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Motion Planning Strategy for Autonomous Assistance Robot Based on Visual Recognition

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Abstract

Service robotics has become a reality of robotics, and a broad research niche with very specific problems. It is a field of robotics that, aside from industrial applications, has managed to bring this technology closer to the user at home. Among the specific problems that must be overcome are those related to movement planning in dynamic and unstructured environments, interaction with human beings safely and effectively, processing capacity and communication in real-time, and prediction of user behavior to improve the experience with the robot. In this paper, we present a strategy for identifying specific objects in the environment for the Nao robot from SoftBank Robotics. This strategy was designed to support the autonomous planning of the robot's movement in the environment. The strategy uses OpenCV to identify specific color shapes through the robot's cameras, estimate distances, and plan the movement in the environment. The code was written in Python using Naoqi, and was successfully tested on a Nao V5 robot in the laboratory.

Keywords: Autonomous Robot, Image Processing, Path Planning, Real Time, Service Robotics.

I. INTRODUCTION

The interaction of human beings with the environment is strongly influenced by their sense of sight [1]. When humans first enter an environment (airport, shopping mall, etc.), they automatically search for and identify specific elements that are known to him and provide him with information (staircase signs, elevator or public restrooms). This strategy can also be used in robots, particularly in service robots [2].

Stand-alone navigation systems for artificial vision-based robots have become increasingly important due to the increased processing power of embedded systems and the high performance of optical sensors. Besides, numerous schemes of image processing and artificial intelligence have been evaluated that have allowed the operation in real-time [3]. In service robotics, it is normal that the working environment of the robot is completely unknown (but observable) and dynamic (but with specific identifiable characteristics) [4, 5]. These are conditions common to other robotic applications, and in all these cases the problem of autonomous navigation must be tackled with a reactive strategy supported by the robot’s sensors [6, 7].

The robot under these operating conditions must be capable of autonomous exploration and some level of reconstruction of the environment (local, partial or global reconstruction) without prior knowledge [8]. Self-localization is performed locally by the robot by identifying specific points in the environment [9]. These specific points are also used to establish distances, to define navigation routes and to define movement strategies.

These strategies are also used in robots with similar work environments. In the case of Unmanned Aerial Vehicles (UAVs), we find aerial vehicles in tasks that were previously performed under continuous control, such as surveillance and photogrammetry. In these autonomous systems, it is normal to identify specific characteristics of the terrain as support in the planning of the navigation route, in low-resolution images the points of interest are identified, which are then optimized and used as a reference for the construction of the path [10, 11].

The robotic ultrasound systems have also become commonly used in medicine [12, 13]. In this case, three-dimensional ultrasound scanning systems are used to produce images with depth detail that contain 3D tissue information. From this information it is possible to identify characteristics of the tissue that allow an automatic route to be established along the surface of the tissue, reducing damage to the maximum [14, 15]. The same strategy is also used in medicine to track small, flexible robots throughout the human body [16].

We propose a low-cost, autonomous navigation strategy for the Nao robot from SoftBank Robotics. This strategy uses as sensors the two frontal cameras located in the head and using binarization and morphological adjustments specific elements are identified in the environment that serves for the location and navigation of the robot.

The following part of the paper is arranged in this way. Section 2 presents preliminary concepts and problem formulation. Section 3 illustrates the design profile and development methodology. Section 4 we present the preliminary results. And finally, in Section 5, we present our conclusions.

II. PROBLEM FORMULATION

Let $W \subset \mathbb{R}^2$ be the closure of a contractible open set in the plane that has a connected open interior with obstacles that represent inaccessible regions. Let $\mho$ be a set of obstacles, in which each $O \subset \mho$ is closed with a connected piecewise-analytic boundary that is finite in length. Furthermore, the obstacles in $\mho$ are pairwise-disjoint and countably finite in number. Let $E \subset W$ be the free space in the environment, which is the open subset of W with the obstacles removed.

We place an agent (autonomous robot) in the free space of this environment. This agent can know the environment from observations using its sensors. These observations allow it to build an information space I. An information mapping is of the form:

$$q\colon E \longrightarrow S \tag{1}$$

where S denote an observation space, constructed from sensor readings over time, i.e., through an observation history of the form:

$$\tilde{o}\colon [0, t] \longrightarrow S \tag{2}$$

The interpretation of this information space, i.e., $I \times S \longrightarrow I$, is that which allows the agent to make decisions.

We assume the agent is able to sense the proximity, i.e., identify obstacles in the environment, using minimal information. The environment E is unknown to the robot. Furthermore, the robot does not even know its own position and orientation. Our goal is to design the control rules for the robot in order to independently solve navigation tasks in a dynamic and unknown environment.

The system is completely independent, i.e. there are no actions on it produced by some superior control unit, internal or external to the robot. The system must actively seek the inherent characteristic of the target, and keeping track. Trace information is comprised of marks on the navigation environment, landmarks, recognizable by its geometric shape and color. This concept can be extended to any other recognizable trace information.

III. METHODOLOGY

Our recognition scheme uses traditional strategies to identify shapes and colors in images through digital image processing. The overall operation is detailed in the block diagram in Fig 1.

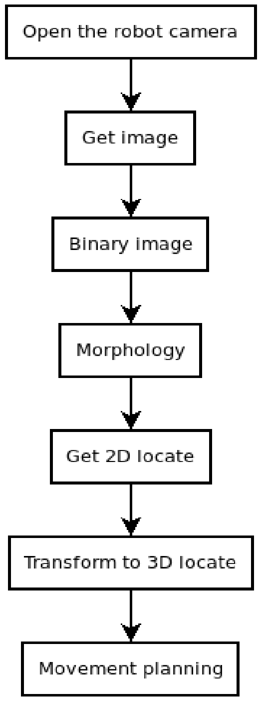

Fig. 1. Functional description of the identification algorithm

Our scheme uses the two cameras of the Nao robot (top and bottom). The code is implemented in the Nao robot using Naoqi. The video from the cameras is captured at 15 frames per second in RGB color model (color model in which Red, Green and Blue light are added together) with a frame size of 640*480 pixels (kVGA resolution). The frames are not scaled, all image processing is done in the same resolution. All images are captured and stored in PNG (Portable Network Graphics) format.

The first filter applied to each frame is the binarization of the image in two colors. This binarization is done with OpenCV in the HSV color space (Hue, Saturation, Value; alternative representations of the RGB color model) using as pattern a color between yellow, red or blue. Then we perform morphological image processing on the images to identify basic geometric shapes. The initial tests have been developed with yellow circles.

Once the regions of interest have been identified, they are labeled and characterized. Using Numpy matrix operations, the 2D location of the object in the image is identified. For verification, this information is superimposed on the original image captured by the Nao's camera. Then, we transform the 2D location to an absolute distance using the principle of ranging. The estimation is not completely accurate due to the lack of information regarding the depth, however, combining the information from the two cameras achieves a value quite close to the real. Finally, the Nao robot is programmed to respond in coherence with the identified object (walk to the ball). This last step consists in transferring the estimated 3D measurements from the images into a 3D location system on the environment, which allows the definition of movement policies to the robot's joints.

All our search and recognition scheme is written in Python 3.7.3 with the use of OpenCV 4.1.0.25, Numpy 1.16.2, Pillow 5.4.1 and Naoqi. Fig. 2 shows the result of one of the laboratory tests (object to recognize: yellow ball).

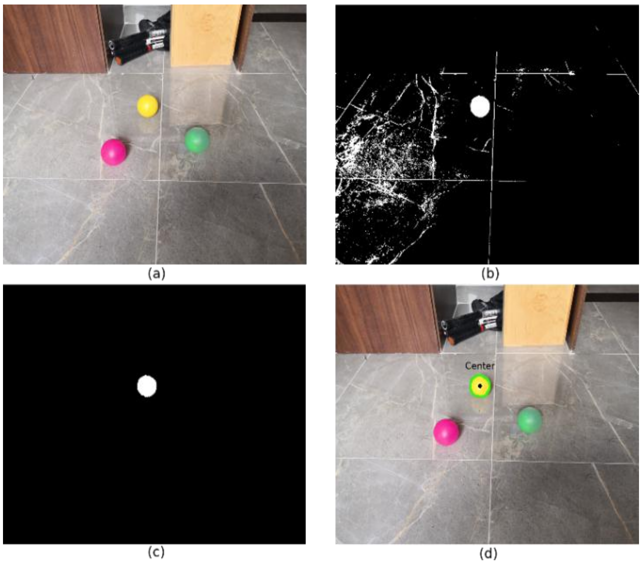

Fig. 2. Operation of the algorithm in the laboratory. (a) The three balls used for evaluation: yellow, green and red. (b) Image binarized by HSV color space. (c) Identification of regions by morphological adjustment, and (d) Initial image with superimposed localization information

IV. RESULTS AND DISCUSSION

The tests were performed on our robotic platform. Our assistive robot consists of two robotic platforms: A humanoid Nao robot from SoftBank Group for interaction with humans and the environment, and an ARMOS TurtleBot 1 robot from the ARMOS research group for indoor navigation (Fig. 3). Communication with the two platforms is via a Wi-Fi connection.

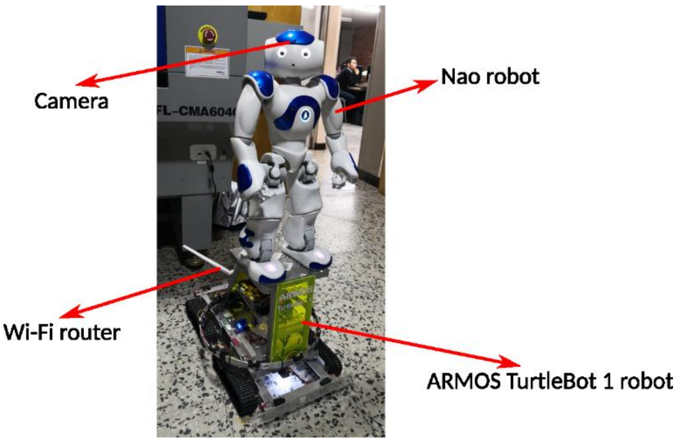

Fig. 3. Experimental setup for the identification system. It is composed of a humanoid Nao robot from SoftBank Group at the top and an ARMOS TurtleBot 1 tank robot from the ARMOS research group at the bottom

We evaluate the performance of the strategy in the laboratory with different configurations varying the position of the balls, distances to the robot, number of balls and even different lighting conditions. Despite the great possibilities offered by the environment, the algorithm was always able to correctly identify the object of interest. In some frames, the algorithm confused the ball with the environment when the light conditions were particularly poor, however, from neighboring images it was possible to establish the 2D location of the robot in 100% of cases.

From the results, it is proposed to improve the algorithm by including stereoscopic vision. In our platform we have the problem of incorporating a system of two cameras to the robot, or in its defect, to add some sensor that is able to inform about the depth to the object of interest.

V. CONCLUSION

In this paper, we show the setup of a feature identification algorithm in the environment for a service robot operating indoors, capable of real-time operation on the Nao robot. The algorithm uses OpenCV to identify the elements of interest from colors and shapes. In particular, we have evaluated the operation by filtering by yellow, blue and red colors, and for circular shapes. The tests were performed with balls of different colors within reach of the robot's cameras. The scheme uses color binarization and morphological adjustment over the regions to determine the target point. Once the area has been identified in the 2D image, this information is tagged and transformed into 3D location to coordinate the robot's movement. Laboratory tests showed high algorithm performance and very low computational cost.

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