An Autonomous Shopping Assistance Robot for Grocery Stores*

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***Abstract*— The use of robot assistants in grocery stores can aid in improving overall customer experience. In general, due to the large number and variety of products available, the layouts of these stores can be stressful for customers. This results in customers not purchasing all their intended products which impacts both the customer and the grocer. To help address this problem our research focuses on the development of an autonomous service robotic system named Blueberry. This system is designed to escort customers to their desired products within any grocery store. The novelty of this proposed architecture is that it does not require an a priori acquired map of the environment and uses contextual information in the store to guide the customers. In this paper we present a Human-Robot Interaction (HRI) study with Blueberry to investigate the feasibility of the robot to assist users. Preliminary results of experiments conducted with the Shopping Assistant Robot Blueberry showed that the overall system was easy to learn, helpful and enjoyable, and participants would use it again in the future.**

I. Introduction

An emerging area of robotics is retail grocery stores. Grocery stores are known for their vast product inventory and often confusing layouts. Out-of-stock products, crowding, and queuing often create stress and anxiety for shoppers with time pressures [1], and elderly shoppers who are less able to cope with stressful situations [2]. Studies suggest that increased stress while shopping can result in customers more frequently failing to make their intended purchases [3]. This results in stores losing customers and revenue which can be significant as the average person makes three trips to the grocery store a week [4]. Robot assistants can be used in grocery stores to improve overall customer experience by providing product information and location.

In this paper we present the architecture and development of an autonomous robot to aid customers with shopping in grocery stores. A customer's grocery list is provided to the robot through its Graphical User Interface (GUI). The robot then guides the customer to the desired products on the list in an a priori unknown store by uniquely considering contextual information in the environment such as aisle signs. Our objective is to have the assistive robot be deployed in any store on-the-fly to help those in need. Therefore, our methodology does not require a previously generated map of the environment or the locations of products.

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II. Robots in Grocery Stores

The majority of existing service robots developed for grocery store applications such as Tally [5], Bossa Nova [6], and Scarab [7] have focused on tracking shelf product inventory using previous knowledge of aisle locations and shelving planograms. Robots with baskets have also been developed to carry a customer's shopping items [8]-[10]. Only a handful of robots have been developed to either verbally communicate the locations of products while remaining stationary [11], or escort customers to the locations of products [12],[13]. However, these require prior knowledge of the environment layout and the locations of the products.

III. Robot Shopping Assistance Methodology

Our shopping assistant robot, Blueberry, consists of a mobile base with a torso containing a touchscreen and a 2 degrees of freedom head with an animated face, Fig. 1. Blueberry has the following sensors: 1) a laser range finder used for mapping and navigation, and 2) two 2D cameras on its head (aisle sign detection) and body (shelf product detection and classification).

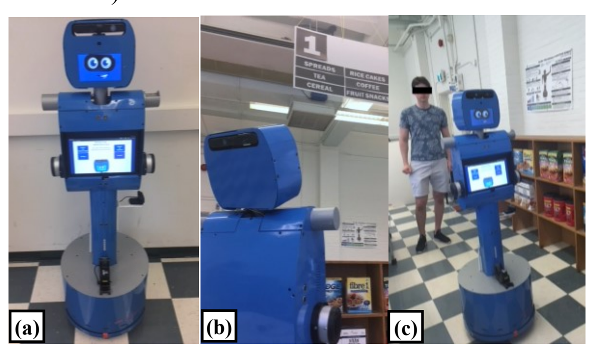

Fig. 1. a) Blueberry Robot, b) Aisle Sign Detection, c) Aisle Escorting

To allow Blueberry to assist users with their shopping needs, a system architecture has been developed for the robot, Fig. 2. The main modules of the architecture are discussed below in the following sub-sections.

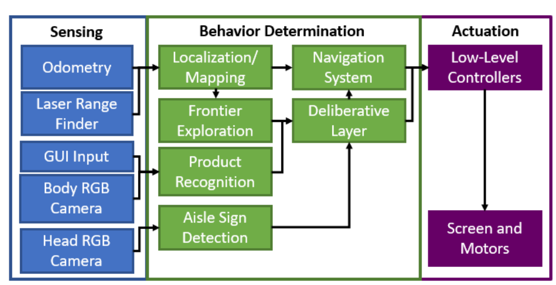

Fig. 2. Blueberry HRI System Architecture

A. *Graphical User Interface Input*

Human Robot Interaction begins with the user providing their grocery items to the robot through a GUI displayed on the robot's chest mounted tablet. The GUI begins with a welcome page, Fig 3(a) to allow the user to pick products by either keywords or images. The user can select between eleven different product categories, Fig 3(b). They are then shown a list of products within the category they can choose to add to the product list, Fig 3(c). Upon adding the desired products, the user selects the checkout button to review their list, Fig 3(d). Finally, they select the finish button to send the product list to Blueberry to begin exploration of the grocery store and escorting the user to their chosen products.

B. *Frontier Exploration and Deliberative Layer*

To direct the robot's search to find the grocery items, a nearest frontier exploration approach is implemented [14]. Namely, Blueberry explores the nearest frontier to its current location. While exploring, Blueberry may encounter contextual information in the form of product category text that is displayed on aisle signs showing what products may be found in that area. If this occurs, the robot's deliberative layer switches to an aisle search state, where the robot travels down the aisle while performing product recognition.

C. *Aisle Sign Detection*

During exploration, aisle signs and their corresponding category labels are detected and interpreted as contextual information using the two-stage process shown in Fig. 4. The sign label detection stage begins by performing edge detection on the 2D image of the environment, Fig. 5. Closed contours that are approximated as rectangles (including skewed rectangles) by satisfying a minimum width-to-height ratio are bounded as a set of potential labels. A perspective transform is performed to de-skew the labels which are then extracted from the full image by cropping along the boundary. The resulting label is then processed by applying a bilateral filter and binarization, so the label can be classified by Tesseract OCR in the next stage.

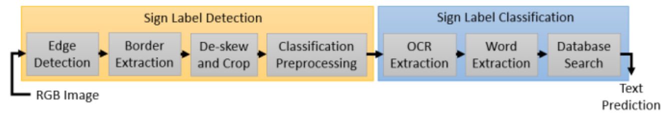

Fig. 4. Aisle Sign Detection Pipeline

In the sign label classification stage, text is extracted as single words from the cropped sign labels using the Tesseract OCR engine [15] Fig 5(c). Spell check is performed on the OCR output by computing the minimum Levenshtein distance [16]. Then the text is compared to a database of product categories. If there is a match, the category is used to predict aisle products for the aisle at that time step. The text is saved with the current robot pose with previously observed environment context.

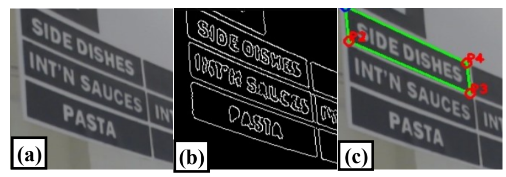

Fig. 5. Aisle Sign Detection: a) Captured 2D Sign image, b) Binarized image, c) Classified Sign Label

D. *Product Recognition*

Product recognition is performed as a two-step process as the robot navigates down an aisle, Fig. 6. The RGB channels of the 2D image of potential products are first binarized and background subtraction through a series of morphological transformations is applied to mask shelves. Contour detection is then used to define product candidate regions, Fig. 7.

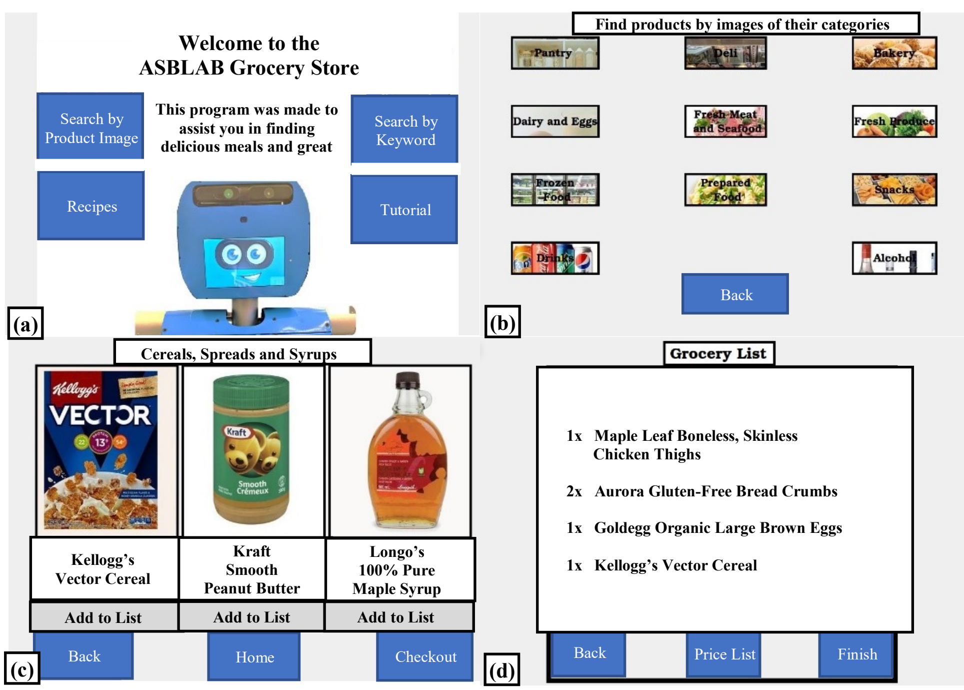

Fig. 3. GUI Application: a) Welcome Screen, b) Search by Product Image, c) Item Selection, and d) Checkout Screen

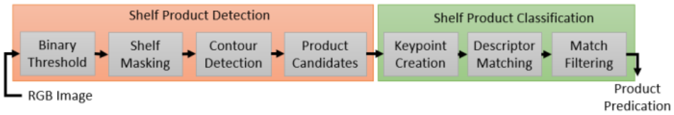

Fig. 6. Shelf Product Algorithm Pipeline

These candidates are compared to a database of grocery store product template images using SIFT keypoints and descriptor matching [17]. They are scored on the Euclidean distance between the candidate and database descriptors of all products in the aisle. Match filtering is done to remove false-positives from the initial match set by evaluating the ratio between the first and second nearest neighbor matches found in each candidate-template pair. RANSAC [18] is also used to filter geometric outliers. Candidate regions are then classified as corresponding products based on the highest scoring matches.

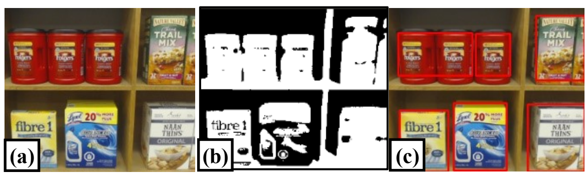

Fig. 7. a) 2D shelf image, b) Binarized image, c) Bounding box

IV. HRI Study with the Shopping Assistant Robot

We conducted an HRI study consisting of the Blueberry robot receiving a shopping list of products from a user via its GUI and escorting the user to these products in a multi-aisle store-like environment developed in our lab. We investigated the user's acceptance and perceived usefulness of both the GUI interface and the Blueberry system.

A. Environment Set-up

A store-like environment was designed in our lab, consisting of two aisles. Aisle signs of size 91 cm x 62 cm were hung overhead at the front of each aisle. Each aisle sign had six sign labels (each 43.5 cm by 9.5 cm), corresponding to common product categories, Fig. 8. The aisle signs were orientated in a manner commonly seen in grocery stores, where the aisle sign is parallel to the direction of travel in the aisle, allowing the sign labels to be read before entering the aisle. Corresponding products were placed on shelves in each aisle Fig. 8.

Fig. 8. a) Aisle sign 1, b) Aisle sign 2, c) Shelves with Products

B. Experimental Procedure

Participants for this HRI study were recruited from the University of Toronto and ranged in age from 20-31 years old (μ=24.9, σ=2.7). Each participant provides the robot with a three-item grocery list using the GUI. Then Blueberry escorts the participant while exploring the environment for predetermined items. During the escorting phase, the robot provides vocal feedback regarding: 1) its intended movements, 2) when it has chosen an aisle to search for an item on the list, and 3) when it located an item on a shelf. Once the robot found the items, the participant was requested to complete a questionnaire on their experience with the robot.

The questionnaire consisted of three parts, where the first two parts used a 5-point Likert Scale, 1 – strongly disagree and 5 – strongly agree. Part one of the questionnaire was to obtain feedback on the user's experience with the GUI. These questions were adapted from the User Experience Questionnaire [19]. The second part focused on their overall experience with Blueberry as a Shopping Assistant Robot. These questions were similar to statements used in our previous HRI studies [21][22]. Part three consisted of short answer questions focusing on the characteristics/features of the robot and additional aspects the participants want the robot to have.

C. Results

The descriptive statistics for the GUI questionnaire results are presented in TABLE I. All the statements had a median value of at least 3. The responses showed that participants had a positive experience using the GUI and felt that it was practical, helpful, intuitive and easy to learn.

TABLE I. GUI Questionnaire Results

	Statement	Min	Max	Median
Interacting with the GUI was:	Wonderful	3	5	4
	Easy	2	5	4
	Satisfying	2	5	4
	Enjoyable	2	4	3
	Understandable	3	5	4
	Helpful	3	5	4
	Interesting	3	5	4
	Pleasing	3	5	4
	Motivating	3	4	3
	Efficient	2	5	4
	Practical	2	5	5
	Organized	3	5	4
	Attractive	3	4	3
Screen and System Statements:	Text on the screen was easy to read.	1	5	4
	Organization of information on the screen was very clear.	3	5	4
	Sequence of screen displays to complete the task was very clear.	3	5	4
	Position of information on the screen was consistent.	5	5	5
	The GUI keeps me informed about what is happening.	3	5	4
Learning Statements:	Learning to operate the GUI was easy.	3	5	5
	Finding items by trial and error is easy.	2	5	4
	Tasks can be performed in a straight-forward manner.	3	5	5
	Experienced and inexperienced users' needs are considered.	3	5	4

The descriptive statistics for the Blueberry questions are presented in TABLE II. All questions had a median value of at least 4, with the exception of the speed at which Blueberry navigates (median=3). In general, the participants found the robot helpful, enjoyed interacting with it, would use it again in the future and trusted the robot.

TABLE II. BLUEBERRY SHOPPING ASSISTANT QUESTIONNAIRE RESULTS

Statement	Min	Max	Median
I enjoyed interacting with Blueberry.	3	5	4
I believe Blueberry was helpful in finding products.	3	5	4
Blueberry moves at an appropriate speed while escorting me.	1	5	3
I think Blueberry searching for products in the store is useful.	3	5	4
Blueberry can help me.	2	5	4
I would ask Blueberry for help in the future.	2	4	4
I find Blueberry easy to use.	3	5	5
I think Blueberry could be helpful to other shoppers.	4	5	5
I think Blueberry makes grocery shopping more enjoyable.	2	4	4
I think that that the feedback from Blueberry's voice is helpful.	1	5	5
I like Blueberry's appearance.	3	5	5
I am comfortable interacting with Blueberry.	4	5	5
I find Blueberry intimidating*.	4	5	5
I trust Blueberry's help.	2	5	4.5
I trust to follow Blueberry while it guides me to the products.	4	5	4.5

*Statement was negatively worded and reverse-scored

D. Open Ended Questions

The majority of participants stated that their favorite aspects of Blueberry were its appearance and ability to vocalize its intentions. Three participants stated that the GUI was their favorite characteristic of the robot. Five participants suggested that the robot should move faster. We had chosen the speed so that people of all ages (including older adults) would be able to comfortably keep up with the robot. Participants also suggested that future iterations of Blueberry should have speech recognition so that they could interact with the robot more intuitively and add items to the shopping list during the product exploration phase

V. CONCLUSIONS

In this paper we present the design and implementation of the shopping assistant robot Blueberry which can assist users to find products on their grocery list in a grocery store. A preliminary study was conducted to evaluate user experience while interacting with Blueberry as it escorted participants within a store-like environment. In general, participants found the robot to be both helpful and useful in finding products. They also found the interactions with the robot and its GUI intuitive and easy to use. The participants requested that Blueberry should move faster in the future. However, overall, they felt that the service provided by Blueberry was valuable and they would use it again while shopping.

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