Smart Shopping Cart Learning Agents Modeling And Evaluation

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***Abstract*—The paper describes the design, implementation and user evaluation of utility and goal-based intelligent learning agents for smart shopping cart. In keeping user's shopping list, they guide visitors through the shops and the goods in the shopping center or according to new promotions in the shops, respectively. It is envisaged that concrete implementation of the shopping agents will be running on each shopping cart in the shopping centers. The k-d decision tree and reinforcement-learning algorithm are used for agents learning. The task environment is partially observable, cooperative, deterministic, and a multi - agent environment, with some stochastic and uncertainty elements. It incorporates text-to-speech and speech recognizing technology, Bluetooth low energy technology, holographic technology, picture exchange communication system. Machine learning techniques are used for agents modeling. This kind of intelligent system enables people with different communication capabilities to navigate in large buildings and in particular to shop in the large shopping centers and maximize user comfort. Some initial user opinions of the shopping cart agents are presented.**

Keywords – Smart shopping cart virtual learning agent; machine learning; reinforcement learning; decision tree; Ambient intelligence; holographic technology; beacon-based technology; assistive technologies.

I. INTRODUCTION

In big and unfamiliar indoor spaces, such as shopping centers, airports, stadiums, hotels, office buildings, people may have difficulties with finding the desired destination. Many categories of people – the elderly, the children, the people with visual or hearing impairment, with difficulties in communication etc. – need specialized ways of communication [2][20][21]. This paper presents modeling, implementation and user evaluation of two intelligent learning agents for smart shopping cart. They guide visitors through the shops and the goods in the shopping center according to user's shopping list or according to new promotions in the shops, respectively. It is envisaged that concrete implementation of the shopping agents will be running on each shopping cart in the shopping centers.

The task environment incorporates text-to-speech and speech recognizing technology, Bluetooth low energy technology, holographic technology, information kiosks, picture exchange communication system.

The rest of the paper is structured as it follows: in Section II the technologies that the task environment incorporates are briefly discussed; in Section III the task environment specification, including performance measure, properties, environment actuators and sensors description is presented; the agent programs realization of the goal-based learning agent and utility goal-based learning agent by means of a decision k-d tree and reinforcement-learning are explained in Section IV; the degree of development of the proposed cognitive architecture components is explained in Section V; an empirical survey about the interest of end customers to the used technologies and a survey about the way the customers perceive the two developed agents are considered in Section VI; in the VIIth Section a number of conclusions are drawn.

II. BACKGROUND TECHNOLOGY USED FOR TASK ENVIRONMENT

Beacons are used to mark the location of objects and navigate people in indoor spaces [10][25][26][33][34]. They work on the principle of lighthouses by emitting signals at short intervals based on Bluetooth Low Energy (BLE) technology. The distance to the Beacon can be defined depending on the signal strength [3]. In addition to emitting advertising or other types of announcements, it is also possible to locate beacons [10][26][34].

Holograms are made of light and sound, appear in the around space and reply to gestures, voice and gaze commands [9]. A hologram can be placed and integrated in the real world or can tag along with user as an active part of user's world helping for navigation in indoor spaces.

Another possible solution to the problem of orientating people in indoor spaces is the use of embodied conversational information kiosks [27][31]. These systems use the information they have both about their own location and about the layout of the building and give instructions to the users how to find the desired place in the building.

The information kiosks are a collection of different technologies such as video processing from face detection, speaker-independent speech recognition, array microphone for noise cancellation, a database system, and a dynamic question answering system [16][31].

The Picture Exchange Communication System (PECS) [1][30] allows people with little or no communication abilities to communicate using pictures. People using PECS

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are taught to approach another person and give them a picture of a desired item in exchange for that item [4][5].

Screen readers [7][11][17] and text-to-speech (TTS) systems [6][14] enable blind and vision impaired people to use computers and provide the key to education and employment.

According to [13], the first step in designing an agent must always be to specify the task environment as fully as possible. That includes performance measure, environment actuators and sensors description. That’s why we will consider smart shopping problems, task environment specifying and shopping learning agents modeling in the next section.

III. SPECIFYING THE TASK ENVIRONMENT

It is envisaged that shopping agents will be implemented on the shopping cart. The consumers will run their cart following the directions given by the agents. In the future, the shopping agents can be implemented on a robotic shopping cart like an autonomous Kuka robot that can be controlled by gestures [8][22][23][28][29] to follow the user. Then, the environment will become very complex and similar to the environment of the automated driver.

The modulus of the system prototype is given in Figure 6. The task environment consists of four main blocks: input, output, shopping, and navigation.

The technologies, used in the input block, are face detection and speech recognition. The equipment comprises a camera, a microphone, a keyboard, a mouse, and a touch screen. The general object detection algorithm consisting of a cascade of classifiers proposed by Viola and Jones [35] is used to detect faces. For video processing, C# and Intel OpenCV library [15] is used.

The output block uses speech synthesis and virtual character visualization for giving information to the user.

The shopping block includes: drag and drop pictures for creating the shopping list (Figure 4); pictures-to-speech convertor;

The navigation block includes: Beacons/iBeacons or/and Holograms for smart buildings, smart shopping mall navigation. Using of Google Beacon Platform or/and Microsoft HoloLens respectively is needed.

Agent programs include goal-based learning agent and utility goal-based learning agent realization by means of a decision k-d tree and reinforcement-learning.

A. *Performance Measure*

The performance measure to which the shopping agents are aspired include getting to the correct shop in the shopping mall; getting to the new promotion in the shopping mall; minimizing the path when going through the shops from the shopping list; maximizing passenger comfort; maximizing purchases; and enabling people with different communication possibilities to navigate in big buildings and in particular to shop in the big shopping centers.

B. *Environment*

Any shopping agent deals with a variety of shops in the shopping malls; the newest promotion could be in each and any of the shops in a mall; the agents can recommend visiting the shops in a mall in various sequences. An option is to visit all desired shops following the shortest possible way. Another option is to go around the shops in accordance with the arrangement of the items on the shopping list. A third option is to go to the shops in accordance with the availability of sales or new promotions. The location of the shops in an exemplary Mall is given in Figure 1. The model of the environment in Figure 3 is presented in the form of a graph. The nodes are the shops and the edges are the connecting corridors.

Figure 1. Exemplar location of eight shops in a shopping center

C. *Actuators*

The shopping agents are visualized on the display screen. Only the head of an agent is modeled by means of the program Crazy Talk. Face animation includes synchronization of the lip movement with the pronounced text and expressed emotions. The agents’ faces normally express friendliness and calmness and when a new promotion or sale is announced they express excitement and joy. The emotions of elevation are realized through changing the strength and the height of the speech and by visualizing a model of the emotion “joy” on the face.

D. *Interaction and Sensors*

For interaction both with the intelligent agents and the consumers are used: Keyboard entry; Microphone; Touch Screen; Camera – OpenCV, Face Detecting; Natural Language Understanding; Speech recognizing; drag-and-drop pictures, pictures to speach convertor; Beacons/iBeacons or/and Holograms for smart shopping mall navigation.

E. *Properties of a Task Environment*

The behavior of the two intelligent agents is mutually complementary. They aim at facilitating the user access to the desired commodities and increasing the number of purchases, made by him/her, as well as at offering information about promotions and sales, in which he/she is interested.

The agent does not know when a new promotion or a new customer will appear. Therefore he/she periodically

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checks on the site of the mall if there are files, containing information about new promotions or sales and reads them if available. Then, he/she transmits this information to the customers, planning to visit the corresponding shops. Whenever a new customer appears, the agent receives his/her shopping list and defines the sequence for visiting the shops in the mall. That's why task environment is partially observable, cooperative and a multi-agent environment.

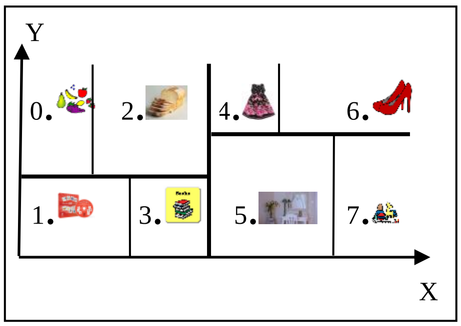

Figure 2. Shop k-d decision tree

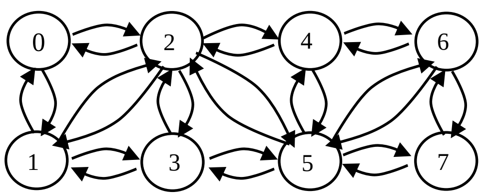

Figure 3. Presentation of the location of the shops in an exemplary mall by an orientated graph

The shopping world is also deterministic with some stochastic elements and contains elements of uncertainty of the environment. The task environment is episodic and it can be realized either as static or as semi-dynamic environment. The environment can be regarded as static as the location of the shops in the mall is known. The agent receives the whole shopping list and suggests a certain path around the shops. Whenever there is information about a new promotion or sale appearing during the shopping, the agent can dynamically recommend a change in that shopping sequence.

The environment can be regarded as both known and sequential because every next shop to visit is determined by the current location of the user and by the items he/she has pointed at as important to buy.

IV. SMART SHOPPING LEARNING AGENTS MODELING

Two software agents have been realized. The first one is a Utility Goal–based learning agent, while the second is a Goal-based learning agent.

A. *Utility Goal-Based Learning Agent*

One of the agents can be regarded as a Utility goal-based agent. That is because it feels happy when discovering that there is a promotion or a sale in a shop, in which the customer is interested to go.

The utility goal-based agent uses a decision k-d tree to quickly find where (in which shop) the customer is located according to his/her coordinates. The theory of building and implementing a decision k-d tree is given in [18]. The customer is depicted in Figure 1 by means of an emoticon, which can be moved using the mouse and placed everywhere on the shown map of the shops in the shopping center. Another way of finding the location of the customer is by using estimate beacons sensors or holograms.

The Utility goal-based agent checks if there are new files about promotions or sales published on the site of the shopping center. In case there are such files, it withdraws them and informs the customer about those of them, which are related to the shops the customer intends to visit.

The information about promotions and sales is given to the customer also in the case when it can be seen from the shopping list that the customer has planned to visit a particular shop where there is a promotion or a sale.

The customer receives notifications about promotions/sales when he/she goes past a beacon as well.

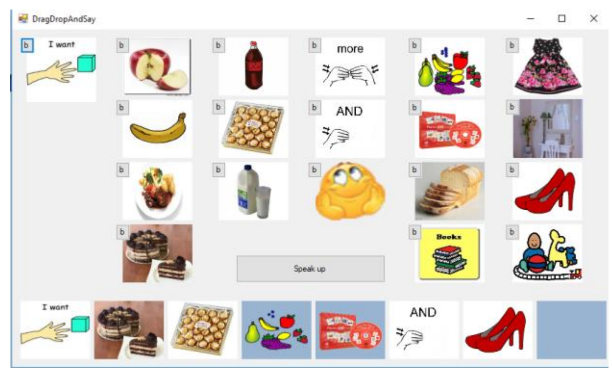

Figure 4. Making a shopping list by dragging and dropping pictures

1) *Decision k-d Tree Realization*

In order to build the decision tree, the location of the eight shops in the exemplary shopping mall, given in Figure 1, is considered. As it is described in [18][24] all shops are divided first by width alone into two sets, each with an equal number of shops. Next each of the two sets is divided by heights alone. Finally, each of those four sets is divided by width alone, producing eight sets of just one block each. The shop sets are divided horizontally and vertically until only one block remains in each set as it is shown in Figure 2. The overall result is called a k-d tree, where the term k-d is used to emphasize that the distances are measured in k-dimensions.

Finding the nearest block is really just a matter of following a path through a decision tree that reflects the way the objects are divided up into sets. As the decision tree in Figure 2 shows, only three one–axis comparisons are required to guess the shop in which the user is positioned.

In general [18], the decision tree with branching factor k=2 and depth d=3 will give 2^3= 8 leaves (shops in our task). Accordingly, if there are n shops (or goods, or users) to be identified, d will have to be large enough to ensure that $2^d \geq n$. Then, the number of comparisons required, which corresponds to the depth of the tree, will be of the order of $\log_2 n$.

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B. Goal-Based Learning Agent

According to [12][19][32], Reinforcement learning is a method of learning, by which what to do is taught, i.e., how to match a situation to an action, so that a numerical reward received as a signal, is maximized. The teacher does not point at the actions to be undertaken. Instead, the trainee has to find out those, leading to the greatest reward and try to realize them. In the most interesting and challenging cases, not only the immediate reward could be taken into account when choosing an action, but also the further situations and the future rewards.

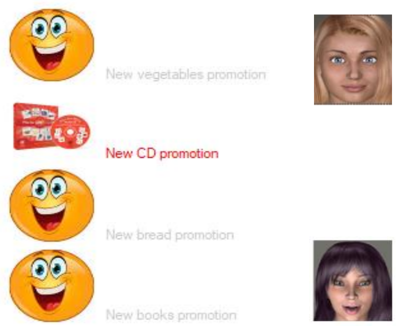

Figure 5. Message about a promotion of a new Compact Disk

All reinforcement learning agents have explicit goals, can sense aspects in their environment and choose actions, which influence it. The agent is realized by a program, matching the way the agent perceives reality and the actions it undertakes.

A reinforcement learning algorithms is used for the second Goal-based learning agent. The agent receives the shopping list from the customer (this is what the agent perceives) and informs the customer about the sequence of shops he/she can visit in order to buy all the goods needed (these are the actions the agent undertakes). The shortest possible route is suggested, in accordance with the particular shopping list.

Since the goal is to visit all the shops from the shopping list, the particular shopping list can be regarded as a plan or a sequence of goals to achieve in order to fulfill the task completely.

It is also possible for the agent to get the exact location of a customer and a particular shop to get to. The shortest possible path to the desired shop is suggested in this case as well.

In order to realize the agent's learning process the following is to be developed: Environment model; Rewards model; Agent's memory model; Agent's behavior function; Value of the training parameter.

The environment model is a graph (Figure 3) of the different environment conditions. The nodes in the graph (Figure 1) are the shops in the exemplary shopping mall. The edges point at the shops, between which there is a transition. Then, this graph is presented by an adjacency matrix. The number of rows and columns in this matrix is equal to the number of shops in the mall. Zero is put in the matrix in a place where there is a connection between the number of a shop, set by a number of a row, and the number of a shop, given by a number of a column. Values of -1 are placed in the other positions of the adjacency matrix.

The rewards model is needed to set a goal for the agent. Reaching every shop from the customer's shopping list is such a goal. Since the agent is a goal-based one, it behavior can be changed by just setting a new goal, changing the rewards model [12]. A reward is only given when the agent gets to a particular shop.

The agent's memory is modeled by presenting it with the help of an M-matrix (Memory of the agent). The rows in the M-matrix represent the current location of the customer, while the columns are the shops, where he/she can go. It is assumed at the beginning that the agent does not have any knowledge and therefore all elements in the M-matrix are zeros.

The rule for calculating the current location of the customer at the moment of choosing the next shop to visit is as it follows:

M (cuurent location of the customer, chosen shop to visit next) = **R**(current location of the customer, next shop) + **Υ. Max**[**M**(next shop, all possible shops where the customer could go from the next shop)].

The following is taken into account in the above formula:

The immediate reward, obtained when the customer decides from the current location to go to a next shop: **R**(current position, chosen shop to go next);

The biggest possible future reward. This is the biggest reward, chosen from among the rewards, which would have been obtained when the customer goes out of the next shop and enters any possible shop: **Max**[**M**(next shop, all possible shops where it is possible to go from the next shop)].

The value of the learning parameter **Υ** defines the extent to which the agent will take into account the value of the future reward. The value of the learning parameter **Υ is** within 0 to 1 ($0 \leqslant \Upsilon < 1$). If Υ is closer to zero, then the agent will prefer to consider only the immediate reward. Experiments have shown that in this case it is impossible to teach the agent to achieve the goal. If **Υ** is closer to one, then the agent will consider the future reward to a greater extent. This is the better option for successful training of the agent. The value of the learning parameter was experimentally chosen to be **Υ=0.8**. At this value, the obtained weights for all possible actions are clearly identifiable and the process of training is reliable. A random initial position is chosen for the customer in the algorithm for training the agent. The following steps are realized until the target shop is reached:

One of all possible shops is chosen, where it is possible to go from the current position. The shop to which the customer would go next is considered. For this next position now all the shops, to which it is possible to go further are considered. The value of the highest reward is taken. The next position is then set as a current one.

V. Degree of Development of the Proposed Cognitive Architecture Components

The goal-based learning agent and the utility goal-based learning agent are fully developed. The head of each agent is modeled and visualized. We have used Crazy Talk 6 for emotion modeling. The decision k-d tree and reinforcement-learning algorithm are completed and used for agents function realization. The program for creating a shopping list by using key combinations and drag and drop pictures is ready. The picture to speech converter program can pronounce all the existing pictures and the created shopping list. The agents can recognize and react to a few speech commands. They start communication with the users when detecting a face in front of themselves. A number of experiments are conducted with some Estimote beacons and a notification program [14]. The complete beacon based navigation system and the corresponding software are not ready yet, however. The holograms and holographic computer have not been used for now. We hope to obtain and use the holographic computer soon. Experiments in a real shopping center are planned as well.

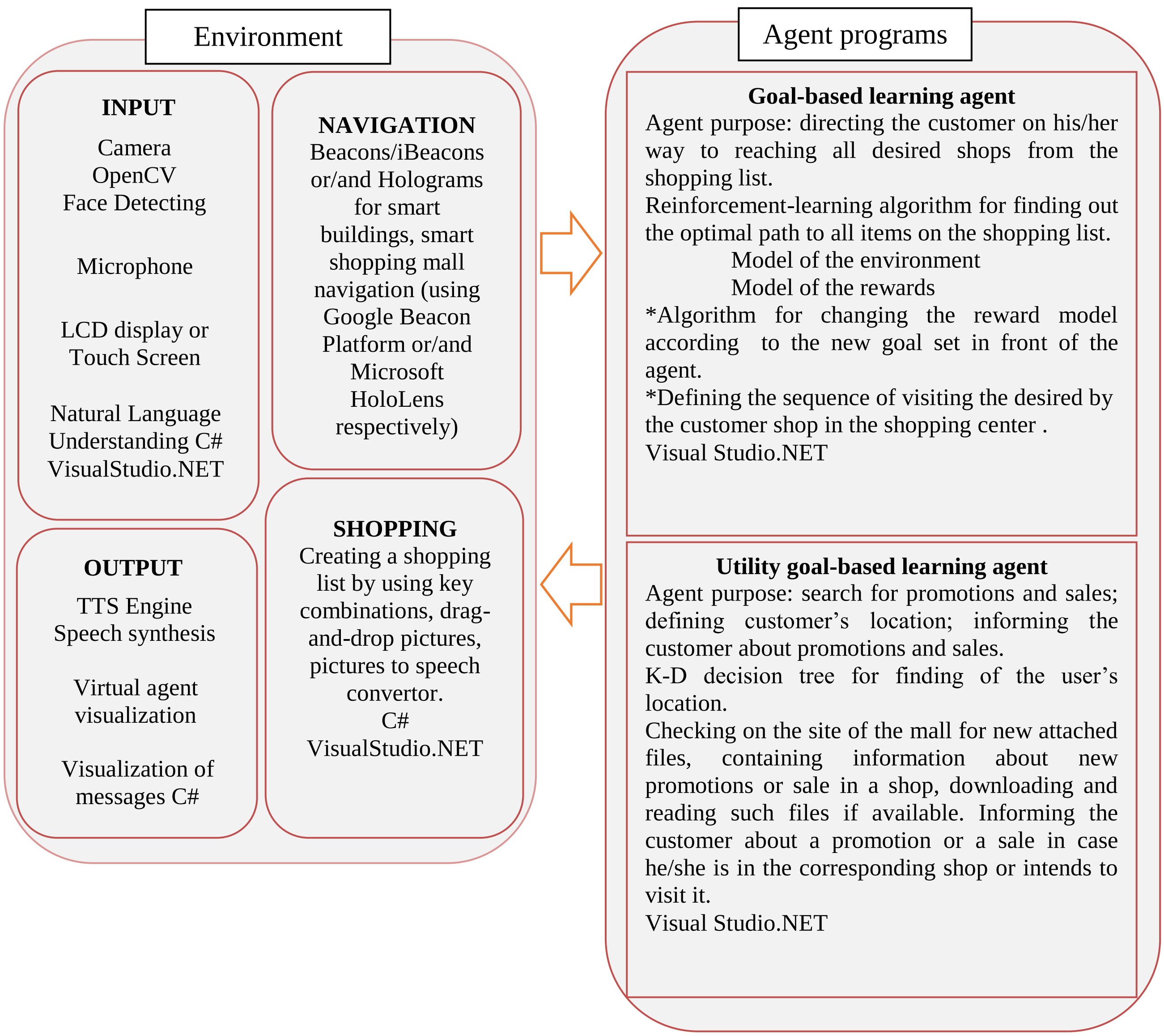

Figure 6. Specifying the task environment and smart shopping learning agents modeling.

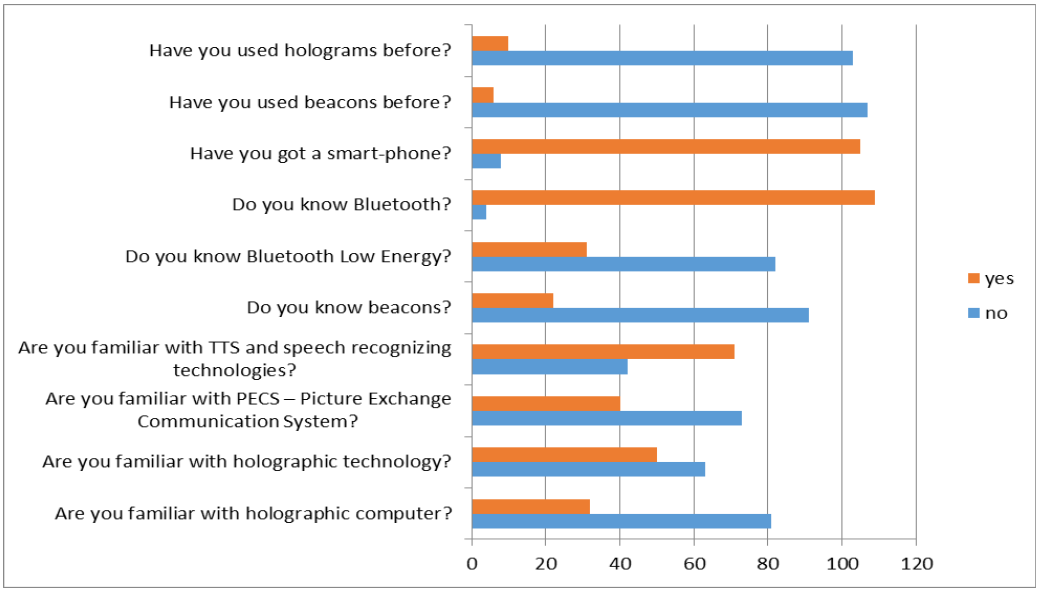

Figure 7. A survey about the interest of end customers in beacon-based services, holographic technology, PECS, TTS and Speech Synthesis technologies.

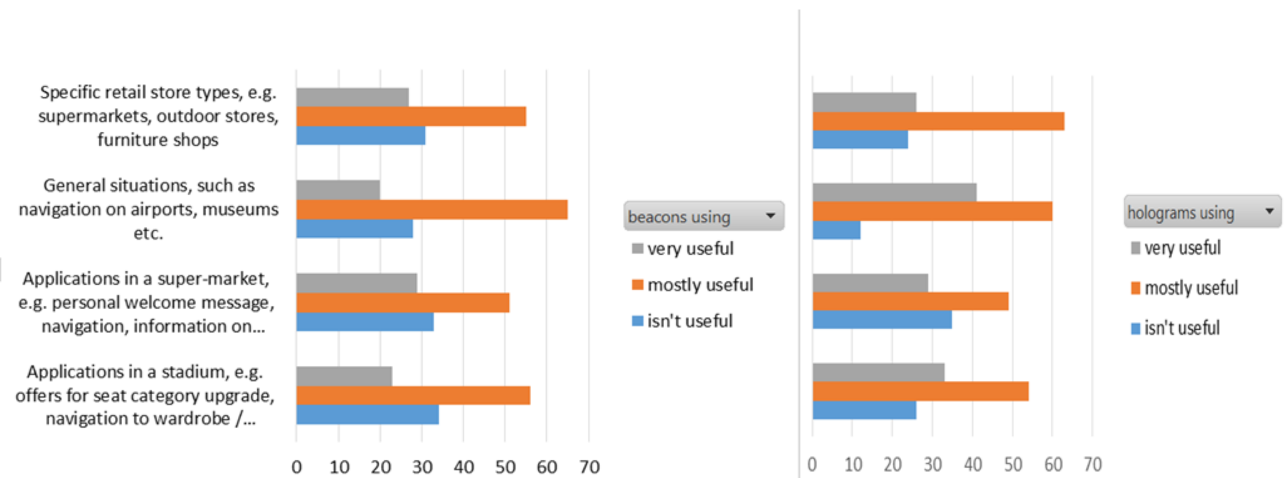

Figure 8. A survey about rediness of the user to use beacon-based services and holographic technology.

VI. Empirical Survey

The survey was conducted at the university. The total number of 115 students were offered the questionnaire. All of the participants were between the ages of 18 to 23 years old.

A. *A survey about the interest of end customers in beacon-based services, holographic technology, PECS, TTS and Speech Synthesis technologies.*

To investigate people's mindset towards the use of beacons, the use of holograms, drag-drop pictures, pictures to speech, TTS and Speech Synthesis an empirical study was conducted. The survey's purpose was to explore the interest of end customers in beacon-based services, holographic technology, PECS, TTS and Speech Synthesis technologies and the willingness to use them. As a base we use [34] but append some questions about new technologies.

With this end in view, we designed a questionnaire with the following tree sections. The participants were asked (Figure 7), whether they (1) own a smart-phone, (2) know Bluetooth, (3) know Bluetooth Low Energy, (4) know Holographic computer, (5) know Holographic technologies, (6) know beacons, (7) have used beacons before, (8) have used holograms before, (9) are familiar with PECS, (10) are familiar with TTS and speech recognizing technologies.

This helps to understand, whether consumers are aware of beacons. Then, they were given a short introduction of the beacon technology, holographic technology, PECS, TTS and

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speech recognizing technologies, as a preparation for the remaining questions. Participants were asked to assess the usefulness of typical applications, which were based on already existing scenarios by using beacon-based or holographic realizations (Figure 8): General situations, such as navigation on airports, coupons in stores, information on exhibits in museums, etc.; Specific retail store types, e.g., supermarkets, outdoor stores, furniture shops.; Applications in a super-market, e.g., personal welcome message, navigation to products on the shopping list, information on products, special offers, and electronic payment at the checkout.; Applications in a stadium, e.g., offers for seat category upgrade, navigation to wardrobe/restrooms, special offers for drinks and snacks.

Beacon-based technology and holographic technology are little known and the services based on them are not used widely yet, but the respondents declared willingness and readiness to use them.

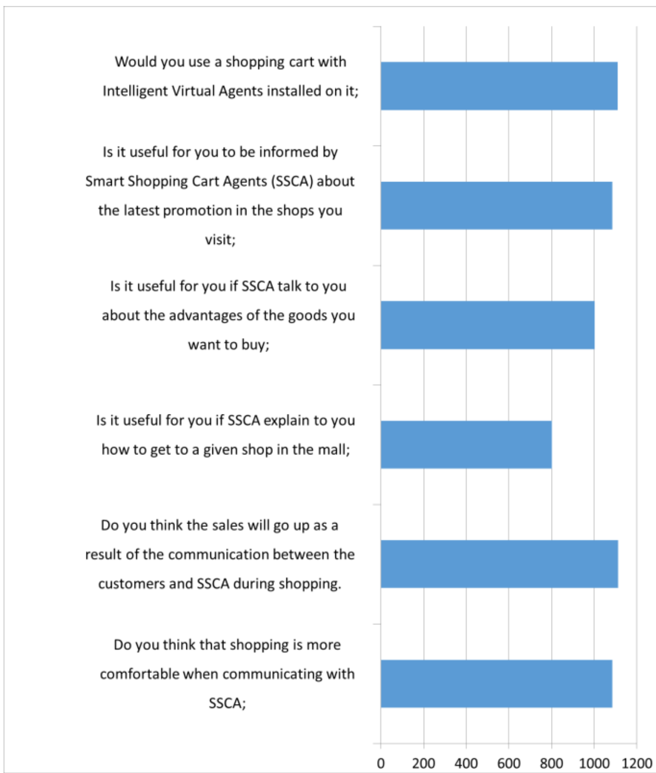

Figure 9. A survey about the way the customers perceive the two developed agents and whether they consider their purpose useful (values 1-10)

Five blind people aged 45-65 also took part in the survey. These respondents were not familiar with the described technologies and had not used them before. However, they do know and use in their daily routine Internet, Skype, smartphones, e-mail, all TTS programs and desktop reading programs. They showed great enthusiasm and willingness to get acquainted with beacon-based services and holographic services for navigation in buildings.

B. A survey about the way the customers perceive the two developed agents and whether they consider their purpose useful.

The capabilities of the two agents were demonstrated in front of the students. The idea of Smart Shopping and Smart Shopping Cart Agents was presented. Then, the students were asked to evaluate usefulness of the two agents, to compare their functionality and to consider the services of which agent prefer; to say their opinion about shopping with Shopping Cart Smart Agents. Some of the questions were: Would you use a shopping cart with Intelligent Virtual Agents installed on it; is it useful for you to be informed by Smart Shopping Cart Agents (SSCA) about the latest promotion in the shops you visit; is it useful for you if SSCA explain to you how to get to a given shop in the mall; do you think that shopping is more comfortable when communicating with SSCA; do you think the sales will go up as a result of the communication between the customers and SSCA during shopping.

It can be seen from Figure 9 that, the customers would use SSCA and they think the agents will be useful and their presence would make the shopping practice more comfortable. The utility goal-based learning agent that search for promotions and sales is the preferred one.

VII. Conclusion

The paper describes the design and implementation of an intelligent Smart Shopping Cart Learning Agents prototype and their environment. The system differs from other intelligent systems by the combination of machine learning techniques, beacon-based navigation and/or hologram-based navigation in the mall, the integration of Picture Exchange Communication System in it and by its language understanding and speech synthesis capabilities, drag-and-drop techniques and keyboard button combinations enabled access.

The task environment is partially observable, cooperative and a multi-agent environment. The shopping world is deterministic with some stochastic and uncertainty elements. The task environment is episodic and can be realized either as static or as semi-dynamic.

The utility goal-based agent uses a decision k-d tree to quickly find where (in which shop) the customer is located according to his/her coordinates. It getting to the new promotion in the shopping mall according to user‘s shopping list and inform them.

Reinforcement learning algorithm is used for the other Goal-based learning agent. The agent gets the shopping list from the customer and informs the customer about the sequence in which he/she can visit the shops to buy all needed goods.

The performance measure to which the shopping agents are aspired includes getting to the correct shop in the shopping mall; getting to the new promotion in the shopping mall according to user‘s shopping list; minimizing the path when going through the shops from the shopping list; maximizing customer comfort; maximizing purchases; and enabling people with different communication capabilities to

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navigate in big buildings and in particular to shop in big shopping centers.

The empirical survey conducted with a limited number of users showed their positive mindset for using such Smart Shopping Cart Learning Agents in indoor spaces. The utility goal-based learning agent that search and informs for promotions and sales is the preferred one. In the future work, it is intended to develop other commercial agents, such as those who will be familiar with users shopping habits.

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