OBJECT DETECTION BASED ON SEMANTIC CAMERA FOR INDOOR ENVIRONMENT

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ABSTRACT

This paper deals with a new simulation camera used MORSE simulator (modular open robot simulation engine) which is based on Blender (game engine) and Python, this camera can discover the environment (indoor or outdoor) according to its components, also can give us the type and coordinates of each element which exists in the environment, the semantic camera has been controlled by using ROS (robot operating system) node. Based on the informations that have been getting from the camera, we can build the robot map and discover the environment easily. We put in the researchers hands especially who are working with the simulation programs a new sensor for detecting the objects locations easily in the environments, this will be very useful in the robot navigation and path planning issues. This paper is a part of a project for handicapped people, we used semantic camera as sensor for discovering the objects coordinates but we used manipulator JACO robotic arm instead of mobile robot

Keywords

ROS, MORSE, semantic camera

1. INTRODUCTION:

Robotics systems are becoming highly complex and sophisticated, with an increasing number of hardware and software components there is also an increasing variety of tasks involved in performing robotics experiments, which induces much time and resources for validation the use of a simulator can ease the development, allowing to verify the component integration and to evaluate their behavior under different controlled circumstances [1]. Knowledge about the structure and the current state of the world is usually encoded in the form of a map [2]. Robots build environment maps for many purposes most robot maps so far have been proposed for navigation robot maps for navigation enable robots to estimate their position in the environment, to check the reachability of the destination and to compute navigation plans depending on their purpose maps have to store different kinds of information in different forms maps might represent the occupancy of environment of 2D or 3D grid cells, they might contain landmarks or represent the topological structure of the environment [3]. Proposed an approach to allow a mobile robot to build a semantic map from sensor data, and to use this semantic information in the performance of navigation tasks in our approach, we maintain two parallel hierarchical representations: a spatial representation, and a semantic one these representations are based on off-the-shelf components from the field of robot mapping and from the field of AI and knowledge representation, respectively [4]. There are several types of the maps like : metric map, topology map, recognized map also its possible to used compound types like metric - topology map the application of the proposed algorithm is to allow a mobile robot to differentiate between the objects in a scenario to obtain properties, which would be used to assign them a meaning and use this information for semantic navigation [5]. A few approaches try to leverage the ability to build and maintain a semantic map, by putting the human in the loop in other words, the robot builds its

representation of the environment, by interacting with the user in this way, the representation can become much richer both in terms of classification of the spaces and in terms of object detection [6]. We see such semantic mapping as a logical extension of the immense amount of research on mobile robot based map making [7]. A semantic mapping algorithm enabling robots to efficiently learn metrically accurate semantic maps from natural language descriptions the algorithm infers rich models of an environment from complex expressions uttered during a narrated tour currently, we assume that the robot has previously visited both the landmark and the referent locations, and that the user has already labeled the landmark [8]. Proposed a semantic mapping approach for indoor environments using laser range data and RGB-D images, mapping system provides a coherent semantic map of the perceived environment which not only well explains the environment on the abstract level but also accurately approximates the environment geometry using a parametric mode [9]. Propose a 6D SLAM approach and continue processing the resulting point clouds into basic elements like walls, floor, and doors, followed by an object detection step [10] . Report about our efforts to equip service robots with the capability to acquire 3D semantic maps the robot autonomously explores indoor environments through the calculation of next best view poses, from which it assembles point clouds containing spatial and registered visual information we apply various segmentation methods in order to generate initial hypotheses for furniture drawers and doors the acquisition of the final semantic map makes use of the robot's proprioceptive capabilities and is carried out through the robot's interaction with the environment [11].

2. OVERALL ALGORITHM :

The semantic map becomes the new requirement in the robot field. In our work we presented a new model for semantic camera, this would be using simulation program (MORSE), it is a simulator completely programmed by python, used for implement the 3-D environments, robots consists of many possible actuators, sensors, this simulator will execute in Blender. MORSE provides several features of interest to robotics projects it relies on a component-based architecture to simulate sensors actuators and robots [12], this program based on Blender, Blender is a game engine used for creating a 3-D animations, also is the free and open source 3D creation suite, it supports the entirety of the 3D pipeline modeling, rigging, animation, simulation, rendering, compositing and motion tracking, even video editing and game creation, advanced users employ Blender's API for Python scripting to customize the application and write specialized tools [13], the communication between this will be with (ROS) to control the robot motion and display the information, ROS : represents the communication ring between various programs, also made possible to share the informations between this programs. Normally there are many middle wares for communicating between MORSE and Blender like socket, yarb, ROS. With ROS there are many facilities options, also the control will be more effective, reliable than others, as shown in the flow chart figure (1). Multi robot types can be chosen, each one of the objects can be defined then can be put in the environment. The semantic camera programmed in python to give us the position of the object related to its orientation in (x,y,z) axis ,also to its position in the environment.

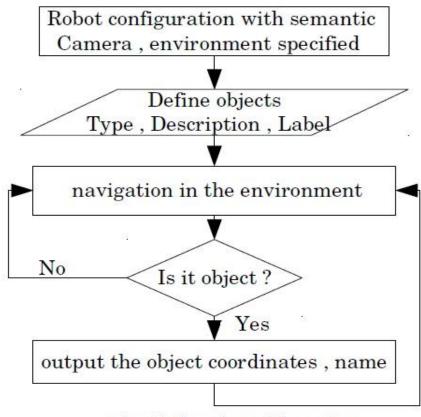


Fig. (1) flow chart of the project.

From the flow chart, the mobile robot with the camera navigated in the environment using ROS controller, the camera is looking for the objects which have been defined before, the ROS topic for the semantic camera gives the status of this topic which represented the informations stored which related to many objects in the simulated environment. The output orientation will be as x,y,z,w. This called a quaternion, the quaternion represented two things, first (x,y,z) components which represented the axis about which rotation occurs, second the w component shows the rotation amount which take place in the axis. When rotating interactively in quaternion mode, the so called *norm* of the quaternion will remain constant the norm of a quaternion *q* is defined mathematically as **[14]:**

$$\|q\| = \sqrt{X^2 + Y^2 + Z^2 + W^2} \tag{1}$$

W can be used to retrieve the actual rotation around the defined angle the following formula applies: $W = \cos(a/2)$, where *a* is actually the rotation angle we are looking for **[14]**

3. RESULTS :

The semantic camera implemented in MORSE by writing python script for calling this camera and others environment contents (the robot that has been chosen , the indoor environment components) as shown in figure 2, shows the robot with apartment environment consist of sofa ,office chair , walls , plant , tables , bed .



Fig(2) the virtual environment in the simulation program.

There are too many objects in the environment, many possible objects should be programmed to give the camera ability for recognizing the object correctly. The definition of many objects gives the camera the efficiency for being used in many environments. In this work we took a different samples as follow :

- Table
- Office chair
- Plant
- Sofa
- Walls

The semantic camera will be fixed on the mobile robot as shows in figure (3) .The semantic camera will fix on the robot while the robot is moving the camera will look to the environment object, recognize it but the object has to be defined before, As the first step the objects definition is required.

The objects that will be defined in three main categories :

- Type : usually the type of the objects that will be recognized.
- Label: simple label or name to define the object.
- Description: more objects details can be added here.



Fig.(3) the camera fixed on the mobile robot.

There are more options related to the some logically operations which have multiple functions. Figure 4 shows clearly an example for office chair, when we selected its obvious in the left sown corner the object propitiates which defined in blender with its type, label, description.

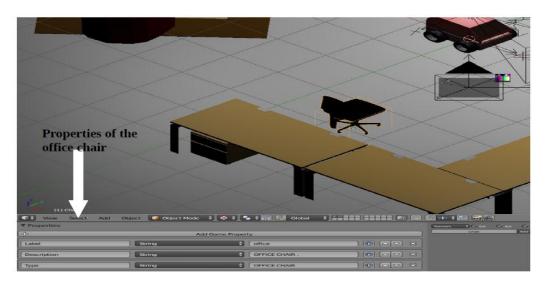


Fig. (4) selected office chair and defined its proprieties.

The semantic camera gives us the coordinates of the object according to the environment .Every environment in blender has been implemented in orientation axis in additional to the position axis . This would be using ROS instruction to show us the status of the semantic camera . The following figures show every object that has been chosen in our work as sample with its coordinates .in the figures below many cases has been shown for many objects . In each figure you can see the object name, position and orientation. two objects can be seen by one camera , the camera in this case gives us the name , position and orientation of both objects as shown in case (6)

Case 1: Object : The table



Orientation	Х	Y	Z	W
	0	0	0	1

Position	Х	Y	Z
	5.05254938	-0.47345295	-0.10973405

Case 2: Object : The office chair

Orientation	Х	Y	Z	W
	-1.244103	-7.607808	0.02144917	0.999769

Position	Х	Y	Z
	1.462752	-3.853212	0.645689

Case 3: Object : The wall

	data: [["type": "blocks", "name": "Wall", "position": [-7.778501510620117, -4.747738361358643, 2.040383815765381], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}]]
	data: [["type": "blocks", "name": "Wall", "position": [-7.778501510620117, -4.747738361358643, 2.040383815765381], "description": "', "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}]]
	data: [["type": "blocks", "name": "Wall", "position": [-7.778501510620117, -4.747738361358643, 2.040383815765381], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}]]
	data: [["type": "blocks", "name": "Wall", "position": [-7.778501510620117, -4.747738361358643, 2.040383815765381], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}]]
V 🖉	data: [{"type": "blocks", "name": "Wall", "position": [-7.778501510620117, -4.747738361358643, 2.040383815765381], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}}]
, , , , , , , , , , , , , , , , , , ,	<pre>data: [{"type": "blocks", "name": "Wall", "position": [-7.778501516620117, -4.747738361358643, 2.040383815765381], "descri ption": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}]]</pre>

Orientation	Х	Y	Z	W
	0	0	0	1

Position	Х	Y	Z
	-7.7785015	-4.747738	2.0403838

Case 4: Object : The plant

- UM	data: [{"type": "green ", "name": "room Plant", "position": [2.663062868118286, 3.477796792984009, 64038], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0]}]	-0.109734475612
	data: [{"type": "green ", "name": "room Plant", "position": [2.603062868118286, 3.477796792984089, 64038], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}]]	-0.109734475612
	<pre>data: [{"type": "green ", "name": "room Plant", "position": [2.60306/2860118286, 3.477796792984009, 64038], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}}]</pre>	-0.109734475612
	data: [{"type": "green ", "name": "room Plant", "position": [2.603062868118286, 3.477796792984089, 64038], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}}]	-0.109734475612
	data: [{"type": "green ", "name": "room Plant", "position": [2.603062868118286, 3.477796792984069, 64038], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}}]	-0.109734475612
	<pre>data: [{"type": "green ", "name": "room Plant", "position": [2.603062868118286, 3.477796792984009, 64038], "description": "", "orientation": {"z": 0.0, "y": 0.0, "w": 1.0, "x": 0.0}]]</pre>	-0.109734475612
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Orientation	Х	Y	Z	W
	0	0	0	1

Position	Х	Y	Z
	2.60306	3.477796	-0.10973447

Case 5: Object : The Bed

	escripti data: [[escripti data: [[escripti data: [[data: [[escripti data: [[on": "sleep bed", "orientation "type": "Bed", "name": "Bed", on": "sleep bed", "orientation "type": "Bed", "name": "Bed", on": "sleep bed", "orientation "type": "Bed", "name": "Bed", on": "sleep bed", "orientation "type": "Bed", "name": "Bed",	<pre>"position": [-6.676663398742676, 6.001694 ": {"z": 0.7071067094802856, "y": 0.0, "v "position": [-6.676663398742676, 6.001694 ": {"z": 0.7071067094802856, "y": 0.0, "v</pre>	<pre>#": 0.7071068286895752, "x": 0.0)}] 338772583, -0.10973507165908813], "d #": 0.7071068286895752, "x": 0.0}}] 338772583, -0.10973507165908813], "d #": 0.7071068286895752, "x": 0.0}]] 338772583, -0.10973507165908813], "d #": 0.7071068286895752, "x": 0.0}]] 338772583, -0.10973507165908813], "d #": 0.7071068286895752, "x": 0.0}]] 338772583, -0.10973507165908813], "d</pre>
Orientation	Х	Y	Z	W
	0	0	0.787106	0.707106

Position	Х	Y	Z
	-6.6766633	6.00169	-0.1097350

Case 6: Two objects : The wall and the sofa



For the wall :

Orientation	Х	Y	Z	W
	0	0	0	1

Position	Х	Y	Ζ
	-7.7785015	-4.747738	2.04038

For the sofa :

Orientation	Х	Y	Z	W
	0	0	0.908209	0.4185155

Position	Х	Y	Z
	-6.902915	-2.6458209	-0.10973507

4. CONCLUSION AND FUTURE WORK :

in this paper we presented a semantic camera as a new sensor to discover the object locations using simulation program which programmed by Python and controlled with ROS. In many robot applications such as smart navigation and path planning it is very necessary to discover the objects locations related to the environment. For the next work there are two developments that can be used as a new projects ideas :

- take this coordinates then we will choose appropriate path for reaching the objects (path planning)
- navigation in the environments, discovering the new environments which consist of many objects

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