Smart Shopping Cart Learning Agents

Dilyana Budakova
Department Of Computer Systems and Technologies
Technical University of Sofia, Branch Plovdiv, Plovdiv, Bulgaria
email: dilyana_budakova@yahoo.com

Lyudmil Dakovski
Department of Communication & Computer Technologies
European Polytechnic University
Pernik, Bulgaria
email: lyudmil.dakovski@epu.bg

Veselka Petrova-Dimitrova
Department of Computer Systems and Technologies
Technical University of Sofia, Branch Plovdiv, Plovdiv, Bulgaria
email: vesi_s_petrova@yahoo.com

***Abstract*—The paper describes the design, implementation and user evaluation of utility-based and goal-based intelligent learning agents for smart shopping cart. In keeping user's shopping habits or 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 or on holographic displays. The k-d decision tree, the best identification 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. Different embodiments of the shopping agents are discussed like holographic agent embodiment, embodied virtual agent or social robot embodiment. Some approaches of realization of a smart robotic shopping cart that can follow the user are discussed too. The performance of the Q learning algorithm with an introduced environment measures model (a model of the environment criteria) is proposed and explored. Study of the learning parameter is presented. Smart Shopping Cart Learning Agents modeling and development task allows for applying and improving the learning algorithms.**

Keywords-smart shopping cart learning agent; machine learning; reinforcement learning; Q learning; decision tree; identification 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 [1][2][3][4]. This paper presents modeling, implementation and user evaluation of three intelligent learning agents for smart shopping cart. They guide visitors through the shops and the goods in the shopping center according to users' shopping habits, user's shopping list or according to new promotions in the shops, respectively [1]. It is envisaged that concrete implementation of the shopping agents will be running on each shopping cart in the shopping centers or on holographic displays [1]. The paper is inspired by [1] presented at the Cognitive 2019 conference.

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, personal utility-based learning agent and utility-based learning agent by means of a decision k-d tree, identification 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; a survey about the way the customers perceive the three developed agents; a survey about users' opinion and possibilities for shopping agents embodiments and user following smart shopping cart realizations; a survey of the performance of the Q learning algorithm with an introduced environment measures model (a model of the environment criteria) and study of the learning parameter Υ are considered in Section VI; A section for future work is Section VII; in the VIIIth 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 [5][6][7][8][9]. 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 [10]. In addition to emitting advertising or other types of announcements, it is also possible to locate beacons [5][7][9].

Holograms are made of light and sound, appear in the around space and reply to gestures, voice and gaze commands [11]. 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 [12][13]. 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 [13][14].

The Picture Exchange Communication System (PECS) [15][16] allows people with little or no communication abilities to communicate using pictures. People using PECS are taught to approach another person and give them a picture of a desired item in exchange for that item [17][18].

Screen readers [19][20][21] and text-to-speech (TTS) systems [22] enable blind and vision impaired people to use computers and provide the key to education and employment.

According to [23], 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 [24][25][26][27][28] 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 [29] is used to detect faces. For video processing, C# and Intel OpenCV library [30] 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, utility-based learning agent and personal utility-based learning agent realization by means of reinforcement-learning, decision k-d tree and identification tree building.

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 or in accordance with shopping habits of the user. 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.

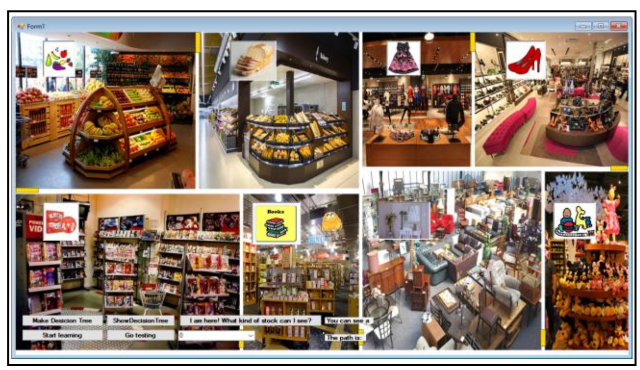

Figure 1. Exemplar location of eight shops in a shopping center.

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.

The shopping agents can be realized as holographic agents. In this case they will be visualized on holographic displays. Then not only the heads of the agents will be modeled, but also their bodies, their gestures, clothes, as well as the way of keeping the appropriate distance to the consumer;

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 speech convertor; Beacons/iBeacons or/and Holograms for smart shopping mall navigation.

E. Properties of a Task Environment

The behavior of the three 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 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.

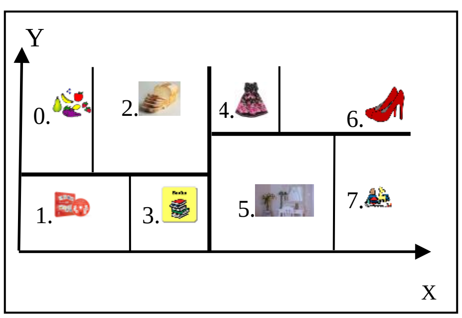

Figure 2. Shop k-d decision tree.

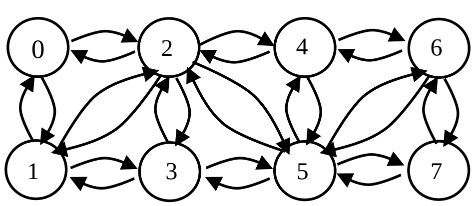

Figure 3. Presentation of the location of the shops in an exemplary mall by an orientated graph.

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

Three software agents have been realized. The first one is a utility-based learning agent, the second is a goal-based learning agent, while the third is personal utility-based learning agent.

A. Utility-Based Learning Agent

One of the agents can be regarded as a Utility-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-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 [31]. 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-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.

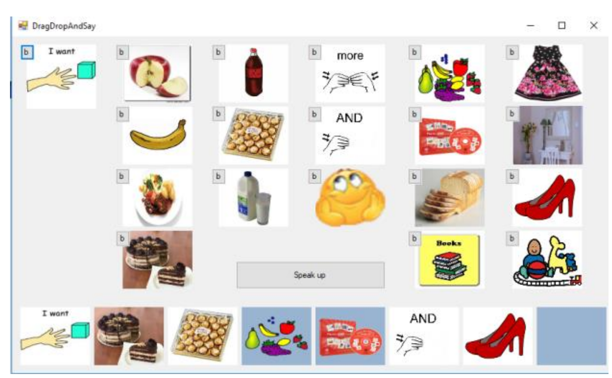

Figure 4. Making a shopping list by dragging and dropping pictures.

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 [31][32] 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 [31], 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 $\log_2 n$.

B. *Goal-Based Learning Agent*

According to [33][34][35], 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.

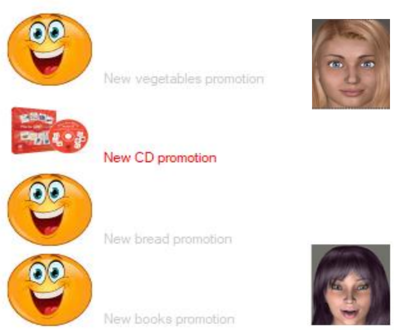

Figure 5. Message about a promotion of a new Compact Disk.

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 [33]. 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 (current location of the customer, chosen shop to visit next) = **R**(current location of the customer, next shop) + $\boldsymbol{\Upsilon}$**.** **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 $\boldsymbol{\Upsilon}$ 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 ≤ϒ< 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:

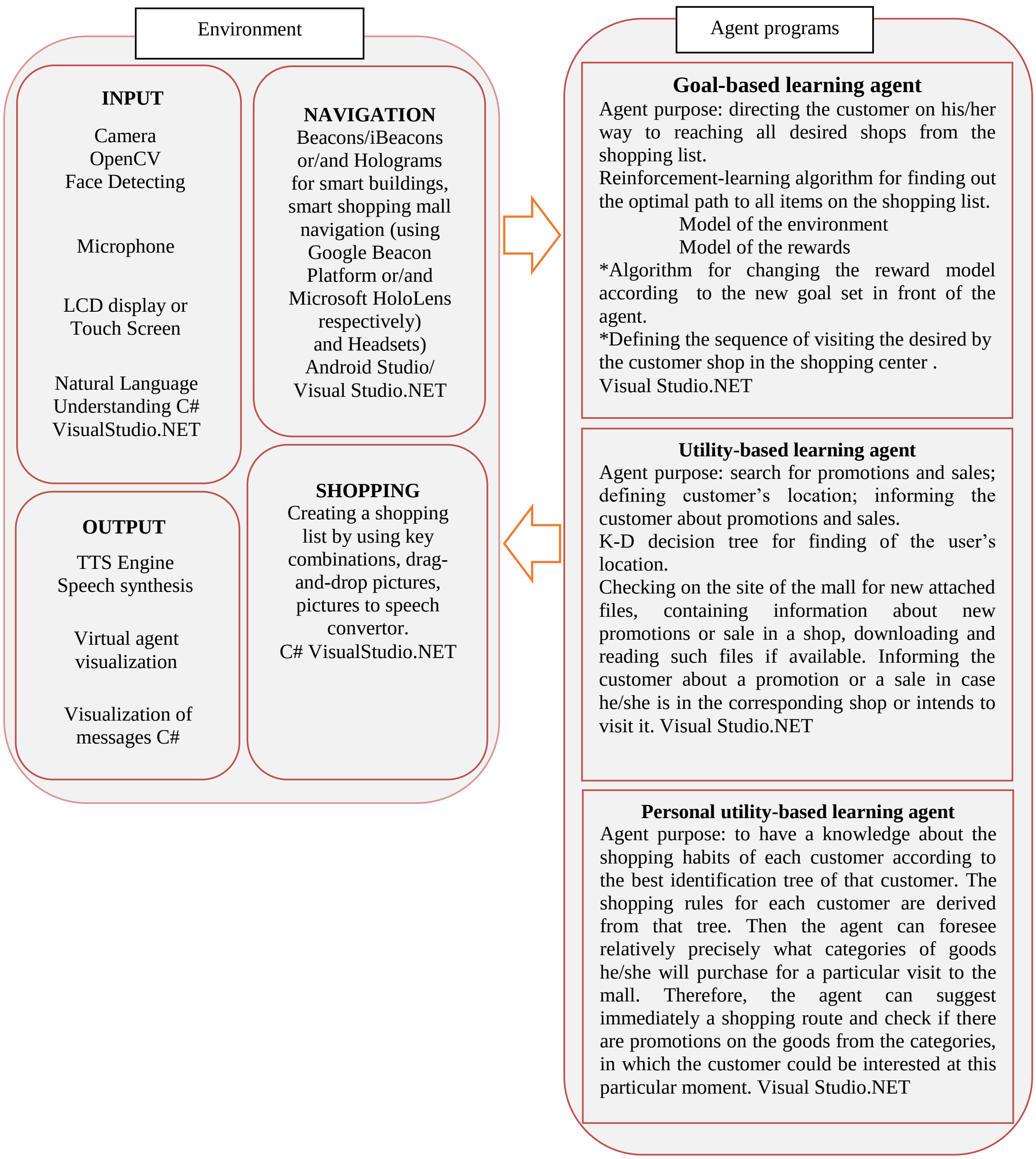

Figure 6. Specifying the task environment and smart shopping learning agents modeling.

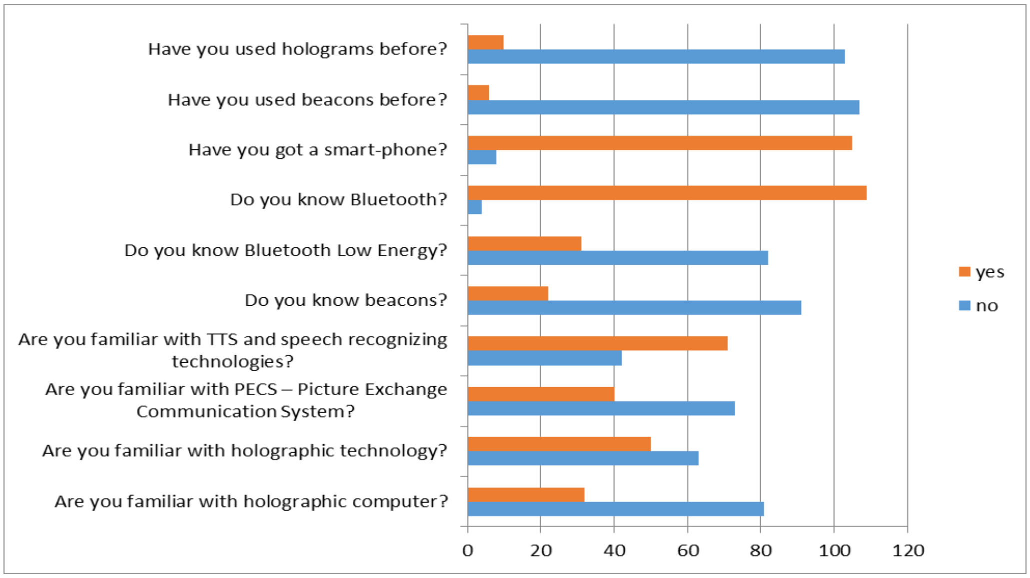

Figure 7. A survey about the interest of end customers in beacon-based services, holographic technology, PECS, TTS and Speech Synthesis technologies.

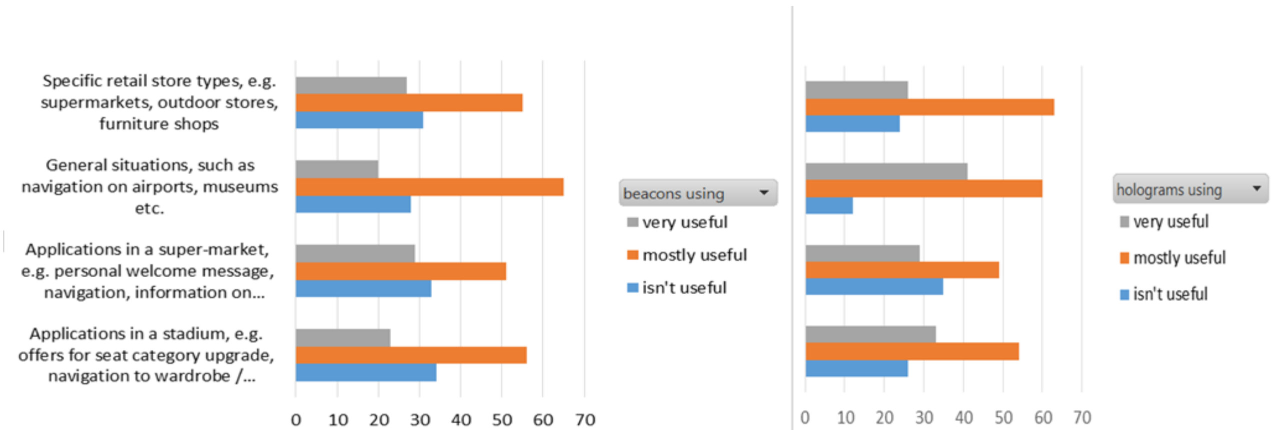

Figure 8. A survey about rediness of the user to use beacon-based services and holographic technology.

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.

C. Personal shopping Utility-Based Learning agent

The purpose of the personal shopping utility-based learning agent is to have a knowledge about the shopping habits of each customer. The personal shopping utility-based learning agent recognizes the customer at the moment he/she registers himself/herself by means of his/her shopping card.

All the purchases are grouped in categories in accordance with the shops in the shopping mall. A characteristic table with positive and negative examples is created for each category of goods. When a product from a considered category is purchased during a given visit of a customer to the mall, this is a positive example for this category of goods. For each realized purchase the following characteristics are saved in the characteristic table: season (spring, summer, autumn, winter); month (1-12); number of the week in the month (1-4); day (workday, weekend, public holiday, birthday); purchased good from another category (the categories, related to the other available shops in the mall are considered); if there were promotions of goods from the considered category at the moment of the purchase.

These characteristics are used for tests, allowing to make a classification of the examples of purchases for each category of goods. The most important characteristic for each customer is found out. This is the characteristic, for which the biggest number of examples fall into a subset of either positive or negative examples.

A subset, in which the examples are either positive or negative is called homogeneous. The examples, fallen into a non-homogeneous subset should be classified once again by using another characteristic, i.e., another criterion for classification. The procedure is repeated until all examples are classified, i.e., until all examples fall into homogeneous subsets. Thus the smallest identification tree is built. This is the tree, which classifies the examples in the best way. The shopping rules for each customer are derived from that tree. Each test (characteristic) is regarded as a prerequisite, while the result from the test, i.e., the fact if a given category of goods is purchased or not, is regarded as a conclusion. Here is an example of an obtained shopping rule for a customer: If the season is summer and it is a weekend, then the customer buys a product from the category of desserts.

When the agent has at disposal the shopping rules of a customer, it can foresee relatively precisely what categories of goods he/she will purchase for a particular visit to the mall. Therefore, the agent can suggest immediately a shopping route and check if there are promotions on the goods from the categories, in which the customer could be interested at this particular moment.

V. Degree of Development of the Proposed Cognitive Architecture Components

The goal-based learning agent, the utility-based learning agent and personal utility-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, identification tree algorithm 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 [36]. 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 have just obtained the holographic computer and we have got start to use it now. The holographic agent's visualization are planned. Experiments in a real shopping center and with real users shopping data are planned as well. User following smart shopping cart realizations is forthcoming too.

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 [9] 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 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.

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 three 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 three 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; would you use a shopping cart with Personal Shopping Utility Based Learning Agent 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 personal shopping utility agent and utility-based learning agent that search for promotions and sales are the preferred agents.

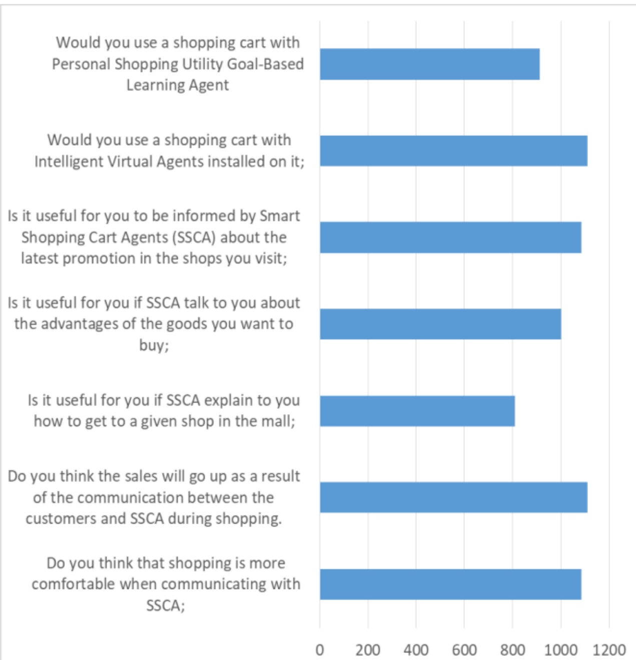

Figure 9. A survey about the way the customers perceive the three developed agents and whether they consider their purpose useful (values 1-10).

C. A survey about user's opinion and possibilities for shopping agents embodiments and user following smart shopping cart realizations

During the third survey the students were asked to guess, which of six possible shopping carts they would use. The options are: 1) a standard shopping cart with a tablet attached to it, on which the virtual shopping agents are visualized; 2) a robotized shopping cart, capable of following the user and controllable by means of gestures; 3) a robotized shopping cart with a robotized hand/arm, capable of following the user and taking/giving objects, and controllable by gestures; 4) a standard shopping cart, pushed by a human-like robot; 5) a standard shopping cart, equipped with a holographic screen, on which a hologram of a human-like shopping robot is visualized; 6) a standard shopping cart, equipped with a holographic screen, on which a 3D scene with a hologram of a human – shopping assistant is visualized.

The results from the survey are given in Figure10. The students have the strongest preference to the following two options: 1) a robotized shopping cart, capable of following the user and controllable by means of gestures; and 2) a standard shopping cart, equipped with a holographic screen, on which a hologram of a human-like shopping robot is visualized;

Having in mind the obtained results, the possibilities for realization of these two shopping cart types will be discussed.

1) A robotized shopping cart, capable of following the user and controllable by means of gestures

It is characteristic of this task that the velocities are very low; all the other shopping carts and users are regarded as dynamic obstacles to be avoided. Commodity shelves are static obstacles, which should be avoided, too. The shopping cart needs to recognize the user to be followed. It has to recognize the user's gestures and have a reaction to them. The distance between the shopping cart and the user should be kept the same as well.

Consequently, it can be summarized, that the autonomous user following is inherently a complex cognitive process associated with object recognition, static or dynamic obstacles avoidance in the environment, in which humans and robots work together; position determining; predicting the direction of movement; decision making, context understanding; working with uncertain and incomplete knowledge; vehicle communication and targeted actions and movements.

User following achievement approaches are Motion planning approaches [37]; Robust motion control approaches [38][39][40]; Game theory approach and Connectionist approach [41][42][43].

2) A standard shopping cart, equipped with a holographic screen, on which a hologram of a human-like shopping robot is visualized

It turns out that the users prefer the holographic shopping agents to look like a human, but not to be modeled as people at 100%. The users know that they are not people actually and reject them, perceiving this overly realistic model as a deception. That is why we are working to find a suitable model for the appearance of a humanoid robot that can be perceived by people well.

Modeling of the whole body of the humanoid robot is envisaged, as well as choosing a 3D scene that fits in the context of the mall.

The holographic robot must adhere to the social norms of communicating with consumers. Not to enter their personal space. Not to intrude. To keep distance when communicating with the user. The robot must behave as a mall officer. Communication and negotiation skills are needed [44], related to directing viewer to the speaker; awaiting for the speaker to finish; taking the turn; answering a question; asking a question; waiting for the answer; analysis of the answer and continuing the conversation; disengagement from the user. Skills for grasping holographic goods and presenting them in front of the user will also be needed. Such skills a holographic agent can learn by using deep neural networks (DNNs) and recurrent neural networks (RNNs) [41][42][43].

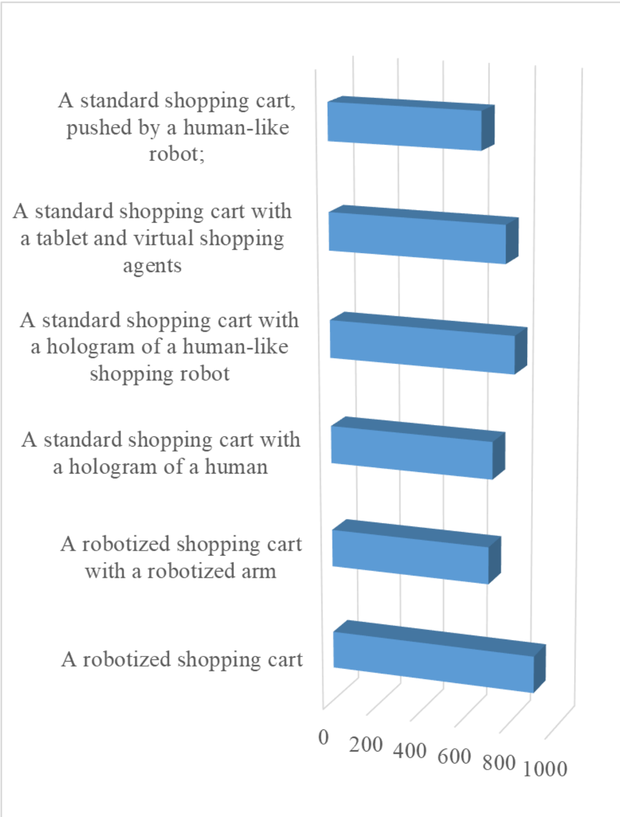

Figure 10. A survey about user's opinion for shopping agents embodiments and user following smart shopping cart realizations. (values 1-10).

The holographic agent has to understand where the user's attention is directed, to understand the user's reaction toward its actions or words. It means that scenarios have to be developed for the human-holographic agent and both reinforcement learning and Learning from Demonstration (LfD) can be used for the purpose [39][40].

In multi-agent scenarios, Learning from Demonstration paradigm already allows the robot to observe the partner's reaction that matches its movement. On the one hand, LfD speeds up reinforcement learning algorithms and can be used to re-demonstrate policies as well as to build new policies. LfD develops with the introduction and improvement of ways to obtain teacher feedback. In the latter algorithms the feedback may even be in the form of corrective advice. Therefore these algorithms could be successfully used to develop algorithms for acquiring social behavior by the holographic agents. Training can also be done by encoding the action-reaction patterns in a Hidden Markov Model (HMM) using [38].

D. A survey of the performance of the Q learning algorithm with an introduced environment measures model (a model of the environment criteria), presented as Matrix K

Q learning that is simplification of reinforcement learning is an extremely flexible method. It allows to easily find an optimal path from each position in the modeled environment to the goal state.

It is known that Imitation Learning is a way to optimize the Reinforcement learning and Q learning in particular. The task considered here is related to smart shopping realization but it does not allow a teacher to show how to reach the goal in order to achieve better results.

This is due to the availability of lots of ways for achieving a particular goal. Besides, the goal is different every time. The shops and stands in the Shopping Center that consumers want to reach are different. Some consumers look for promotional goods; others need artwork. Some customers use shopping as a therapy and want to reach the most frequently visited shops and to go through the busiest lobbies and hallways; others want to avoid the crowded zones. So in this task it is important not only to reach the goal. It is of the same level of importance how it is reached and what criteria a certain path meets.

In order to make the Q learning agent find the optimal sequence of lobbies or hallways, meeting a specific criterion, the use of environment measures model represented as matrix K is introduced.

For the purposes of the experiment the Shopping Center is represented by a graph with 17 nodes and 36 edges between them as shown in Figure 11. Every shop in the considered Shopping Center is represented as a graph. Every lobby or a hallway, connecting the shops, is represented by an edge. The busiest and most wanted to go through lobbies or hallways are marked in orange color and have a measure of 1 in the K matrix (Figure12). The secondary, distant, non-desirable pathways are marked in blue and have a measure of 2 in the K matrix (Figure12). The environment measures model presented by matrix K is similar to the environment reward model, presented by matrix R (Figure12). The values of a given criterion, to which corresponds each edge in the graph, are kept in the K matrix. The minus one (-1) in the matrix R and in the matrix K says that has no edge on this place in the graph. Now the learning algorithm is changed. The agent has to go only through those edges in the graph, which have a specific measure value.

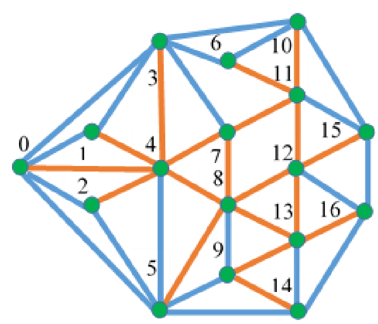

Figure 11. A Shopping Center with 17 shops and lobbies or hallways between them, presented by an undirected graph.

The experiment is conducted in the following way: a goal is set in front of the agent to reach node 15 in the graph; a reward of 100 for going through the edge, connecting nodes 11 and 15 is announced as well in reward matrix R. Other edges have zero reward (Figure 12). The black dot line denotes the optimal path found from node 0 to node 15.

First stage. No criterion is set, which the desired sequence of edges should meet in order to reach the goal.

```
//R - reward matrix
public static int [,] R = new int[,] {
        { -1,  0,  0,  0,  0,  0, -1, -1,  -1, -1, -1, -1, -1, -1, -1, -1, -1 },
        {  0, -1,  -1, 0,  0, -1, -1, -1,  -1, -1, -1, -1, -1, -1, -1, -1, -1 },
        {  0, -1, -1, -1,  0,  0, -1, -1,  -1, -1, -1, -1, -1, -1, -1, -1, -1 },
        {  0,  0, -1, -1,  0, -1,  0,  0,  -1, -1, 0, -1, -1, -1, -1, -1, -1 },
        {  0,  0,  0,  0, -1,  0, -1,  0,   0, -1, -1, -1, -1, -1, -1, -1, -1 },
        {  0, -1,  0, -1,  0, -1, -1, -1,   0,  0, -1, -1, -1, -1,  0, -1, -1 },
        { -1, -1, -1,  0, -1, -1, -1, -1,  -1, -1,  0,  0, -1, -1, -1, -1, -1 },
        { -1, -1, -1,  0,  0, -1, -1, -1,   0, -1, -1,  0, -1, -1, -1, -1, -1 },
        { -1, -1, -1, -1,  0,  0, -1,  0,  -1,  0, -1, -1,  0,  0, -1, -1, -1 },
        { -1, -1, -1, -1, -1,  0, -1, -1,   0, -1, -1, -1, -1,  0,  0, -1, -1 },
        { -1, -1, -1,  0, -1, -1,  0, -1,  -1, -1, -1,  0, -1, -1, -1, 0, -1 },
      { -1, -1, -1, -1, -1, -1,  0,  0,  -1, -1,  0, -1,  0, -1, -1,  100, -1 },
        { -1, -1, -1, -1, -1, -1, -1, -1,   0, -1, -1,  0, -1,  0, -1,  0,  0 },
        { -1, -1, -1, -1, -1, -1, -1, -1,   0,  0, -1, -1,  0, -1,  0, -1,  0 },
        { -1, -1, -1, -1, -1,  0, -1, -1,  -1,  0, -1, -1, -1,  0, -1, -1,  0 },
        { -1, -1, -1, -1, -1, -1, -1, -1,  -1, -1,  0,  0,  0, -1, -1, -1,  0 },
       { -1, -1, -1, -1, -1, -1, -1, -1,  -1, -1, -1, -1,  0,  0,  0,  0, -1 }};

//K- measure matrix
public static int[,] K = new int[,] {
        { -1,  2,  2,  2,  1,  2, -1, -1,  -1, -1, -1, -1, -1, -1, -1, -1, -1 },
        {  2, -1,  -1, 2,  1, -1, -1, -1,  -1, -1, -1, -1, -1, -1, -1, -1, -1 },
        {  2, -1, -1, -1,  1,  2, -1, -1,  -1, -1, -1, -1, -1, -1, -1, -1, -1 },
        {  2,  2, -1, -1,  1, -1,  2,  2,  -1, -1,  2, -1, -1, -1, -1, -1, -1 },
        {  1,  1,  1,  1, -1,  2, -1,  1,   1, -1, -1, -1, -1, -1, -1, -1, -1 },
        {  2, -1,  2, -1,  2, -1, -1, -1,   1,  2, -1, -1, -1, -1,  2, -1, -1 },
        { -1, -1, -1,  2, -1, -1, -1, -1,  -1, -1,  2,  1, -1, -1, -1, -1, -1 },
        { -1, -1, -1,  2,  1, -1, -1, -1,   1, -1, -1,  1, -1, -1, -1, -1, -1 },
        { -1, -1, -1, -1,  1,  1, -1,  1,  -1,  2, -1, -1,  1,  1, -1, -1, -1 },
        { -1, -1, -1, -1, -1,  2, -1, -1,   2, -1, -1, -1, -1,  1,  1, -1, -1 },
        { -1, -1, -1,  2, -1, -1,  2, -1,  -1, -1, -1,  1, -1, -1, -1,  2, -1 },
        { -1, -1, -1, -1, -1, -1,  1,  1,  -1, -1,  1, -1,  1, -1, -1,  2, -1 },
        { -1, -1, -1, -1, -1, -1, -1, -1,   1, -1, -1,  1, -1,  1, -1,  1,  2 },
        { -1, -1, -1, -1, -1, -1, -1, -1,   1,  1, -1, -1,  1, -1,  2, -1,  1 },
        { -1, -1, -1, -1, -1,  2, -1, -1,  -1,  1, -1, -1, -1,  2, -1, -1,  2 },
        { -1, -1, -1, -1, -1, -1, -1, -1,  -1, -1,  2,  2,  1, -1, -1, -1,  2 },
       { -1, -1, -1, -1, -1, -1, -1, -1,  -1, -1, -1, -1,  2,  1,  2,  2, -1 }};
```

Figure 12. Reward matrix R and Measure matrix K.

The optimal path found from node 0 to the goal is given in Figure 13. It can be seen that the path goes through edges with a different value of the criterion, set in the K matrix.

Second stage. The agent receives a requirement to reach the goal by going only through edges with a measure value of 1. The optimal path found from node 0 to the goal is given in Figure 14. As it can be seen, the path goes only through edges with a measure value of 1 for the criterion, set in the K matrix.

Third stage. The agent has to reach the goal by going only through edges, having a measure value of 2. The optimal path for this case, starting from node 0 and going to the goal, is shown in Figure 15. As it shows, the path goes only through the edges with a measure value of 2 for the criterion, set in the K matrix.

In the example under consideration, there are primary and secondary paths that connect all locations in the example Shopping Center. There might be a situation, in which a primary or a secondary path to a given place is missing. Then the algorithm can be modified by allowing the agent to go through a certain number of edges, which do not correspond to the value of the criterion "measure" in the K matrix.

An advantage of the proposed modification of the Q learning algorithm is that it allows the agent to give explanation of the reasons why a given path to the goal has been chosen. In addition, the proposed modification allows to introduce various criteria for a path choice. If the criteria from Maslow's theory of personality motivation are used [45], a model of a system of values could be developed using different scenarios.

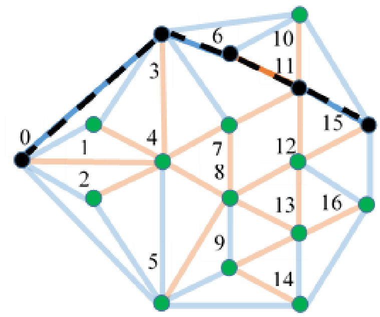

Figure 13. Optimal path from node 0 to node 15. Requirement for measure value not set.

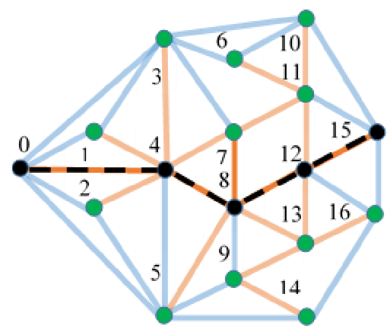

Figure 14. Optimal path from node 0 to node 15. Requirement for measure value: to be equal to 1.

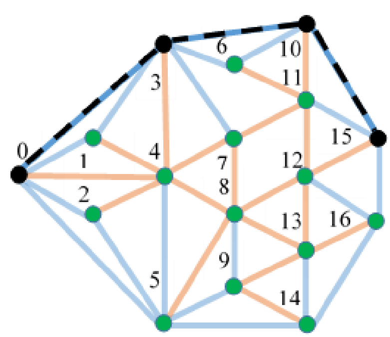

Figure 15. Optimal path from node 0 to node 15. Requirement for measure value: to be equal to 2.

E. Study of the learning parameter ϒ

It is known that the value of the learning parameter ϒ is within 0 to 1 (0 ≤ϒ< 1). The aim is to study if any of these values is more appropriate to be preferred during a Q learning agent training.

The experiment is conducted in the following way: the graph in Figure 11 is considered; a goal is given to the agent and the training gets started. Twelve experiments are carried out actually with each value of the learning parameter ϒ - from 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 to 1, respectively.

First stage: The number of episodes required to train the agent to reach the goal using the optimal path from each node in the graph is considered. The exploration by the agent of each node-to-node path until it reaches the goal node is called an episode.

The training is considered completed when any further change of the assessment of each edge in the graph does not lead to a change in the optimal paths found. The results from this stage are shown in Figure 16. It is obvious that values from 0.3 to 0.9 of the learning parameter ϒ are appropriate for realizing the process of training. When these values are 0, 0.1, 0.2 and 1, no paths to reach the goal are found.

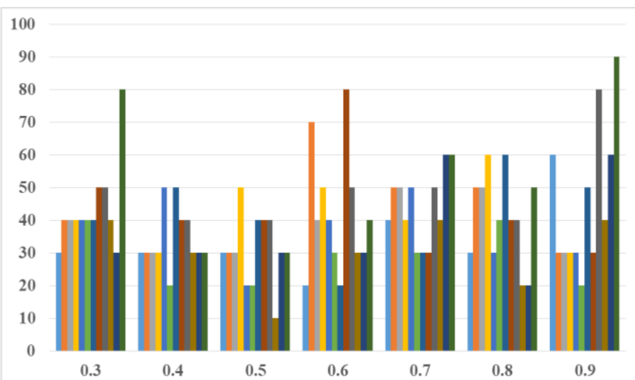

Figure 16. Number of episodes needed to find the optimal paths at values of the learning parameter from 0 to 1 during a Reinforcement learning agent training.

Second stage. The number of episodes required to train the agent to reach the maximum value in the assessment of each edge in the graph is considered. During the training process the assessment of each edge in the graph increases until it reaches its maximum value. When the maximum value is reached, the further training no longer changes the assessments of the edges in the graph. The results from this stage are presented in Figure 17.

Comparing the results of the two stages of the experiment, it can be seen that finding the optimal paths to the goal requires much fewer episodes than reaching the maximum value of each edge in the graph. Besides, the values of the learning parameter of 0.8 and 0.9 offer the greatest possibilities both for training and for finding optimal paths. As it can be seen in Figure 17, these learning parameter values require an average of 800 and 1600 episodes, respectively, until the maximum value in the assessment of each edge in the graph is reached.

VII. Future Work

Many tasks remain to be solved. The work on the development of the Reinforcement learning algorithm will continue in the first place; opportunities for modeling the training agent's value system will be looked for; efforts will be put to modeling a system for generating explanations by the trained agent. Using the holographic computer, it is now possible to model and visualize a virtual advertising agent. It is assumed that the communication with such an agent will be engaging and helpful to consumers. As mentioned in this article, there is a lot of interest in modeling a robotic shopping cart to follow the consumer. Efforts will therefore be made to this end. For example, it is important to combine and share intelligent behaviors such as: wander behavior; path following; collision avoidance; obstacle and wall avoidance; patrol between a set of points; flee behavior.

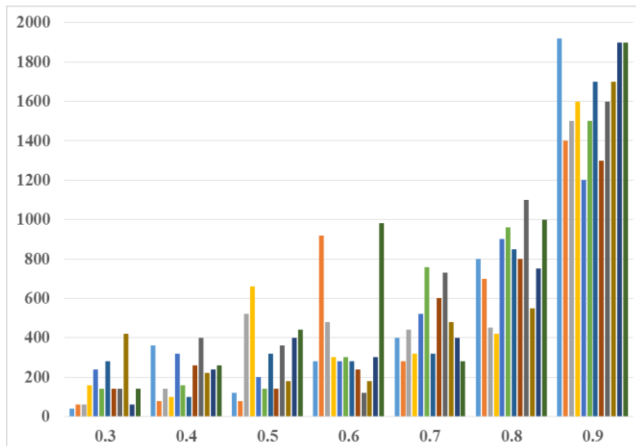

Figure 17. Number of episodes needed to reach the maximum value of the assessment for each edge in the graph under consideration.

VIII. 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-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 personal utility-based agent makes the best identification tree according to the shopping data of each user. That way the agent knows their shopping habits and can suggest a shopping route and check if there are promotions on the goods from the categories, in which the customer could be interested.

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 or according to user’s shopping habits; 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 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-based learning agent that search and informs for promotions and sales is the preferred one.

The performance of the Q learning algorithm with an introduced environment measures model (a model of the environment criteria) is proposed and explored. Study of the learning parameter ϒ is presented.

In the future work, it is intended to realize user following smart shopping cart and holographic visualization of the shopping agents.

Acknowledgment

The authors gratefully acknowledge the financial support provided within the Ministry of Education and Science of Bulgaria Research Fund Project FNI DN17/11.

References

[1] Dilyana Budakova, Lyudmil Dakovski, Veselka Petrova-Dimitrova, “Smart Shopping Cart Learning Agents Modeling and Evaluation,” The Eleventh International Conference on Advanced Cognitive Technologies and Applications (COGNITIVE 2019) IARIA, 05-09 May 2019, Venice, Italy, pp. 12-19, ISSN: 2308-4197, ISBN: 978-1-61208-705-4.

[2] Y. J. Chang, S. M. Peng, T. Y. Wang, S. F. Chen, Y. R. Chen, and H. C. Chen, “Autonomous indoor wayfinding for individuals with cognitive impairments,” Journal of NeuroEngineering and Rehabilitation, 7(1), pp. 1– 13, 2010.

[3] V. Kulyukin, C. Gharpure, J. Nicholson, and G. Osborne, “Robot-assisted wayfinding for the visually impaired in structured indoor environments,” Autonomous Robots, Springer, 21(1), pp. 29–41, 2006.

[4] L. Niua and Y. Song, “A schema for extraction of indoor pedestrian navigation grid network from floor plans,” In The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, volume XLI-B4, Prague, Czech Republic, pp. 325-330, 2016.

[5] My Dream Companion project – YGA. [Online]. Available from: https://www.yga.org.tr/en/visually-impaired-techologies [retrieved: 12, 2019].

[6] Y. Zhuang, J. Yang, Y. Li, L. Qi, and N. El-Sheimy, “Smartphone-based indoor localization with Bluetooth low energy beacons,” Sensors, April 2016. 16(5), pp. 596, doi: 10.3390/s16050596.

[7] D. Ahmetovic, et al. “Navcog: A navigational cognitive assistant for the blind,” In International Conference on Human Computer Interaction with Mobile Devices and Services, ACM, 2016, pp. 90-99.

[8] A. Ch. Seyed, N. Vinod, and S. Kaushik, “IBeaconMap: Automated Indoor Space Representation for Beacon-Based Wayfinding,” Human-Computer Interaction arXiv: 1802.05735v1 [cs.HC], USA, 2018.

[9] A. Thamm, J. Anke, S. Haugk, and D. Radic, “Towards the Omni-Channel: Beacon-based Services in Retail,” International Conference on Business Information Systems (BIS 2016), Springer, Leipzig, Germany, July 2016, pp. 181-192. July 2016. DOI: 10.1007/978-3-319-39426-8_15.

[10] Google Beacon Platform. [Online]. Available from: https://www.youtube.com/watch?v=0QeY9FueMow, [retrieved: 12, 2019].

[11] Microsoft HoloLens holographic computer. [Online]. Available from: https://developer.microsoft.com/en-us/windows/mixed-reality/, [retrieved: 12, 2019].

[12] J. Cassell, et al. “MACK: Media lab Autonomous Conversational Kiosk,” Imagina’02, Monte Carlo, 2002 vol. 2, pp. 12–15. [Online]. Available from: https://www.media.mit.edu/gnl/pubs/imagina02.pdf, [retrieved: 12, 2019].

[13] L. McCauley and S. D’Mello, “MIKI: A speech enabled intelligent kiosk,” IVA 2006, LNAI 4133, Springer, 2006, pp.132-144.

[14] Tomorrow‘s digital signage, today with 3d holographic kiosks, Intel IoT Digital kiosks, Solution brief, [Online], Available from: https://d1io3yog0oux5.cloudfront.net/_35cb5a593466915af09244e7df3c153e/provision/db/255/661/pdf/Intel+Provision+3D+Brief+2016.pdf, [retrieved 12, 2019].

[15] A. Bondy and L. Frost, PECS - Picture Exchange Communication System. [Online]. Available from: https://pecsusa.com/apps/, [retrieved: 12, 2019].

[16] C. Lord, M. Rutter, P. C. Dilavore, and S. Risi, “ADOS - Autism Diagnostic Observation Schedule,” Western Psychological Services, 2002.

[17] National Autism Resources Inc. [Online]. Available from: https://www.nationalautismresources.com/the-picture-exchange-communication-system-pecs/, [retrieved: 12, 2019].

[18] What is PECS. [Online]. Available from: https://pecs-unitedkingdom.com/pecs/, [retrieved: 12, 2019].

[19] JAWS. [Online]. Available from: http://www.freedomscientific.com/Products/Blindness/JAWS [retrieved: 12, 2019].

[20] NVDA. [Online]. Available from: https://www.nvaccess.org/, [retrieved: 12, 2019].

[21] Vocalizer Android Dariya Bulgarian voice. [Online]. Available from: https://play.google.com/store/apps/details?id=es.codefactory.vocalizertts&hl=bg, [retrieved: 12, 2019].

[22] Innoetics TTS Reader Female Bulgarian Voice IRINA. [Online]. Available from: https://www.innoetics.com/, [retrieved: 12, 2019].

[23] S. Russell and P. Norvig, “Artificial Intelligence A Modern Approach”, Prentice Hall, Third Edition, 2010, ISBN-13 978-0-13-604259-4, ISBN-10 0-13-604259-7.

[24] Kuka robot. [Online]. Available form: https://cyberbotics.com/doc/guide/robots, [retrieved: 12, 2019].

[25] N. Ç. Kılıboz and U. Güdükbay, “A hand gesture recognition technique for human–computer interaction,” Journal of Visual Communication and Image Representation, Elsevier, Volume 28, pp. 97-104, April 2015.

[26] N. G. Shakev, S. A. Ahmed, A. V. Topalov, V. L. Popov, and K. B. Shiev, “Autonomous Flight Control and Precise Gestural Positioning of a Small Quadrotor,” Learning Systems: From Theory to Practice, Springer, pp. 179-197, 2018. |

[27] E. Coupeté, et al. “New Challenges for Human-Robot Collaboration in an Industrial Context: Acceptability and Natural Collaboration,” Fifth workshop "Towards a Framework for Joint Action", IEEE RO-MAN, 2016, pp. 1-4.

[28] S. R. Fletcher and P. Webb, “Industrial robot ethics: facing the challenges of human-robot collaboration in future manufacturing systems,” A world with robots: international conference on robot ethics (ICRE 2015) Springer, 2015, pp. 159-169.

[29] P. Viola and M. Jones, “Rapid object detection using a boosted cascade of simple features,” Computer Vision and Pattern Recognition (CVPR 2001) IEEE, Vol.1, 2001, pp. I-511-I-518. doi: 10.1109/CVPR.2001.990517.

[30] The Intel Open Source Computer Vision Library, vol. 2006. [Online]. Available from: https://software.intel.com, [retrieved: 12, 2019].

[31] P. H. Winston, “Artificial Intelligence,” Addison-Wesley Publishing Company, ISBN-13: 978-0201533774 ISBN-10

[32] Y. Y. Song and Y. Lu, “Decision tree methods: applications for classification and prediction,” Shanghai Archives of Psychiatry, Vol. 27, No.2, pp. 130-135, 2015. doi: 10.11919/j.issn.1002-0829.215044, PMID: 26120265.

[33] R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction, The MIT Press, Cambridge, London, England, 2014. [Online]. Available from: http://incompleteideas.net/book/ebook/the-book.html, [retrieved: 12, 2019].

[34] A. Gosavi, “Reinforcement Learning: A Tutorial Survey and Recent Advances,” INFORMS Journal on Computing, Vol. 21 No.2, pp. 178-192, 2008.

[35] R. R. Torrado, P. Bontrager, J. Togelius, J. Liu, D. Perez-Liebana, “Deep Reinforcement Learning for General Video Game AI,” IEEE Conference on Computatonal Intelligence and Games, CIG. 2018-August, 10.1109/CIG.2018.8490422

[36] Estimote Beacons. [Online]. Available from: https://estimote.com/, [retrieved: 12, 2019].

[37] A. Best, S. Narang, D. Barber, and D. Manocha, “AutonoVi: Autonomous Vehicle Planning with Dynamic Maneuvers and Traffic Constraints”, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2017) IEEE, 2017, DOI: 10.1109/IROS.2017.8206087.

[38] D. Lee, C. Ott, and Y. Nakamura, “Mimetic communication model with compliant physical contact in human-humanoid interaction”, International Journal of Robotics Research, SAGE, Volume 29 issue13, pp. 1684–1704, November 2010.

[39] B. Argall, “Learning Mobile Robot Motion Control from Demonstration and Corrective Feedback”, Robotics Institute Carnegie Mellon University Pittsburgh, PA 15213, March 2009.

[40] H. B. Amor, D. Vogt, M. Ewerton, E. Berger, B. Jung, J. Peters, “Learning Responsive Robot Behavior by Imitation,” IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2013) IEEE, Tokyo, Japan, November 3-7, 2013, pp. 3257-3264.

[41] K. Takahashi, K. Kim, T. Ogata, S. Sugano, “Tool-body assimilation model considering grasping motion through deep learning,” Robotics and Autonomous Systems, Elsevier, Volume 91, pp. 115–127, 2017.

[42] G. I. Parisi, J. Tani, C. Weber, S. Wermter, “Emergence of multimodal action representations from neural network self-organization,” Cognitive Systems Research, Elsevier, Volume 43, pp. 208-221, June 2017.

[43] K. Noda, H. Arie, Y. Suga, and T. Ogata, “Multimodal integration learning of robot behavior using deep neural networks,” Robotics and Autonomous Systems, Elsevier, Volume 62, pp. 721–736, 2014.

[44] S. Monahan, et al., “Autonomous Agent that Provides Automated Feedback Improves Negotiation Skills,” Chapter in Artificial Intelligence in Education, Springer International Publishing, volume 10948, 2018.

[45] A. Maslow, Motivation and Personality, Harper & Row Publishers, 1970. [Online]. Available from: https://www.academia.edu/29491165/Motivation_and_Personality_BY_Abraham_Maslow, [retrieved: 12, 2019].