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The Impact of Technology in Orientation Aid

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Abstract: Statistic states that 285 million people are estimated to be visually impaired worldwide: 39 million are blind and 246 have low vision. About 90% of the world's visually impaired people live in developing countries. Taking in consideration that Mechatronics is a methodology used for the optimal design of electromechanical products, and by combining technologies that are available to us we can develop a very useful tool that blind people and people with sight problems can change their lives. Combining smart phones and digital camera there are possibilities to build smart glasses which will give information to blind people. In this paper definitely a new approach for making peoples life easy is proposed. Initially the results are reached from simulation using Matlab/SIMULINK package which will lead this research to real time experimental results.

Keywords: Visually impaired, mechatronics, blind people, smart phones and digital camera

1 Global Positioning System (GPS)

The Global Positioning System (GPS) is a space-based satellite navigation system that provides location and time information in all weather conditions, anywhere on or near the Earth where there is an unobstructed line of sight to four or more GPS satellites. The system provides critical capabilities to military, civil and commercial users around the world. It is maintained by the United States government and is freely accessible to anyone with a GPS receiver. [3] A GPS receiver calculates its position by precisely timing the signals sent by GPS satellites high above the Earth. Each satellite continually transmits messages that include [3]

- the time the message was transmitted
- satellite position at time of message transmission[3]

The current GPS consists of three major segments. These are the space segment (SS), a control segment (CS), and a user segment (US) [3] GPS has become a widely deployed and useful tool for commerce, scientific uses, tracking, and surveillance. GPS's accurate time facilitates everyday activities such as banking, mobile phone operations, and even the control of power grids by allowing well synchronized hand-off switching. [3]

1.2 Navigation System

A navigation system is a (usually electronic) system that aids in navigation. Navigation systems may be entirely on board a vehicle or vessel, or they may be located elsewhere and communicate via radio or other signals with a vehicle or vessel, or they may use a combination of these methods.[3]

Navigation systems may be capable of:

- containing maps, which may be displayed in human readable format via text or in a graphical format
- determining a vehicle or vessel's location via sensors, maps, or information from external sources
- providing suggested directions to a human in charge of a vehicle or vessel via text or speech
- providing directions directly to an autonomous vehicle such as a robotic probe or guided missile

- providing information on nearby vehicles or vessels, or other hazards or obstacles
- providing information on traffic conditions and suggesting alternative directions [3]

Types of navigation systems

- Automotive navigation system
- Marine navigation system
- Global Positioning System, a group of satellites and computers that can provide information on any person, vessel, or vehicle's location via a GPS receiver.[3]

GPS navigation device, a device that can receive GPS signals for the purpose of determining the device's location and possibly to suggest or give directions. [3]

Surgical navigation system, a system which determines the position of surgical instruments in relation to patient images such as CT or MRI scans.[3]

Inertial guidance system, a system which continuously determines the position, orientation, and velocity (direction and speed of movement) of a moving object without the need for external reference.[3] Robotic mapping, the methods and equipment by which an autonomous robot is be able to construct (or use) a map or floor plan and to localize itself within it.[3]

Web navigation

XNAV for Deep Space[3]

1.3 Mobile phone tracking

Mobile phone tracking refers to the attaining of the current position of a mobile phone, stationary or moving. Localization may occur either via multi lateration of radio signals between (several) radio towers of the network and the phone, or simply via GPS. To locate the phone using multilateration of radio signals, it must emit at least the roaming signal to contact the next nearby antenna tower, but the process does not require an active call. GSM is based on the signal strength to nearby antenna masts. [4] Mobile positioning, which includes location based service that discloses the actual coordinates of a mobile phone bearer, is a technology used by telecommunication companies to approximate the location of a mobile phone, and thereby also its user (bearer). The more properly applied term locating refers to the purpose rather than a positioning process. Such service is offered as an option of the class of location-based services (LBS). [4]

Localization-Based Systems can be broadly divided into:

- Network-based, Handset-based, SIM-based, Hybrid, Wifi from all possible system for product that we are developing the sim based location system sames the easiest and cheapest

1.4 SIM-based

Using the SIM in GSM and UMTS handsets, it is possible to obtain raw radio measurements from the handset. The measurements that are available can include the serving Cell ID, round trip time and signal strength. The type of information obtained via the SIM can differ from what is available from the handset. For example, it may not be possible to obtain any raw measurements from the handset directly, yet still obtain measurements via the SIM.[4]

1.5 Digital Processing

The general digital image processing system may be divided into three components:
The input device (or digitizer), the digital processor, and the output device (image display).
1. The digitizer converts a continuous-tone and spatially continuous brightness distribution f [x, y] to an discrete array (the digital image) fq [n, m], where n, m, and fq are integers.[1][2][6]

2. The digital processor operates on the digital image fq[n, m] to generate a new digital image g q[k, c], where k, c, and g Q are integers. The output image may be represented in a different coordinate system, hence the use of different indices k and c. [1] [5] [6]
3. The image display converts the digital output image g q[k, c] back into a continuous tone and spatially continuous image g [x, y] for viewing. It should be noted that some systems may not require a display (e.g., in machine vision and artificial intelligence applications); the output may be a piece of information. [1][2][5][6]

2 The Impact of Technology in Orientation Aid

Given the current technological findings and by joining them we can create a tool which can help blind people to orient them in space more easily.

If we take in consideration that The majority of the world's 8 million service robots are toys or drive in preprogrammed patterns to clean floors or mow lawns, while most of the 1 million industrial robots repetitively perform preprogrammed behaviors to weld cars, spray paint parts, and pack cartons [9]. To date, the vast majority of academic and industrial efforts have tackled these challenges by focusing on increasing the performance and functionality of isolated robot systems. However, in a trend mirroring the developments of the personal computing (PC) industry [10], recent years have seen first successful examples of augmenting the computational power of individual robot systems with the shared memory of multiple robots. In an industrial context, Kiva Systems successfully uses systematic knowledge sharing among 1,000 individual robots to create a shared world model that allows autonomous navigation and rapid deployment in semi structured environments with high reliability despite economic constraints [11], [12]. Other examples for shared world models include research on multi agent systems, such as RoboCup [13], where sharing sensor information has been shown to increase the success rate of tracking dynamic objects [14], collective mapping of autonomous vehicles [15], [16], or distributed sensing using heterogeneous robots [17].
However, in most cases, robots rely on data collected once in a first, separate step. Such pooled data have allowed the development of efficient algorithms for robots, which can then be used offline without access to the original data. Today's most advanced personal assistant robots rely on such algorithms for object recognition and pose estimation [18], [19]. Similarly, large training data sets for images and object models have been crucial for algorithmic advances in object recognition [20]–[21].
The architecture and implementation of RoboEarth is guided by a number of design principles, centered around the idea of allowing robots to reuse and expand each other's knowledge. To facilitate reuse of data, RoboEarth supports and leverages existing standards. The database is made available via standard Internet protocols and is based on open-source cloud architecture to allow others to set up their own instance of RoboEarth, resulting in a truly distributed network. The code generated by the RoboEarth Consortium will be released under an open-source license, and will provide well-documented, standardized interfaces. Finally, RoboEarth stores semantic information encoded in the World Wide Web Consortium (W3C) - standardized Web Ontology Language (OWL [24]) using typed links and uniform resource identifiers (URIs) based on the principles of linked data [22].

3 Architecture

RoboEarth is implemented based on a three-layered architecture (Figure 1). The core of this architecture is a server layer that holds the RoboEarth database [Figure 1(a), the "Architecture: Database" section]. It stores a global world model, including reusable information on objects (e.g., images, point clouds, and models), environments (e.g., maps and object locations), and actions (e.g., action recipes and skills) linked to semantic information (e.g., properties and classes), and provides basic reasoning Web services. The database and database services are accessible via common Web interfaces.
As part of its proof of concept, the RoboEarth Consortium [23] is also implementing a generic, hardware-independent middle layer [Figure 1(b)] that provides various functionalities and communicates with robot-specific skills [Figure 1(c)]. The second layer implements generic components. These components are part of a robot's local control software. Their main purpose is to allow a robot to interpret

RoboEarth's action recipes. Additional components enhance and extend the robot's sensing, reasoning, modeling and learning capabilities and contribute to a full proof of concept that closes the loop from robot to the World Wide Web database to robot.
The third layer implements skills and provides a generic Interface to a robot's specific, hardware-dependent functionalities via a skill abstraction layer .

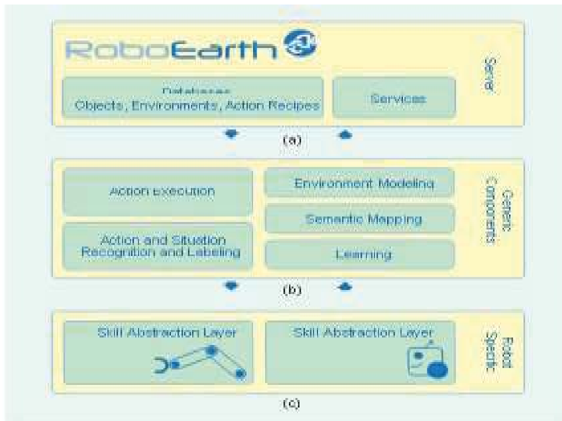

Fig. 1. RoboEarth's three-layered architecture. [8]

3.1 Database

RoboEarth stores CAD models, point clouds, and image data for objects. Maps are saved as compressed archives, containing map images and additional context information such as coordinate systems. Robot task descriptions are stored as human-readable action recipes using a high-level language to allow sharing and reuse across different hardware platforms. Such action recipes are composed of semantic representations of skills that describe the specific functionalities needed to execute them. For a particular robot to be able to use an action recipe, the contained skills need to have a hardware-specific implementation on the robot. To reduce redundancy, action recipes are arranged in a hierarchy, so that a task described by one recipe can be part of another more complex recipe. In addition, database services provide basic learning and reasoning capabilities, such as helping robots to map the high-level descriptions of action recipes to their skills or determine what data can be safely reused on what type of robot.

The RoboEarth database has three main components (Figure 2).

First, a distributed database contains all data organized in hierarchical tables [Figure 2(a)]. Complex semantic relations between data are stored in a separate graph database [Figure 2(b)]. Incoming syntactic queries are directly passed to the distributed database for processing. Semantic queries are first processed by a reasoning server. Data are stored in a distributed database based on Apache Hadoop [45], which organizes data in hierarchical tables and allows efficient, scalable, and reliable handling of large amounts of data.

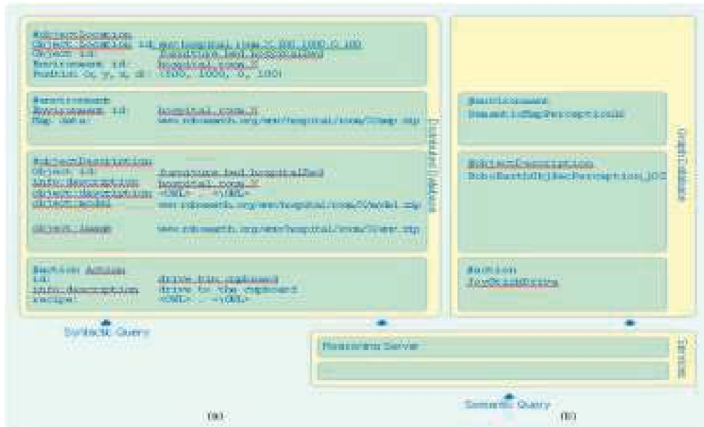

Fig. 2. The three main components of the RoboEarth database [8]

Second, a centralized graph database holds semantic information encoded in the W3C-standardized OWL [24]. It stores the following data and their relations.

Objects: The database stores information on object types, dimensions, states, and other properties as well as locations of specific objects a robot has detected and object models that can be used for recognition (Figure 3). Figure 3(a) describes a recognition model for a certain kind of object (defined by the property providesModelFor), giving additional information about the kind of model and the algorithm used. The actual model is linked as a binary file in the format preferred by the respective algorithm (defined by the property linkToRecognitionModel). Figure 3(b) describes the recognition of a specific object. An instance of a RoboEarthObjRec- Perception is created, which describes that the object Bottle2342 (linked through the property objectActedOn) was detected at a certain position (linked through the property eventOccursAt) at a given point in time using that recognition model (defined by the property recognizedUsingModel).

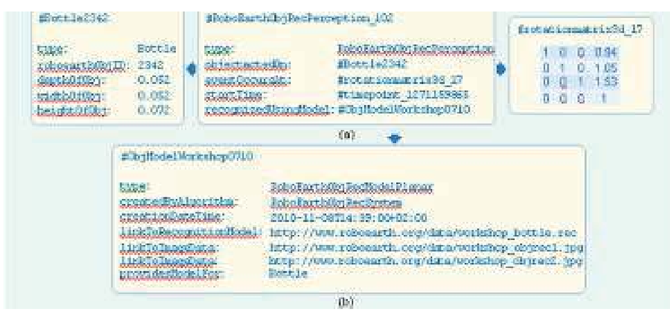

Fig. 3. The object description, recognition model, and one particular perception instance of the bottle used in the second demonstrator [8]

Environments: The database stores maps for self-localization as well as poses of objects such as pieces of furniture (Figure 4). The semantic map combines a binary map that is linked using the linkToMapFile property with an object that was recognized in the respective environment. The representation of the object is identical to the one in Figure 3. This example shows that both binary (e.g., occupancy grids) and semantic maps consisting of a set of objects can be exchanged and even combined. The given perception instance not only defines the pose of the object but also gives a time stamp when the object was seen last. This can serve as a base for calculating the position uncertainty, which increases over time.

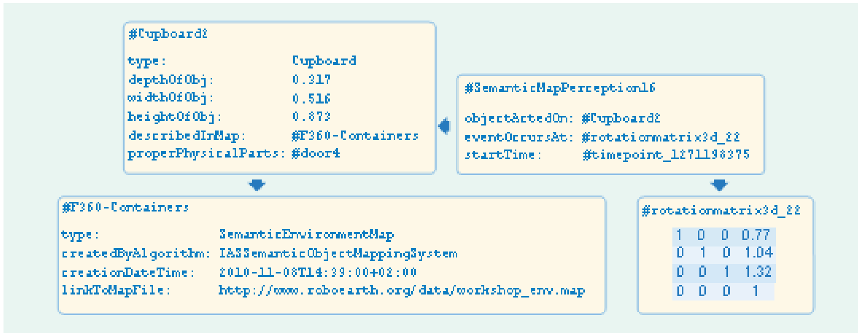

Fig. 4. The environment map used in the second demonstrator [8]

Action Recipes: The stored information includes the list of subaction recipes, skills, and their ordering constraints required for executing an action recipe as well as action parameters, such as objects, locations, and grasp types (Figure 5). Action classes are visualized as blocks, proper- ties of these classes are listed inside of the block, and ordering constraints are depicted by arrows between the blocks. The recipe is modeled as a sequence of actions, which can be action recipes by themselves, e.g., the GraspBottle recipe. Each recipe is a parameterized type-specific subclass of an action such as Translation. Atomic actions, i.e., actions that are not composed from subactions, represent skills that translate these commands into motions. Third, services that provide advanced learning and reasoning capabilities at the database level. A first type of service is illustrated by RoboEarth's reasoning server. It is based on KnowRob [25] and uses semantic information stored in the database to perform logical inference. Services may also solely operate on the database.

RoboEarth's learning and reasoning service uses reasoning techniques [26], [25] to analyze the knowledge saved in the RoboEarth database and automatically generates new action recipes and updates prior information. For example, given multiple task executions, the database can compute probabilities for finding a bottle on top of the cupboard or on the patient's nightstand. Using the additional information that cups are likely to be found next to bottles, the service can automatically create a hypothesis for the probability of finding cups on top of the cupboard. Such cross correlations between objects can provide powerful priors for object recognition and help to guide a robot's actions.

Additionally, if there are two action recipes that reach the same goal in different ways, the learning and reasoning service can detect this, fuse the recipes, and explicitly represent both alternatives. For example, if robot A was equipped with a dexterous manipulator but robot B only with a tray, the component could create a single action recipe "serve drink to patient" with two branches depending on the robot's abilities, which would have different requirements: the first branch would require a graspable bottle, whereas the second branch would require the availability of human or robotic help to place the bottle on the tray.

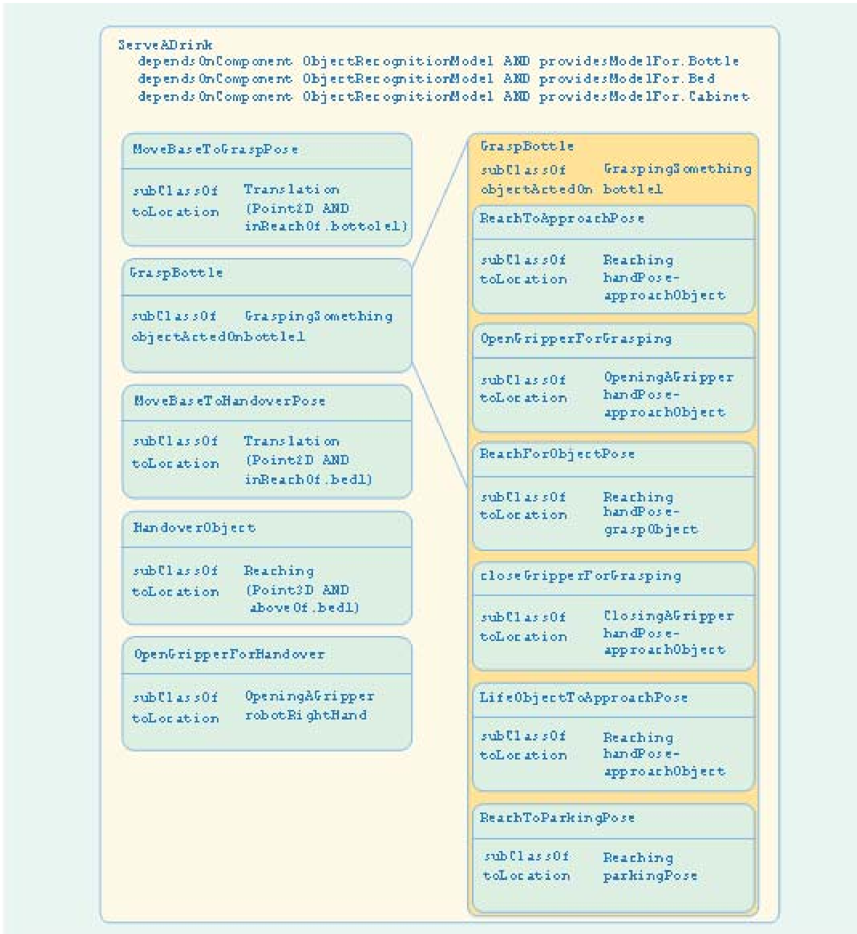

Fig. 5. The action recipe used for the second demonstrator [8]

Taking this as inspiration and applying technologies used for developing Smart Robots and using there ability to orient them self in there surroundings and ability to learn and to share the learned we tuck the liberty to apply and combine other technologies such as Smart phones who very often have already installed GPS and Navigation systems with whose help we can tell a persons location and can be used to guide us to reach a designated location. But for blind people it is also essential that you tell them the obstacles which may appear on the road to the given location. By means of a digital camera which records objects that are before us at a certain distance. The picture is then send sent to an application installed on the smart phone, this new application which is connected to a central data- base which one containing the list of possible objects that could be faced along the way, but with enlargement opportunities ,that means if the user saw an unknown object that is not registered in the database, the object will be recorded saved , analyzed and registered in the database, and when we encounter it on the road again, it will be registered in the database and it will be available to users. All objects that are registered in the database must be encoded in advance and each of them is given a code to identify them , therefore all new objects which we encounter and are not encoded , are recorded by the digital camera which then sends the picture to the application which then notifies the database for an object unknown, the user of the tool is then automatically notified even though we don’t know what kind of object are we talking about of an potential risk in certain distance and size of that object.

Our task is to enlist and to give an identity code to all unknown objects which we may encounter in the environment so in the future it may be to the users disposition.

The new application will embody on it self functions of GPS, Navigational system and all the registered date in the central data base all input about the environment will be delivered via digital camera.

Thanks to GPS and Navigational System the user needs just to put the desired destination and the installed new application will calculate the fastest and safest route given the users location. The camera will record full time all objects and potential risks who are in front of the user it will send them to the application who will check with the data base and hopefully identify and notify the user for example:
1 meter from the user is the sidewalk 1 meter to his left there are 3 people walking and to his right in an unknown object (whose picture will be send to the data base as an unknown object which is to be identified and given an id code so in the future it can be useful). The dimensions of the digital camera have to be small enough so it may fit on sun glasses and record the objects and send them to the application who contacts the data base where the identification is being done and through the same route information will be sent back to the user who will receive them verbally via headphones.
Users of the tool will be informed to all the objects which are 180 degrees around them, but we need to be aware that this tool should not recognize every thing around because that will create confusion and total de concentration to the user. It should therefore describe only objects that could cause injury to the users who is unable to see.

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