OMNIDIRECTIONAL VISION TACKING SYSTEM BASED ON KALMAN FILTERING AND OMNICAMSHIFT

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Abstract: This paper deals with a robotised assistance dedicated for Handicap person. In this paper, we will propose to discus about one of the main functionality of this project: the tracking of the wheelchair from an autonomous mobile platform on which the Manus (c) arm is mounted. To ensure the tracking, we will present a method based on Kalman filter's algorithm that we have upgraded in combination with two Kalman filtering levels. The first level permits an estimation of the wheelchair configuration in its environment and the second is used to compute the mobile platform configuration in connection with its environment. The association of the two filtering processes allows a robust tracking between a mobile target (wheelchair) and a mobile observer (assistive platform). More over, the team project was also composed with a clinical group; hence we present some interesting real-life testing of this technical assistance.

1 INTRODUCTION

Our laboratory works on an assistive prehensile mobile robot project and has to ensure the tracking of a wheelchair from the mobile platform. In this article, we propose an approach to solve the problem known as target motion analysis (TMA). We propose a target tracking filter based on a probabilistic approach with the Kalman Filtering which will be fed by omnidirectional vision sensors and dead-reckoning sensors mounted on the mobile platform. The problem of tracking is classical in the world of robotics. It's generally linked to the data association stage and state estimation. 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. The Probabilistic Data Association Filter (PDAF) for single target and the Joint Probability Data Association Filter (JPDAF) (Y. Bar Shalom *et al*, 1988), (Bar-Shalom Y *et al*, 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. The general JPDAF framework can be implemented using Monte Carlo techniques, making it applicable to general non-linear and non-Gaussian models (D.Schulz *et al*, 2003).

A second classical paradigm of data association is the Multiple hypothesis tracking (MHT) (S.Blackman, 1986) which permits to represent multimodal distributions with Kalman filters (Y. Bar Shalom *et al*, 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

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postulated association between the target and a measured feature.

For our application, we have chosen to use two Kalman filters to solve the problem of target tracking from a mobile observer.

The originality of this approach in connection with the classical solutions resides in two points:

- Solving the problem of data association with a dedicated image-processing filter (camshift).
- Solving the problem of simultaneous moving of the target and the tracker with two embedded Kalman filters.

The combination of the prior two points contributes to solving the non-linearity problem of the global filter.

Paper Organisation. In the next paragraphs (§1.1, §1.2, §1.3, §1.4), we will mention the specific context of this study, outline the perception system and describe the functionalities of the proposed assistive platform. After that in part 2, we will briefly explain the first tracking method (1TM) based on the iterative algorithm CAMSHIFT with a specific use for omnidirectional images. We also present very original clinical results of the tests made under genuine conditions by disabled people. In the last part (§3), we deal with the multi-level Kalman filtering tracking (second Tracking Method, 2TM). Moreover, in this section, we will describe our Embedded Extended Kalman Filtering (EEKF). Finally (§4), we will conclude with an explanation of the experimental results.

1.1 Context Overview

This project, ARAP (Robotised Assistance for Prehensile Help), came into being from a human synergy, which grew out of a definition of problems faced by peoples of reduced mobility. The idea of robotised assistance for handicapped people followed an observation: there is generally a significant delay between technology, no matter how advanced, and assistance for peoples of reduced mobility. Above all, however, this project meets a social demand, that was defined by patients of reduced mobility confined to the Berck Hopale group (Hospital), who are taking part in this project. An interesting specificity of this project was composing a strongly plural-disciplinary team:

- “Science for the Engineer” skills of the IUT of Amiens (University of Picardie, Jules Verne) have been used for the integration of a system of detection on the mobile platform and for the development of the prototype.
- The “Human and Social Science” team was in charge of the psychological impact of this mobile assisting platform on the end-user.
- The “Clinical group” (the Calvé Centre in Berck-Sur-Mer) used its clinical knowledge of the problem of disability, which will allow an evaluation of the work done.

A lot of work has been carried out in connection with the problems defined by technical assistance. Some of them are describe in (B.Marhic *et al*, 2006).

We have proposed studying the technical, psychological and clinical impact of robotised assistance for persons of reduced mobility by combining a mobile platform with a grasping arm in its usual role as robotics for handicapped persons (robot arm MANUS®).

1.2 Main Perception System

The mobile platform, in other words “the observer”, is mounted by the two classical kinds of sensors; *i.e.* the Inner Navigation System (INS) and the External Position System (EPS). The INS are dead-reckoning sensors and the EPS is a stereoscopic omnidirectional vision sensor used in a goniometric mode (figure 2). Moreover, this exteroceptive sensorial system is also used for the target observation (wheelchair) as a “classical” vision system involving the intrinsic properties (colour).

The well-known equation (first order) of “dead-reckoning”, considering the figure 1 is given by: $X^m = [x^m, y^m, \theta^m]^T$

$$\begin{cases} x^m(n+1) = x^m(n) + \delta S(n)\cdot\cos\left(\theta^m(n)\right) \\ y^m(n+1) = y^m(n) + \delta S(n)\cdot\sin\left(\theta^m(n)\right) \\ \theta^m(n+1) = \theta^m(n) + \delta\theta(n) \end{cases}$$

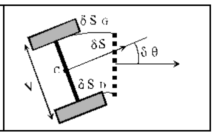


Figure 1: Small movements of the robot during a period.

Stereoscopic Omnidirectional Vision System. Main vision applications in mobile robotics use the classical pinhole camera model. Depending on 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.

We have opted for a catadioptric vision system (figure 2).

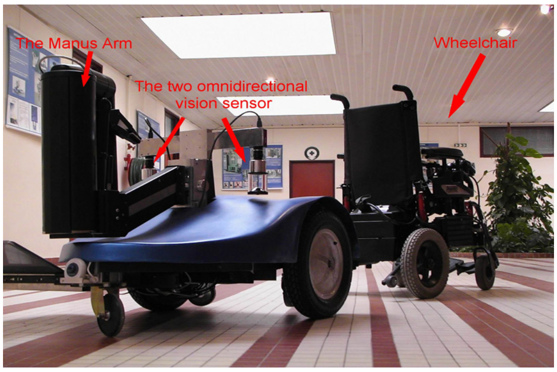


Figure 2: The mobile platform and stereoscopic sensors.

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, the same system can be used as EPS and also as a “bearing sensor”. Finally, even if the visual interpretation of omnidirectional pictures is difficult, it is possible to compute a “classical perspective view” of the scene. The previous functionality is not discussed in this paper.

The figure 3 shows an omnidirectional view of an environment with a wheelchair.

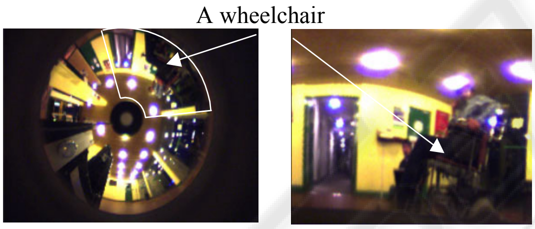


Figure 3: (left) an omnidirectional view of a scene with a wheelchair in the field of view. (right) “un-warped” picture of the white area from the omnidirectional view.

1.3 Main Functional Specificities

Two functional specificities have been integrated into the robotised assistance (ARAP). Firstly (automatic mode), the mobile platform follows the patient’s wheelchair whenever the patient does not wish to use it. Secondly, a remote controlled mode for the grasping arm MANUS$^{(R)}$ and for the mobile base, used when the patient wishes to carry out a task involving grasping.

1.4 Scientific Problematic

The two main scientific themes associated with the automatic mode are the tracking and the path planning according to the obstacle avoidance and map building (locally). The coordination of the tracking and of the detection of obstacles is very important for the proper progress of our system.

The block diagram below (figure 4) shows the concomitance between the local map and the tracking phase. These can sometimes give orientation orders to the mobile platform that are contradictory.

In this paper, we focus only on the tracking problem.

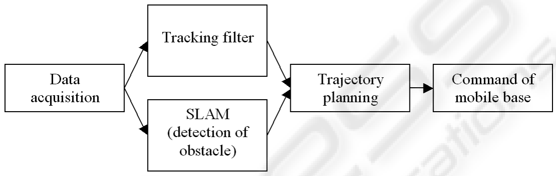


Figure 4: Coordination of tracking and detection of obstacle.

2 1TM: OMNICAMSHIFT

We wished to achieve the greatest possible degree of flexibility regarding the use of this robotic assistance. We therefore did not want to restrict our method to the use of one wheelchair in particular. More over, the wheelchair is not equipped with any particular marker; we have to track it as it is. Thus, in the first stage, our strategy for wheelchair recognition and tracking was based on a specific use of the CAMSHIFT. We have named the calculation of a CAMSHIFT directly into an omnidirectional image “OmniCAMSHIFT”. (C. Cauchois *et al*, 2005)

The Continuously Adaptive Mean SHIFT (CAMSHIFT) algorithm (Bradski, 1998), is based on the mean shift algorithm (Comaniciu *et al*, 1997), a robust non-parametric iterative technique for finding the mode of probability distributions including rescaling.

2.1 Initialisation (Target-wheelchair)

Our construction of the model accommodates not only the wheelchair, but also the patient. This is why we turned our work towards an intrinsic model, directly calculated from a stereoscopic colour video signal. The figure below (Figure 5) shows omnidirectional images: they illustrate the extraction of the background and the extraction of the wheelchair. Once the model is computed, a histogram (acts as density function) representation is calculated.

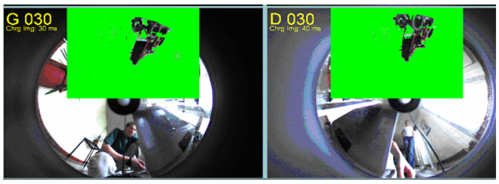


Figure 5: Target Initialisation. Subtraction of the image.

2.2 OmniCAMShift Results

The next figure (Figure 6) shows an example of the OmniCAMShift application.

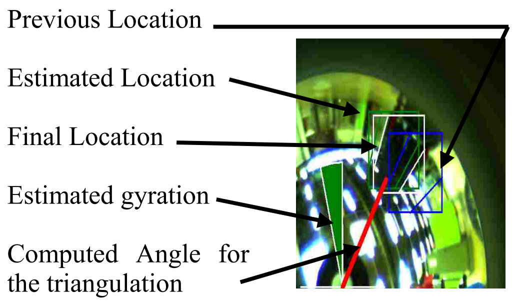
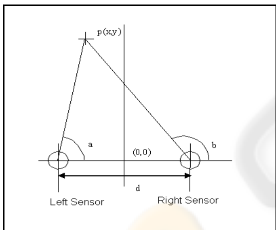


Figure 6: Wheelchair recognition using OmniCAMShift.

Once the wheelchair is identified in the two omnidirectional images, computing the relative position of the wheelchair by triangulation (figure 7) using the two computed angles is easy:

$X^{tri} = [x^{tri}, y^{tri}]^T$



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

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

Figure 7: triangulation by two bearing angles. The referential frame is between the two omnidirectional sensors.

2.3 Evaluation and Clinical Results

As we explained at length, the prototype that we designed is based on an actual social demand. The prototype has thus been tested in a hospital. Unfortunately, the automatic mode, i.e. 1TM: OmniCamShift was not secure enough (loss of target) to be used and tested by handicaped people. The required reliability for wheelchair tracking was too strict to establish an evaluation with tetraplegic subjects in clinical conditions. In a first stage we chose to test the platform with 13 non handicapped subjects placed in the same constrained motor conditions as tetraplegic subjects.

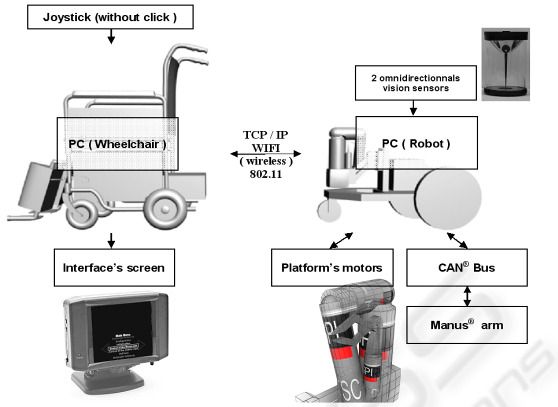


Figure 8: Operation's schema.

However, under laboratory conditions, the mobile platform was able to follow the wheelchair at a low speed and at a distance of 2m without any oscillation in the trajectory (automatic mode). In order to be manually controlled by the end-user, the base has to go around the wheelchair automatically when ordered to, without any prior warning. This intermediary phase corresponds to the transition from the automatic mode to the remote-controlled mode. This transitory trajectory was chosen in a reliable manner based on obstacle avoidance and the platform positioned itself without difficulty in front of the wheelchair in order to start the remote-controlled operation.

Real-life testing has shown that the end-user will encounter no difficulties operating the platform. The main clinical evaluation was dedicated to validate that the end-user can operate the mobile base + robot arm as easily when he is seated in the wheelchair as when he is in bed.

During the grasping operation with a moving base, the time needed to place the base was not significantly different between for 5meters near 84sec (standard deviation, s.d. 40) and 9 meters (105sec s.d. 36). The time needed to accomplish a grasping task was significantly longer when the joystick was driven by the chin (108sec s.d. 24) than by a hand blocked in an orthosis (102sec s.d. 33) or by a digital device (95sec s.d. 25). The difference in distance for the grasping action to be undertaken (between 1, 5 and 9 meters) had a non-significant impact on the outcome, respectively 56sec s.d. 17; 64sec s.d. 17 and 67sec s.d. 25, with a significant difference between 1 to 9 meters. With a fixed base and randomly presented at either 90° or 45° to the subject, the average time needed to grasp showed a significant increase between conditions (respectively 61sec s.d. 18 and 141sec s.d. 56). No significant difference was found during the task combining the movement of the base and the grasping of an object, no matter if the patient was in the wheelchair or in bed, nor if the object was on the ground or on a table. However, the change in distance from 5 meters to 9 meters increased significantly the average grasping time from 102sec s.d. 56 to 151 s.d. 80.

In short, the results presented by this research project show that whether feasible, the time for grasping with a mobile platform increases considerably with the distance and with the base orientation in comparison to the patient place. Grasping with a mobile robot seems to be a solution to a wider demand than that originally targeted by the first studies into the use of robotic assistance. As there are many people, other than from tetraplegic people, who are bed-ridden, a far wider target-group can benefit from the use of robotic assistance.

However, the evaluation also proved that the wheelchair tracking by a mobile platform had its limitations and an actual use in an environment outside of the laboratory is very complicated. This necessitated the implementation of new software elements. A part of this future improvement is discussed in the next part of this article.

3 2TM: KALMAN FILTERING

For solving the problems of target loss presented above, we add at the previous tracking method Kalman filtering. That way, we can pinpoint some detection errors that weren't detected before (divergence of the OmniCamShift).

3.1 Problem Formulation

The target, i.e. the wheelchair, located at coordinates (x^f, y^f) in the world frame, moves with a constant velocity. The state vector is defined by: $X^f = \begin{bmatrix} x^f & y^f \end{bmatrix}^T$.

The discrete-time state equation for this problem can be written as:

$$X^f_{n+1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \times X^m_{n+1} + X^{f/m}_{n+1} + v_{n+1} \qquad (1)$$

Where $X^m_{(n+1)}$ is defined figure1 and $v_{(n+1)}$ is centred Gaussian white noise v(n+1) ~ (0, Q) with Q = σ.I_2, here σ is a scalar and I_2 is the 2x2 identity matrix. The superscript $^{f/m}$ indicates the position of the wheelchair in relation to the mobile platform.

We assume that during the prediction stage the relative movement between the wheelchair and the mobile platform remains constant:

i.e. $X^{f/m}_{(n+1)} = X^{f/m}_{(n)}$. This classical target-observer geometry is depicted in the figure 9.

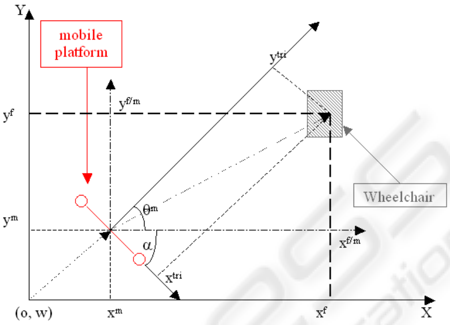


Figure 9: Target-observer geometry.

3.2 First Level of Filtering

We use the dead-reckoning data (INS) to compute the observer state, *i.e.* our mobile platform state (step 1: the prediction stage); the non-linear equation 8. Afterwards, the relative position X^{tri} of the wheelchair in connection with our mobile platform is computed by triangulation (figure 7) of data provided by the two omnidirectional vision sensors.

The equation (2) enables us to obtain the state vector $\hat{X}^f = \begin{bmatrix} \hat{x}^f & \hat{y}^f \end{bmatrix}^T$ which gives us the position of the wheelchair in the environment (World frame), based on the addition of two vectors $\vec{X}^m$ and $\vec{X}^{f/m}$.

$$\begin{bmatrix} \hat{x}^f \\ \hat{y}^f \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \times \begin{bmatrix} x^m \\ y^m \\ \theta^m \end{bmatrix} + \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) \\ \sin(\alpha) & \cos(\alpha) \end{bmatrix} \times \begin{bmatrix} x^{tri} \\ y^{tri} \end{bmatrix} \qquad (2)$$

where : $\alpha = 90° - \delta\theta^m$. The previous vector $\hat{X}^f = \begin{bmatrix} \hat{x}^f & \hat{y}^f \end{bmatrix}^T$ is computed outside the filter; $\hat{X}^f$ is used as the measurement in the observation equation (step 2: update Stage) defined as follow:

$$\hat{X}^f = H_n \times X^f_n + w_n \qquad (3)$$

where $w_{(n)}$ is a zero-mean white Gaussian noise.

The observation matrix $H_{(n)}$ of the filter becomes the matrix identity. The observation stage is thus linear. The diagram below (figure 10) summarises this process. Some actual results are shortly shown in the figure 11. This figure represents the position of our mobile platform and the wheelchair in a real scenario. The result obtained was satisfactory for a straight trajectory but insufficient during the phase where the mobile platform turned, due to errors of dead-reckoning and the non-repositioning of the mobile platform. The state vector estimation $\hat{X}^f$ is highly dependant of the of dead-reckoning vector $\vec{X}^m$; thus if an error occurs on $\vec{X}^m$, it appears on $\hat{X}^f$. This method is not efficient.

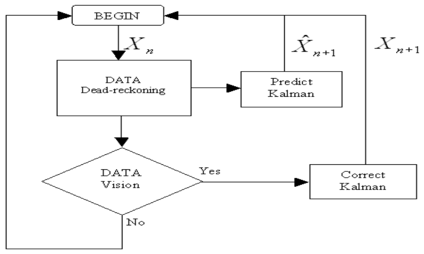


Figure 10: Filter's algorithm.

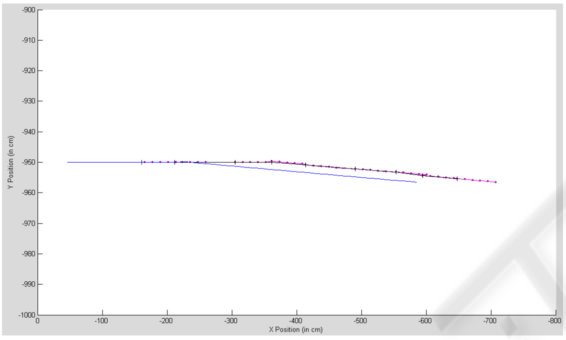


Figure 11: First filter results. (In blue the mobile platform position, in purple the estimated wheelchair position and in black the real wheelchair position).

So, to resolve this new problem and to make our application robuster, we add a second level of Kalman to this filter, which then deletes this imperfection. We have named this second filter the Embedded Extended Kalman Filter (EEKF).

3.3 Second Level: EEKF

We now propose to fully estimate the platform state vector ("the observer") by a classical EKF. Thus, this method requires knowledge of the environment's landmarks (EPS). We will be able to determine, with precision, the position of our mobile platform and thus be able to re-inject the platform position in the first Kalman loop.

For indoor application, these landmarks are walls, doors, objects, angles which one will be able to detect in an omnidirectional image using segmentation processing. Therefore, it is necessary for us to know the map of the environment to be able to match the omnidirectionnal image primitive to the known landmarks (doors and windows) of the environment (see figure 12). In order to extract the landmarks' angles of the ominidirectionnal picture, we compute a Deriche-Canny filter before applying a classical Hough transform algorithm.

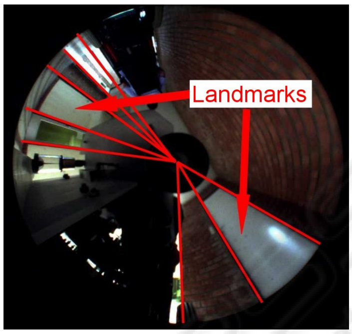


Figure 12: Segmentation and landmarks in an omnidirectional image.

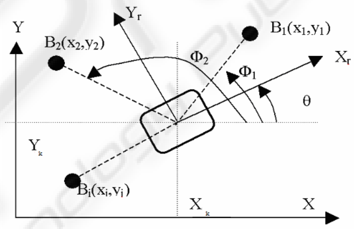


Figure 13: Relation between landmarks and mobile platform.

For this process, the equation of observation of the extended Kalman filter is as follows. The vector of observation is:

$$z_k^* = \begin{bmatrix} 1_k^\tau \\ 2_k^\tau \\ . \\ . \\ n_k^\tau \end{bmatrix} + v_k = h(X_k, k) + v_k \tag{4}$$

where i_k^τ, which contains the azimuths angles, is the layer of $i^{ème}$ landmark 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:

$$i_k^\tau = \arctan\left(\frac{y_k - y_i}{x_k - x_i}\right) \tag{5}$$

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

$$H_k = \begin{bmatrix} -(y_k - y_1)/_1\, d_k^2 & -(x_k - x_1)/_1\, d_k^2 & 0 \\ . & . & . \\ -(y_k - yn)/_n\, d_k^2 & -(x_k - x_n)/_n\, d_k^2 & 0 \end{bmatrix}_{X_k = \hat{X}_{k/k-1}} \tag{6}$$

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

We add this second Kalman filter before the correction of the first Kalman filter as can be seen in the graphic figure 14.

The result of this add-on is a reposition of the mobile platform in the environment reference (see figure 13). This better knowledge of the base location also allows us to have a better estimation of the wheelchair. Moreover, the update stage of the first level Kalman filter is now achieved by data from both the triangulation and the platform location (second level Kalman filter).

Moreover the errors induced by the dead-reckoning such as skids and slips, errors of quantification and others, are taken into account in an improved way. This improvement stems from our multi-level Kalman filter that performs a more accurate location.

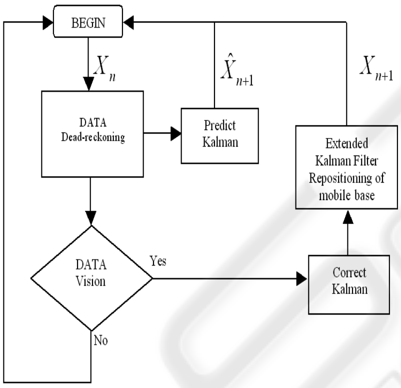


Figure 14: New process of filtering.

We can see that the second filter corrects the dead-reckoning as seen in figure 15, represented by the arrow. Here it is a big error because the wheelchair is suddenly turning.

As we can see in the figure 16, the result of our process follows the curve well, which our system did not manage to do before.

Figure 17 shows us the error in X and Y of your system. These results are given by the matrix of variance/covariance and allows us to see that our system tracks the target with the precision as expected. This way we can confirm the importance and the need of our second Kalman filter.

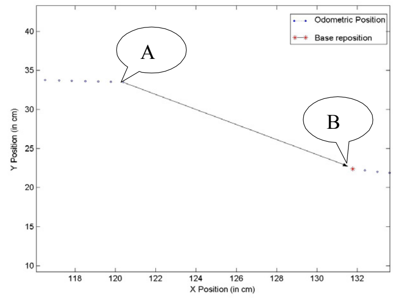


Figure 15: repositioning of the mobile platform. A: dead-reckoning prediction location; B: EKF estimation.

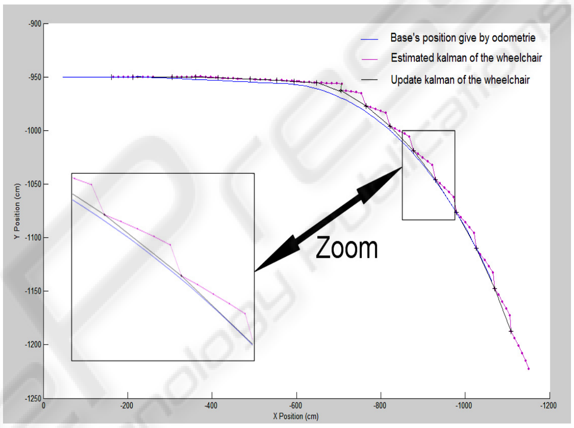


Figure 16: System in a straight trajectory following in a curve.

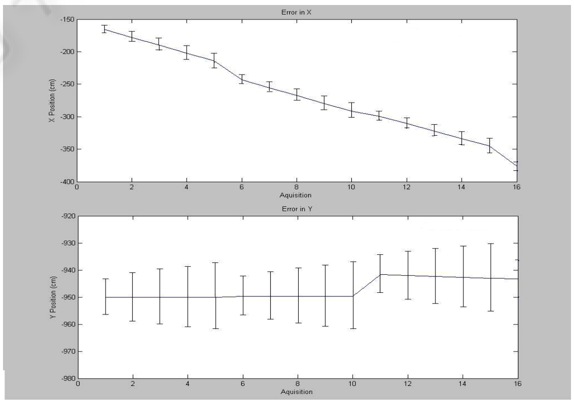


Figure 17: Error of our wheelchair's system in X and Y.

4 CONCLUSIONS

In this article, we studied a target tracking application dedicated to an assistive platform for the disabled. The aim was 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. We have named this architecture the EEKF. 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 precision 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 allows us to solve the problem of the non-linearity of the system due to the triangulation. However, our paradigm integrates a strong coupling of the camshift algorithm and the Kalman estimation state. This new target tracking approach shows that it is possible to compensate the loss of tracking by the camshift, whilst continuing to track.

This paradigm can be considered as a contribution to solving the problem of TMA (target & tracker). The robustness of the filtering process is very important because it is used in a clinical context. Future works will study the integration of a supplementary layer based on a particle filter.

Moreover, in this paper we have presented some original results concerning the clinical tests. These tests have permitted to evaluate the impact of the remote controlled mode of this assistive platform. The results seem to be encouraging. The automatic mode will also be evaluated in the near future.

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