CHAPTER X

ASIBOT ASISSTIVE ROBOT WITH VISION IN A DOMESTIC ENVIRONMENT

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Robotic devices are progressively being incorporated into our everyday lives. Advanced robot technology has been making its move from the dull, stationary regime of production plants and industries to consumer stores, and finally into our own homes. From automatic window shades to motorized vacuum cleaning units, these technologies are constantly being introduced to make our everyday lives easier. Many still live unaware of how deeply we have been submerged into a world of automatic systems which help us perform everyday tasks, starting by the simplest ones. Moreover, as technology advances, more complex systems are being incorporated into our daily lives. Current world-wide research focuses on how to introduce dynamic and mobile elements to perform "household chores", chores that require dexterous manipulation and advanced sensing and reasoning. This is a huge objective that implies great improvement and advances in current robotic technologies related to 24 hour availability, safety, and user satisfaction. As a consequence, there is an imminent need to develop perception mechanisms that offer a sufficient degree of reliability for the end-user. These mechanisms may be based on visual, tactile, or other types of sensed information. Additionally, they must be integrated within fully functional robotic systems that comply with the user's needs. A perception mechanism based on camera vision has been developed for the ASIBOT assistive robot. Recognition and identification is performed through color segmentation, whereas localization is achieved using non-linear interpolations on data based on predefined look-up tables. The entire system has been implemented and is being tested on the ASIBOT-based Domestic Aided Kitchen test-bed.

1 Introduction

Historically, technology used in household environments has been in the form of electrical appliances such as washing machines, ovens, microwaves and televisions. Later on, the classic “Home Automation” concept was introduced, which involves improvements such as computer-controlled lights, alarms, sensors, etc. These are all still classic, static consumer electronic devices. They are installed in homes, and perform the same task repeatedly throughout their complete useful cycle of life. Current world-wide research focuses on how to introduce more dynamic and intelligent elements into homes. Most recent studies, including our own, concentrate on the introduction of mobile and dynamic systems capable of performing “household chores” that require dexterous manipulation and advanced sensing and reasoning.

Our particular robotic system’s goal is to help elderly and disabled people to restore their autonomy, performing Daily Life Activities (DLAs) by themselves. All low-level design decisions are focused on providing the means for task accomplishment. The scope of this paper is on one specific user-oriented task: serving a can of drink to a person who is sitting in a wheelchair. This is a task that implicitly requires a sequence of steps, each of which may be performed using diverse technologies and paradigms. Throughout Subsection 1.1, a review of modern paradigms related to environmental intelligence and perception will be given. A brief on the actual robot will be given in Subsection 1.2, and the domestic aided kitchen test-bed will be described within Subsections 1.3. Section 2 will be dedicated to the vision algorithms used for detection as part of the actual task.

1.1 Paradigms on Environmental Intelligence

If we consider the potential services and functionalities that this kind of mobile domestic technologies could provide to the elderly and disabled population, we must keep in mind that the design process must generate solutions to their special needs. Even though this idea is not new [1]-[3], many previous attempts have failed to achieve the desired functionality for several reasons: complex intelligence needed on-board makes it too expensive, not enough flexibility to be used by many kinds of users, or oversized functionalities that did not fit user's expectations. In order to improve the profit/cost ratio, several strategies are revised [4].

The Ambient Intelligence paradigm (AmI) [5] is contributing to integrate and simultaneously dislocate all the devices to work together, presenting a Ubiquitous Computing Environment that provides IT services.

As AmI technology is intrinsically designed for everybody everywhere, it is the low-cost and effective solution that is bound to make robotic assistants reliable, useful, and autonomous in close interaction with real, smart environments [6].

Alternative approaches have been provided for the “Design for All” paradigm. Their main idea is to redesign our surroundings in order to make them accessible for all. Some special designs of furniture and domestic adaptations are very interesting for simplifying robot modeling and planning task. The Robotic Kitchen Counter [7], was a novel kitchen counter with sensors to monitor a user's actions, and had the capability of changing its top plate height according to his preference. Another example of introduction of robotic aid in a kitchen was CAPDI [8] that proposed a Cartesian manipulator hanging from the ceiling. A radically different approach is the scenario proposed by the Integrated Kitchen (see Fig. 1) [9].

Fig. 1. Conceptual Design of the Integrated Kitchen (iK)

It describes a design concept that explores future domestic kitchens where pantries communicate with refrigerators, and ovens coordinate meal preparation. This futuristic model can serve as inspiration for developing new creative real solutions.

1.2 ASIBOT Assistive Robot

ASIBOT (see Fig. 2) [10] is a climbing robot drawn from the inspiration of robotics for use as a domestic aid. It is a 5 Degree of Freedom (5 DOF) self-contained, portable manipulator. All of its control systems are included on-board, and it only needs power supply to operate. This is why only low-cost Docking Station (DS) and a 24V supply are necessary to connect it to be used anywhere. The main user interfaces include joystick and voice commands, along with PDA and PC-based graphical environments. They are designed to be capable of launching pre-programmed tasks or teleoperation commands. The arm currently executes a wide variety of preprogrammed tasks: feeding, washing, small size object transportation, etc. One of the main advantages of this robot is its light weight, about 11 kg, counting with a 1.3m reach.

Fig. 2. ASIBOT assistive climbing and portable robot

Another important feature of the ASIBOT system, presented in previous papers [11][12], is its capability of moving around wall, ceiling and furniture via reachable Docking Stations. This ability to “jump” between connectors located in an adapted environment allows it to dramatically unlimitedly increase its workspace. The fact that it is anchored to a single point at a time allows it to manipulate with tools attached to its free end, such as a retractable three-finger gripper [13]. The robot can also transfer itself to DS fixed to a wheelchair, and take power from the chair batteries. This is of great interest for people with motor disabilities in their upper extremities. It allows them to bring objects closer, and pick up and move utensils to a work area nearer to themselves. These features can partially restore the users' autonomy for everyday activities.

Compared to any classical electrical appliance, the robot can be used in a much wider variety of locations within a house, and for a much wider range of applications. As an assistant manipulator designed to help people, full tasks can be performed under control of the motion impaired.

1.3 ASIBOT-based Domestic Aided Kitchen

The ASIBOT-based Domestic Aided Kitchen is the adaptation of a handicapped adapted kitchen for the operation of the portable climbing robot ASIBOT. The adaptation of the environment to let the system work is minimal. Docking Stations (i.e. Figure 3, both large circles) have been installed in order to let the robot move around the environment, minimizing the number of them while still optimizing the robot reach volume.

Fig. 3. The ASIBOT-based Domestic Aided Kitchen

The kitchen surface is about $25m^2$ and is located at *Laboratorio de Robótica Asistencial* at UC3M. It consists of a fully furnished kitchen provided with fixed Docking Station, and one wheelchair-mounted one. They support ASIBOT fixation and energy requirements. Four IP-server cameras have been placed around the environment (i.e. Figure 3, top circle). They send raw image data to be processed as part of the perception mechanisms. Many other devices are linked by a smart controller using an EIBbus [14]. These devices exchange services to keep tabs on each other and, most importantly, the user.

2 Specific Implementation – Vision Algorithms

In this Section, the Vision algorithms that have been developed for task achievement will be described. As cited in the Introduction, the final goal that has been set is to retrieve a can from a kitchen counter. Assumption is that the can is standing up in a defined area of this flat kitchen counter. Due to the rotational symmetry of the can, calculating the orientation of the can is not necessary, as its shape does not depend on its orientation from the robot's perspective. As an additional variation in the experiment, it has been decided that the robot is docked at the wheelchair. Thus, the can position must be calculated, as must the wheelchair position and orientation to localize the robot.

2.1 Vision Algorithms for Recognition/Identification

Vision algorithms are known to be slow, and processor time consuming. As developers that work with embedded and low-memory systems, our priority is keeping algorithms fast. The ASIBOT kitchen test bed can be somewhat adapted, so color segmentation on specific colored items was adopted as a first approximation. Separating an image in different color layers can even be performed by physical means using filters screens. Two markers were added to the wheelchair, one yellow one, and one green one. They can be seen on the inferior part of Figure 3. The color segmentation algorithm has been developed to detect the wheelchair makers, and a red can that completes the system.

In a later stage of the development, morphological operations were added. They increase the performance accuracy of the centroid calculator.

2.1.1 Color Segmentation

Color segmentation is performed in the RGB space. Originally, algorithms where based on setting thresholds on each of the RGB components (red, green, blue). A final logical AND operation was performed on corresponding pixels. Performance was fast, as no transformation to HSL or other color spaces were necessary. However, results were highly dependent on environmental conditions such as daylight.

Best results were obtained with a modified version of the algorithm. In this current algorithm, only one threshold operation is performed. It is applied on the image that results the subtraction of two image layers. This can be seen clearly on Figure 4. At the top left of the Figure, the red layer of the IP camera can be seen. At the top right of the Figure, the green layer can be seen. The bottom left represents the subtraction of both images. The results obtained by applying a reasonable threshold on this resulting image and calculating the center of mass of the binary blob are already quite reliable for obtaining the centroid of the red can.

Fig. 4. Color Segmentation on Real Kitchen IP Camera View

In practice, the subtraction implies eliminating the mean off the color space, which actually gives information on the amount of daylight or artificial light but not on the object of interest. This is, it acts as a filter so that we only work with information that is relevant for us. The algorithm is applied once for the red can (red minus green, as cited above), and once for each of the two markers on the wheelchair (green minus blue for the yellow marker, and green minus red for the green marker).

2.1.2 Morphological Operations

Morphological operations are performed on each of the three obtained images before applying the threshold to obtain binary images. The sequence of operations that has proved most effective is the following: `close`, `erode, erode, dilate, dilate`. Closing operations are performed with a disk-type structural element, while erosion and dilatation operations are performed with identity matrixes.

The blobs that are obtained from applying the threshold on the images that result from the morphological operations are more precise than those obtained without them.

2.2 Localization

For localization, both static collections of datasets and geometrical transformations for approximation are used. Initially, only geometrical transformations were used. However, experience gave that loss of resolution with the increment of the distance between the camera and the object of interest could result in task failure. Therefore, static datasets of camera–object relationships in zones of interest were obtained and merged with the initial geometrical transformation approximation.

2.2.1 Static Dataset

A set of camera–object relationships was determined using the following methodology. The objects of interest were placed within zones of interest and camera view. Figure 5 depicts these places in the zone of interest for the red can, all on the kitchen counter (seen from above).

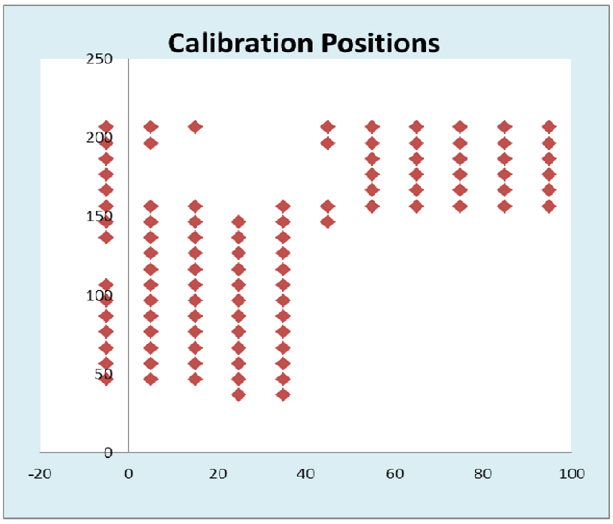

Fig. 5. Matrix of Positions for the Red Can in the Kitchen Counter Space

For each object position, an image was taken, and the algorithms described in Section 2.1 were applied. The results of applying these algorithms can be joint to form matrixes of the centroids in the camera pixel space. Figure 6 depicts the matrix of the centroids of the red can in kitchen counter space. These centroids correspond to the physical centers of the object in the kitchen counter space in a one-to-one relationship.

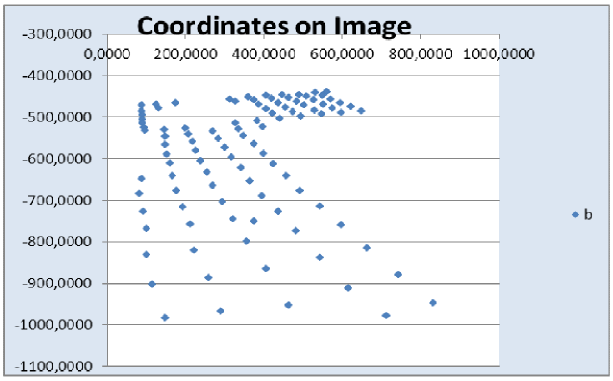

Fig. 6. Matrix of Centroids in the Camera Pixel Space for the Red Can

This procedure was performed for the red can, and for the yellow and green wheelchair markers, with the resulting tables of correspondence between pixel space centroids and real space centers. In practice, they are pre-calculated look-up tables that can (and are) loaded into full machine vision programs at initialization time.

3.2.2 Geometrical Transformations

The pre-calculated look-up table is the main feed of the on-line localization algorithm. However, the matrixes of positions for the objects of interest set the objects at intervals of 5 or 10 centimeters. Such an error is not tolerable, as it affects task achievement. Some kind of interpolation must be applied between the points whenever the object is not situated on a precise point of the look-up table. This relationship is non-trivial and non-linear. For the sake of program understandability, a geometrical and object-oriented approach has been taken. A small library for calculating geometrical relationships has been used. It contains classes that represent points and lines, and functions that relate the two. The need for directly using non-linear equations for interpolation is obviated through its use.

Calculations are based on the relationships similar to those that are depicted on Figure 7, with the following explanation given on the particular case for calculating the real distance from the camera to a red can on the plotted plane.

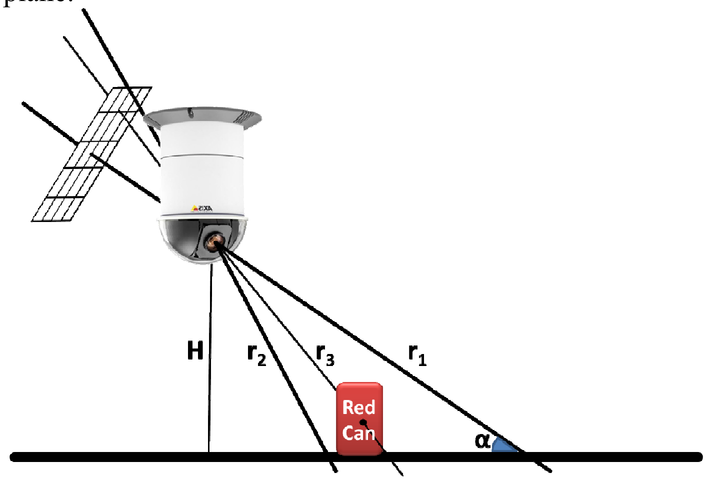

Fig. 7. The Interpolation Problem becomes Linear Using the Correct Projection

The height (**H**) and the angle (**α**) of the camera are fixed. The main axis of the camera is drawn ($\mathbf{r_1}$) and prolonged. It passes between the camera and the point that is perceived as the central pixel. The line that passes between the camera and the points that are perceived as the bottom or top pixel is also drawn ($\mathbf{r_2}$) and prolonged. A representation of the camera CCD is set, perpendicular to the main axis of the camera ($\mathbf{r_1}$). The line that passes between the camera and the points that are perceived as the bottom or top pixel ($\mathbf{r_2}$) touches it on its extreme. A linear interpolation is applied on the CCD representation, as it can be considered the pixel space. From the resulting calculated point, a line is drawn ($\mathbf{r_3}$). It passes through the camera and gives the can position in real distances. The final distance is given between where **H** crosses the kitchen counter representation and where $\mathbf{r_3}$ crosses the kitchen counter representation.

The process is used twice for the can (to obtain its X and Y position), and four times for the markers of the wheelchair (to obtain the X and Y position of each marker). Heights (Z) are previously known. The relative position between the robot base and the red can can be calculated as the result from a simple 3D subtraction.

3 Path Planning Algorithm

The planning algorithm for the task is represented on Figure 8. Assumption is that the command from the user interface implies that the user wants a red can of drink to be picked up, brought to him or her, and then retrieved.

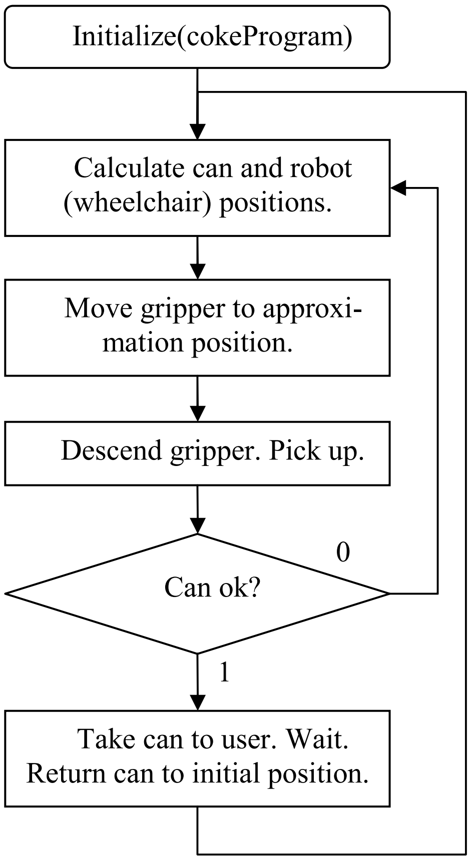

Fig. 8. Path Planning Algorithm

First, the can position and the wheelchair position and orientation are calculated. The algorithms used have been explained in Section 2. The 2D object positions actually give us the 3D object positions as object height is constant, and previously known. Once the 3D object positions are known, commands may be sent to the robot to move it to an approximation position (vertically on top of the can).

The next step is descending the gripper to get the can. The gripper will have a binary sensor to determine if the can has been picked up. In case it has been**,** the correct movements will be performed for the user to drink and then the can will be retrieved and set in its original position. If not, the robot will attempt to localize and grab the can again.

4 Results and Conclusions

The following is a collection of the most relevant results and conclusions. The authors would like to emphasize that this is work in progress and that the results are very preliminary.

4.1 Notable Results

Much work has been performed, yet still much is to be done. The authors have knowledge of the limitations of the current system. However, it is worthy to mention that the localization mechanism that is based on look-up tables and is described in Subsection 2.2 eliminates the necessity of correcting barrel-type distortion at run-time.

Additionally and most importantly, the results received by the vision module have been verified as information that results vital and correct for task achievement. An actual grip of a red can is depicted in Figure 9.

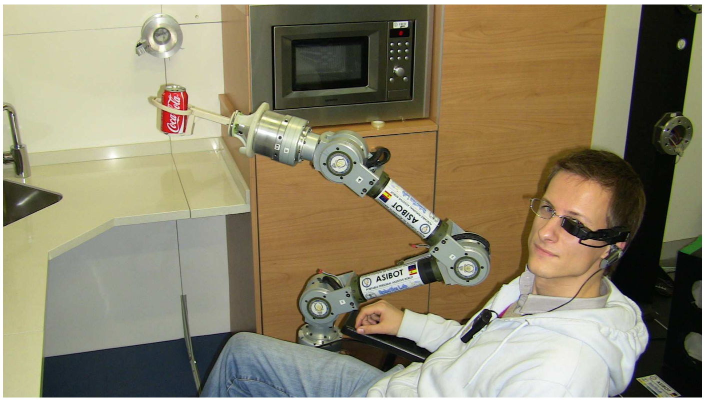

Fig. 9. The ASIBOT Can Gripper Holding a Real Red Can

4.2 Future Lines of Research

Although functionality based on haar-like features has been achieved with OpenCV in C++, results are still not satisfactory (low ROC curve). When perfected, these developments will be incorporated into the architecture.

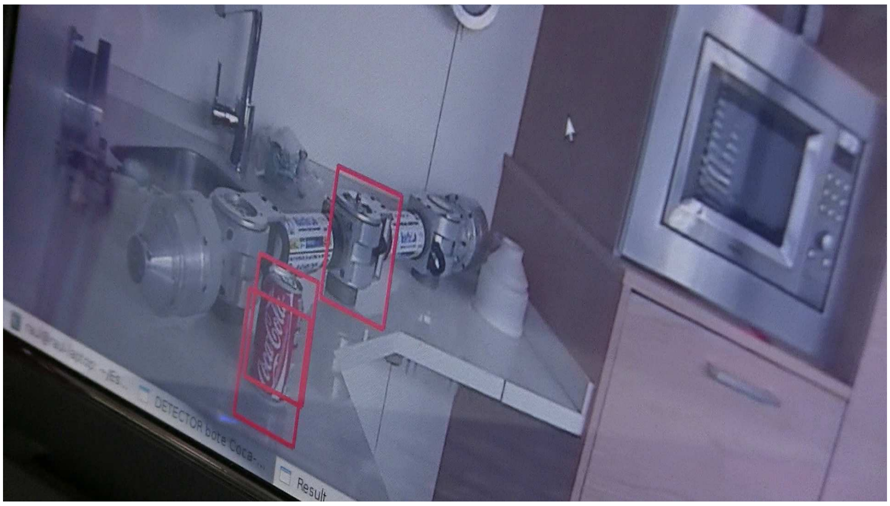

Fig. 10. Results with OpenCV are still premature

Other future lines of research are related with hospital visits and clinical trials. We have worked with the Hospital Nacional de Parapléjicos de Toledo and are now currently in progress with the Hospital Universitario de Getafe.

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