PALADYN Journal of Behavioral Robotics

Research Article · DOI: 10.2478/s13230-012-0011-6 · JBR · 2(4) · 2011 · 202-210

Stereo bearings-only tracking of a wheelchair from a robot

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Received 2011/10/31
Accepted 2012/02/09

Abstract

This project deals with technical assistance for people of reduced mobility. The goal of this work is to have a mobile platform with an embedded prehensive arm (MANUS®) track a wheelchair. The use of this mobile unit in relation to the patient's wheelchair is carried out on a master-slave basis. This study, therefore, has a plural-disciplinary nature: Science for the Engineer, Human, Social and Clinical Sciences. To ensure the tracking of the wheelchair by the mobile platform, we applied a stereo bearings-only tracking (BOT) paradigm to a single moving target. The observer, the mobile platform (robot), is equipped with two omnidirectional vision sensors, that each provides output with which we compute two bearing angles. Having two bearing angles makes it possible to track a manoeuvring target. In this paper we will show how we take advantage of the multi-sensor data fusion to improve the BOT process and hence obtain a more reliable wheelchair tracking.

Keywords

wheelchair tracking · mobile platform · manoeuvring target · omnidirectional vision · multi-sensor

1. Introduction

This project (Fig. 1) came into being from a human synergy which grew out of a definition of problems faced by persons of reduced mobility. Above all, this project meets a social demand, stemming directly from demands from people who's mobility is reduced. An interesting specificity of this project was the composition of a strong pluridisciplinary team.

The substitution of the prehension by a robotised grasping arm poses numerous problems for the handicapped person. The obstacles to overcome are both technical and psychological [1]. Contrary to what the professionals expected, the use of a totally autonomous robot is not widely appreciated by tetraplegics [2]. The main reason is that the patients wish to at least participate in the act of grasping, when this is an action that they can no longer physically perform themselves. Complete automation of the task renders the patient inactive. A slower but patient controlled task would therefore be more appreciated. Our different trials since the beginning of this project incited the development of an independent mobile base, with the Manus® arm mounted on it. Two modes were developed: 1)-the automatic tracking of the wheelchair and 2)-the remote controlled mode (*i.e.* tele-operation). The main objective of this part of the project was to develop the base for the Manus arm, with functionalities that will allow it to track and avoid obstacles so that it can be used as described above.

This paper proposes a single approach to solve the problem of tracking the kinematics (typically position and velocity) of a moving target observed by a moving robot. In our work, we consider the wheelchair (target) in relation to the mobile platform (robot). The tackled problem is

Figure 1. Overview of the project.

the target tracking with several cameras in motion. The difficulties are linked to the continuous changing of the camera's position, variation of the appearance of the target in motion and alteration of the light conditions. We track a moving object with sensors, which measure only the bearings (or angles) of the target. The target motion analysis method (TMA) is required in order to estimate and analyse the motion of a target. In this paper we propose a multi-sensor Bearings-Only Tracking (BOT) to estimate the 2D-location of a single target.

The Bearings-Only TMA paradigm has attracted much interest over the last 30 years; considerable research has been actively conducted for this kind of system [3]. The BOT technique estimates the target trajectory using bearing measurements from an observer. One of the characteristics of the BOT method is the nonlinearity of the measurement equations and this is why the classical Kalman Filter is not suitable in this case. To address this problem, several methods exist that are based on the measurement equation transformation. However, these methods still suffer from drawbacks.

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The linear Kalman filter theory was applied to Bearings-Only Tracking by linearizing the nonlinear measurement equation of bearing. In [4], the extended Kalman filter (EKF) was used in BOT with the nonlinear equation of bearing measurements, but the EKF remains relatively unstable. The pseudo-measurement filter (PMF) was suggested in [5] to linearize the nonlinear measurement equations but this filter has been proven to be biased. Hence the modified gain EKF (MG-EKF) theory, whose gain is a function of only past bearings, was suggested to reduce interrelation between measurements and its residues and to solve the problem of the biased estimates caused by measurement noises [6]. In addition, a new system of coordinates, modified polar coordinates (MPC) was proposed to improve stability and convergence of EKF, engendering the MP-EKF [7].
Our approach combines a tracking filter and a visual target movement estimator. We have identified the CamShift, more precisely the Omni-CamShift (OCS) [8], as responding best to our application constraints. We have chosen different approaches of Kalman filtering (EKF, UKF, ...) to integrate the target state estimation. These filters will be fed by omnidirectional vision sensors and dead-reckoning sensors mounted on the mobile platform. In spite of its instability, we chose to implement an EKF because the presence of two bearing sensors allows an acceptable convergence.
In the first part, we present the context of our robotics assistance and the used perception system which permits to track the wheelchair, *i.e.* a stereo omnidirectional sensor. In the second part we address the problem of vision wheelchair recognition. In the third part we deal with the multi-sensor Bearing-Only Tracking. Finally we discuss the simulation and experimental results and we conclude on the perspectives inherent to our research.

2. The mobile platform

2.1. Context overview

This work deals with technical assistance for persons of reduced mobility. The mobile platform is built with a wheelchair frame. The reader interested by this robotic assistance can find details in [9].

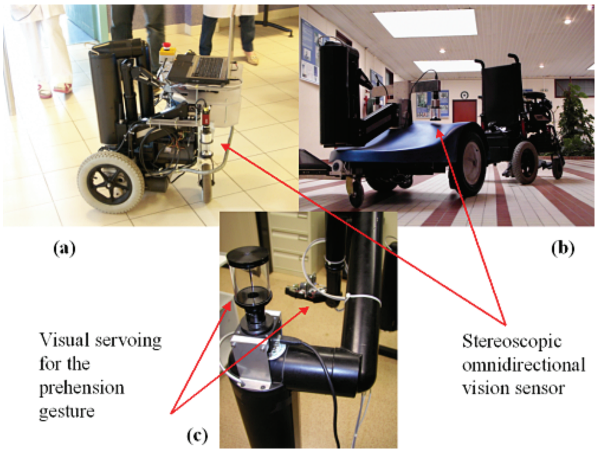

Figure 2. *Two prototypes of our assistive mobile robot (a) and (b) which allow us to manage the clinical evaluations. We show on (c) the MANUS® prehension arm equipped with the sensors permitting the automatic prehension.*

Two functional specificities have been integrated into the robotised assistance. The first is the automatic mode; the mobile platform follows the patient's wheelchair whenever the patient does not wish to use it. The second is a remote controlled mode for the grasping arm MANUS® and for the mobile base, used when the patient wishes to carry out a task involving grasping. Our assistance has to be able to function with all types of existing wheelchairs. All the sensors have to be mounted exclusively on the mobile base.

2.2. Sensors involved in this paper

The mobile platform is mounted with two classical kinds of sensors. The INS (Inner Navigation System) is made up of dead-reckoning sensors. The EPS (External Position System) is a stereoscopic vision sensor used in a goniometric mode.

2.2.1. The Inner Navigation System (INS)

Through odometry, we can determine the position (x, y) and the bearing θ of a vehicle navigating on a flat surface, in relation to its reference point, *i.e.* that of the robot in its initial configuration. This technique is based on the integration of elementary movements of the wheels measured by incremental sensors. As the radius R of the wheel is known, and also the number n impulses delivered by the resolution sensor α during time-span Δt, it is possible to compute the distance Δd that the wheel covered: $\Delta d = Rn\alpha$.

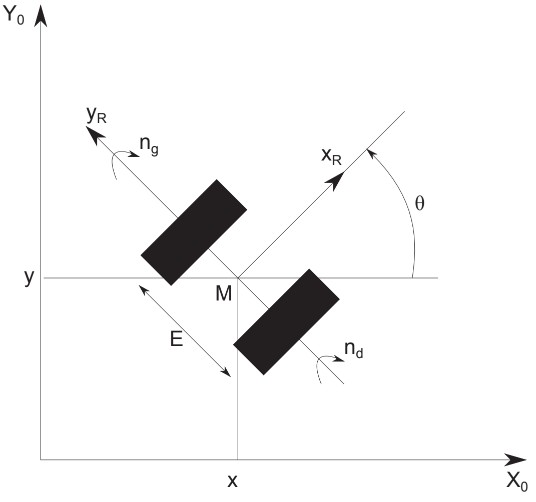

Figure 3. *Parameters of a robot with differential wheels.*

The evolution model of a ground robot shows its movement within a reference frame R_0 by the movement of its wheels. In our test case, the robot has two independent motorised wheels that are diametrically opposed and whose common axe caries the origin M of reference point R_r which is attached to the robot (Fig. 3). The configuration of the vehicle at time k is defined by (x_k, y_k, θ_k).

A simple and sufficiently effective description of the dead reackoning trajectory is to use ΔD_k for the distance, θ_k for the direction and $\Delta\theta_k$ for the rotation. The well-known equation (first order) of dead-reckoning is given by:

$$x_{k+1} = x_k + \Delta D_k \cos\left(\theta_k + \frac{\Delta\theta_k}{2}\right)$$
$$y_{k+1} = y_k + \Delta D_k \sin\left(\theta_k + \frac{\Delta\theta_k}{2}\right) \quad (1)$$

And the state equation of robot is defined by:

$$X_{robot} = [x_{robot}, y_{robot}, \theta_{robot}]^T \quad (2)$$

When we take the proposed hypothesis into account for the dead reckoning equation, this method engenders too many errors. However, it is not necessary to analyse the errors because, as we will show further on, we are faced with a relative framework: the position of the wheelchair is estimated in relation to the robot's position.

2.2.2. The External Position System (EPS)

In the figure 4, we can see the configuration of the two omnidirectional vision sensors.

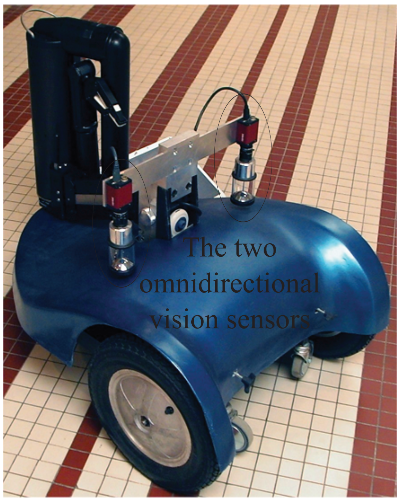

Figure 4. The mobile platform.

Main vision applications in mobile robotics use the classical pinhole camera model. Thus according to the lens used, the field of view is limited. Nevertheless, it is possible to enlarge the field of view by using cameras mounted in several directions [10], but the information flow is very important and time consuming. Other applications [11] use only one camera, with a rotation motion, in order to sweep a large space. The disadvantage of such a system is that the camera's movement takes time; and what's more, a mechanical slack can appear in the course of time. To get wide-angle pictures another possibility exists: omnidirectional vision. These kinds of sensors allow acquiring scenes with a $360°$ field of view [12]. There are two major classes of omnidirectional vision systems. First of all, systems made of a mirror and a camera are called "catadioptric systems" [13] [14]. The second one is composed of a classical camera with a fish-eye lens; such mountings are called "dioptric systems" [15]. We focus on the first class.
There are many advantages to using omnidirectional vision. Firstly, in one acquisition, we obtain a full view of the environment with no mechanical system. Secondly, even if the interpretation of omnidirectional picture is difficult for novices, we can provide with only few computations a "classical perspective view" of the scene. Finally, providing a picture in a chosen direction is instantaneous.
The omnidirectional vision system we use is made up of a digital colour video camera and a hyperbolic mirror. Fig. 5 shows an omnidirectional view of an environment with a wheelchair in the field of view.

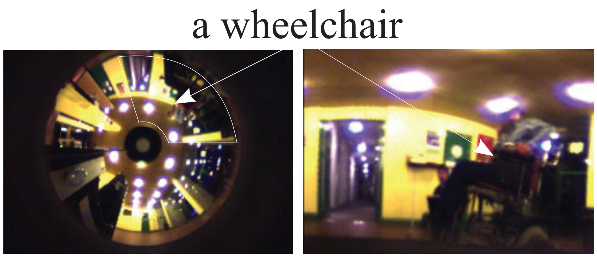

Figure 5. (left) an omnidirectional view of a scene with a wheelchair in the field of view. (Right) "Un-warped" picture of the white area from the omnidirectional view.

3. The wheelchair recognition and bearing measurements

3.1. Initialisation (target-wheelchair)

We wished to achieve the greatest possible degree of flexibility regarding in the use of the robotised assistance. We therefore did not want to restrict our method to the use of one wheelchair in particular. Our construction of the model accommodates not only the wheelchair, but also the patient. The figure below (Fig. 6) shows omnidirectional images: they illustrate the extraction of the background and the extraction of the model (patient + wheelchair).

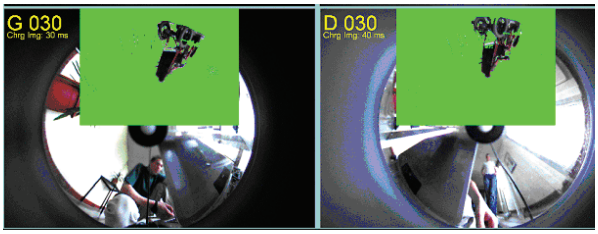

Figure 6. Stereo target Initialisation.

Once the model is computed, a histogram representation is calculated.

3.2. The OmniCAMShift recognition and bearing measurements

As the wheelchair is not equipped with any particular marker, we have to track it as it is. In this way, we use the CAMShift algorithm, which performs a tracking, by using an image of the object to track. The Continuously Adaptive Mean Shift (CAMShift) algorithm [16], is based on the mean shift algorithm [17], a robust non-parametric iterative technique for finding the mode of probability distributions including rescaling.

We have named “Omnicamshift” the calculation of a CAMShift directly in an omnidirectional image. We have also applied some specificity linked to the sensor used (fast rotation...). The next figure (Fig. 7) shows an example of the OmniCAMShift application (for the interested reader, more details can be found in our earlier works in [8]).

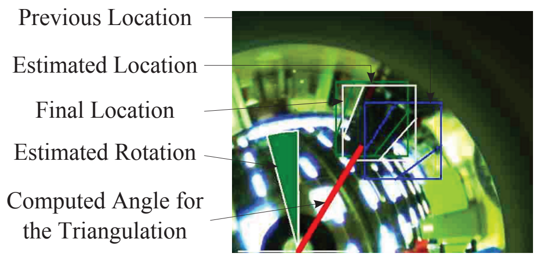

Figure 7. *Wheelchair recognition using OmniCAMShift: The estimated rotation is used to initialise the next target matching.*

Once the wheelchair is identified in both omnidirectional images, computing the relative position of the wheelchair becomes a minor feat with the two bearing measurements deduced (Fig. 8):

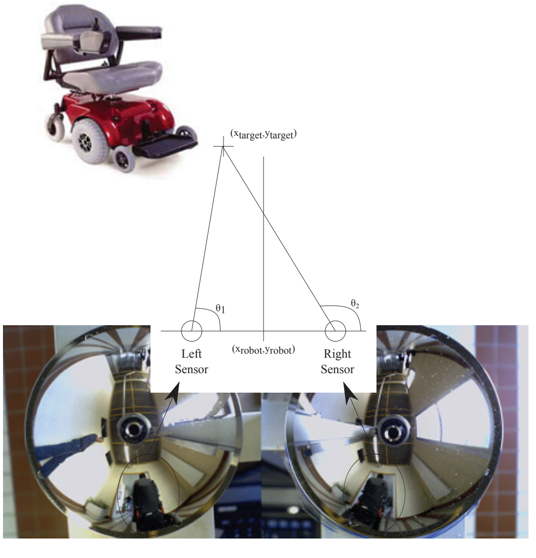

Figure 8. *The bearing measurements.*

4. Stereo bearing-only tracking with Kalman filters

4.1. Problem formulation

The multisensor bearings-only method involves a slight modification to the original problem, where a second static sensor sends its target bearing measurements to the original platform.

Conceptually, the basic problem in bearings-only tracking is to estimate the trajectory of a target (*i.e.*, position and velocity) from noise-corrupted data. For the multi-sensor case, these bearing data are obtained from two sensors from a single-moving observer. The target state in Cartesian coordinates at time k is:

$$X_k^{tgt} = \begin{pmatrix} x_k^{tgt} & y_k^{tgt} & \dot{x}_k^{tgt} & \dot{y}_k^{tgt} \end{pmatrix}^T \quad (3)$$

where (x_k^{tgt}, y_k^{tgt}) and $(\dot{x}_k^{tgt}, \dot{y}_k^{tgt})$ are the position and speed of the target. In the same way, the observer state vector at time k is defined by:

$$X_k^{obs} = \begin{pmatrix} x_k^{obs} & y_k^{obs} & \dot{x}_k^{obs} & \dot{y}_k^{obs} \end{pmatrix}^T \quad (4)$$

The observer state being known, we introduce the relative state vector defined by:

$$X_k = X_k^{tgt} - X_k^{obs} = (x_k \quad y_k \quad \dot{x}_k \quad \dot{y}_k)^T \quad (5)$$

Throughout this paper, we will be concerned with the tracking (estimation) of this relative state vector.

The state equation
To solve the problem, it is supposed that we have some information about the target trajectories. So the target dynamics can be mathematically written as:

$$X_{k+1}^{tgt} = F\, X_k^{tgt} + w_k \quad (6)$$

The process noise structure is represented by the Q matrix. The matrices F and Q are specified below. Depending on the application, a wide variety of target dynamics has been considered in the literature (see [18]). We have chosen to work with model (6) as it is sufficient for our application. We study the motion of the target in relation to the observer and we introduce the motion equation of the observer:

$$X_{k+1}^{obs} = F\, X_k^{obs} - u_k \quad (7)$$

where uk represents the known motion of the observer at time k.
Combining equations (6) and (7), the relative motion equation of the target is obtained by:

$$X_{k+1} = F\, X_k + u_k + w_k \quad (8)$$

The observation equation
The available measurement at time k is the angle from the observer's platform to the target. The target state is connected to the angular measurement via the following equation:

$$z_k = arctan\left(\frac{y_k}{x_k}\right) + v_k \quad (9)$$

where v_k is a zero-mean independent Gaussian noise with variance σ^2. The covariance matrix is $R = I\sigma^2$ where I is the identity matrice of dimension 2 and:

$$z_k = h(X_k) + v_k \quad (10)$$

is the true bearing angle with $h(X_k) = arctan\left(\frac{y_k}{x_k}\right)$.

This equation (10) is generally called measurement equation.

The equations (8) and (10) form the framework of the BOT filtering method. One can notice at this point that we are confronted to a nonlinear problem of filtering.

The bearings-only tracking problem for this multi-sensor case then has to estimate the state vector x_k given a sequence of measurements $Z_k = \{z_1, z'_1, ..., z_k, z'_k\}$.

4.2. Tracking algorithms

This section describes two recursive algorithms designed for tracking a manoeuvring target using bearings-only measurements. We opted for an absolute state of the target, in which case the movement of the observer, provided by the dead-reckoning data, is taken into account in the observation equation.

4.2.1. Filters initialisation

The chosen state model is an application of conventional filtering, where we follow the track of a moving object using sensors that measure only the angle they make with respect to this object. We study an electrical wheelchair (the target) and two angle measurements from omnidirectional vision sensors that are placed on an autonomous mobile platform (the observer). The prior can be expressed as follows:

$$X_k = \begin{pmatrix} x_k & y_k & \dot{x}_k & \dot{y}_k \end{pmatrix}^T \tag{11}$$

After discretization, the dynamics of the chair reads:

$$X_k = \begin{pmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} x_{k-1} \\ y_{k-1} \\ \dot{x}_{k-1} \\ \dot{y}_{k-1} \end{pmatrix} + w_{k-1} \tag{12}$$

where w_{k-1} is a centred white Gaussian noise and a covariance matrix Q.

$$Q = \begin{pmatrix} \frac{1}{3}\Delta t^3 & 0 & \frac{1}{2}\Delta t^2 & 0 \\ 0 & \frac{1}{3}\Delta t^3 & 0 & \frac{1}{2}\Delta t^2 \\ \frac{1}{2}\Delta t^2 & 0 & \Delta t & 0 \\ 0 & \frac{1}{2}\Delta t^2 & 0 & \Delta t \end{pmatrix} q \tag{13}$$

where q is the spectral density of the state noise w_{k-1}. It is a constant in the case of a Gaussian white noise.

The observation model associated with the TMA can be defined as follows:

$$Z_k = \begin{bmatrix} \theta_k^1 & \theta_k^2 & \dots & \theta_k^i \end{bmatrix}^T \tag{14}$$

where i is the number of sensors.
and

$$\theta_k^i = h^i(X_k) + v_k^i \tag{15}$$

with

$$h^i(X_k) = \arctan\left(\frac{y_k - S_y^i}{x_k - S_x^i}\right) \tag{16}$$

where S_x^i and S_y^i represent the position of sensor i at time k, computed from the dead-reckoning of the mobile platform. (in our case, $i = 2$). This observation model $h(.)$ is nonlinear. Thus we calculate a linearized Jacobian matrix H.

$$H = \begin{pmatrix} \frac{-\left(y_k - S_y^1\right)}{\left(x_k - S_x^1\right)^2 + \left(y_k - S_y^1\right)^2} & \frac{\left(x_k - S_x^1\right)}{\left(x_k - S_x^1\right)^2 + \left(y_k - S_y^1\right)^2} & 0 & 0 \\ \frac{-\left(y_k - S_y^2\right)}{\left(x_k - S_x^2\right)^2 + \left(y_k - S_y^2\right)^2} & \frac{\left(x_k - S_x^2\right)}{\left(x_k - S_x^2\right)^2 + \left(y_k - S_y^2\right)^2} & 0 & 0 \end{pmatrix} \tag{17}$$

4.2.2. EKF algorithm

The EKF has been widely used in many applications where the mathematical model is non-linear. One can find numerous references about the implementation of this traditional filter in [4]. In simple terms, the objective in our case is to linearise the measurement equation (10 and 14) by a Taylor expansion. However, due to numerous hypotheses on linearisation and due to the transformation itself, the EKF is well known not to be an optimal solution. The convergence (*i.e.* the solution) is thus only reliable when the system is not far from a linear system. Another problem with the EKF is that the estimated covariance matrix tends to underestimate the true covariance matrix. Finally, the linearisation (Jacobian computation) is not necessarily easy to calculate, which can render the implementation of the filter algorithm quite difficult. To palliate these problems, a new version of the Kalman filter has been implemented: the UKF (Unscented Kalman Filtering).

4.2.3. UKF algorithm

It is clear that when the prediction and the update functions are highly non-linear, the Extended Kalman Filter can give a particularly poor performance. The Unscented Kalman Filter (UKF) uses a deterministic sampling technique known as the Unscented Transform (UT) to pick a minimal set of sample weighted-points (called sigma points) around the mean. These sigma points are then propagated through the non-linear functions and the covariance of the estimate is recovered. The result is a filter, which captures the true mean and covariance more accurately. For this reason, the UT is commonly used to estimate the statistics of the random variables that undergo the non-linear transformations. In addition, this technique removes the requirement to analytically calculate Jacobians (linearisation).

5. Simulation results and discussion

In this section, we present a performance comparison of the two tracking algorithms described in the previous section. The comparison will be based on a set of 20 Monte Carlo simulations for one scenario.

5.1. Criteria of comparison

We are interested in the accuracy criteria of the filters. One type of error is analysed: RMSE (Root-Mean-Square Error).
The following notations are adopted in this paragraph: X is the exact state vector to estimate, its estimation is $\hat{X}$ and the error estimation $\tilde{X} = X - \hat{X}$. For each scenario, the total number of independent Monte Carlo trials is denoted M. The index i therefore represents the i^{th} trial.

The Root Mean Square Error (RMSE) is the most well known measure of accuracy. It is defined by:

$$RMSE\left(\hat{X}\right)_k = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(x_k^i - \hat{x}_k^i\right)^2 + \left(y_k^i - \hat{y}_k^i\right)^2} \quad (18)$$

5.2. Presentation of the scenarios of simulation

We propose two scenarios in order to study the two estimators. The initialisations of constants are indicated in the table 1.

Scenario 1 (Fig. 9) is representative of our system, the mobile platform (observer) really follows the wheelchair (target), their trajectories are very close and similar. The simulation time is $80\ seconds$.The wheelchair and the mobile platform execute manoeuvres in the intervals $14-18\ seconds$, $38-42\ seconds$, $42-44\ seconds$, $45-49\ seconds$, $49-52\ seconds$, $52-57\ seconds$, $66-68\ seconds$ and $76-80\ seconds$; between each manoeuvre they maintain their course.

Scenario 2 (Fig. 10) represents a standard BOT case. At the start, the wheelchair and the mobile platform are distant from each other and their dynamics of trajectory are very different. The simulation time is $40\ seconds$. The mobile platform executes manoeuvres in the intervals $8-10\ seconds$, $20-24\ seconds$ and $32-34\ seconds$ and the wheelchair executes a single manoeuvre in the intervals $20-24\ seconds$; between each manoeuvre they maintain their course.

We used identical parameters in experimental conditions, namely dead-reckoning data every $20\ ms$, an omnidirectional image (i.e bearings measurements) every second. The accuracy of bearings measurements is $\sigma = 0.1\ rad$, or $\sim 5.7\ degree$.

Table 1. Constants of the manoeuvering target scenarios.

	Scenario 1	Scenario 2
$x^{obs}(0)$	$0\ m$	$0\ m$
$y^{obs}(0)$	$0\ m$	$0\ m$
$\dot{x}^{obs}(0)$	$1\ m/s$	$0.9\ m/s$
$\dot{y}^{obs}(0)$	$0.05\ m/s$	$1.2\ m/s$
$x^{tgt}(0)$	$0.5\ m$	$40\ m$
$y^{tgt}(0)$	$0.25\ m$	$10\ m$
$\dot{x}^{tgt}(0)$	$1\ m/s$	$-0.7\ m/s$
$\dot{y}^{tgt}(0)$	$0.06\ m/s$	$-1\ m/s$

5.3. Single sensor case

It seemed interesting to study our first mobile platform wheelchair (observer-target) for the single-sensor case to show the contribution of an additional sensor especially when manoeuvring the wheelchair. For this case, we analyse our estimators for the scenario 1 of simulation.

We can observe that from the first wheelchair movement, the two filters fall short (see Fig. 11) and they can't at any time reconverge to the actual state of the target. Furthermore, the precision errors keep increasing until the end of the test run. The estimation of the target in a context where it is very near to the observer can not be obtained with just one angle. This is resumed in table 2. The precision criteria prove that the performance of our filters is poor in this case.

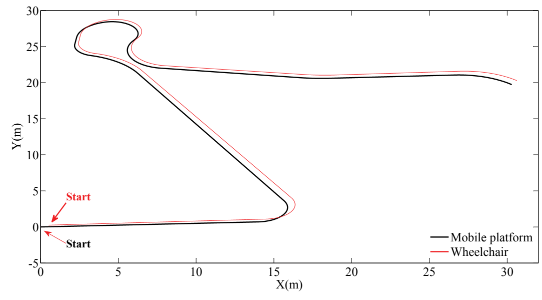

Figure 9. The first bearings-only tracking scenario with a manoeuvring target.

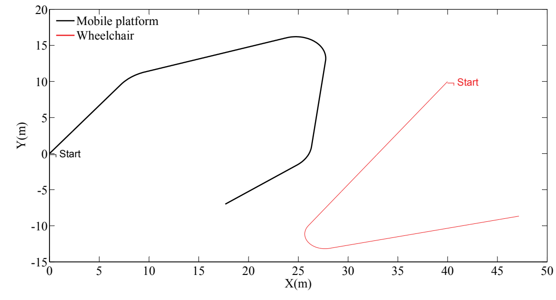

Figure 10. The second bearings-only tracking scenario with a manoeuvring target.

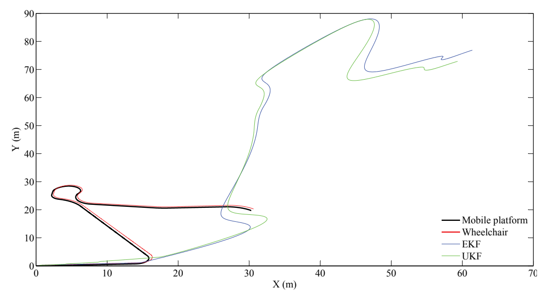

Figure 11. EKF and UKF results for the single-sensor case.

Table 2. Performance comparison for the single-sensor case.

	RMSE	
	mean	max
EKF	44.97	76.16
UKF	43.02	75.61

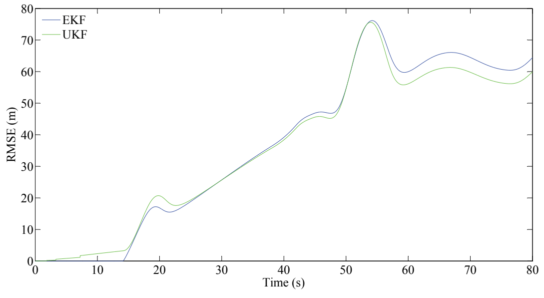

Figure 12. *RMSE in the single-sensor case.*

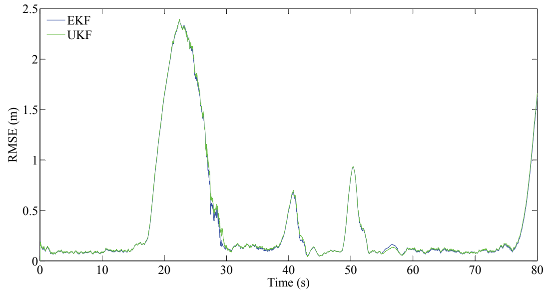

Figure 14. *RMSE for the scenario 1 in the multi-sensor case.*

5.4. Multi-sensor case

Here, we consider our system presented in sections 2 and 3. Our mobile platform with its stereo omnidirectional sensors tracks the wheelchair.
The advantage of a supplementary sensor can be clearly seen in this case (see Fig. 13). We now obtain a first-rate estimation of our mobile wheelchair from the mobile platform and the precision errors in table 3 confirm this result. The filters only waver slightly at each movement of the wheelchair, because the omnidirectional sensor renders our filters more robust. We can also observe that in the present case, which is very non linear, the UKF and EKF render a similar outcome.

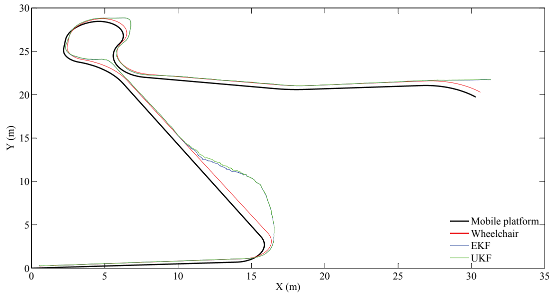

Figure 13. *EKF and UKF results for the multi-sensor case (scenario 1).*

Table 3. *Performance comparison for the multi-sensor case (scenario 1).*

	RMSE	
	mean	max
EKF	0.67	2.68
UKF	0.67	2.68

For scenario 2 that contains a better dynamics of the wheelchair and the mobile platform and that presents a distance configuration of the two objects, the results are satisfying in terms of estimation (see Fig. 15 and Tab. 4). In this case we also obtain equivalent performances between the UKF and the EKF.

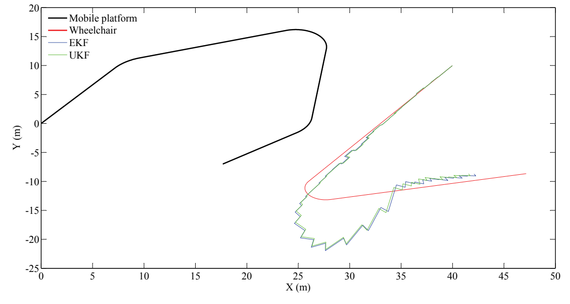

Figure 15. *EKF and UKF results for the multi-sensor case (scenario 2).*

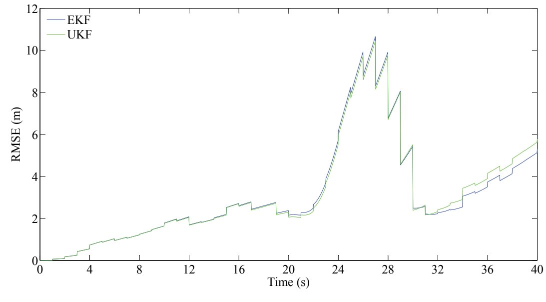

Figure 16. *RMSE for the scenario 2 in the multi-sensor case.*

We note that for our system as presented here and in which the mobile platform has to be able to track the wheelchair from a short distance (approx. 1 m), the stereoscopic omnidirectional vision rendering two measurement angles, is perfectly adequate. The stereoscopic omnidirectional vision system is used for both detecting and tracking the wheelchair.

Table 4. Performance comparison for the multi-sensor case (scenario 2).

	RMSE	
	mean	max
EKF	3.91	10.90
UKF	3.93	10.73

In all simulations we have been done, EKF and UKF show equivalent performances. However, we know that the reliability of the EKF decreased when the modelisation of the system moves away from the linear hypothesis (Jacobian computation then becomes relatively inefficient) while the UKF is reliable all the time. But the computationally cost of the UKF is significant and the EKF is the most reliable filter under linear conditions.

6. Experimental results and discussion

We explore the results from a real-life test using the EKF and UKF that were previously mentioned. The experiment was held in the corridor of our University building (IUT, Amiens, France). The average distance of the experimental path is about 80 metres. Fig. 17 illustrates the configuration of the real trajectory. We can add that the floor of this corridor contains some irregularities that affect the measures from the dead-reckoning sensors. Moreover, this corridor contains many different light conditions such as: artificial lighting, French windows and classical windows. This implies that the lighting conditions are not controlled at all and have a partial impact on the recognition rate of our modified OmniCamShift.

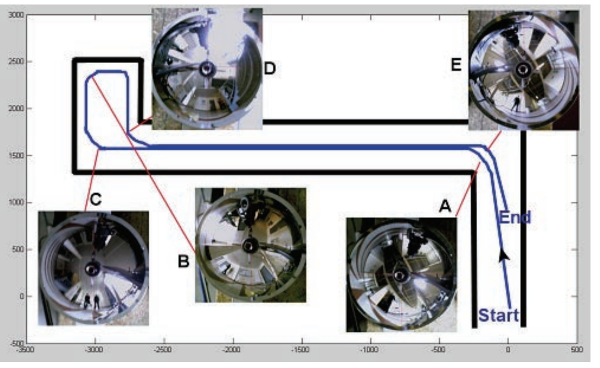

Figure 17. Configuration of the real-life experiment.

The images A to E of the Fig. 17 show the different lighting conditions during the run. Thus the automatic correction of the white balance in the image highly perturbs our colorimetric model and consequently the wheelchair recognition. Furthermore, we can observe that some omnidirectional images do not have a round occlusive contour and are also blurred. This is due to vibration during the run. The combination of these processing difficulties clearly indicates that there is a need for an effective tracking filter. This can palliate the problems that are inherent to computer vision and assure a continuous wheelchair tracking. The recognition rate of the wheelchair in the zone labelled 1 in Fig. 18 is about 15% and around 80% in zone 2. Our first comment deals with the well-known weakness of the dead-reckoning sensors. If we compare the path plan illustrated in Fig. 17 to the path saved by the dead-reckoning sensors shown in Fig. 18, we can observe a significant shift at each change of direction of our mobile platform. The two blocks labelled 2, in Fig. 18, are normally meant to be superposed and this is clearly not the case. Considering such a level of deficiency of our dead-reckoning sensors, it is obvious that the absolute tracking of the wheelchair would be a great improvement but the objective of this paper is the relative tracking of the wheelchair by the mobile platform.

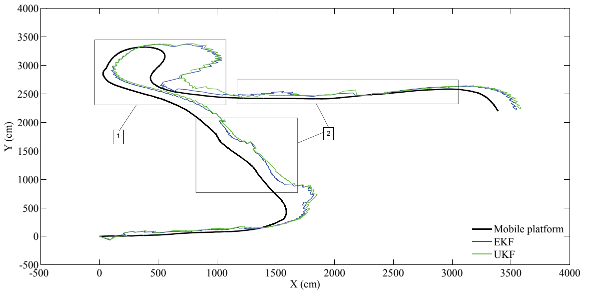

Figure 18. Wheelchair position give by EKF and UKF in the real-life.

As the objective of this paper is the relative tracking of the wheelchair by the mobile platform, an absolute position is not necessary. However, in a SLAM paradigm this relative tracking would need to be reconsidered. These real-life tests have clearly shown that the loss of images has a minor influence on our EKF and UKF tracking because we don't observe any divergence of the filters.

7. Conclusion

Nowadays, assistive techniques for handicaps are more and more successful. Our research is aimed at developing an autonomous robotised assistance for people in wheelchairs.

This paper focussed on a visual servoing between a wheelchair and an autonomous mobile platform. We presented a comparative study of two Kalman filters (EKF and UKF) for the problem of bearings-only tracking of a manoeuvring target. The tracking filters propose a reliable prediction when the vision data are absent or inconsistent and allow to solve the problem of occlusion and alteration of the illumination conditions. The results overwhelmingly show an equivalent performance between the two filters. It is also important to note the significant contribution in terms of performance when an additional sensor is built into our system.

For future research, it would seem important to study more robust filters than the EKF or the UKF, such as for instance a IMM (Interactive Multiple Model) filter or even a Particle Filter (PF).

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