the first set-up can be seen directly on Rviz, ROS compatible viewer (top right). The results of the second set-up can be displayed, either directly with the Veloview, Velodyne viewer provided by the company (bottom right), or go through the ROS node ”velodyne-pointcloud” to be converted to a regular ROS message and seen again on Rviz. The same idea is therefore applied to every real sensor (2D/3D LIDARs, IMU, Camera, Odometers, etc) implemented in the simulator: the end-user is able to use it either with the middleware for preliminary tests or the real protocol and drivers to prepare for the transition to the real sensor.

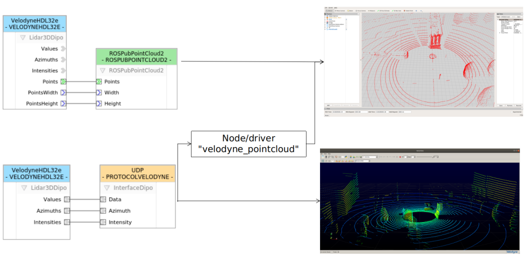


Figure 5: Velodyne sensor with ROS and brand interface seen on Rviz and Velodyne viewer.

This simulator offers sensors with diverse degrees of realism: it was possible during early prototyping to use a ”perfect” LIDAR, providing perfects measured ranges, without any measurement noise. Later, when our algorithm obtained appropriate results, we increased the complexity by adding random Gaussian measurement noise. Finally, before field testing, we experimented the algorithm with the virtual replica of the real sensor.The virtual replica has exactly the same characteristics than the real one: FOV, resolution, noise measurement, maximum range, frequency, appearance and the communication protocol. In the figure 6, we can observe several real sensors (top) and their virtual replica. From left to right, we have a Marlin camera, a HDL-64E Velodyne (3D lidar), a LD-MRS Sick (multi-layer lidar) and an UTM-30LX-EW Hokuyo (2D lidar).

The simulator is able to work in an HIL (hardware in the loop) fashion which means that once the source code is validated with the virtual platform, it can be instantaneously carried to the real platform to be executed without modifications.

Figure 6: Real and virtual sensors.

The use of a simulator also gives the opportunity to have exact repeatability to compare the results, access to ground truth and produce various datasets with different environments and robot set-ups, advantages we do not posses with experiments in real environment.

4.0.2 Robot Set-up

The simulated robot is a Dr. Robot Jaguar, virtually equipped with a URG-4LX Hokuyo lidar and a 640x480 global-shutter camera (pinhole model). The simulated lidar has the same parameters than the real URG-04LX (min angle, max angle, resolution, frequency, etc.) and the noise added to the measures is Gaussian distributed with parameters provided by the factory data-sheet.

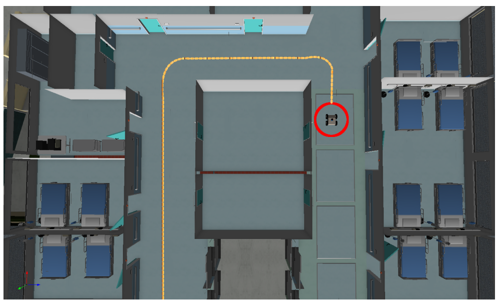
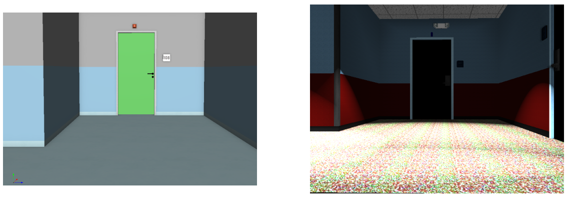
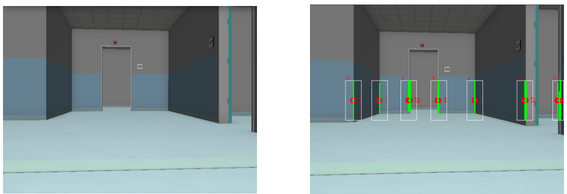


Figure 7: Simulated indoor environment containing the robot (red circle) and command trajectory (yellow).



(a) Simple (b) Complex

Figure 8: Same environment, different complexity.



(a) Original image (b) Features

Figure 9: Use of ROI and the 2D features results in the SLAM map.

The environment we used is a replica of a real American hospital (Figure: 7). All doors, doorways, beds, hallways have the right scale and materials effects. In preliminary work, we used two different sets of textures and lighting effects to improve gradually the performance of the vision algorithm (Figure: 8) by adding more complexity to the scenario, accordingly to the previously explained method. We will focus the results produced with the most realistic scenarios.

4.0.3 Localization

We implemented the vertical detector presented previously and added the lidar data to obtain our 3D features. In order to reduce the computation time we limited the number of detected vertical lines and narrowed this to the lines around the horizon, we can observe the projection of the 3D extracted features from the previous image in cooperation with the lidar using camera intrinsic and extrinsic parameters (Figure: 9b).

The average time needed to extract verticals in a ROI is 1.6623ms. Using a sparse SLAM system (even without multi-threading), we can reasonably track enough features in real time to feed a localization process.

We performed our experiments in the simulated environment using the described robot and setup. The final virtual result is displayed in the Figure: 10. The blue stars are the extracted and tracked features. One can recognize the shape of the building shown in top-view from Figure: 7. The green track is the ground truth given by the simulator. The blue track is the estimated localization using only the odometry of the robot. We can notice the rapid drift of the odometry during turns and it's relative precision during forward motion. The black track is the estimated position of the robot using the kalman filter. The track is split in two parts, the first part has a very precise localization (an average 2cm error relatively to the ground truth), then a diverging part. The final error is 0.3m over a 40m trajectory. Blue stars are our observed landmarks and red one are registered in the map created. This conclude our virtual tests, considering that further tests should be on a real robot to confirm the results.

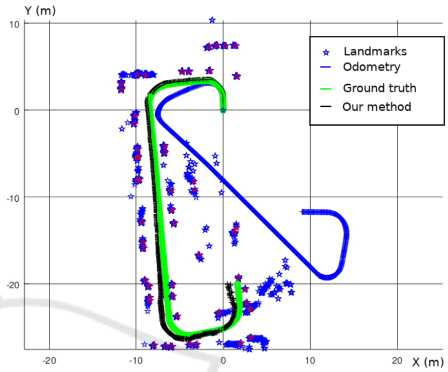


Figure 10: Localization results.

4.1 Real Experiments

Real experiment were conducted in the hallway of a public building. We used a Kobuki TurtleBot2 platform with an Hokuyo 04LX and an Intel Realsense D435 placed on the top of the robot. The RealSense sensor is used only to provide a global shutter 640x480 image, we didn't use the RGB-D feature because it did not provide depth information with sufficient range and precision (the corner seen on the left of the hallway is not seen at 3m). The environment we experienced in is about 40m long, having several patio doors with large panes, solid doors and shiny floor.

The real environment brought additional complexity to the sensors due to two facts: the large windows panes and the floor that reflects the environment. The first issue comes from the sun light that blinds the LIDAR sensor depending on the intensity of the rays. The second is brought by the clean plastic floor that create "false" verticals in the image by reflecting lights on the ceiling and doors. The first issue was solved by filtering the LIDAR data while the second one was only a matter of ROI focusing to exclude misleading verticals.

Our strong initial hypothesis, 2D movement and camera-lidar rig coplanar to the floor, is reasonable:

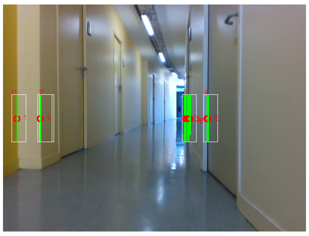


Figure 11: Detections with the real set-up.

even with small angular errors, we still manage to detect vertical lines in our image.

As explained before, we do not have a proper ground-truth available for real experiment, thus we can't know the exact position of the robot during the experiment but we do have the 2D model of the building provided by the architects. This model have been produced using precise ($< 1cm$) measurement by professional surveyors, therefore, we can estimate the efficiency of the robot localization using the comparison between the landmarks registered by our system and the solid shape given by exact model (black shape in figure 12).

We compared the localization efficiency with another method: the canonical scan matcher (CSM) (Censi, 2008). We tried the ORB-Slam (Monocular) but the complex light rendered the initialization impossible. Since there is no loop closing in this hallway, the CSM should not have particular disadvantage.

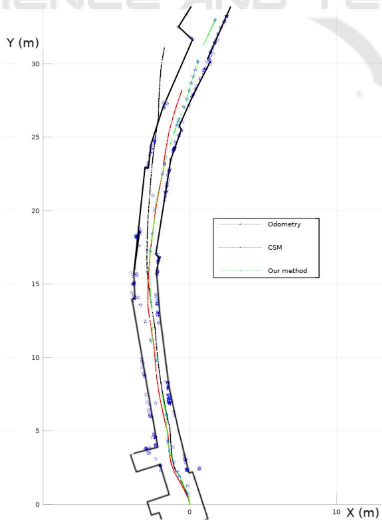


Figure 12: Localization results.

On the figure 12, we can observe the results of the different methods. The black trajectory is the lone odometry. The red one is the CSM result. The Blue stars are the landmarks registered by our method, and the trajectory is green. The odometry is outside the building frame but not that much, contrary to the virtual odometry, this one is more precise. This can be explained by the motion method of the robot: the virtual is a 4 wheeled robot and the TurtleBot is a 2 wheeled. The later present a reduced slippery during the turns, thus reducing the error on the odometry that made the assumption of slip-free rolling condition. The low range of the LIDAR and narrow FOV of the camera limits the number of landmarks available but the algorithm manages to detect several of them and successfully tracked, even with a complex lighting. The use of RGB-D sensors to combine the image and depth with less calibration and more accurate results is an interesting perspective with more depth range.

5 CONCLUSIONS

In this paper, we proposed an idea of features an advanced robotic simulator would require. There are two main features, beside the ability to provide real-time simulation. The first is having multiple interfacing capacity to be used at first with a middleware and then with the real sensor protocol. The second would be the ability of the simulator to provide increasing level of complexity to reduce the gap created by the transition between simulation and reality. A real accurate emulation of the sensor (measure, protocol, appearance) is a key to have a seamless transition. We established a use case (robot navigation), built an extended Kalman filter to provide fast robot localization, re-using sensors data from others purposes. We evaluated the interest in focused images processing to reduce the computation time and observed a significant improvement, enough to process all features in real-time on a low grade computer. The early developments were done using the described simulator, using ROS to simplify data exchanges and a growing complexity of simulation. This increment have been simultaneously focused on the sensor and the environment realism to match the final test. Our last experiment was performed with real robot and sensors and we managed to connect to this set-up without any modifications in our code. The algorithm worked "out of the box" with some parameters tuning and therefore, proves the interest in the proposed features.

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