Using Omnidirectional Vision within the Spatial Semantic Hierarchy

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Abstract— ***This paper reports the new steps undertaken in our work aimed to demonstrate the effectiveness of an omnidirectional vision sensor when conjugated with the Spatial Semantic Hierarchy. The Spatial Semantic Hierarchy was proposed by Benjamin Kuipers as a method for map building with robots. In our work, a robot builds a topological map of an unknown environment, using the Spatial Semantic Hierarchy and an omnidirectional vision system as the only sensor. In the paper, we present the new omnidirectional mirror and the new robot. The new mirror was expressly designed for this application, the robot's chassis was designed to create a synergy with the omnidirectional vision sensor. A complete description of our project is reported, underlying the strict link it is possible to create between omnidirectional vision and the Spatial Semantic Hierarchy. Experiments in simulated environments and in real environments produced positive results.***

I. Introduction

Since the beginning of mobile robotics the map building problem was one of the most addressed by researchers [4]. Several researchers used omnidirectional vision for robot navigation and map building becuse of its wide field of view. Omnidirectional sensors offer in one shot a global view of the surroundings. So, the robot does not need to look around using moving parts (cameras or mirrors) or turning on the spot [22].

The *global view* offered by omnidirectional vision is specifically suitable for highly dynamic environments like the popular international RoboCup competitions (www.robocup.org). Lima used an omnidirectional sensor for the self-localization of the robot in the field of play. In this application, the omnidirectional mirror is designed to give a bird's eye view of the pitch. This permits the exploitation of the natural landmarks of the soccer field (goals and field lines) for reliable self-localization [11]. In another robot team, Asada used a goal-keeper fitted with an omnidirectional vision system with a learning capability. To reduce the learning time, the omnidirectional sensor was fitted with an attention control provided by an active zoom mechanism that permits to select a restrict area of the omnidirectional image [18]. In our team, "Artisti Veneti", we use omnidirectional vision sensors both on the goal-keeper robot and on two of the attackers. In [13] is described the approach we used to design the two different mirror profiles of the goalie and of the attacker. The profiles of the mirrors are designed on a task dependent basis.

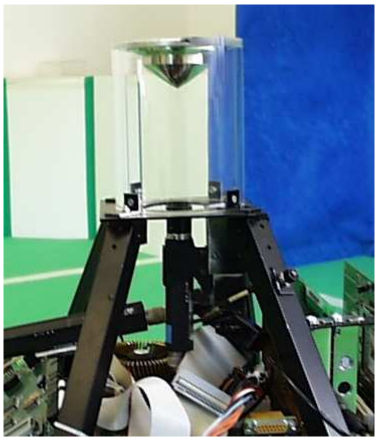


Fig. 1. The omnidirectional vision sensor of the robot. Note the multi-part mirror, whose profile is depicted in Figure 11

The main disadvantage of omnidirectional vision with respect to perspective vision is the poor resolution of the images. In the map building task the low resolution of the omnidirectional images is not a shortcoming, we are more interested in the position of the objects in the environment, than in the details of their surfaces. An example of a successful navigation with very low-resolution omnidirectional image is reported in [2]. However, for particular applications, there might be an interest to observe at higher resolution certain areas around the robot. Within certain limits, it is possible to design mirrors that maximize the image resolution in the most interesting regions of the scene. The robot we used in this work mount a new mirror, whose profile was designed to increase the image resolution near the base of the robot [13]. The chassis of the robot was designed in order to avoid occlusions of the floor around the base of the robot. This was done to solve some of the problems encountered in the first part of this project, where we used a robot, whose chassis was not optimized to be used in conjunction with an omnidirectional vision sensor [16].

Most of the systems presented in literature use the knowledge of the motion of the robot to interpret the visual data. In this work, the movements of the robots were extract from the visual data, without using the information from the odometers or the knowledge of previous commands sent to the motors, as it was done in [23]. In other words, the robot had to "infer" its movements from the vision sensor[1].

The aim of this paper is to show that a catadioptric omnidirectional sensor is a good sensor for the Spatial Semantic Hierarchy (SSH) [8]. In Section II, we summarise the basics of the SSH, focusing on the concepts exploited by our vision system. In Section III, we present the omnidirectional sensor used. The omnidirectional mirror is different from the one used in our previous work [16]. In Section IV, we show the strict link that is possible to create between the SSH and the omnidirectional frame sequences. In Section V, we state the assumptions made in our research. In Section VI, we explain which features and events we decided to extract from the omnidirectional sequences. In Section VII, we present the simulated experiments and the actual experiments we carried out to test our system. In Section VIII we will sketch the directions in which our research is evolving. Eventually, conclusions are drawn in Section IX.

II. Spatial Semantic Hierarchy

The Spatial Semantic Hierarchy (**SSH**) is a model of the knowledge of large-scale spaces of humans, intended to serve as a "method for robot exploration and map building" [6]. The SSH is made up of several layers [7]. Each layer can be implemented independently, even if they strongly interact. The layers are:

- The *Sensory Level* is the interface with the agent's sensory system.
- The *Control Level* describes the world in terms of continuous actions called "*control laws*". A control law is a function which relates the sensory input with the motor output and it is retained until a transition of state is detected with a function called a **distinctiveness measure**.
- The *Causal Level* abstracts, from the continuous world, a discrete model of the environment composed of **views** , **actions** and the causal relations between them. A **view** is defined as the sensor's reading at a **distinct** place. A **distinct place** is a place where a transition of state is detected. An **action** is defined as the application of a sequence of control laws. It is convenient to classify actions into two categories: *travels* and *turns*. "A **turn** is an action that leaves the agent at the same place. A **travel** takes the agent from one place to another" [17].
- The *Topological Level* represents an environment with geographical features in the world, such as places, paths and regions connected or contained one in the other.
- The *Metrical Level* augments the topological representation of the environment by including metrical properties. This may be useful, but is seldom essential.

[1]On the possibility to estimate the egomotion with omnidirectional vision sensor, see the work of Svoboda [19]

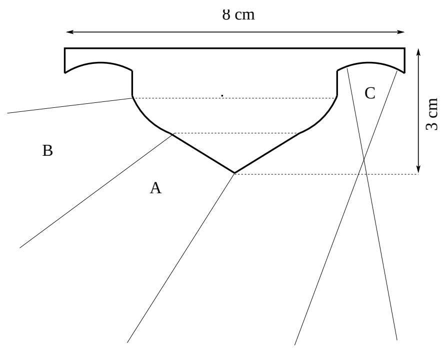


Fig. 2. A rough sketch of the mirror profile where the curvatures of the different sections are exaggerated for sake of clearness.

So far, the SSH has only been implemented either on simulated robots or on real robots with very simple sensors (such as sonars). As far as we know, no attempt to use an omnidirectional vision sensor has been made. In the following, we will present the omnidirectional sensor used and we will show why an omnidirectional sensor is a good sensor for building a topological map within the Spatial Semantic Hierarchy frame.

III. Omnidirectional Sensor

The mobile robot used in this work is fitted with an omnidirectional sensor composed of a perspective camera pointed upwards at the vertex of a multi-part omnidirectional mirror. The robot is depicted in Figure 10 and it is one of the players of the Artisti Veneti RoboCup team.

The optical axis of the camera and the geometrical axis of the mirror are aligned. The mirror is supported by a transparent Perspex cylinder. The shape of the mirror is designed in order to maximise the resolution in the regions of interest. This shape permits better exploitation of the information it is possible to gather from the environment with respect to the mirror we used in [16]. In addition, the new mirror is smaller and lighter than the old one, compare the two mirror profiles presented in Figure 11 and in Figure 14, noting the different scales in the plots.

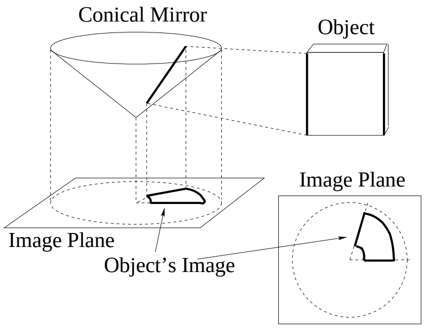


Fig. 3. The conical projection showing how a vertical line is mapped in a radial line in the image plane (adapted from Yagi).

The mirror used is a multi-part mirror, where each segment is designed to view a specific region of space. The design of this mirror was inspired by the work of Marchese and Sorrenti [10]. To understand the mirror profile consider the rough sketch in Figure 2. The inner part of the mirror (Part A in Figure 2) is designed to view objects from 60 cm around the robot up to six meters, without displaying the body of the robot. This part produces the main part of the image. As it is evident from Figure 6b) and Figure 12, the area close to the center of the image is strongly deformed, because of the derivative's discontinuity at the vertex of the mirror. This is not a disadvantage. In fact, with this choice, the central part of the image is not wasted displaying the body of the robot and can be used to discriminate between vertical edges and accidentally apparent radial edges [12]. The middle ring (Part B) permits to view very distant objects and can be used for better planning of the exploration movements, using the ideas about the catastrophe theory exposed in [21]. The external ring (Part C) displays at higher resolution (compared to the resolutions attainable in the other two sections) the area closer to the robot. This will be useful for the design of more complex reactive control laws like *corridor following* and *wall following*. The actual mirror profile is displayed in Figure 11. The height of the mirror tip from the floor, i.e. 48 cm. The pin hole of the camera is at 32 cm over the floor.

Consider Figure 3 to understand how an omnidirectional sensor maps the scene into the image plane[2]. The vertical edges in the scene are mapped in the image plane as radial lines originating from the point corresponding to the tip of the mirror. The azimuth of a radial line in the image corresponds to the azimuth of the vertical edge in the scene, as viewed from the optical axis of the camera. The horizontal lines are mapped to curved lines, the shape of which depends strongly on the geometry of the mirror. Note that the omnidirectional mirrors have a rotational invariance. If the sensor rotates through a certain angle about the vertical, the relative position of the objects in the image does not change. The image is only rotated and all the objects appear to have experienced an azimuthal shift equal to the angle of rotation.

[2]In this figure a conical mirror is represented, but the properties which are illustrated apply to any kind of omnidirectional mirror.

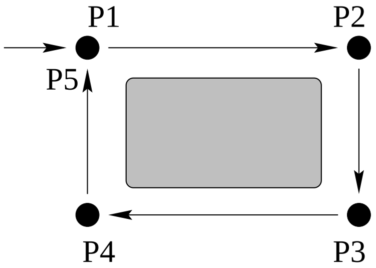


Fig. 4. The "exploring around the block" problem. The problem of recognizing the same place under different state labels.

IV. Omnidirectional vision suits the SSH.

In the introduction we reported the reasons for the success of omnidirectional vision sensor in the map building task. When working within the SSH frame, other benefits of omnidirectional vision come into view.

The omnidirectional images can be strictly correlated with the **views**[3] introduced in the causal level of the SSH. A **view** is the sensor reading at a **distinct** place, the omnidirectional image is a global reading of the surrounding at a certain place. Associating **view**s with omnidirectional images simplifies the data interpretation. Consider the following example. The robot stands in a distinct **place**. It takes an omnidirectional picture. It turns on the spot and then it takes a new picture. The new omnidirectional image will be the old one rotated by the same angle the robot rotated. The two pictures can be considered the same **view**, because of the rotational invariance. So, the robot will experience the same **view** before and after the **action** it took. This permits the robot to recognize that the **action** it took, was a **turn**, i.e. an action that leaves the agent at the same place. With a perspective camera the robot would have a totally different **view** after a turn on the spot. It would be really difficult to infer it is at the same **place**.

The rotational invariance and the link between **views** and **actions** permit a straightforward solution to the problem of *exploring around the block*, i.e. the problem of recognising the same place under different state labels, see Figure 4. Here the robot is moving around the block following the arrows. When it

[3]In the following, the bold font is used to indicate we are using the SSH meaning of the words.

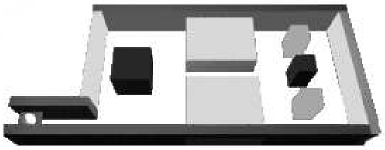


Fig. 5. The virtual environment. The robot is the dark-gray square with the white sphere on the top, positioned in the left most part of the corridor.

reaches Place 5 from Place 4, it is very difficult to recognize it as the previously visited Place1, unless it is equipped with an omnidirectional camera and it makes use of the rotational invariance. Using the SSH terminology, it is easy to spot whether the current **view** is the same which has been experienced before and therefore to consider this view not as a different **place** but as the same **place** reached from a different direction.

The *distinctiveness measure* of the SSH permits to abstract **distinct** places from the continuous world. This is a function of the surrounding of the robot. An omnidirectional sensor permits the creation of a more effective distinctiveness measure that takes in to account all the feature of the world around the robot. As we will see in the Section VI, it is possible to identify in the omnidirectional frame sequence a set of events strictly related to the topological structure of the environment. These events correspond to the discontinuities of the distinctiveness measure [21]. The occurrence of such a discontinuity determines the transitions of state in the SSH.

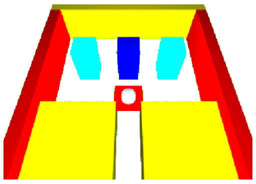
V. Assumptions

In this work, we make use of some assumptions:

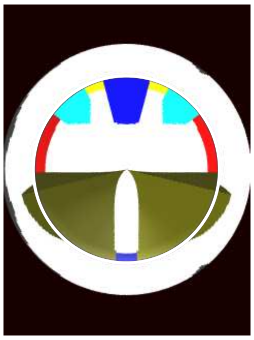
- The robot is moving in an indoor environment. This is a man-made environment like a building;
- The robot can either turn on the spot, or move in a straight line. It cannot make more complex movements;
- The robot does not have direct access to the information about its movements;
- The lighting in the environment does not change during the motion of the robot;
- The objects present in the scene are static: they do not change their positions;
- The floor is almost flat and horizontal;
- The walls and the objects present in the scene have vertical edges and surfaces;
- The axes of the camera and the mirror are vertical;

VI. Features and Events Selection

We built a simulator to generate omnidirectional images of a virtual environment. The aim of the simulator was to permit us to carry out extensive preliminary tests to extract clues about the features and the events that could be extracted from the omnidirectional image sequence. These features and events will be used to design the distinctiveness measure that abstracts distinct places from the continuous world. In this first part of the research, simulated images were preferred over real images because the simulations provide an environment which was easily controllable, repeatable reconfigurable. Eventually, the vision system was tested both on simulated and real image sequences. The omnidirectional images were created using POV-Ray, a free software package for creating three-dimensional graphics (www.pov-ray.org). The virtual environment is designed to present typical views of a man-made environment to the robot (i.e. corridors, doors, corners, objects, etc.), Figure 5.



(a)



(b)

Fig. 6. (a) The perspective view of the virtual environment. The robot is the dark-gray square with the white sphere on top of it. (b) How the same scene is seen from the simulated omnidirectional sensor. Note that, because of the mirror profile, there is a strong distortion at the image center and that the body of the robot does not appear in the image.

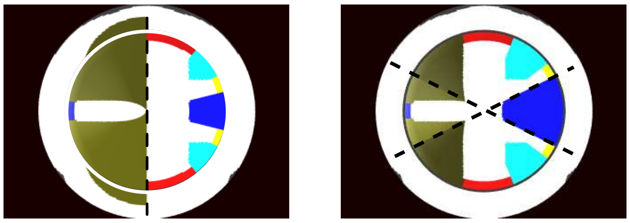
Selected features are extracted from each omnidirectional image. When the robot moves the selected features appear to move in the sequence of omnidirectional images. The movement of the features originates the topological events we use within the SSH. These events happen at single points in the space, therefore they can be used to identify distinct points in the space. This is the key that permit us to extract from the continuous world a set of distinct places.

The features we extract from the pictures are the vertical edges present in the environment [24]. The vertical edges are features strictly binded to the objects present in the world and therefore easily recognizable by humans. Several authors selected non-intuitive features, instead, like brightness patterns or other image features only loosely related to the objects [20] [5]. We believe that for an application like patrolling or remote surveillance the human readability is a must, so we selected features closely related to the objects in the environment, as in [9]. Vertical edges present a double advantage: in a man-made environment like an office or a building, they are diffusely present [4] and they are

[4] Examples of vertical edges are doors, the sides of a cabinet,

easy to extract from the image. In fact, as mentioned in Paragraph III, the vertical edges are mapped into radial lines by the omnidirectional mirror. Therefore, they can be straightforwardly extracted with the use of a Hough transform [3] simplified by a opportune choice of the reference frame.

When the robot moves in the environment the vertical edges appear to move in the image. The movements of the vertical edges in the frame sequence generates the topological events. While the robot wanders several events happen: new objects come into view, other objects disappear from the image, the robot enters a door or a corridor, etc. Objects come into view either because the robot approaches an object that was too far away to be in the field of view or because the object is no longer *occluded* by another one. Objects enter in the field of view of the vision sensor more than six meters apart. This is a big distance from the sensor. Because we are interested in what happens in the surrounding of the robot, we will focus only on the process of occlusion of the object's edges by other objects.



(a) (b)

Fig. 7. (a) Event 3: the robot enters a corridor (on the left): the two edges are 180 apart (b) Event 4: the robot sees two pairs of edges at 180.

During a translation following events can happen:

1. a new edge exits from occlusion;
2. an edge disappears occluded by another object;
3. two vertical edges are 180 apart in the vision sensor;
4. there are two pairs of vertical edges 180 apart.

Event 3 is particularly meaningful. In fact, it occurs when the robot enters a door or a corridor, i.e. a natural topological division of the space, see Figure 7. Each topological event causes a transition of state in our system, i.e. once one of these events occur a new **place** is abducted from the continuous space. The result is a segmentation of the space, see Figure 9.

During a rotation there is no relative displacement from the robot and the objects. No edge appears or disappears. In other words, the image does not change, it is only rotated around its center. An invariance for rotation must be introduced in the distinctiveness measure.

the legs of a chair, etc.

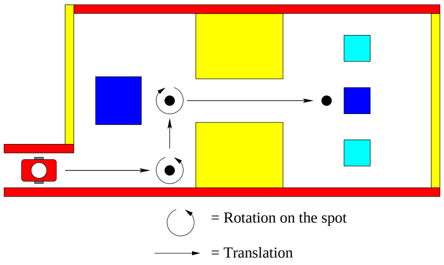


Fig. 8. The path of the robot through the virtual environment.

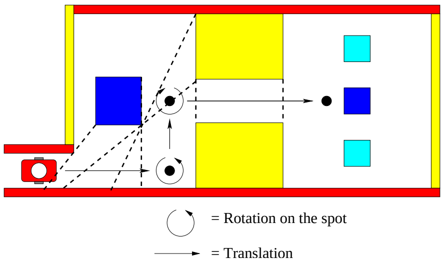


Fig. 9. The segmented path

VII. Experiments

We performed experiments in the simulated environment and in the real world. In these experiments, we tested the software for extracting the features and the events from the image sequences.

In the simulated experiments, the robot traveled through the virtual environment along the path shown in Figure 8. The path is composed of two rotations and three translations. The vision system software is able to track the edges all along the path and to detect the topological events. The edges present in the picture are extracted with a Canny edge detector [1]. The tracking of the edges is done using the colour information present in the image. The vision software is able to recognize the turns and to retrieve the angle by which the robot turned. The output of the vision system is a division of the virtual environment into distinct places, in Figure 9 some of the segmenting lines encountered along the path are drawn. A new place is created every time a topological event is detected and the corresponding view is stored. In the end, we obtain a topological map of places (associated to views) connected by actions: *travels* or *turns*.

In the experiments with the real robot, we encountered an implementation problem. Despite the vision system software working properly in the simulations, the tracking of the vertical edges worked properly when the robot translated but it was not reliable when the robot turned on the spot. See Figure 12, for a picture acquired by the vision system of the real robot. This problem prevented the production of topological maps of paths containing **turns**. We discovered that the problem was caused by reflections on the Perspex cylinder. At the moment of writing, we solved the problem and we are carrying on new experiments with the real system.

As stated before, we are using a new robot mounting a new omnidirectional mirror we designed for this application. The chassis of the new robot has been shaped in order to avoid unnecessary occlusions in the omnidirectional images. The tripod supporting the camera has a pyramidal shape and the robot base is rounded avoiding corners resulting in a chassis with circular symmetry. Differently from the chassis of the old robot this one was designed thinking of mounting an omnidirectional vision sensor on top of it. In Figures 10 and 13, you can see respectively the new robot, called Nelson, and the old one, called Caboto. The new robot has a rounded chassis in order to avoid

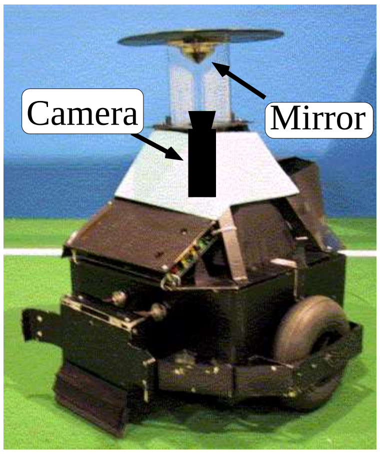


Fig. 10. The new robot (Nelson) with its omnidirectional sensor.

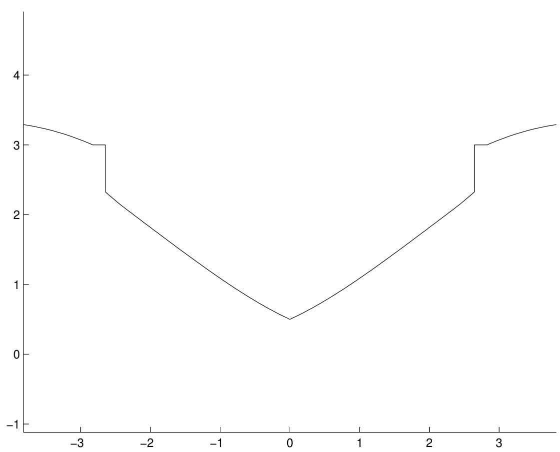


Fig. 11. The actual mirror profile of the new omnidirectional mirror designed for this application.

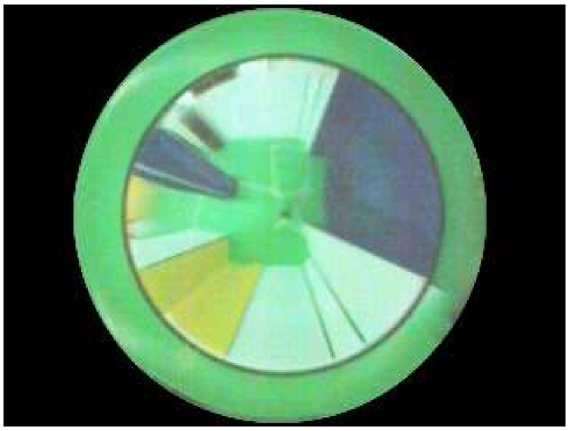


Fig. 12. An omnidirectional picture acquired by Nelson while it moves in the test environment.

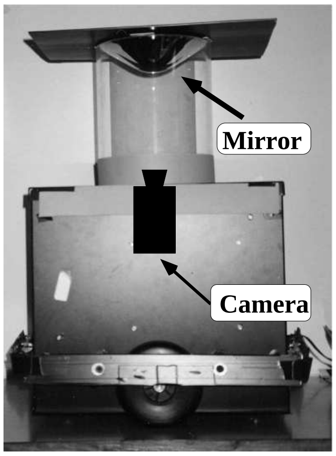


Fig. 13. The old robot (Caboto) with its omnidirectional sensor.

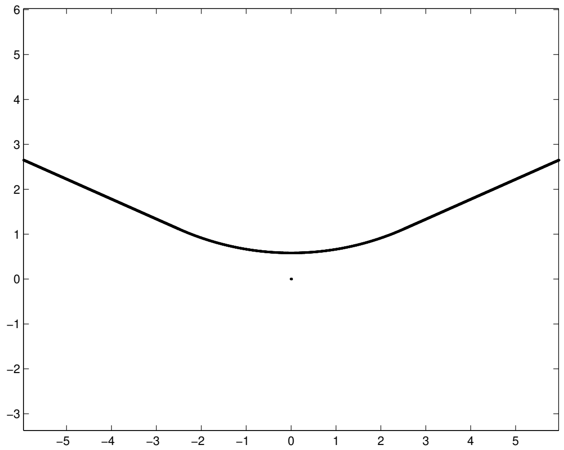


Fig. 14. The actual mirror profile of the old omnidirectional mirror.

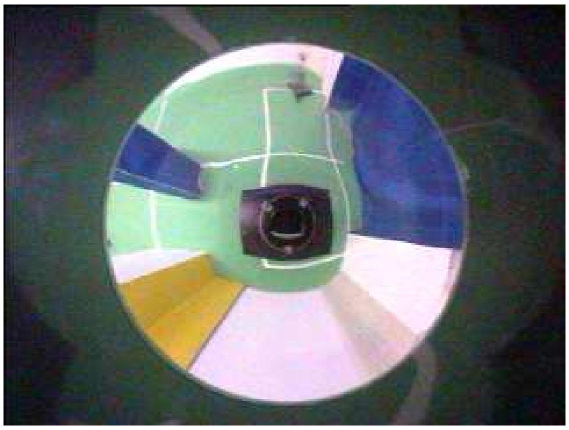


Fig. 15. An omnidirectional picture acquired by Caboto while it moves in the test environment.

to display the corners of the chassis in the image. Figure 11 shows the actual profile of the new multi-part mirror, while Figure 14 presents the actual profile of the old mirror that Prof. Bonarini lent us. The two profiles generate quite different omnidirectional images. In Figure 12 and 15 are presented two snapshots of the same scene acquired with the new and the old mirror.

VIII. Future work

Up to now, the middle part of the mirror is not used. In the future, we will implement an algorithm that will guide the exploration of an unknown environment using the ideas from catastrophe theory exposed in [21]. This should assure the robot to explore all interesting location not previously visited. Also the outer mirror's ring is not fully exploited. It will be useful for the future design of more complex reactive control laws like *corridor following* and *wall following*. Up to now, we are using this high resolution area of the image just to detect with a good precision the baseline of the walls and objects in the world.

In addition, we are porting the techniques developed in this project to a multi-robot project. In that project, a team of robots perform a parallel exploration and mapping of an unknown environment, merging their local maps, built within the SSH frame, in a global map using techniques of distributed vision [15] [14].

IX. Conclusions and Acknowledgments

In this paper, we reported the steps taken to overcome the limitations raised in the first part of this project [16]. The body of the robot has been reshaped in order to avoid occlusions and to obtain an omnidirectional image offering a more complete information on the surroundings. The omnidirectional mirror has been changed with a multi-part mirror composed of three parts at different resolution each of them devoted to the observation of a particular region around the robot. In the paper, we did not discuss only these practical issues but we gave a detailed description of the project and we showed that a catadioptric omnidirectional vision sensor is a good sensor for building a topological map using the Spatial Semantic Hierarchy.

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