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Control Camera and Light Source Positions using Image Gradient Information

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Abstract— **In this paper, we propose an original approach to control camera position and/or lighting conditions in an environment using image gradient information. Our goal is to ensure a good viewing condition and good illumination of an object to perform vision-based task (recognition, tracking, etc.). Within the visual servoing framework, we propose solutions to two different issues: maximizing the brightness of the scene and maximizing the contrast in the image. Solutions are proposed to consider either a static light and a moving camera, eitheror a moving light and a static/moving camera. The proposed method is independent of the structure, color and aspect of the objects. Experimental results on both synthetic and real images are finally presented.**

I. OVERVIEW

In this paper we investigate the problem of relative placement between an object, a camera and a light source. Ensuring an optimal placement of the camera or of a light source is an essential step in the development of industrial vision systems. Indeed good lighting conditions ensure good image quality and thus enable to simplify or improve reliability of vision algorithms.

Most of the research regarding illumination are focused on shape from shading (eg, [24], light source position estimation (eg, [9]), tracking (eg, [14], [7]). Some of these works assume the conservation of the point luminance over the image sequence [12] but most of them assume more complex illumination models such as the Phong model [19] or the Torrance-Sparrow model [22]. Nevertheless, few works have considered lighting conditions, and especially illumination control or camera control wrt. illumination conditions, within robotics tasks or active vision.

Sakane and Sato [20] present an automatic planning method of light source and camera placement to minimize shadow caused by the surrounding environment. Cowan et al. [2][4] extend the CAD-based system presented in [3] in order to maintain the brightness of the object surface within the dynamic range of the camera [2] (the surface must not be either too bright or too dark). Furthermore light placement has to be optimized for edge detection [4]. The method presented in [3] is used to synthesize 3-D regions of acceptable camera locations for the specified task. Each criterion (spatial resolution, field of view, visibility, edge contrast, camera dynamic range, etc.) allows to define 3-D regions which provide the space of possible viewpoints when they intersect. The system ICE presented in [23] determines the best camera view and light source location to optimally observe a given edge and to maximize the accuracy of its position. The camera and light positions are chosen such that measurements data can be obtained with minimum uncertainty. Mainly contrast on the edge is considered and the system is based on the illumination model described in [22]. Murase and Nayar [17] used an eigenspace-based method to determine the illumination for which the objects are most distinguishable for recognition purpose. More recently Eltoft et al. [5] proposed a system than can optimally enhance image features such as edges or points by active scene illumination. More complex illumination models are considered [11], [21]. Let us not that in most of these systems a good knowledge of the object or of the environment has to be known in order to evaluate off-line the various criteria related to the specified task and to determine the best light-source and camera location.

In the different context of 2D tracking, Hager et al.[8] derive the interaction matrix that link the time variation of image intensity to the 2D motion of an object. In this paper, we also consider models used in motion analysis and determine the variation of image intensity due to camera or light source motion. Obviously the underlying model, based on the derivation of the *optical flow constraint equation* (OFCE) is, apparently, very restrictive. Nevertheless, experimental results show that it remains usable in many cases.

This paper presents a method to control camera position with respect to a light source. Our goal is to ensure a good illumination of an object or a good camera location to be able to perform efficiently vision-based tasks. Within the visual servoing framework, we propose solutions to two different issues: maximizing the brightness of the scene and maximizing the contrast or gradient in the image. Solutions are proposed to consider either a static light and a moving camera, or a moving light and a static/moving camera. Thanks to the simplicity of the illumination model based on the OFCE, the proposed method is independent of the structure, color and aspect of the objects. Two different goodness functions may be proposed to achieve this goal: one is directly based on the intensity within the image while the second is based on the intensity gradient. To outline the issue, our primary goal will be to move the camera while the lighting remains static (see Figure 1.a). Then, we will propose to move the lighting while the camera remains static (see Figure 1.b).

In the reminder of this paper we first recall the optical flow constraint equation and show how it can be used to control a moving camera in Section II. Goodness functions based on brightness are shown in Section III and their integration

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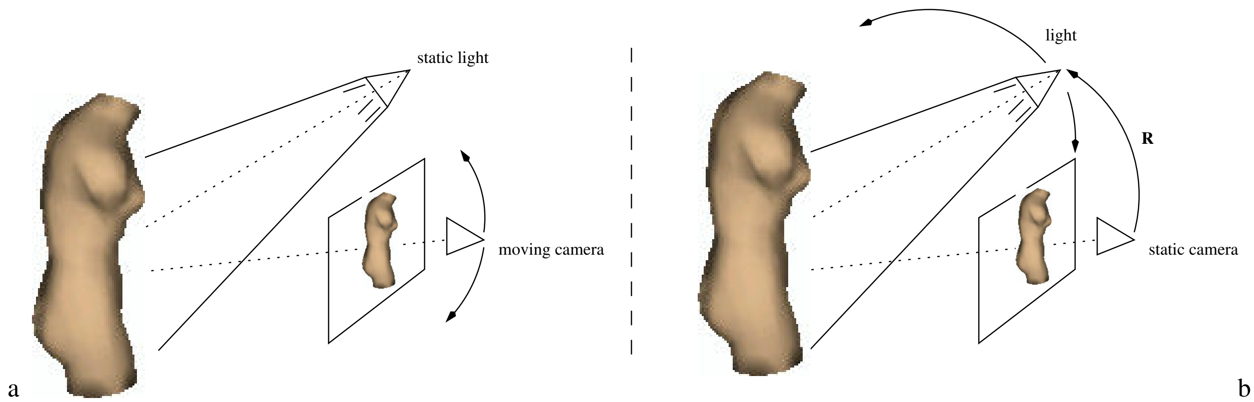


Fig. 1. Controlling lighting conditions. (a) static light/moving camera (b) moving light/static camera

within a visual servoing control law presented in Section IV. Finally, experimental results showing the validity of our approach are presented.

II. Temporal variation of the lighting information

a) Optical flow constraint equation: The basic hypothesis assumes the temporal constancy of the brightness for a physical point between two images. This hypothesis leads to the so-called *optical flow constraint equation* (OFCE) that links the temporal variation of the luminance to the image point motion.

More precisely, assuming that the point has a displacement $(dx, dy)^T$ in the time interval dt, the previous hypothesis leads to:

$$I(x + dx, y + dy, t + dt) = I(x, y, t). \tag{1}$$

A first order Taylor expansion of this equation gives:

$$\frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt = 0. \tag{2}$$

Denoting $\frac{dx}{dt} = \dot{x}$ and $\frac{dy}{dt} = \dot{y}$ the motion of the point in the image and $\nabla I_x = \frac{\partial I}{\partial x}$ and $\nabla I_y = \frac{\partial I}{\partial y}$ the spatial gradient of the intensity and $\frac{\partial I}{\partial t} = \dot{I}$ the temporal variation of the luminance, we finally obtain the *optical flow constraint equation* given by:

$$\dot{I} = -\nabla I_x \dot{x} - \nabla I_y \dot{y} \tag{3}$$

b) Interaction matrix associated to the luminance: Our goal is to link the temporal variation of the luminance to the time variation of the camera pose (or kinematic screw $\mathbf{v} = (\boldsymbol{v}, \boldsymbol{\omega})$ where $\boldsymbol{v}$ is the instantaneous linear velocity and $\boldsymbol{\omega}$ is the instantaneous angular camera velocity). This is in fact straightforward knowing the interaction matrix associated to the point. We indeed have:

$$\dot{x} = \begin{pmatrix} -1/Z & 0 & x/Z & xy & -(1+x^2) & y \end{pmatrix} \mathbf{v} \tag{4}$$

that we can rewrite $\dot{x} = \mathbf{L}_x \mathbf{v}$ and

$$\dot{y} = \begin{pmatrix} 0 & -1/Z & y/Z & 1+y^2 & -xy & -x \end{pmatrix} \mathbf{v} \tag{5}$$

that we rewrite $\dot{y} = \mathbf{L}_y \mathbf{v}$. Using these equations and the OFCE we have $\dfrac{\partial I}{\partial t} = \dfrac{\partial I}{\partial \mathbf{r}} \dfrac{d\mathbf{r}}{dt}$ or:

$$\dot{I} = -\left(\nabla I_x \mathbf{L}_x + \nabla I_y \mathbf{L}_y\right) = \mathbf{L}_{I(x,y)} \mathbf{v} \tag{6}$$

$\mathbf{L}_{I(x,y)}$ is the interaction matrix associated to the luminance of a point in the case of a moving point and a static camera.

III. Controlling lighting conditions

As already stated, our goal is to control the illumination of an object. We will then consider two informations related to the lighting condition:

- the intensity in the image. For such task, our goal will be to maximize the perceived luminance of the object in the image.
- the contrast. Maximizing the luminance is not always significant. Indeed, for some object, too much light may suppress some information (due, for example to specularities). Therefore, in a second time we will try to maximize the value of the intensity gradients in the image (which is related to a contrast information).

With respect to these specifications of "good" lighting condition, we can propose two cost functions that reflect these behaviors.

A. Maximizing the luminance

Our goal is to position the camera wrt. the enlightened aspect of the object. We therefore want to maximize the quantity of light (re)emitted by the object of interest and perceived by the camera to ensure good lighting condition. Applying the proposed methodology, we want to maximize the following cost function:

$$h_s = \sum_x \sum_y I(x, y) \tag{7}$$

where $I(x, y)$ is the intensity of the 2D point (x, y). The variation of the cost function h_s due to camera motion, that will be used to control camera or light source motion (see Section IV), is then given by

$$\frac{\partial h_s}{\partial \mathbf{r}} = \sum_x \sum_y \frac{\partial I(x, y)}{\partial \mathbf{r}} \tag{8}$$

where $\mathbf{r}$ denote the camera pose (translation and rotation). $\frac{\partial I(x,y)}{\partial \mathbf{r}}$ is nothing but the interaction matrix $\mathbf{L}_{I(x,y)}$ as defined in (6). Considering equation (6) we got:

$$\frac{\partial h_s}{\partial \mathbf{r}} = \sum_x \sum_y \left(\nabla I_x \mathbf{L}_x + \nabla I_y \mathbf{L}_y \right). \tag{9}$$

B. Maximizing the contraste.

If our goal is to maximize the contrast within the image, a good criterion is to maximize the sum of the components of the spatial intensity gradient within the image. The corresponding cost function is given by:

$$h_s = \sum_x \sum_y \left[\nabla I_x^2 + \nabla I_y^2 \right]. \tag{10}$$

As in Section III-A We therefore need to compute the gradient $\frac{\partial h_s}{\partial \mathbf{r}}$ that is in fact given by:

$$\frac{\partial h_s}{\partial \mathbf{r}} = \sum_x \sum_y \left(\frac{\partial h_s}{\partial x} \mathbf{L}_x + \frac{\partial h_s}{\partial y} \mathbf{L}_y \right) \tag{11}$$

with

$$\frac{\partial h_s}{\partial x} = 2 \left(\frac{\partial^2 I}{\partial x^2} \frac{\partial I}{\partial x} + \frac{\partial^2 I}{\partial x \partial y} \frac{\partial I}{\partial y} \right)$$

and

$$\frac{\partial h_s}{\partial y} = 2 \left(\frac{\partial^2 I}{\partial x \partial y} \frac{\partial I}{\partial x} + \frac{\partial^2 I}{\partial y^2} \frac{\partial I}{\partial y} \right)$$

After some rewriting, we finally get:

$$\begin{aligned} \frac{\partial h_s}{\partial \mathbf{r}} = \; & 2 \sum_x \sum_y \left[\left(\frac{\partial^2 I}{\partial x^2} \nabla I_x + \frac{\partial^2 I}{\partial y \partial x} \nabla I_y \right) \mathbf{L}_x \right. \\ & \left. + \left(\frac{\partial^2 I}{\partial x \partial y} \nabla I_x + \frac{\partial^2 I}{\partial y^2} \nabla I_y \right) \mathbf{L}_y \right] \end{aligned} \tag{12}$$

IV. Introducing Illumination constraints in visual Servoing

In this section we study how to use the constraints presented in Section III to control the camera or the light source position. In both cases the method relies on the well known visual servoing approach and takes advantage of the redundancy framework.

A. Positionning Camera wrt. Visual Targets

The *image-based visual servoing* consists in specifying a task as the regulation in the image of a set of visual features[6][10]. A good review and introduction to visual servoing can be found in [13].

Let us denote $\mathbf{s}$ the set of selected visual features used in the visual servoing task. To ensure the convergence of $\mathbf{s}$ to its desired value $\mathbf{s}^*$, we need to know the interaction matrix $\mathbf{L_s}$ that links the motion of the object in the image to the camera motion. It is defined by the classical equation [6]:

$$\dot{\mathbf{s}} = \mathbf{L_s}(\mathbf{s}, Z) \;\; \mathbf{v} \tag{13}$$

where $\dot{\mathbf{s}}$ is the time variation of $\mathbf{s}$ (the motion of $\mathbf{s}$ in the image) due to the camera motion $\mathbf{v}$. The parameters Z involved in $\mathbf{L_s}$ represent the depth information of the considered objects expressed in the camera frame.

A vision-based task $\mathbf{e}_1$ is defined by:

$$\mathbf{e_1} = \mathbf{C}(\mathbf{s} - \mathbf{s}^*) \tag{14}$$

where $\mathbf{s}^*$ is the desired value of the selected visual features, $\mathbf{s}$ is their current value (measured from the image at each iteration of the control law), and $\mathbf{C}$, called combination matrix, has to be chosen such that $\mathbf{CL_s}$ is full rank. It can be defined as $\mathbf{C} = \mathbf{L_s^+}(\mathbf{s}, \mathbf{p})$.

For making $\mathbf{e_1}$ exponentially decreases and then behaves like a first order decoupled system, the camera velocity given as input to the robot controller is given by:

$$\mathbf{v} = -\lambda \mathbf{e_1} \tag{15}$$

where λ is the proportional coefficient involved in the exponential convergence of $\mathbf{e}$.

B. Introducing constraints within the positioning task

If the vision-based task does not constrain all the n robot degrees of freedom, a secondary task can be performed and we obtain the following task function:

$$\mathbf{e} = \mathbf{W}^+\mathbf{W}\mathbf{e_1} + (\mathbf{I_6} - \mathbf{W}^+\mathbf{W})\mathbf{e_2} \tag{16}$$

where

- $\mathbf{e_2}$ is a secondary task. Usually $\mathbf{e_2}$ is defined as the gradient of a cost function h_s to be minimized ($\mathbf{e_2} = \frac{\partial h_s}{\partial \mathbf{r}}$). This cost function is minimized under the constraint that $\mathbf{e_1}$ is realized.
- $\mathbf{W}^+$ and $\mathbf{I_6} - \mathbf{W}^+\mathbf{W}$ are two projection operators which guarantee that the camera motion due to the secondary task is compatible with the regulation of $\mathbf{s}$ to $\mathbf{s}^*$. Indeed, thanks to the choice of matrix $\mathbf{W}$, $\mathbf{I_6} - \mathbf{W}^+\mathbf{W}$ belongs to Ker $\mathbf{L_s}$, which means that the realization of ***the secondary task will have no effect on the vision-based task***.

The control is now given by:

$$\mathbf{v} = -\lambda \mathbf{e} - (\mathbf{I_6} - \mathbf{W}^+\mathbf{W}) \frac{\partial \mathbf{e_2}}{\partial t} \tag{17}$$

Considering redudancy in visual servoing has been already considered [1], [18] but usualy related to robot manipulability. Information directly extracted from the images have been also considered (eg, in [15] for occlusion avoidance).

C. Eye-in-hand versus Eye-to-light control

To control the camera/light source relative position, we will consider two cases. In the former one, the camera is controlled and focused on the object while the light remains static. This experimental context is not always the most interesting one. Indeed, if the camera is moving the aspect of the object will change with time. It is often more interesting to control the light position and orientation while the camera remains static. This is the second case that is considered.

Dealing with the former case, the camera is focused to the object of interest using a classical visual servoing task. If $\mathbf{s} = (x, y)$ defined the object center of gravity, $\mathbf{s}^*$ is defined as $\mathbf{s}^* = (0,0)$ and the task function that enforces the focusing task and ensures a "good" lighting of the object is given by:

$$\mathbf{e} = \mathbf{W}^+\mathbf{W}\mathbf{L}_\mathbf{s}^+(\mathbf{s}-\mathbf{s}^*) + (\mathbf{I}-\mathbf{W}^+\mathbf{W})\frac{\partial h_s}{\partial \mathbf{r}} \tag{18}$$

where $\frac{\partial h_s}{\partial \mathbf{r}}$ is given by either equation (9) or (12).

Considering the second case, object is static in the image (acquired by a camera C_1) and we want to maximize brightness or contrast by moving the light-source. Here again we consider the visual servoing framework to point the light toward the object of interest and to achieve good conditions. We first add to the light a second camera C_2 whose optical axis is aligned with the light direction. The main task is specified as a simple focusing task that constrains the virtual camera/light system (two dof are constrained). We then consider the redundancy to control the camera/light system to impose a correct illumination of the object within the image acquired by the other camera. The task function is then defined as:

$$\begin{aligned}\mathbf{e} \;=\; & \mathbf{W}^+\mathbf{W} \underbrace{\mathbf{L}_\mathbf{s}^+(\mathbf{s}-\mathbf{s}^*)}_{\text{main focusing task}} \\ & +(\mathbf{I}-\mathbf{W}^+\mathbf{W}) \underbrace{\begin{pmatrix} \mathbf{R} & -\mathbf{R}[-\mathbf{R}^T\mathbf{t}]_\times \\ 0 & \mathbf{R} \end{pmatrix} \frac{\partial h_s}{\partial \mathbf{r}}}_{\substack{\text{secondary task defined}\\ \text{wrt. to the other camera}}}\end{aligned} \tag{19}$$

with $\mathbf{R}$ and $\mathbf{t}$ denotes the rotational and translational mapping of the fixed camera frame $\mathcal{R}_{C_1}$ onto the moving camera/light frame $\mathcal{R}_{C_2}$.

Let us note here that if the camera C_1 is now moving, the problem remains exactly the same as long as we know the transformation $\mathbf{R}$ and $\mathbf{t}$ between the camera and the light (see Result in paragraph V-B).

V. Experimental Results

Results obtained in this section has been obtained either in simulation using Open GL simulation tools or a real robotics cell at IRISA. The system has been implemented using the ViSP software [16].

A. Eye-in-hand coordination

1) Simulation: The goal of this first simulation is to validate our approach on a simple scene. The goal is to perform a positioning task wrt. a sphere and to control the camera in order to see this sphere under good lighting condition (criterion (7) is considered). In this experiment the light-source is static and the camera is moving as described by Figure 1a. Control law presented in equation (18) is considered. The advantage of the sphere is that its aspect remains the same whatever the camera position. Only the sphere luminance will be modified. In this experiment we considered a positional light source.

Results of this positioning task are presented on Figure 2.a. It is worth noting that the average intensity increases very smoothly (see Figure 2.b). We also plot the distance between the camera and the object-light axis (see Figure 2.c). We can note that this distance tends towards zero, i.e. at the end of the positioning task, the camera is located between the sphere and the light as can be expected (see Figure 2.d).

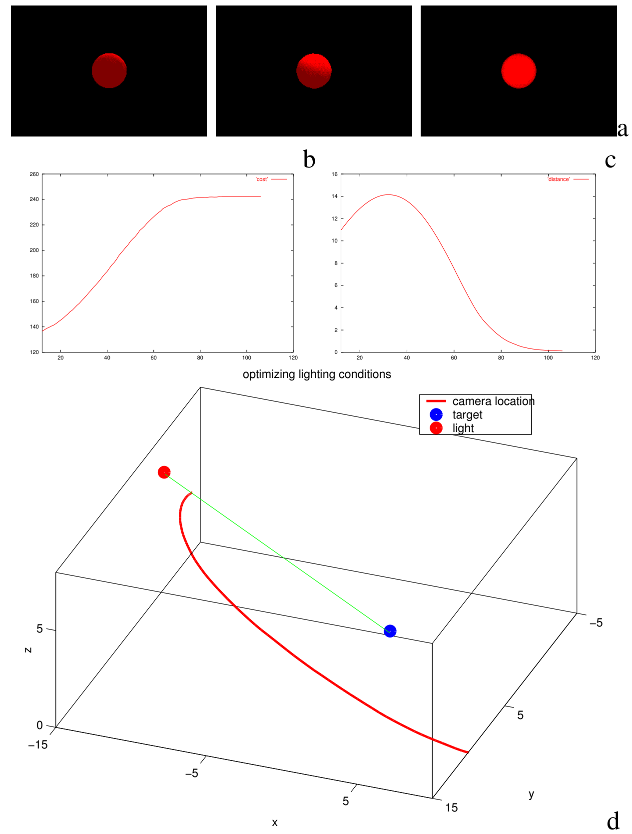


Fig. 2. [Simulation] Positioning wrt. a sphere under good lighting conditions: (a) scene observed by the camera (illumination increases) (b) average intensity in the image (c) distance to sphere-light axis (d) camera/sphere/light position over time

2) Real Experiments:

a) Maximizing luminance on a sphere: The same experiment was carried out on our experimental setup. A white ball is lighted by a spot. As in the previous section the camera mounted on the robot end-effector is focused on the ball and controlled using equation (18) in order to maximize the ball luminance. As expected, the luminance increases (see Figure 3a-b-c and plot 4.c) until the camera/robot moves between the ball and the light-source creating a "lighting occlusion" (see Figure 3.d and the last iteration of plot 4.c). As expected, the behavior of the system is very similar to simulation results presented in the previous paragraph. Similar results for this object is obtained when the contrast goodness function is considered.

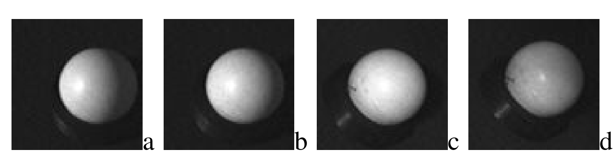


Fig. 3. [Real experiment] Positioning wrt. a sphere (a) first image (b-c) luminance increases (d) the camera is now between the sphere and the light (that is the actual expected position but that in practise create a "light occlusion")

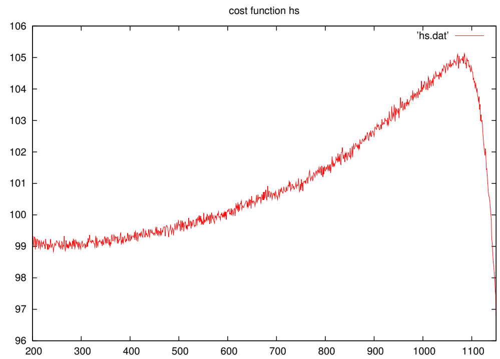
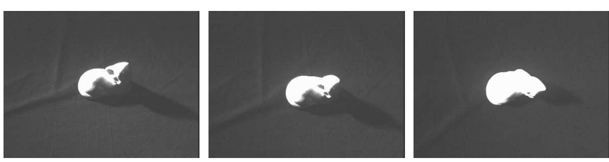


Fig. 4. [Real experiment] Positioning wrt. a sphere :cost function h_s that reflects ball luminance

b) Maximizing luminance on a complex object: Same experiment can be done with more complex object (see Figures 5.a and 5.b). Although the shape of the object is modified during the experiment, the average luminance increases as specified in the task (see Figure 6 that is related to images in Figure 5.b).

a



b

Fig. 5. Maximizing luminance on more complex object

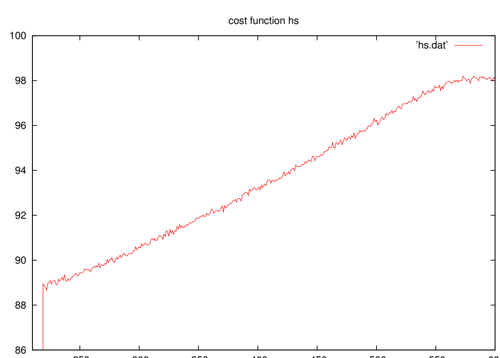
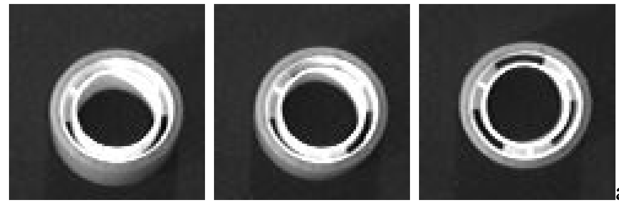
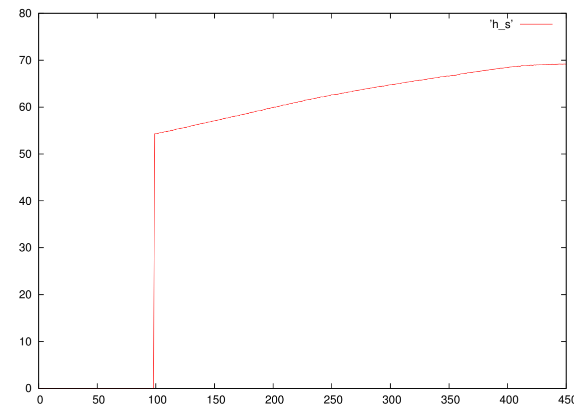


Fig. 6. Maximizing luminance (correspond to the experiments presented on [Figure 5b]) : goodness function h_s

c) Maximizing contrast on a complex object: In Figure 7 we consider the goodness function based on the contrast information (that is maximize the norm of the gradient in the image). As can be seen on Figure 7, the gradient in the image increases which is due to both the light and the modification in the object aspect due to the camera motion. It is clear that the last image of the object is better suitable, due the presence of important gradient, for task such as recognition or tracking.



a



b

Fig. 7. Scotch experiment: maximizing gradient/contrast (a) images of the sequence (b) evolution of the goodness function h_s

In this paragraph we considered a moving camera and a static light-source. The consequence of such a configuration is that it implies modifications in the aspect of the scene which is not always suitable. In the next experiment we consider a static camera and a moving light source.

B. *Eye-in-hand/Eye-to-light coordination*

As regards this issue, we first perform a positioning experiment involving complex object. We consider, in simulation, a model of the Venus of Milo. In this experiment we first consider a static camera and a moving light as depicted in Figure 1b. In a second time, when a minimum of the cost function is reached, we impose an arbitrary motion to the camera. The light must then move in order to maintain a correct lighted of the statue. The results presented (see Figure 8) show the validity of our approach for both goodness function (luminance on Figure 8a and contrast on Figure 8b). One can see that the light trajectories around the statue on Figure V-B.

VI. CONCLUSION

We presented a method to ensure correct viewing or illumination of an object using a visual servoing scheme and only luminance or gradient information. The illumination model considered in this is indeed very coarse and is in many cases false. Nevertheless, it allows to servo the camera or the light source in order to achieve a “good” illumination of the scene (at least wrt. the considered criteria). Experimental results in simulation or on real scenes show the

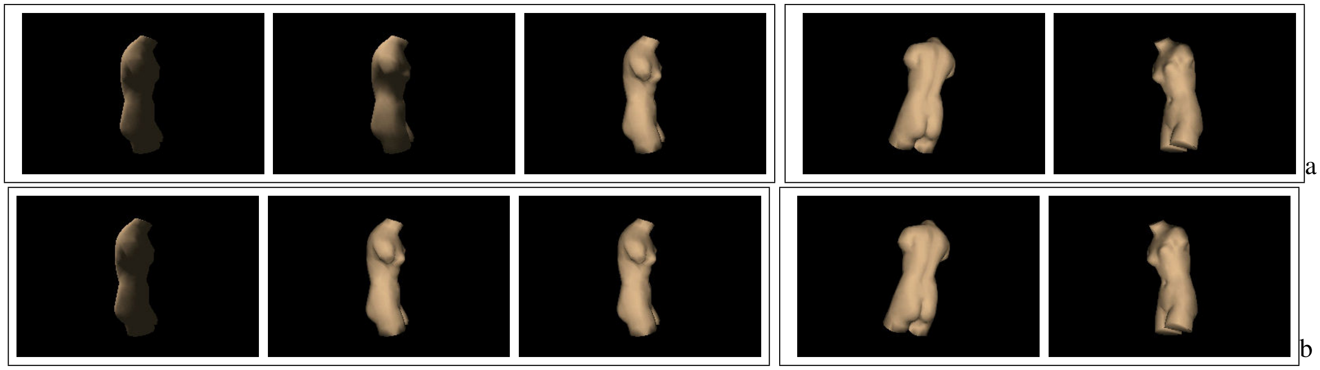


Fig. 8. Illuminating the Venus of Milo (a) maximizing the venus luminance (b) Maximizing the contrast. In the three first columns the camera remain fixed then an arbitrary motion is given to the camera. The light source moves to ensure the specified task.

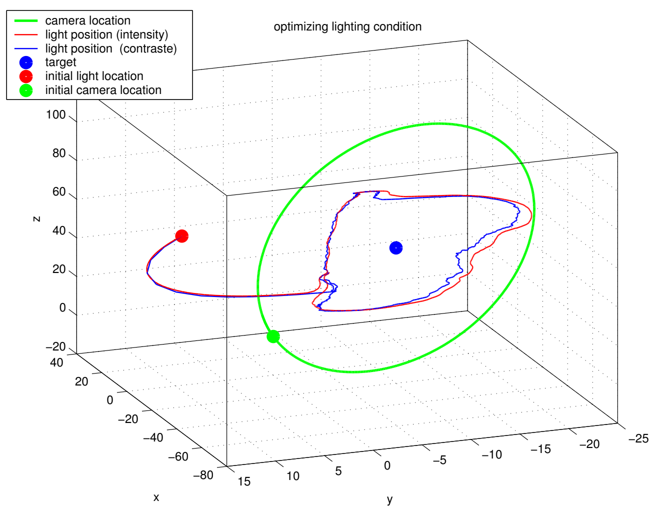


Fig. 9. Illuminating the Venus of Milo : Camera and light trajectory

validity of the approach. Nevertheless, it is well known that image luminance of a scene depend of the objects (albedo, reflectance, ...), of relative surface camera orientation, and of the camera/object/light source position. Future work will be devoted to study more complex illumination models. This may require either more information about the scene (3D model and surface information), or the estimation of the unknown parameters (such light source position).

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