TRACKING A WHEELCHAIR WITH A MOBILE PLATFORM

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Abstract: This article deals with a target tracking application for the disabled. The objective of this work is to track a wheelchair with a mobile platform and an embedded grasping arm (MANUS). We propose an approach based on an association of two Kalman filtering levels. The first level permits an estimation of the wheelchair configuration. The second is used to compute the mobile platform configuration in connection with its environment. The association of the two filtering process allows a robust tracking between two objects in movement.

1 INTRODUCTION

In this article we propose an original approach to solve the problem of configuration estimation of a target observed by a robot in movement. We propose a probabilistic approach based on Kalman Filtering. The problem of tracking is classical in the world of robotics. It's generally linked to the data association stage. The data association problem is that of associating the many measurements made by a sensor with the underlying states or trajectories that are being observed. It includes issues of validating data, associating the correct measurement to the correct states or trajectories, and initializing, confirming or deleting trajectories or states. This way, the Probabilistic Data Association Filter (PDAF) (Y. Bar Shalom et T.E. Fortmann, 1988) for single targets and the Joint Probability Data Association Filter (JPDAF) (Y. Bar Shalom et T.E. Fortmann, 1988 and Bar-Shalom Y, Xiao-Rong Li,1995) for multiple targets are two inescapable approaches. They are both Bayesian algorithms that compute the probability of correct association between an observation and a trajectory. We can combine the Sequential Monte Carlo method to decline the JPDAF method.

A second classical paradigm of data association is the Multiple hypothesis tracking (MHT) which permits to represent multimodal distributions with Kalman filters (Y. Bar Shalom et T.E. Fortmann, 1988). It has been used with great effectiveness in radar tracking systems, for example. This method maintains a bank of Kalman filters, where each filter corresponds to a specific hypothesis about the target set. In the usual approach, each hypothesis corresponds to a postulated association between the target and a measured feature.

For our application, we have made the choice to use two Kalman filters to solve the problem of tracking between two objects in movement.

In a first part we present the used perception system, which permits to track the wheelchair that is to say a stereo omnidirectional sensor.

In a second part, we address the problem of wheelchair recognition using vision sensors.

In the third part, we deal with the multi-level Kalman filtering tracking.

We conclude with an explanation of experimental results.

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 (B. Marhic, L. Delahoche ,F. de Chaumont, and O. Remy-Néris, 2006).

The SPI group of the IUT of Amiens has applied its skills in the domains of mobile robotics and detection of the surrounding environment. It is involved in the integration of a system of detection via a motorised platform that can be mounted by a grasping arm MANUS [(R)].

2.2 Sensors Involved in this Paper

2.2.1 Dead Reckoning and its Uncertainty

We are going to establish the discontinuous equations of the platform position considering small displacements (Figure 1)

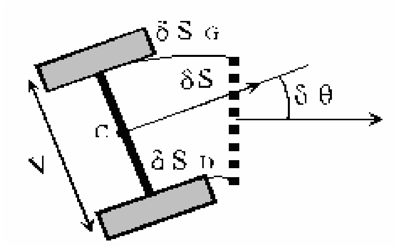


Figure 1 : Displacement of the robot during a period.

We thus obtain: $q(n+1) = q(n) + \Delta q(n)$
where q is the position of the mobile platform.
In which:

$$\Delta q(n) = \begin{bmatrix} \delta S(n) \cdot \dfrac{\sin(\delta\theta(n)/2)}{\delta\theta(n)/2} \cdot \cos(\theta(n) + \delta\theta(n)/2) \\ \delta S(n) \cdot \dfrac{\sin(\delta\theta(n)/2)}{\delta\theta(n)/2} \cdot \sin(\theta(n) + \delta\theta(n)/2) \\ \delta\theta(n) \end{bmatrix} \quad (2)$$

The vector from the equation (2) which is exact, can be simplified if we consider that the sampling period is small enough (sin(δθ (n)/2)/ (δθ (n)/2))≈1.
Thus (order 0),

$$\Delta q(n) = \begin{bmatrix} \delta S \cdot \cos(\theta(n)) \\ \delta S \cdot \sin(\theta(n)) \\ \delta\theta \end{bmatrix} \quad (3)$$

The sampling period being very small, it is possible to assimilate the elementary displacement to a segment. Therefore we will use the development to the order 0 (3), into the following calculations:

$$\begin{cases} X_{odo}(n+1) = X_{odo}(n) + \delta S(n) \cdot \cos(\theta(n)) \\ Y_{odo}(n+1) = Y_{odo}(n) + \delta S(n) \cdot \sin(\theta(n)) \\ \theta(n+1) = \theta(n) + \delta\theta(n) \end{cases} \quad (4)$$

With the matrix form, we obtain (F is a non-linear function in *q):*

$$\begin{aligned} & q(n+1) = F(q(n), \Delta(n)) \\ & \Delta(n) = [\delta S(n), \delta\theta(n)]^t \\ & \Delta(n)_{mes} = \Delta(n) + Bq = \hat{\Delta}(n) \end{aligned} \quad (5)$$

$Bq \sim N(0,V^{bq})$ (Gaussian noises, centred)

We will apply the Taylor development of F (equation 5) around $(\hat{q}(n-1), \hat{\Delta}(n-1))$, in order to render the equations linear.

2.2.2 Stereoscopic Omnidirectional Vision System

On the figure 2, we can see the configuration of the two omnidirectional vision sensors.

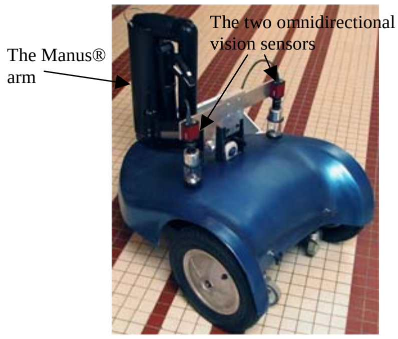


Figure 2: The mobile platform.

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 (H. Ishiguro, S. Tsuji, 1993), but the information flow is very important and time consuming. Other applications (E. Colle, Y. Rybarczyk, P. Hoppenot, 2002) 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 looseness 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 360° field of view (El. M. Mouaddib, B. Marhic, 2000). There are two major classes of omnidirectional vision systems. First of all, systems made of a mirror and a camera, are called “catadioptric systems” (C. Cauchois, E. Brassart, L. Delahoche, T. Delhommelle, 2000)(H. Ishiguro, S. Tsuji, 1996). The second one is composed of a classical camera with a fish-eye lens; such mountings are called “dioptric systems” (Z. L. Cao, S. J. Oh, Ernest L. Hall, 1986). We focus on the first class.

There are many advantages to using an omnidirectional vision sensor. Firstly, in one acquisition, we obtain a full view of the environment without using a sophisticated mechanical system. Secondly, even if the interpretation of omnidirectional pictures is difficult for novices, we can easily compute 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 of a digital color video camera and a hyperbolic mirror. Figure 3 shows an omnidirectional view of an environment with a wheelchair in the field of view.

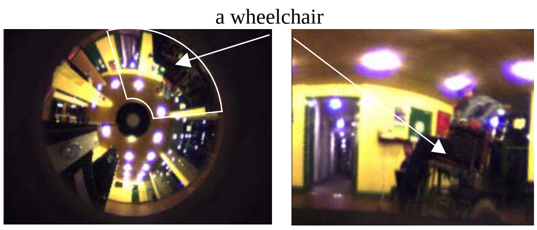


Figure 3: (left) an omnidirectional view of a scene with a wheelchair in the field of view. (right) “un-warped” picture of the white area from the omnidirectional view.

3 TRACKING RECOGNITION

3.1 Initialisation (Target-wheelchair)

We wished to achieve the greatest possible degree of flexibility regarding 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. This is why we turned our work towards an intrinsic polymorph (self re-configuring), directly calculated from a stereoscopic colour video signal. The figure below (Figure 4) shows omnidirectional images: they illustrate the extraction of the background and the extraction of the wheelchair.

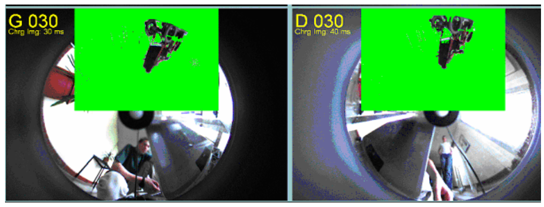


Figure 4: Target Initialisation.

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

3.2 The OmniCAMShift Recognition and Triangulation

As the wheelchair is not equipped with any particular marker, we have to track it as it is. 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 (C. Cauchois, E. Brassart, L. Delahoche, T. Delhommelle, 2000), is based on the mean shift algorithm (B. Marhic, L. Delahoche ,F. de Chaumont, and O. Remy-Néris, 2006), 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 gyration, …). The next figure (Figure 5) shows an example of the OmniCAMShift application:

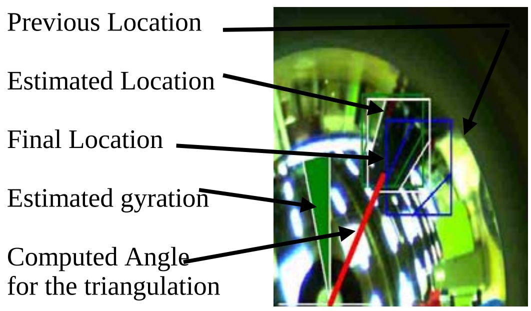
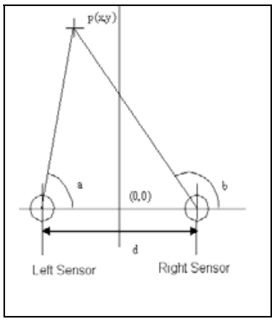


Figure 5: Wheelchair recognition using OmniCAMShift.

Once the wheelchair is identified in both omnidirectional images, computing the relative position of the wheelchair by triangulation is a minor task (Figure 6) :



$$x = \frac{d \times \tan(b)}{\tan(b) - \tan(a)} + \frac{d}{2}$$

$$y = \frac{d \times \tan(b) \times \tan(a)}{\tan(b) - \tan(a)}$$

Figure 6: triangulation.

4 TRAKING WITH KALMAN FILTER

4.1 The Kalman Filter

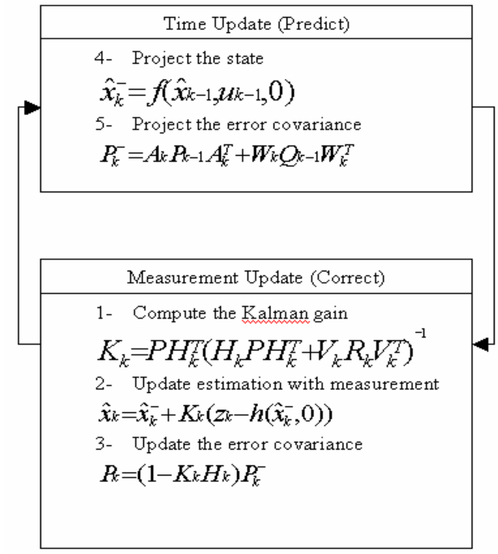


Figure 7: Kalman filter.

We would like to recall at this point that the process that manages the movement of the RMA is discontinuous and non linear in θ. The measurements Y(n) are linked to q(n) by an equation of observation (or equation of measurement).

$$q(n+1) = F\big(q(n), \Delta(n)\big) + v$$

$$\Delta(n) = \left[\delta S(n), \delta\theta(n)\right]^t \qquad (6)$$

$$Y(n) = H \cdot q(n) + w$$

with :

⇨ v is a centred Gaussian white noise, of the variance matrix Cpro.

⇨ w is a Gaussian white noise which perturbs the measurement.

⇨ Δ(n) is the vector of command.

⇨ q(n) is the trajectory of the state vector, representing the localisation of the mobile platform.

⇨ H is the observation matrix.

4.2 Filtering with Non-inner Observation

In this application, we have two objects in movement, a wheelchair and a mobile platform. However, we only have proprioceptive movement information on the mobile platform. Using dead-reckoning we compute the position of our mobile platform and using the omnidirectional vision system (exteroceptive), we calculate the relative position of the wheelchair compared to our mobile platform.

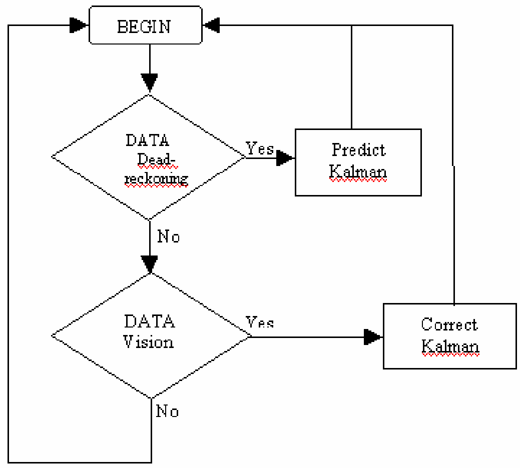


Figure 8: Filter's algorithm.

From the implementation of our model, we decided to use for the prediction of the Kalman filter the data give by the odometric sensor and for the step of update the data give by triangulation of the two omni-directional sensor.

We decide to make the triangulation operation out of your filter and injected directly the result in the update step of kalman filter. That makes it possible to bring us back to a linear system.

The vision module permits to obtain $Xf = \left[x_f \quad y_f\right]^t$, where :

$$X_f = X_{odo-1} + \Delta D_n * \cos(\theta_{n-1} + \frac{\Delta\theta_n}{2}) + X_{tri} \qquad (7)$$

$$Y_f = Y_{odo-1} + \Delta D_n * \sin(\theta_{n-1} + \frac{\Delta\theta_n}{2}) + Y_{tri} \qquad (8)$$

with Xtri and Ytri the position between the mobile platform and the wheelchair and, X_{odo} and Y_{odo} the result of odometric equations .

In order to have a homogeneous filtering, the vision uncertainty of the localisation is considered to be a Gaussian white noise.

Thus, we obtain :

$$\boxed{\begin{aligned} Y &= Xf + w \\ H &= I \end{aligned}}$$

"I" being the identity matrix.

The result obtained was satisfactory for straight lines (figure 9) but insufficient during the phase where the mobile platform turned due to errors of odometry.

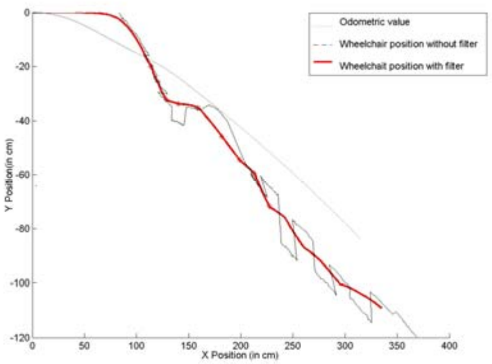


Figure 9: Filter with a good precision.

4.3 Extended Filtering

To remove the problem of the imperfection of the dead-reckoning, we will use a method which requires a knowledge of the landmarks. We will be able to determine with precision, the position of our mobile plateform and to thus replace it to avoid the errors of the dead-reckoning.

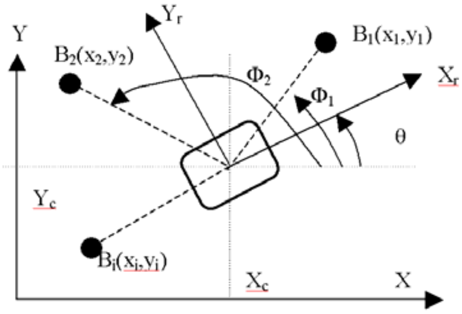


Figure 10: Relation between beacon and mobile platform.

For us, these landmarks are walls, doors, objects, angles which one will be able to detect in an omnidirectional image. Therefore, it is necessary for us to know the map of the environment to be able to mark it out.

Moreover, this method is based on an extended Kalman filter that can be integrated into our preceding process.

For this process, the equation of observation of the extended Kalman is as follows.

The vector of observation is written:

$$z_k^* = \begin{bmatrix} 1_k^\tau \\ 2_k^\tau \\ . \\ . \\ n_k^\tau \end{bmatrix} + v_k = h(X_k, k) + v_k \tag{9}$$

where i_k^τ is the layer of $i^{ème}$ beacon B_i of co-ordinates (x_i, y_i) i the world landmark in the moment k. And v_k is a measurement noise, presumably white and Gaussian.

The exact position of the beacon B_i is expressed according to the state vector X_k of the system as follows:

$$i_k^\tau = \arctan\left(\frac{y_k - y_i}{x_k - x_i}\right) \tag{10}$$

The matrix of the Jacobien of the vector function H is, in the case of measurements of absolute angle:

$$H_k = \begin{bmatrix} -(y_k - y_1)/_1\, d_k^2 & -(x_k - x_1)/_1\, d_k^2 & 0 \\ . & . & . \\ -(y_k - yn)/_n\, d_k^2 & -(x_k - x_n)/_n\, d_k^2 & 0 \end{bmatrix}_{X_k = \hat{X}_{k/k-1}} \tag{11}$$

where d is the distance between the landmark and the mobile platform

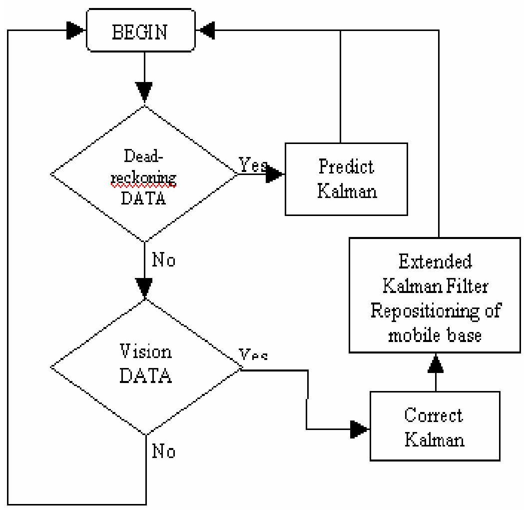


Figure 11: Process of filtering.

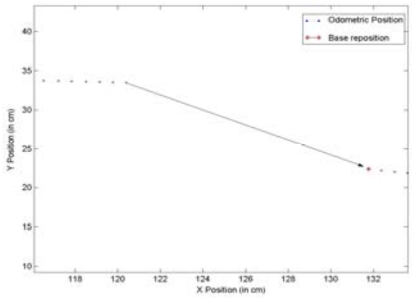


Figure 12: Repositioning of the mobile platform.

Table 1: Data after simulation of the system.

Reel base position		Estimate base position with kalman filter	
X (in cm)	Y (in cm)	X (in cm)	Y (in cm)
-166	-950	-168	-950
-240	-950	-240	-950
-327	-949	-327	-949
-365	-949	-365	-949
-400	-949	-419	-949
-463	-974	-463	-974

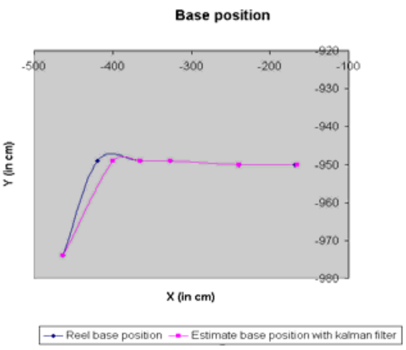


Figure 13: System's result.

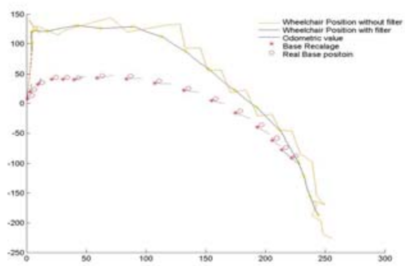


Figure 14: Other Result of the application.

With this method, we clearly see a marked improvement of the localisation, especially when the mobile platform turns. (Figure 12) which enabled us to improve the precision of our system (Table 1, Figure 13 where we can see the result of the system in a right line and Figure 14 which is the system's result in a turning).

5 CONCLUSION

In this article, we studied a target tracking application for the physically disabled. The aim is to track a wheelchair with a mobile platform mounted with a grasping arm (MANUS). We propose an approach based on an association of two Kalman filtering levels. The first level permits to estimate the wheelchair configuration. The second is used to compute the mobile platform configuration in connection with its environment. We have shown that the second level increases the robustness of the configuration estimation of the wheelchair in the platform frame. The use of the identity matrix in the first stage of the Kalman filtering permits to solve the problem of the non-linearity of the system.

This paradigm can be a contribution to finding a solution for tracking several objects in movement. The robustness of the filtering process is very important. Future works will study the integration of a supplementary layer based on a particle filter.

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