Int. Workshop on Intelligent Robotic Systems, IRS'94, pp 311-318, Grenoble, France, July 1994

Real Time Estimation of 3D Environment with an Active Vision System

Eric Marchand* and François Chaumette**

IRISA / INRIA - Rennes
Campus de Beaulieu
35042 RENNES Cedex, France
fax: (+33) 99.38.38.32

Abstract. This paper deals with the problem of 3D structure estimation of a set of geometrical primitives in an active vision context. Our method is based on the structure from controlled motion approach which consists in constraining the camera motion in order to obtain an optimal estimation of the 3D structure of a geometrical primitive. Since this approach involves to focus on the considered primitive, we present a method for connecting up many estimations. It is centered on visual 2D information and rough estimation of the structure of the studied primitives. It allows us to have an optimal estimation of each primitive of a scene composed of cylinders, segments and polygons. Our method has been implemented with an automata network using the real time SIGNAL language. These automata are able to connect up the different stages of the reconstruction process: selection, focusing, optimal estimation of the selected primitive and, simultaneously, rough estimation of the other ones. Real time experiments on a robotic cell are presented and experimental results are given.

Keyword : Active vision, Structure from motion, Visual servoing, Perception strategy.

1 Problem statement

Many applications in robotics involve a good knowledge of the robot environment. For such applications, the aim of this paper is to obtain a complete and precise description of a scene using the visual data provided by a camera mounted on the end effector of a robot arm.
The observability of the camera motion which is necessary for the 3D structure estimation characterizes a domain of research called dynamic vision [7]. Furthermore, when the camera motion is controlled using vision data, dynamic vision becomes active vision [1][13], which generally provides more precise results. Our method is based on the structure from controlled motion approach, which consists in constraining the camera motion in order to obtain a precise and robust estimation of geometrical primitives such as points, straight lines and cylinders [3][6]. This related work deals with the reconstruction of only one primitive, which is insufficient to consider real scenes containing several objects. In this paper, the reconstruction problem is handled at two levels:

- **local aspect:** Since the method proposed in [6] involves to focus on the considered primitive, it has to be successively performed for each primitive of the scene. This local aspect of the reconstruction is divided into four steps: focusing, recognition, optimal estimation and spatial localization of the primitive ;
- **global aspect:** Developing perception strategies to get the spatial organization of complex scenes is necessary in order to obtain a complete map of the scene. So, we present a method for connecting up successive estimations of different primitives. It has been implemented with an automata network using a real time synchronous language.

The remainder of this paper is organized as follows: the next section describes a method for 3D scene reconstruction based on an active vision paradigm. The third section is devoted to perception strategies and their implementation using an automata network. Real-time experiments dealing with the 3D reconstruction of scenes containing several objects are finally presented.

* Email : marchand@irisa.fr
** Email : chaumett@irisa.fr

2 Scene reconstruction

2.1 General overview

The aim of this work is to investigate the problem of recovering a complete and precise description of a 3D scene using the visual data provided by a camera mounted on the end effector of a robot arm. In particular, we are interested in the reconstruction of environment constituted by cylinders and polyhedral objects. In order to obtain an optimal estimation of the structure of a selected primitive, previous works have shown that it is necessary that the camera focus on it and realizes particular motion. So, if we consider a scene composed of a set of geometrical primitives, the estimation has to be successively realized for each primitive of the scene. For doing that, a database containing 2D visual data is first created. With this database, a selection process focus on a primitive, and after a recognition process based on a statistical test, an optimal estimation of its 3D structure is performed. After each estimation of a primitive the database is updated, then, a new selection is done. When all the database elements have been treated, an exploration process is required in order to ensure that the whole scene has been reconstructed.

2.2 Focusing on a primitive

According to the hypothesis that the scene is composed with polyhedral objects and cylinders, all the objects are projected in the image plane as a set of segments (they will be called limbs in the case of cylinders). The first step in the whole scene reconstruction process is to build a 2D database composed of the set of segments in the image for the initial camera position. The database is simply obtained by extracting the edges in the image with a Shen Castan filter, and using a Hough transform on the edge image (see Figure 5a).
A weight is given to each element of the database. This weight is function of the position of the corresponding segments in the image in keeping with a given strategy. The segment with the highest weight is extracted from the database, then, an optimal estimation based on this segment is performed.
We now describe the different steps of this optimal estimation.

2.3 Structure from controlled motion

In order to get the spatial structure of a primitive, we have used the 3D reconstruction method developed in [6][3], which has been applied to the most representative primitives such as points, straight lines, spheres and cylinders. A geometrical primitive $\mathcal{P}$ is specified by an equation of the type: $h(\underline{x}, \underline{p}) = 0, \forall \underline{x} \in \mathcal{P}$ where parameters $\underline{p}$ represent the location and the 3D structure of the primitive in the scene. These parameters can be estimated using a structure from known motion method. More precisely, they are obtain from the measure of camera velocity T, parameters $\underline{P}$, which describe the position of the primitive in the image, and $\dot{\underline{P}}$, which represent the motion of the primitive in the image due to the camera motion.
When no particular strategy concerning camera motion is defined, important errors on the structure estimation can be observed. This is due to the fact that the method is based on the measure of $\dot{\underline{P}}$, the temporal derivative of $\underline{P}$. The exact value of $\dot{\underline{P}}$ is generally unreachable and the image measurements only supply $\Delta\underline{P}$, the "displacement" of $\underline{P}$ between two successive images. Using $\Delta\underline{P}/\Delta t$, instead of $\dot{\underline{P}}$, induces errors in the 3D reconstruction. To suppress these errors, a fixation tasks is required: the primitive must constantly appear at the same position in the image while the camera is moving. Furthermore, effects of the measurement errors on image data and camera motion can be minimized, leading to a robust and optimal 3D reconstruction if the primitive is located at particular position in the image [6]. The camera motion must therefore be controlled in order to reach these particular positions. Such camera motions combined with the fixation task are performed using visual servoing *i.e*, a control law in closed loop with respect to visual data [8].

Optimal estimation in the case of a cylinder. A cylinder can be represented by an equation of the type:

$$h(\underline{x}, \underline{p}) = (x - x_0)^2 + (y - y_0)^2 + (z - z_0)^2 - (ax + by + cz)^2 - r^2 = 0, \quad \text{with} \begin{cases} a^2 + b^2 + c^2 & = 1 \\ ax_0 + by_0 + cz_0 & = 0, \end{cases} \qquad (1)$$

where r is the radius of the cylinder, a, b, c represent the direction of its axis and x_0, y_0, z_0 are the coordinates of a point belonging to the cylinder axis. Assuming the non degenerate case where the image of a cylinder takes the form of two straight lines $\mathcal{D}_i(\rho_i, \theta_i), (i = 1, 2)$, it is possible to use the proposed 3D reconstruction method to estimate parameters $(a, b, c, x_0, y_0, z_0, r)$. More details about this derivation can be found in [6]. In order to obtain a non-biased and robust estimation, the cylinder must always appear centered $(\rho_1 = -\rho_2)$ and horizontal $(\theta_1 = \theta_2 = \frac{\pi}{2})$ or vertical $(\theta_1 = \theta_2 = 0)$ in the image sequence (see figure 1a) and the camera has to turn around it (see figure 1b).

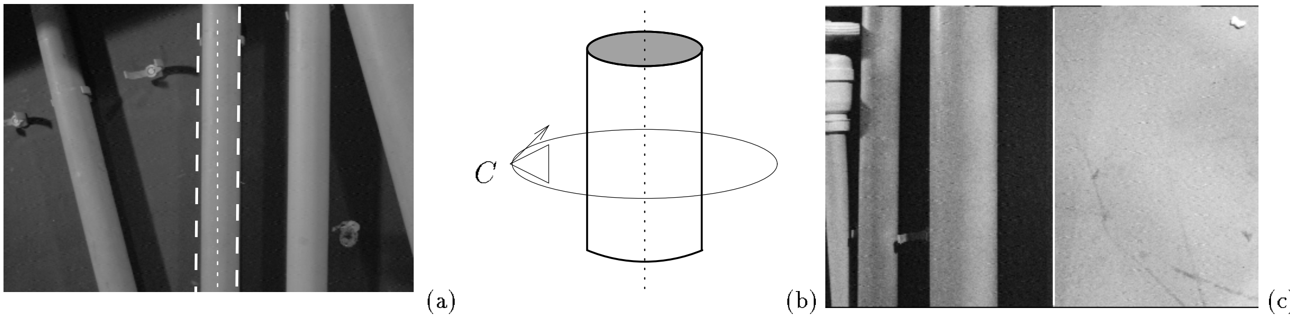

Fig. 1.: *(a) Optimal cylinder position in the image (b) Optimal camera trajectory during the estimation task (c) Optimal straight line position in the image*

Let us note that this method can be applied using only the projection of one limb. A two limbs based estimation provides a more robust and precise estimation. But it is impossible without a priori knowledge on the structure of a cylinder to determine the position in the image of its two limbs. To solve this problem, an estimation based on one limb is first performed. This estimation is good enough to predict the position of the second limb in the image by projecting the 3D estimated cylinder in the image. Then, after a simple matching algorithm, a robust estimation based on the two limbs can be performed.

Optimal estimation in the case of a straight line A straight line is represented by the intersection of two planes:

$$h(\underline{x}, \underline{p}) = \begin{cases} a_1 x + b_1 y + c_1 z = 0 \\ a_2 x + b_2 y + c_2 z + d_2 = 0 \end{cases} \quad \text{with} \begin{cases} a_1^2 + b_1^2 + c_1^2 = 1 \\ a_2^2 + b_2^2 + c_2^2 = 1 \\ a_1 a_2 + b_1 b_2 + c_1 c_2 = 0. \end{cases} \tag{2}$$

In that case, we have to estimate the seven parameters representing the location of the two planes. As previously, the effect of the measurement errors are minimized and the discretization error is suppressed if the line always appears centered in the image ($\rho = \dot{\rho} = 0$) and vertical ($\theta = \dot{\theta} = 0$) in the image sequence (see figure 1c) and if the camera turns around the straight line.

This method provides an optimal reconstruction of 3D parametric geometrical primitives. But, some knowledge on the scene are necessary, such as the nature of the considered primitive. To achieve an optimal estimation by generating adequate camera motion, we first have to determine which kind of primitive (cylinder, straight line,...) the camera is focusing on. In such a way, we have developed a recognition method based on a statistical test. Furthermore, as can be seen on equation (1) and (2), vertices and length of the primitive are not taken into account in the previous method. So, we have developed a method, based on visual servoing, to estimate the length and 3D position of the vertices.

2.4 A maximum likelihood ratio test for primitive recognition

The only information we initially have on the considered scene is composed by a set of 2D segments extracted from the initial image acquired by the camera. We assume that these segments correspond to either a limb of a cylinder, either a 3D segment. As the structure estimation method is peculiar to each kind of primitive, a recognition process is necessary. Vaillant [14] proposed a criterion to determine whether the considered 2D segment corresponds to the projection of a 3D segment or to a cylinder limb. The observed segment is assumed to be part of a cylinder, and according to this hypothesis the radius of the cylinder is estimated. Since a 3D segment is characterized by a zero radius, the criterion proposed in [14] is based on the probability for zero to be in the interval of confidence: $r - 2\sigma < 0 < r$. Our experiments have shown that this criterion is not always able to correctly detect which kind of primitive was observed. So, in order to obtain a robust criterion, we have developed a method based on a maximum likelihood ratio test.
To determine the nature of the observed primitive, we firstly assume that it is a cylinder, and a one limb based estimation is performed. When this estimation is done, two competing hypotheses can be acting, respectively:

- $\boldsymbol{H}_0$: the observed primitive is a straight line (or a segment). This hypothesis implies that we have to find a radius r close to 0 ;
- $\boldsymbol{H}_1$: the observed primitive is a cylinder. This hypothesis implies that we have to find $r = r_1$ with $r_1 > 0$;

A maximum likelihood ratio test is used to determine which one of these two hypotheses is the right one.
Let us denote L_0 and L_1 the likelihood function associated with hypothesis H_0 and H_1. Assuming that the cylinder radius follows a Gaussian law of mean r and variance σ^2, we obtain:

$$L_0 = (\frac{1}{2\pi\sigma^2})^{\frac{N}{2}} e^{-\frac{\sum_{i=1}^{N} {r_i}^2}{2\sigma^2}}, \qquad L_1 = (\frac{1}{2\pi\sigma^2})^{\frac{N}{2}} e^{-\frac{\sum_{i=1}^{N} (r_i - r_1)^2}{2\sigma^2}} \tag{3}$$

The likelihood ratio ξ is given by: $\xi = \log \frac{L_1}{L_0}$ [5]. Substituting in this equation for expressions given in (3) leads to:

$$\xi = -\frac{1}{2\sigma^2}(\sum_{i=1}^{N}(r_i - r_1)^2 - \sum_{i=1}^{N} {r_i}^2) \tag{4}$$

The resulting criterion for determining the nature of the primitive can be stated as follows:

$$\max_{r_1} \xi \geq \lambda$$

where λ is a predetermined threshold.
Optimal parameter $\hat{r}_1$ satisfies the relation $\frac{\partial \xi}{\partial r_1} = 0$, which leads to $\hat{r}_1 = \bar{r}$. Using this relation, ξ can finally be expressed in the form:

$$\xi = \frac{N\bar{r}^2}{2\sigma^2} \tag{5}$$

Clearly, hypothesis H_1 (cylinder) is selected versus hypothesis H_0 (segment) if the obtained value for likelihood ratio ξ is greater than λ. This threshold can be easily determined by experiment. Indeed, when the primitive is a segment, the reconstruction process using one limb gives a low radius, with a very high variance (leading to a small value of ξ). On the other hand, when the primitive is a cylinder, the estimated radius is close to its real value and the variance is small (leading to a high value of ξ).

2.5 Position and length estimation

As previously stated, the optimal estimation described in section 2.3 considers that the primitive has an infinite length. In order to determine this length, the vertices of the primitives have to be observed in the image, which generally necessitates a camera motion. For accuracy issues, this motion is performed in the direction of primitive axis Δ, at a constant range (see figure 2b), and until one of the two vertices of the primitive appears at the image center (see figures 2a and 2b). Once the camera has reached its desired position (m_1 for example), the 3D position of the corresponding end point (M_1) is computed as the intersection between the primitive axis Δ and the camera optical axis. A motion in the opposite direction is then generated to determine the position of the other vertex (M_2). Such camera motion, based on visual data, are performed using the visual servoing approach [8].

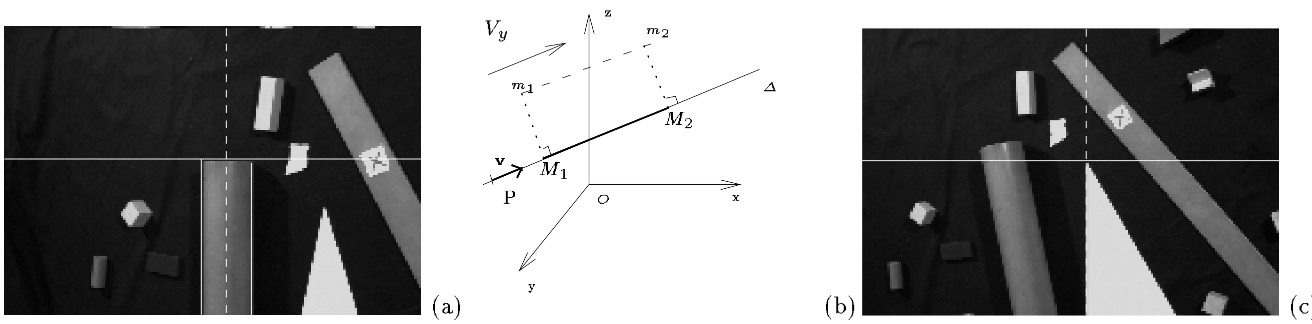

Fig. 2.: *(a) position to achieve in the case of a cylinder (b) camera motion along the primitive (c) position to achieve in the case of a segment*

2.6 Polygons generation

When all the 3D segments of the scene have been reconstructed, it is interesting to group these segments into polygons. Our goal here is to get from a set of segment a set of polygons. In a first time, we look for closed strings of n coplanar 3D segments. A coplanarity condition is given in [16]. At the end of this process, we have a set of strings of coplanar segments corresponding to polygons and some isolated segments or unclosed strings. Next step is devoted to transform these strings of segments in a list of coplanar points: the vertices of the polygon.The equation of the carrier plane can easily be computed by solving a linear system using a least square method. Then, the segments are projected on this plane and the coordinates of the vertices are obtained with the intersection of two neighbor segments [15].
This method gives us all the polygons of the scene. Furthermore, it strongly improves the accuracy of the vertices position (see table 2).

2.7 Exploration problem

This problem, raised by the fact that we must make sure that the whole scene has been reconstructed, has not been yet taken into account in our scheme. Future work will be devoted to determine viewpoints able to bring a new 2D database on which will be performed the complete estimation process. Such viewpoints will be determined using the estimated partial map environment and the part of the 3D space which has not been already observed. Finally, the environment reconstruction process will end when all the primitives in the scene will have been observed.

3 Implementation with an automata network

As previously stated, our method consists in successively focusing on the different primitives of the scene. We thus have developed a method for connecting up several estimations based on the definition of an automata network.

General framework. This whole scheme has been implemented with an automata network using the real time data flow synchronous language SIGNAL [10]. These automata are able to connect up the different stages of the reconstruction process: selection, focusing, optimal estimation of the selected primitive and concurrently, rough estimation of the other ones. Previous works [9][2] have been done to formalize reactive behaviors of vision "guided" robot with Discrete Event Systems (DES) [11]. SIGNAL is an equational synchronous language based on DES. Programming such a state transition networks with this language remains to the same framework and allows to use the same formal tools. Each state of this automata is combined with a certain task such as the creation or the update of the database, the structure estimation process, the camera moving task using visual servoing, etc. The transitions between the states are discrete events and are function of the image data, the estimated parameters of the primitives, and the state of the database. The automata network, which manages the tasks sequencing, has been written in SIGNAL and internal tasks (parameters estimation, visual servoing) have been written in C.

Automata networks. For a given position ϕ of the camera, a database $p(\phi)$ containing the observed segments is created. These segments correspond with the limbs of cylinders or with the projection of segments. A *selection* process ($\mathcal{C}$) (see figure 3) chooses one of the segments. In order to obtain a precise estimation of the structure of the selected primitive, the camera focus on it using visual servoing. The *optimal estimation* process can be represented with a five states automata. First the likelihood ratio test is used to determine what kind of primitive (cylinder or segment) the camera is focusing on ($\mathcal{E}_{cd}$). After this test, an optimal estimation is performed using the appropriate estimation process (in the case of a cylinder, the estimation is based on the two limbs in order to get a better accuracy $\mathcal{E}_c$). Finally, the length and the position of the considered primitive is estimated ($\mathcal{L}_c$ or $\mathcal{L}_d$).

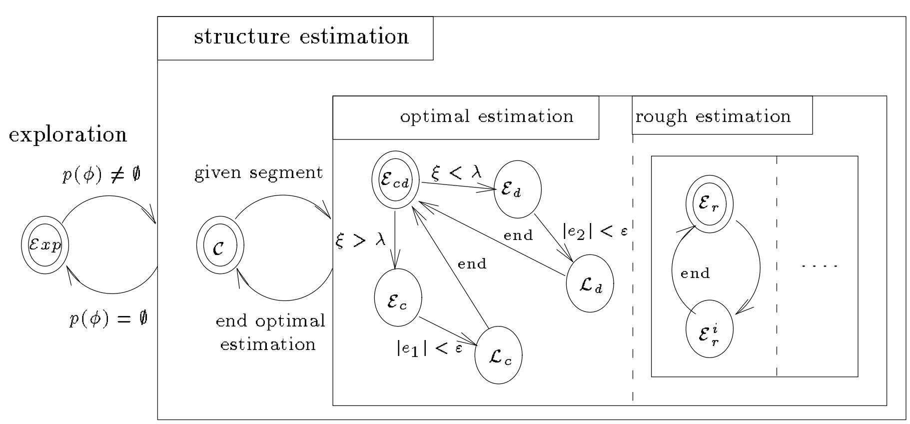

Fig. 3.: *Automata network*

At the same time, a *rough estimation ($\mathcal{E}_r$)* of the structure of the others primitives is done (rough since the camera motion is not adequate for these other primitives, therefore leading to inaccurate results). The interest of this estimation is that it provides 3D informations about the scene which could be used in the exploration process. Each optimal estimation ends when all the primitive parameters have been accurately computed with a sufficient precision. Each rough estimation ends when the corresponding segment gets out from the image or when the optimal estimation ends. The database is then updated, so as the 3D map of the scene, and a new segment is chosen ($\mathcal{C}$). When all the database elements have been treated, an *exploration* process ($\mathcal{E}xp$) should be realized in order to ensure that the whole scene has been estimated.

Application programming. The application of the SIGNAL language to vision and robotics demonstrates its adequacy for task-level robot programming. Tasks and vision algorithms appear to be particularly fitting to the data flow nature of the functions between sensor data, estimation process, and control outputs. Constraining their execution intervals makes it possible to easily specify the sequencing of robotic tasks and perception strategies [12].
There are many interests in using synchronous language like SIGNAL for a robot vision application. SIGNAL is an equational data flow language perfectly suitable to our estimation tasks which are performed using control laws in closed loop with respect to vision data. The implementation of such a loop is easily realized using SIGNAL. The source code of the application is very close to the specification because programming is performed via the specification of constraints or relations between all the involved signals. For the rough estimation tasks, which are simultaneously performed with the optimal estimation tasks, the parallelism is explicitly taken into account at the specification phase, and the SIGNAL compiler manages all the synchronization and communication problems.

4 Experimental results

In order to demonstrate the ability of a robot to get a precise geometric map of its environment, the proposed active 3D reconstruction method has been implemented on an experimental testbed composed of a CCD camera mounted on the end effector of a six degree of freedom cartesian robot (see Figure 4). The image processing part is performed on a commercial board. It consists in tracking the projection of the straight line or the limbs along the image sequence and in determining the (ρ, θ) parameters describing the position of the line in the image. The extraction, maintenance and tracking of the contour segment (in fact a list of edge points) are achieved in 40 ms. The method we have used is described in [4]. It is based on a local and robust matching of the moving edge-points constituting the selected line.

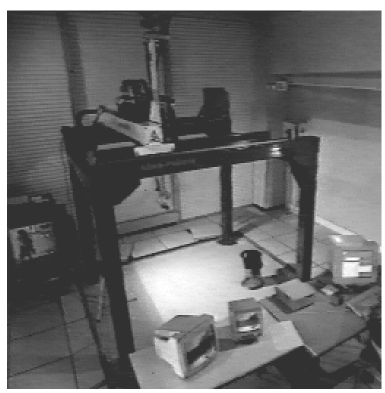

Fig. 4.: *Experimental cell (camera mounted on a 6 dof robot)*

Cylinder scene. The first example shows the reconstruction of a scene made up with a set of 4 cylinders (3 with a 25 mm radius and one with a 40 mm radius). An image of this scene is depicted on Figure 5a. Figure 6a shows the successive estimated radius of the cylinders and their estimated position expressed in the initial camera frame. After each estimation of the parameters of a cylinder, the 2D database and the 3D map is updated. Then a new segment is chosen for the 3D reconstruction process.
Figure 6b shows the reconstruction of a cylinder. It is divided into two parts: the estimation based on one limb and, then the estimation based on the two limbs of the cylinder. This second estimation is far better than the first one. Let us note that the radius r is given with an accuracy less than 0.5 mm when the camera is at one meter from the cylinder. As far as depth z_0 is concerned, the standard deviation is less than 1.5 mm (that is 0.15%).
Figure 6c shows the rough estimation of the second cylinder parameters in parallel with an optimal reconstruction of the first one, then the optimal reconstruction of the second cylinder. Let us note that the rough estimation is far worse than the optimal estimation. It underlines the fact that active vision can significantly improves the estimation accuracy. Figure 5b shows the 3D map of the reconstructed scene.

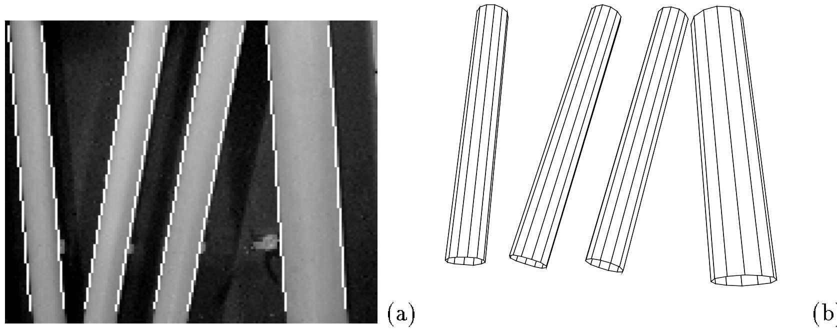

Fig. 5.: *(a) Initial image and extracted segments corresponding to the 2D database (b) reconstructed scene*

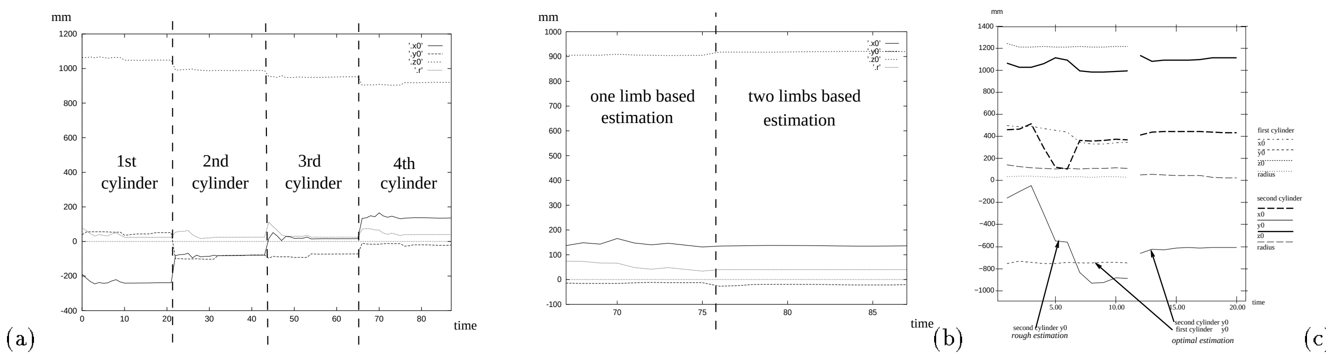

Fig. 6.: *(a) Successive estimated values for the four cylinders (b) zoom on the 4^{th} cylinder (c) Rough estimation of the second cylinder parameters in parallel with an optimal reconstruction of the first one, then optimal reconstruction of the second cylinder*

Cylinder and polygons scene. The second example (see figure 7a) deals with a scene composed by a cylinder (whose radius is 40 mm), a triangle, a rectangular polygon, and an oblong plinth (on the left of the image) which seems to be a cylinder. The first three objects lie in the ground plane, the last one is in another parallel plane located at 20 cm of the first one.
The difficulty here is to make the correct choice on the nature of the considered primitives especially in the case of the plinth. It allows to demonstrate the robustness of the maximum likelihood ratio test that we have presented in section 2.4. Indeed, each time, the correct kind of primitive has been determined after the first estimation based on one limb.

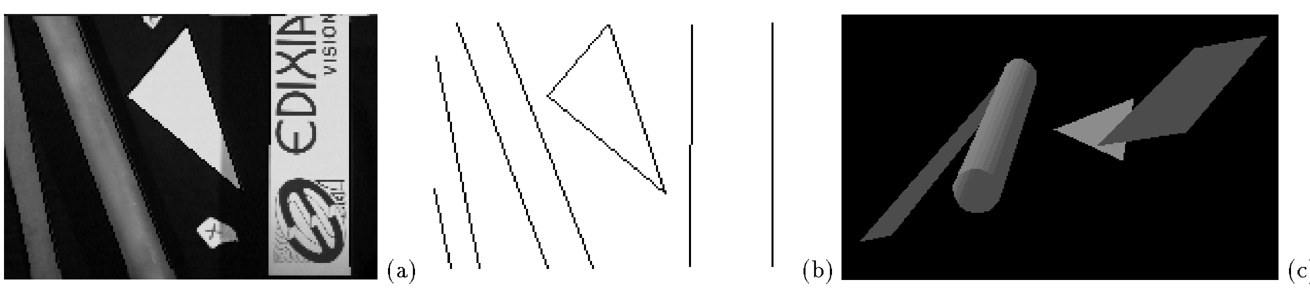

Fig. 7.: *(a) Scene observed from the initial position of the robot. (b) segments corresponding to the 2D database (c) View of the reconstructed scene*

The parameters of the cylinder have been estimated with the same accuracy that in the experiment described above (see table 1). For the triangle which has been recognized as a polygon, the distance between the median plan, which is computed using the six end points of the segments, is never more important than 2 mm. Concerning the spatial position of these points on the line, an error of 1 cm around the correct position can be found. The position of the end points is detected with an accuracy of 1 pixel in the image. Because of the distance between the camera and the segment, a 1 pixel error leads to an error of 1.8 cm in the position of the point on the line. When these points belong to a polygon, the error on their position decreases significantly when they are computed as the intersection between two segments. The position error of the vertices is then around 1 mm (see table 2).

parameters	estimation	standard deviation
a	-0.148098	0.001293
b	0.988958	0.000176
c	-0.005324	0.002089
x_0	-125.90	1.3807
y_0	-11.51	2.8776
z_0	1363.64	2.8564
r	40.51	0.0179
length	655.39	

Table 1.: *Estimated parameters of the cylinder with their standard deviation*

object	segment	real length	length (mm) before correction	after correction	% error
triangle	1	297	277.74	297.75	0.25
	2	183	171.73	185.35	1.28
	3	348	330.17	350.75	0.79
plinth	4	889	886.77	-	0.25
	5	889	876.11	-	1.45
edixia	6	500	466.03	-	6.79
plaque	7	500	489.71	-	2.05
cylinder		658	655.39	-	0.39

Table 2.: *Real and estimated length of the segments and cylinder, the length after correction is given when the segment belong to a polygon*

Acknowledgment

This work was partly supported by the CNRS inter-PRC project VIA (*Vision Intentionnelle et Action*).

References

1. ALOIMONOS Y. Purposive and qualitative active vision. *Proc. on* 10^{th} *ICPR, New Jersey*, Vol. 1, 1990.
2. ALOIMONOS Y., RIVIN E., HUANG L. Designing visual systems: purposive navigation. *in Active Perception, Edited by Aloimonos Y.*, 1993.
3. BOUKIR S. Reconstruction 3D d'un environnement statique par vision active. *PHD Thesis, IRISA, Université de Rennes I, France*, October 1993.
4. BOUKIR S., BOUTHEMY P., CHAUMETTE F., JUVIN D. Real-time contour matching over time in an active vision context. *8^{th}SCIA, Tromso, Norvège*, May 1993.
5. BUSE A. The likelihood ratio, wald and lagrange multiplier test: an expository note. *The American Statistician*, pp.153–157, August 1982.
6. CHAUMETTE F., BOUKIR S., BOUTHEMY P., JUVIN D. Optimal estimation of 3D structures using visual servoing. *Proc of CVPR 94, Seattle, USA*, June 1994.
7. CROWLEY J.L, STELMASZYK P., PUGET P. Measurement and integration of 3D structures by tracking edge lines. *Int. Journal of Computer Vision*, Vol. 8, No. 1:pp. 29–52, July 1992.
8. ESPIAU B., CHAUMETTE F., RIVES P. A new approach to visual servoing in robotics. *IEEE Trans. on Robotics and Automation*, Vol 8, No. 3:pp. 313–326, June 1992.
9. KOŠEKÁ J., BAJCSY R. Discrete event systems for autonomous mobile agents. *Proc. of Intelligent Robotic Systems, Zakopane, Poland*, July 1993.
10. LE GUERNIC P., LE BORGNE M., GAUTIER T., LE MAIRE C. Programming real time application with SIGNAL. In *Another look at real-time programming, Proceedings of the IEEE, 79(9)*, September 1991.
11. WONHAM W.M. RAMADGE P.J. The control of discrete events systems. *Proc. of the IEEE*, 77(1):81–97, january 1989.
12. RUTTEN E., MARCHAND E., CHAUMETTE F. The sequencing of data flow tasks in SIGNAL : application to active vision in robotics. *6th Euromicro Workshop on Real Time Systems, Maerlardalen, Sweden*, June 1994.
13. SANDINI G., TISTARELLI M. Active tracking strategy for monocular depth inference over multiple frames. *IEEE Trans. on PAMI*, Vol. 12, No. 1:pp. 13–27, January 1990.
14. VAILLANT R. Using occluding contours for 3D objects modeling. *Proc of ECCV, Antibes, France*, April 1990.
15. XIE M., RIVES P. Toward dynamic vision. *IEEE Workshop on interpretation of 3D scenes, Austin, Texas*, November 1989.
16. ZHANG Z., FAUGERAS O. Finding clusters and planes frome 3d line segments with application to 3D motion determination. *Proc. of ECCV, Gena, Italie*, June 1992.

This article was processed using the TEX macro package with IRS94 style