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A controller to avoid both occlusions and obstacles during a vision-based navigation task in a cluttered environment

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Abstract— **This paper presents a sensor-based controller allowing to visually drive a mobile robot towards a target while avoiding visual features occlusions and obstacle collisions. We consider the model of a cart-like robot equipped with proximetric sensors and a camera mounted on a pan-platform. The proposed method relies on the continuous switch between three controllers realizing respectively the nominal vision-based task, the obstacle bypassing and the occlusion avoidance. Simulation results are given at the end of the paper.**

I. INTRODUCTION

Visual servoing techniques aim at controlling the robot motion using visual features provided by a camera mounted on the robot or fixed to the environment [1][2]. Different approaches allow to design such control laws. For example, Martinet et al. [3] and Bellot et al. [4] use respectively an H_∞ controller and LMI techniques to perform vision-based tasks. The task function formalism [5] also provides a general framework for designing sensor-based control laws. Indeed, this formalism can be applied to manipulators [6] as well as to nonholonomic mobile robots provided that, in this case, the camera is able to move independantly from the base [7]. The visual servoing techniques mentioned above require that the image features remain always in the field of view of the camera, and that they are never occluded during the whole execution of the task. Most of the works which address this kind of problems are dedicated to manipulator arms. For example, in [8], the authors propose a method allowing to avoid self-occlusions and preserve visibility by path planning in the image for such robots. In [9], Marchand et al. benefit from manipulator arm redundancy to perform a vision-based task while avoiding occlusions, visual features loss and obstacles. In [10], the authors deal with the problem of robust 3D model-based tracking and presents an algorithm which is shown to be robust to occlusions, changes in illumination and miss-tracking. Finally, in [11], Wunsch et al. propose a model-based method allowing a robot to visually track 3D objects while occlusions are continuously predicted.

In this paper, we address the problem of avoiding occlusions and collisions during the execution of a given vision-based task in a cluttered environment. We consider a non-holonomic mobile robot equipped with proximetric sensors and a camera mounted on a pan-platform. The proposed method is in the sequel of previous works where the idea was to merge classical vision-based control to obstacle avoidance techniques based on nonlinear path following design [12], potential field approach [13] or on the task function formalism [14] to perform a visually guided navigation task in a cluttered environment. However, as these works were a first attempt to answer this kind of problem, they were restricted to the case where occlusions could not occur. Therefore, in this article, we aim at extending these techniques to improve the robot abilities and avoid both collisions and occlusions. The proposed strategy consists in designing three controllers, the first one performing the desired vision-based task in the free space, the second one guaranteeing occlusion avoidance whenever a risk of occlusion occurs and the last one insuring non collision in the vicinity of the obstacles. Then, we switch from one controller to the other depending on the risk of occlusion and of collision.

The paper is organized as follows: System modelling and problem statement are given in section II. The different controllers and the control strategy are presented in section III. Finally, simulation results are described in section IV.

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II. MODELLING AND PROBLEM STATEMENT

We consider the model of a cart-like robot with a CCD camera mounted on a pan-platform. The system kinematics

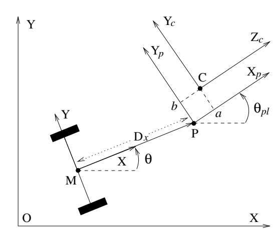

Fig. 1. The mobile robot with pan-platform

is deduced from the whole hand-eye modelling given in [7]:

$$\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \\ \dot{\theta}_{pl} \end{pmatrix} = \begin{pmatrix} \cos\theta & 0 & 0 \\ \sin\theta & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{pmatrix} \begin{pmatrix} v \\ \omega \\ \varpi \end{pmatrix} \tag{1}$$

(x, y) are the coordinates of the robot reference point M with respect to the world frame $\mathcal{F}_O$. θ and θ_{pl} are respectively the direction of the vehicle and the direction of the pan-platform with respect to the x-axis. P is the pan-platform center of rotation, D_x the distance between M and P. We consider the successive frames: $\mathcal{F}_M$ (M, x_M, y_M, z_M) linked to the robot, $\mathcal{F}_P$ (P, x_P, y_P, z_P) attached to the pan-platform, and $\mathcal{F}_C$ $(C, x_C\ , y_C\ , z_C)$ linked to the camera. The transformation between $\mathcal{F}_P$ and $\mathcal{F}_C$ is deduced from a hand-eye calibration method. It consists of an horizontal translation of vector $(a, b, 0)^T$ and a rotation of angle $\frac{\pi}{2}$ about the y_P-axis. The control input is defined by the vector $\dot{q} = (v, \omega, \varpi)^T$, where v and ω are the cart linear and angular velocities, and ϖ is the pan-platform angular velocity with respect to $\mathcal{F}_M$. Let $T^c = (V^c_{\mathcal{F}_C/\mathcal{F}_O}, \Omega^c_{\mathcal{F}_C/\mathcal{F}_O})^T$ be the kinematic screw representing the translational and rotational velocity of $\mathcal{F}_C$ with respect to $\mathcal{F}_O$, expressed in the frame $\mathcal{F}_C$. The kinematic screw is related to the joint velocity vector by the robot jacobian J, that is: $T^c = J\,\dot{q}$. As the camera is constrained to move horizontally it is sufficient to consider a reduced kinematic screw $T^c_{\mathrm{red}} = (V_{y_c}, V_{z_c}, \Omega_{x_c})^T$, and a reduced jacobian matrix J_{red} as follows:

$$T^c_{\mathrm{red}} = \begin{pmatrix} -\sin(\theta_{pl}-\theta) & D_x\cos(\theta_{pl}-\theta)+a & a \\ \cos(\theta_{pl}-\theta) & D_x\sin(\theta_{pl}-\theta)-b & -b \\ 0 & -1 & -1 \end{pmatrix} \begin{pmatrix} v \\ \omega \\ \varpi \end{pmatrix} \quad (2)$$

In addition to the CCD camera, the robot is equipped with proximetric sensors which provide a set of data characterizing locally the closest obstacle.

The problem: We consider the problem of determining a sensor-based closed-loop controller for driving the robot until the camera is positioned in front of a target while avoiding occlusions and obstacles when necessary. For the problem to be well stated, we consider that no obstacle lies in a close neighborhood of the target.

III. Control design

The first three subsections present the controllers dedicated to visual servoing, occlusion avoidance and obstacle bypassing. The global control law is given in the last one.

A. The visual servoing control

Here, we present the nominal vision-based controller in the case that occlusions and collisions do not occur. We consider the visual servoing technique introduced in [6]. This approach relies on the task function formalism, which consists in expressing the desired task as a task function e to be regulated to zero [5]. A sufficient condition that guarantees the control problem to be well conditioned is that e is $\rho-$admissible. Indeed, this property ensures the existence of diffeomorphism between the task space and the state space, so that the ideal trajectory $q_r(t)$ corresponding to $e = 0$ is unique. This condition is fulfilled if $\frac{\partial e}{\partial q}$ is regular around q_r [5].

In our application, the target is made of 4 points, defining an 8-dimensional vector of visual signals s in the camera plane. At each configuration of the robot, the variation of the signals $\dot{s}$ is related to the kinematic screw T^c_{red} by the interaction matrix L_{red} [6]:

$$\dot{s} = L_{\mathrm{red}}\, T^c_{\mathrm{red}} \quad (3)$$

For a point p of coordinates $(x, y, z)^T$ in $\mathcal{F}_C$ projected into a point $P(X, Y)$ in the image plane (see figure 2), L_{red} is directly deduced from the optic flow equations [6] and given by the following matrix which has a reduced number of columns to be compatible with the dimension of T^c_{red}:

$$L_{\mathrm{red}} = \begin{bmatrix} 0 & \frac{X}{z} & XY \\ -\frac{1}{z} & \frac{Y}{z} & 1+Y^2 \end{bmatrix} \quad (4)$$

Following the task function formalism, the task is defined as the regulation of an error function $e_{\mathrm{vs}}(q(t))$ to zero:

$$e_{\mathrm{vs}}(q(t)) = C(s(q(t)) - s^*) \quad (5)$$

where s^* is the desired value of the visual signal and $q = [l,\, \theta,\, \theta_{pl}]^T$, l representing the curvilinear abscissa of the robot. C is a full-rank 3×8 combination matrix which allows to take into account more visual features than available degrees of freedom. A simple way to choose C is to consider the pseudo-inverse of the interaction matrix, that is $C = (L^T_{\mathrm{red}} L_{\mathrm{red}})^{-1} L^T_{\mathrm{red}}$ as proposed in [6]. In this way, the positioning task jacobian $\frac{\partial e_{\mathrm{vs}}}{\partial q} = C L_{\mathrm{red}} J_{\mathrm{red}}$ can be simplified into J_{red}, which is always invertible as $\det(J_{\mathrm{red}}) = D_x \neq 0$. The ρ-admissibility property is then insured. The control law design relies on this property. Indeed, classically, a kinematic controller can be determined by imposing an exponential convergence of e_{vs} to zero:

$$\dot{e}_{\mathrm{vs}} = C L_{\mathrm{red}} J_{\mathrm{red}} \dot{q} = J_{\mathrm{red}} \dot{q} = -\lambda_{\mathrm{vs}} e_{\mathrm{vs}} \quad (6)$$

where λ_{vs} is a positive scalar or a positive definite matrix. From this last relation together with equations (2), (3), (5) and thanks to the $\rho-$admissibility property, we can deduce:

$$\dot{q} = \dot{q}_{\mathrm{vs}} = -\lambda_{\mathrm{vs}} J^{-1}_{\mathrm{red}} e_{\mathrm{vs}} \quad (7)$$

B. The occlusion avoidance control

Now, we suppose that an occluding object $\mathcal{O}$ is present in the camera line of sight. Its projection appears in the image plane as shown on figure 2 and we denote by Y^-_{obs} and Y^+_{obs} the ordinates of its left and right borders. X_{im} and Y_{im} correspond to the axes of the frame attached to the image plane. The proposed strategy only relies on the detection of the two borders of $\mathcal{O}$. As the camera is constrained to move in the horizontal plane, there is no loss of generality in stating the reasoning on Y^-_{obs} and Y^+_{obs}.

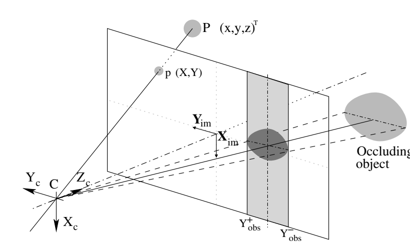

Fig. 2. Projection of the occluding object in the image plane

Our goal is to define a task function allowing to preserve the visual features visibility in the image. To this aim, we have chosen to use the redundant task function formalism [5]. This formalism has been already used to perform a vision-based task while following a trajectory [6] or avoiding joint limits, singularities [15] and occlusions [9] for manipulators. It has also been used to avoid obstacles in visually guided navigation tasks for mobile robots [14]. Let e_1 be a redundant task, that is a low-dimensioned task which does not constraint all degrees of freedom of the robot. Therefore, e_1 is not ρ-admissible and an infinity of ideal trajectories q_r corresponds to the regulation of e_1 to zero. The basic idea of the formalism is to benefit from this redundancy to perform an additional objective. This latter can be modelled as a cost function h to be minimized under the contraint that e_1 is perfectly performed. The resolution of this optimization problem leads one to define e as follows [5]:

$$e = W^+ e_1 + \beta(I - W^+ W) g$$

where $W^+ = W^T(WW^T)^{-1}$ is the pseudo-inverse of W, $g = \frac{\partial h}{\partial q}$ and β is a positive scalar, sufficiently small in the sense defined in [5]. Under some assumptions (which are verified if $W = \frac{\partial e_1}{\partial q}$), the task jacobian $\frac{\partial e}{\partial q}$ is positive-definite around q_r, insuring that e is ρ-admissible [5].

Our objective is to apply these theoretical results to avoid occlusions while keeping the target in the image. We have chosen to define the occlusion avoidance as the prioritary task. The target tracking will then be considered as the secondary objective and will be modelled as a criterion h_s to be minimized. We propose the following occlusion avoidance task function e_{oa}:

$$e_{\mathrm{oa}}(q(t)) = W^+_{\mathrm{occ}} e_{\mathrm{occ}} + \beta_{\mathrm{oa}}(I - W^+_{\mathrm{occ}} W_{\mathrm{occ}}) g_s \qquad (8)$$

e_{occ} is the redundant task function allowing to avoid the occlusions, $W_{\mathrm{occ}} = \frac{\partial e_{\mathrm{occ}}}{\partial q}$, $g_s = \frac{\partial h_s}{\partial q}$, and β_{oa} is a positive scalar as explained above. We propose the following criterion to track the target and keep it in the camera line of sight:

$$h_s = \frac{1}{2}(s - s^*)^T (s - s^*) \Rightarrow g_s = ((s - s^*)^T L_{\mathrm{red}} J_{\mathrm{red}})^T \qquad (9)$$

Now, let us define the prioritary task function e_{occ} to avoid occlusions. Considering figure 3, we denote by (X_{s_j}, Y_{s_j})

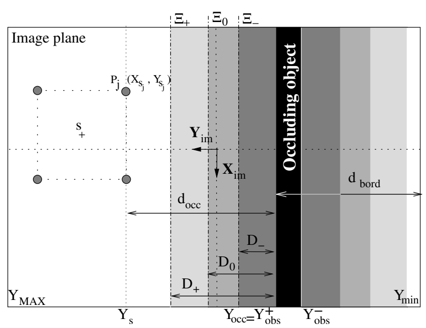

Fig. 3. Definition of the relevant distances for occlusion avoidance

the coordinates of each point P_j of the target in the image frame, $Y_{\min}$ and $Y_{\max}$ representing the ordinates of the two image sides. We introduce the following distances:

- d_{occ} characterizes the distance before occlusion, that is the shortest distance between the visual features s and the occluding object $\mathcal{O}$. It can be defined as:

$$d_{\mathrm{occ}} = \min\left(\min_j \left|Y_j - Y^+_{\mathrm{obs}}\right|, \min_j \left|Y_j - Y^-_{\mathrm{obs}}\right|\right) = |Y_{\mathrm{s}} - Y_{\mathrm{occ}}| \quad (10)$$

where Y_{s} is the ordinate of the closest point P_j to object $\mathcal{O}$, while Y_{occ} represents the closest border of $\mathcal{O}$ to the visual features (in the case of figure 3, $Y_{\mathrm{occ}} = Y^+_{\mathrm{obs}}$).

- d_{bord} is defined by the distance separating the occluding object $\mathcal{O}$ and the opposite image side to the visual features:

$$d_{\mathrm{bord}} = \min\left(\left|Y^+_{\mathrm{obs}} - Y_{\max}\right|, \left|Y^-_{\mathrm{obs}} - Y_{\min}\right|\right) = |Y_{\mathrm{occ}} - Y_{\mathrm{bord}}|$$

where Y_{bord} corresponds to the image border towards which the occluding object must move to leave the image without occluding the target (see figure 3).

- D_+ defines an envelope Ξ_+ delimiting the region inside which the risk of occlusion is detected.

- D_0 and D_- define two additional envelopes Ξ_0 and Ξ_-. They respectively surround the critical zone inside which it is necessary to start avoiding occlusion and the region where the danger of occlusion is the highest. They will be used in the sequel to determine the global controller.

From these definitions, we propose the following redundant task function e_{occ}:

$$e_{\mathrm{occ}} = \begin{pmatrix} \tan\left(\frac{\pi}{2} - \frac{\pi}{2} \cdot \frac{d_{\mathrm{occ}}}{D_+}\right) \\ d_{\mathrm{bord}} \end{pmatrix} \qquad (11)$$

The first component allows to avoid target occlusions: indeed, it increases when the occluding object is getting closer to the visual features and becomes infinite when d_{occ} tends to zero. On the contrary, it decreases when the occluding object is moving far from the visual features and vanishes when d_{occ} equals D_+. Note that, $\forall d_{\mathrm{occ}} \geq D_+$, e_{occ} is maintained to zero. The second component makes the occluding object go out of the image, which is realized when d_{bord} vanishes. Let us remark that these two tasks must be compatible (that is, they can be realized simultaneously) in order to guarantee the control problem to be well stated. This condition is fulfilled by construction thanks to the choice of d_{occ} and d_{bord} (see figure 3). Now, let us determine $W_{\mathrm{occ}} = \frac{\partial e_{\mathrm{occ}}}{\partial q}$. We get :

$$W_{\mathrm{occ}} = \begin{pmatrix} -\frac{1}{D_+}\frac{\pi}{2}\varepsilon_{\mathrm{occ}}\left(1 + \tan^2\left(\frac{\pi}{2} - \frac{\pi}{2} \cdot \frac{d_{\mathrm{occ}}}{D_+}\right)\right)\left(\frac{\partial Y_{\mathrm{s}}}{\partial q} - \frac{\partial Y_{\mathrm{occ}}}{\partial q}\right) \\ \varepsilon_{\mathrm{bord}} \frac{\partial Y_{\mathrm{occ}}}{\partial q} \end{pmatrix}$$

where $\varepsilon_{\mathrm{occ}} = \mathrm{sign}(Y_{\mathrm{s}} - Y_{\mathrm{occ}})$ and $\varepsilon_{\mathrm{bord}} = \mathrm{sign}(Y_{\mathrm{occ}} - Y_{\mathrm{bord}})$ while $\frac{\partial Y_{\mathrm{s}}}{\partial q}$ and $\frac{\partial Y_{\mathrm{occ}}}{\partial q}$ are deduced from the optic flow equations as follows:

$$\left\{ \begin{array}{lcl} \frac{\partial Y_{\mathrm{s}}}{\partial q} & = & \begin{pmatrix} -\frac{1}{z_s} & \frac{Y_{\mathrm{s}}}{z_s} & 1 + Y_{\mathrm{s}}^2 \end{pmatrix} J_{\mathrm{red}} \\ \frac{\partial Y_{\mathrm{occ}}}{\partial q} & = & \begin{pmatrix} -\frac{1}{z_{\mathrm{occ}}} & \frac{Y_{\mathrm{occ}}}{z_{\mathrm{occ}}} & 1 + Y_{\mathrm{occ}}^2 \end{pmatrix} J_{\mathrm{red}} \end{array} \right. \qquad (12)$$

where z_s and z_{occ} are the depth of the target and of the occluding object expressed in frame $\mathcal{F}_C$.

At this step, the task function e_{oa} guaranteeing the occlusion avoidance while keeping the target in the image is completely determined (see relation (8)). Now, it remains to design a controller allowing to regulate it to zero. As W_{oa} and β_{oa} are chosen to fulfill the assumptions of the redundant task formalism [5], the task jacobian $\frac{\partial e_{\mathrm{oa}}}{\partial q}$ is positive definite around the ideal trajectory and e_{oa} is ρ-admissible. This result also allows to simplify the control synthesis as it can be shown that a controller making e_{oa} vanish is given by [6]:

$$\dot{q} = \dot{q}_{\mathrm{oa}} = -\lambda_{\mathrm{oa}} e_{\mathrm{oa}} \qquad (13)$$

where λ_{oa} is a positive scalar or a positive definite matrix.

C. The obstacle avoidance control

The avoidance strategy is based on the proximetric data. From these data, we compute a set of values characterizing locally any obstacle located at a distance inferior to d_+ (see figure 4). We obtain a couple $(d_{\rm av}, \alpha)$, where $d_{\rm av}$ is the signed distance between M and the closest point Q on the obstacle, and α is the angle between the tangent to the obstacle at Q and the robot direction. Note that there exists two angles α corresponding to the two possible directions for the avoidance motion. As the obstacle can also be an occluding object, we propose to maintain the target visibility by defining α so that the robot moves around the obstacle in the direction given by the pan-platform.

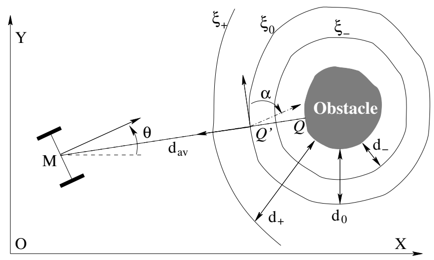

Fig. 4. Obstacle avoidance

Consider figure 4. Around each obstacle, three envelopes are defined. The first one ξ_+ located at a distance $d_+ > 0$ surrounds the zone inside which the obstacle is detected by the robot. For the problem to be well stated, the distance between two obstacles is assumed to be greater than $2d_+$ to prevent the robot from considering several obstacles simultaneously. The second one ξ_0, located at a lower distance $d_0 > 0$ constitutes the virtual path along which the reference point M will move around the obstacle. The last one ξ_- defines the region inside which the risk of collision is maximal (this envelope will be used in the sequel to define the global controller). Using the path following formalism introduced in [16], we define a mobile frame on ξ_0 whose origin Q' is the orthogonal projection of M. During obstacle avoidance, the robot linear velocity is supposed to be kept constant. Let $\delta = d_{\rm av} - d_0$ be the signed distance between M and Q'. With respect to the moving frame, the dynamics of the error terms (δ, α) is described by the following system:

$$\left\{ \begin{array}{l} \dot{\delta} = v \sin\alpha \\ \dot{\alpha} = \omega - v\chi\cos\alpha \end{array} \right. \quad \text{with } \chi = \frac{\frac{\sigma}{R}}{1 + \frac{\sigma}{R}\delta} \tag{14}$$

where $\sigma = \{-1, 0, +1\}$ depending on the sense of the robot motion around the obstacle and R is the curvature radius of the obstacle. The path following problem is classically defined as the search for a controller ω allowing to steer the pair (δ, α) to $(0, 0)$ under the assumption that v never vanishes to preserve the system controllability. Here, our goal is to solve this problem using the task function formalism. To this aim, we have to find a task function whose regulation to zero will make δ and α vanish while insuring $v \neq 0$. We propose the following redundant task function $e_{\rm av}$:

$$e_{\rm av} = \left(\begin{array}{c} l - v_r t \\ \delta + k\alpha \end{array} \right) \tag{15}$$

where l is the curvilinear abscissa of point M and k a positive gain to be fixed. The first component of $e_{\rm av}$ allows to regulate the linear velocity of the mobile base to a nonzero constant value[1] v_r. In this way, the linear velocity never vanishes, guaranteeing that the control problem is well stated and that the robot will not remain stuck on the security envelope ξ_0 during the obstacle avoidance. The second component of $e_{\rm av}$ can be seen as a sliding variable whose regulation to zero makes both δ and α vanish (see [17] for a detailed proof). Therefore, the regulation to zero of $e_{\rm av}$ guarantees that the robot follows the security envelope ξ_0, insuring non collision. As the chosen task function does not constraint the whole degrees of freedom of the robot, we use the redundant task function formalism to perform a secondary objective while the obstacle avoidance is realized. We propose to model this objective to avoid target loss and occlusions at best and we define the corresponding cost function by $h_{\rm occ} = \frac{1}{d_{\rm occ}}$. This criterion can be seen as a potential function allowing to avoid both occlusions and target loss as $d_{\rm occ}$ is defined with respect to the image borders when no occluding object lies in the image plane. The global task function $e_{\rm ob}$ is then given by:

$$e_{\rm ob} = W_{\rm av}^+ e_{\rm av} + \beta_{\rm ob}(I - W_{\rm av}^+ W_{\rm av}) g_{\rm occ} \tag{16}$$

where $\beta_{\rm ob}$ is a positive scalar. We deduce $g_{\rm occ}$ and $W_{\rm av}$ by differentiating equations (10) and (15):

$$\begin{array}{rcl} g_{\rm occ} & = & \dfrac{\partial h_{\rm occ}}{\partial q} = -\dfrac{1}{d_{\rm occ}^2}\dfrac{\partial d_{\rm occ}}{\partial q} = -\dfrac{\varepsilon_{\rm occ}}{d_{\rm occ}^2}\left(\dfrac{\partial Y_{\rm s}}{\partial q} - \dfrac{\partial Y_{\rm occ}}{\partial q}\right)^T \\ W_{\rm av} & = & \dfrac{\partial e_{\rm av}}{\partial q} = \left(\begin{array}{ccc} 1 & 0 & 0 \\ \sin\alpha - k\chi\cos\alpha & k & 0 \end{array} \right) \end{array}$$

where $\frac{\partial Y_{\rm s}}{\partial q}$ and $\frac{\partial Y_{\rm occ}}{\partial q}$ are defined by relation (12). Following the redundant task function formalism, a controller making $e_{\rm ob}$ vanish is given by:

$$\dot{q} = \dot{q}_{\rm ob} = -\lambda_{\rm ob} e_{\rm ob} \tag{17}$$

where $\lambda_{\rm ob}$ is a positive scalar or a positive definite matrix.

D. The global controller

There exist two approaches for sequencing tasks. In the first one, the switch between two successive tasks is dynamically performed using the definition of a differential structure on the robot state space [18], or benefiting from the redundant task function formalism to stack elementary tasks and design control laws guaranteeing smooth transitions [19]. The second class of tasks sequencing techniques relies on convex combinations between the successive task functions [7][14] or the successive controllers [12][13]. In that case, applications can be more easily carried out, but it is usually harder to guarantee the task feasibility. The control proposed here relies on the second approach. Our idea is to combine the three previously defined controllers to drive the robot the best way depending on the environment. To this aim, we introduce two parameters $\mu_{\rm oa}$ and $\mu_{\rm ob} \in [0, 1]$ depending on the risk of occlusion and of collision as follows:

[1] v_r must be chosen small enough to let the robot sufficiently slow down to avoid collision when entering the critical zone.

- If the occluding object $\mathcal{O}$ lies outside the region defined by Ξ_0 or is not in the image and if there is no obstacle in the robot vicinity, μ_{oa} and μ_{ob} are fixed to 0. Only $\dot{q}_{\mathrm{vs}}$ must be sent to the robot in this case.

- If the visual features enter the zone delimited by Ξ_0, the danger of occlusion becomes higher and μ_{oa} progressively increases to reach 1 when they cross Ξ_-. If the visual features naturally leave the critical zone defined by Ξ_0, μ_{oa} goes back to 0 without having reached 1. On the contrary, if Ξ_- is crossed, μ_{oa} is fixed and maintained to 1 until the object $\mathcal{O}$ leaves the image ($d_{\mathrm{bord}} = 0$) or at least goes out the critical zone ($d_{\mathrm{occ}} \geq D_0$). When one of these two events occurs, μ_{oa} is progressively reduced from 1 to 0 and vanishes once the visual features cross Ξ_+. Following this reasoning, μ_{oa} depends on the distance between the occluding object and the visual features in the image, namely d_{occ}. Let OCCLU be the flag indicating that μ_{oa} has reached its maximal value and D_{leave} the value of the distance d_{occ} for which the leaving condition has been fulfilled. We propose the following expression:

$$\begin{cases} \mu_{\mathrm{oa}} = 0 & \text{if } d_{\mathrm{occ}} > D_0 \text{ and } \mathrm{OCCLU} = 0 \\ \mu_{\mathrm{oa}} = \frac{d_{\mathrm{occ}} - D_0}{D_- - D_0} & \text{if } d_{\mathrm{occ}} \in [D_-, D_0] \text{ and } \mathrm{OCCLU} = 0 \\ \mu_{\mathrm{oa}} = \frac{d_{\mathrm{occ}} - D_+}{D_{\mathrm{leave}} - D_+} & \text{if } d_{\mathrm{occ}} \in [D_{\mathrm{leave}}, D_+] \\ & \text{and } (d_{\mathrm{bord}} = 0 \text{ or } d_{\mathrm{occ}} \geq D_0) \\ \mu_{\mathrm{oa}} = 1 & \text{otherwise} \end{cases}$$

- If the mobile base enters the zone surrounded by ξ_0 ($d_{\mathrm{av}} < d_0$), the danger of collision rises and μ_{ob} is continuously increased from 0 to reach 1 when $d_{\mathrm{av}} \leq d_-$. If ξ_- is never crossed, μ_{ob} is brought back to 0, once $d \geq d_0$. If μ_{ob} reaches 1, the collision risk is maximum and a flag AVOID is enabled. As the robot safety is considered to be the most important objective, the global controller must be designed so that only $\dot{q}_{\mathrm{ob}}$ is applied to the vehicle once μ_{ob} has reached 1. In this way, it is possible to guarantee non collision while occlusions are avoided at best. The robot is then brought back on the security envelope ξ_0 and follows it until the condition to leave is fulfilled. This event occurs when the camera and the mobile base have the same direction ($\theta = \theta_{pl}$). A flag LEAVE is then positioned to 1 and μ_{ob} is decreased to vanish on ξ_+. Therefore, μ_{ob} depends on distance d_{av} as follows:

$$\begin{cases} \mu_{\mathrm{ob}} = 0 & \text{if } d_{\mathrm{av}} > d_0 \text{ and } \mathrm{AVOID} = 0 \\ & \text{and } \mathrm{LEAVE} = 0 \\ \mu_{\mathrm{ob}} = \frac{d_{\mathrm{av}} - d_0}{d_- - d_0} & \text{if } d_{\mathrm{av}} \in [d_-, d_0] \text{ and } \mathrm{AVOID} = 0 \\ \mu_{\mathrm{ob}} = \frac{d_{\mathrm{av}} - d_+}{d_s - d_+} & \text{if } d_{\mathrm{av}} \in [d_s, d_+] \text{ and } \mathrm{LEAVE} = 1 \\ \mu_{\mathrm{ob}} = 1 & \text{otherwise} \end{cases}$$

where d_s is defined by the distance d_{av} when LEAVE $= 1$.

This reasoning is summarized on table I. Using this table and recalling that $\dot{q}_{\mathrm{vs}}$, $\dot{q}_{\mathrm{oa}}$ and $\dot{q}_{\mathrm{ob}}$ are given by equations (7), (13) and (17), we propose the following global controller:

$$\dot{q} = (1-\mu_{\mathrm{oa}})(1-\mu_{\mathrm{ob}})\dot{q}_{\mathrm{vs}} + (1-\mu_{\mathrm{ob}})\mu_{\mathrm{oa}}\dot{q}_{\mathrm{oa}} + \mu_{\mathrm{ob}}\dot{q}_{\mathrm{ob}} \quad (18)$$

Remark 1: The presence of an occluding object in the image does not necessarily mean that a collision may occur. Indeed, an obstacle may be detected by the camera before it becomes dangerous for the mobile base. This is the reason why we consider two different controllers $\dot{q}_{\mathrm{oa}}$ and $\dot{q}_{\mathrm{ob}}$ depending on the occlusion occurs far from the obstacle or close to it.

TABLE I
THE SWITCHING STRATEGY

	$\mu_{\mathrm{oa}} = 0$	$\mu_{\mathrm{oa}} \in]0,1[$	$\mu_{\mathrm{oa}} = 1$
$\mu_{\mathrm{ob}} = 0$	$\dot{q} = \dot{q}_{\mathrm{vs}}$	$\dot{q}_{\mathrm{vs}} \longleftrightarrow \dot{q}_{\mathrm{oa}}$	$\dot{q} = \dot{q}_{\mathrm{oa}}$
$\mu_{\mathrm{ob}} \in]0,1[$	$\dot{q}_{\mathrm{vs}} \longleftrightarrow \dot{q}_{\mathrm{ob}}$	$\dot{q} = f(\dot{q}_{\mathrm{vs}}, \dot{q}_{\mathrm{oa}}, \dot{q}_{\mathrm{ob}})$	$\dot{q}_{\mathrm{oa}} \longleftrightarrow \dot{q}_{\mathrm{ob}}$
$\mu_{\mathrm{ob}} = 1$	$\dot{q} = \dot{q}_{\mathrm{ob}}$	$\dot{q} = \dot{q}_{\mathrm{ob}}$	$\dot{q} = \dot{q}_{\mathrm{ob}}$

Remark 2: The different envelops are chosen close enough to reduce the transition phase duration. Recalling that μ_{oa} and μ_{ob} are maintained to 1 once they have reached this value, the control strategy is built to insure that the robot will be rapidly controlled by the most relevant controller. In this way, the risks of instability, target loss or collision during the switch are significantly reduced and the task feasibility can be considered to be guaranteed.

IV. SIMULATION RESULTS

We have simulated a mission whose objective is to position the camera in front of a given target. The environment has been cluttered with two cylindric obstacles which may occlude the camera or represent a danger for the mobile base. For this test, D_-, D_0 and D_+ have been respectively fixed to 40, 60 and 75 pixels, and d_+, d_0, d_- to 0.7m, 0.55m, and 0.45m. The sampling period is the same as on our real robot, that is $T_s = 150$ms. The obtained results are presented on figures 5, 6 and 7. As shown on these figures, the task is correctly performed as occlusions and collisions never occur. At the beginning of the task, there is no risk of occlusion or collision, the robot is only controlled by $\dot{q}_{\mathrm{vs}}$ and starts converging towards the target. When the vehicle enters the vicinity of the first encountered obstacle, μ_{ob} is progressively increased (see figure 6), and the robot first follows ξ_0 before being brought back on ξ_+ once the leaving condition has been fulfilled. During this phase, μ_{oa} remains equal to 0 as there is no risk of occlusion. When ξ_+ is crossed, μ_{ob} vanishes and the robot executes once again the nominal vision-based task. However, the second obstacle induces a risk of both collision and occlusion. μ_{oa} and μ_{ob} are then continuously increased to reach 1 and the sole controller $\dot{q}_{\mathrm{ob}}$ is used to guarantee a safe motion for the robot. Therefore, the vehicle is controlled to follow ξ_0 while occlusions are avoided at best. When the leaving condition is obtained, μ_{ob} is rapidly decreased while μ_{oa} has already vanished because the avoidance motion has made the obstacle leave the image plane. Once again, the robot starts converging towards the target. However, the target and the obstacle positions have been chosen to insure that this motion brings the vehicle back towards the obstacle. As a consequence, instead of vanishing, μ_{ob} rises again, making the robot avoid the obstacle. Thanks to the avoidance motion, the vehicle leaves progressively the obstacle vicinity and μ_{ob} vanishes. The sole visual servoing controller is then applied to the robot and the camera finally reaches its desired position, realizing perfectly the task.

V. CONCLUSION

The proposed sensor-based controller allows a mobile robot to perform safely a vision-based task in a cluttered

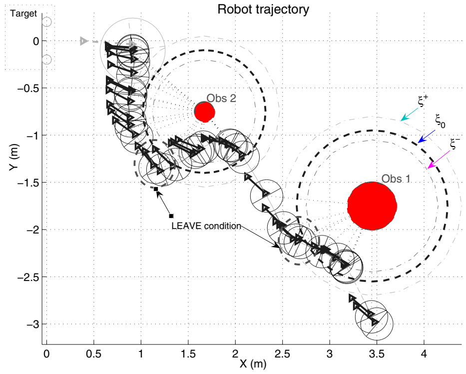

Fig. 5. Robot trajectory

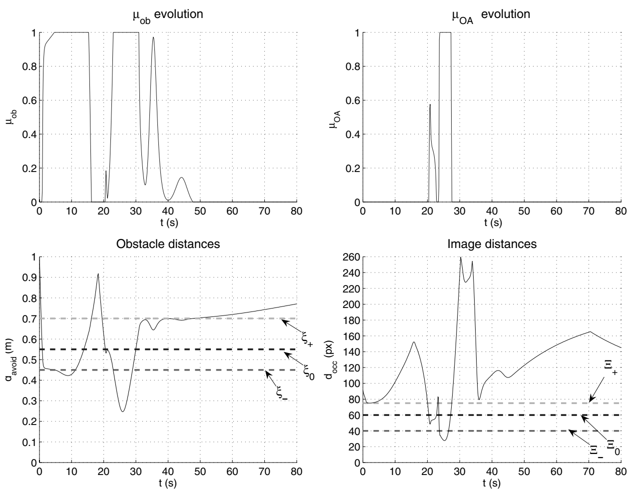

Fig. 6. Evolution of μ and relevant distances for the task realization

environment. The method relies on the switch between different controllers depending on the risk of collision and occlusion. The obtained results are quite satisfying and these control laws are currently being experimented on our mobile robots. However, this work is restricted to missions where occlusions can be *effectively* avoided, which is not the case of all robotic tasks. Therefore, further extensions will have to accept that occlusions may occur rather than to avoid them. A dynamical sequence of the controllers could also be interesting to provide better theoretic feasibility conditions.

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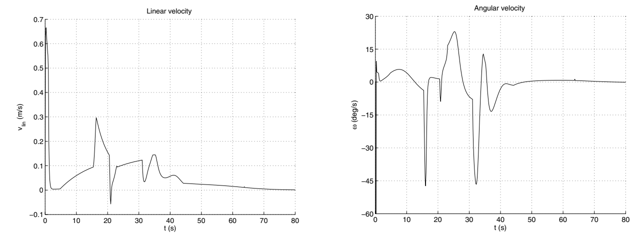

The obtained control inputs are consistent with the obtained robot trajectory and remain continuous during the whole execution of the task, although some jumps only due to the chosen scale seem to appear in their evolution.

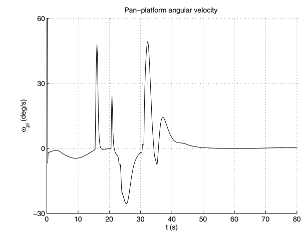

Fig. 7. Evolution of the control inputs

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