

Learning Cognitive Human Navigation Behaviors for Indoor Mobile Robot Navigation

Luz Abril Torres-Méndez and Roberto Cervantes-Jacobo
Robotics and Advanced Manufacturing Group, Cinvestav Saltillo
Carr. Saltillo-Monterrey Km. 13, Ramos Arizpe, Coah, 25900, Mexico
E-mails: abril.torres@cinvestav.edu.mx; bortreo@gmail.com

Abstract—We present a framework to transfer cognitive human navigation behaviors to an artificial agent so it can generate route directions similar to those created by humans. Our method is based on a spatial conceptual map that attempts to emulate the cognitive process carried on by living beings during the navigation process. This conceptual map is modeled as a three-level of interconnected graphs to simulate human spatial reasoning. We based some of our ideas of spatial reasoning on qualitative definitions of neighborhood, distance and orientation. The first level of the conceptual model contains the approximated metric of the environment and the physical obstacles that influence the navigation trajectory. In the second level, we define the abstract characteristics that give information about the ambient, such as the areas of influence and key features. Finally, in the third level, the navigation route obtained from the first two levels is stored. The visual and cognitive skills of each person in the experiments are captured in terms of the space-time perception while navigating. Our experimental results demonstrate that the inference of the route directions can be easily obtained and transferred to an agent from this spatial conceptual map.

Keywords-human navigation; cognitive conceptual maps.

I. INTRODUCTION

Navigation is generally defined as the process of monitoring and controlling the movement of an agent (i.e., a vehicle, person or animal) from one place to another towards a goal. To be able to navigate, the agent has to have the capability of moving in the space and determine if the goal has been reached or not. The study of navigation of living beings has a long history in neuroscience [1], [2], [3], [4], [5]. The discoveries found in the last fifty years have provided a physiological grounding related to the type of representation of spatial locations in our brain. In order to efficiently achieve the navigation task, some information about the environment is required. In robotics, particularly in indoor robotic navigation, this knowledge is commonly represented by a metric map containing distances between walls, doors, objects, corners, etc. However, to obtain precise metric information may result in a cumbersome task. Moreover, for the particular case of human navigation, a metric map seems not to be a natural way to navigate as humans are not good on measuring exact distances from one point to another nor in memorizing them to build an internal map of that kind.

In other words, the notion of navigation does not imply that the current position of the agent must be exactly known. Thus, for human navigation, the cognitive process carried on does not require a precise metric. This cognitive process is mainly based on the relationships we build between the information captured from the environment through our senses (i.e., visual and geometric information) and the conceptual information based on previous knowledge about the functional characteristics of the environment. The last is obtained according to the experience of having navigated before that environment or similar ones.

When walking through an environment, we all have experienced the need to perceive our *spatial* sense, also known as spatial awareness or proximity sense, that is, to know the dimensions our body occupies with respect to the empty space of the environment in which we can walk in. Because of this spatial sense, we are able to get a clearer perception of how much we have moved forward, related to where we were, and associate it to what we see next. This type of perception could be represented in a topological map, which is another representation that is commonly used in robotics. A topological map is a graph of connected landmarks that exist in the environment. However, as we will see in this research work, the whole process of navigation is so complex, that having just a topological or a metric map is not enough to achieve the task efficiently.

In our daily life, humans efficiently achieve a variety of skill-motor tasks. Yet today, it is not well understood the learning processes carried on in our brains that allow us to navigate a familiar environment. More intriguing is to understand how we manage to navigate unfamiliar or even not-seen-before environments – of course, those not-seen-before environments need to fulfill some requirements regarding its geometric structure and physical laws in order to be able to navigate them. However, from research done in behavior and neural sciences [7], [9], [10], [11], we know that the learning process in navigation involves storage of the learned skills for future reference. For the case of human navigation, we store in our memory navigation skills to which our brain automatically assigns weights according to how well or bad the task were carried on. Then, our

brain and memory connections are updated accordingly, so that both types of skills (“good” and “bad” ones) are kept as experiences in order to generate flexible behavioral responses when similar situations are encountered.

In nature, one of the most ubiquitous form of learning skills is by imitation. In general, imitation involves the interaction of perception, memory, and motor control. There is an inherent transference of knowledge as the brain is capable of building networks to recreate actions that have even never executed before. It has been demonstrated that humans build mental images to facilitate the execution of tasks. For the case of navigation, humans build navigation blocks from the mental representation of the environment, generating what it is known as *cognitive maps*.

We have managed to transfer those skills, behaviors or even experiences, to other humans to facilitate their learning process. However, we still have some difficulties on teaching or transferring those skills to artificial agents. The reasons for this are not simple but they could be posited as being primarily twofold. One is because we do not completely understand how our brain builds its own reasoning and type of representations. And two, because we are trying to teach a task that can be developed by complex systems to a simple one. In other words, the computer on a robotic system would need to entirely have the functionality that a human’s brain has in order to truly understand a concept that is being taught. This is still an open problem in artificial intelligence, although big advances has been made.

The research question we are interested to answer in this work is: how do we transfer navigation skills to a mobile robot such that it can generate route directions similar to those created by humans? To answer that question, we need to construct a model capable of emulating the human perception over a navigable environment. This model must have a good understanding of the functional properties of the space that can be used while the robot is navigating. We based our method on a spatial conceptual map to simulate human spatial reasoning. A spatial conceptual map is a computerized analogy of the mental maps generated by humans. There is not a standardized way to build a conceptual map of a given environment. However, some information such as the objects and its area of influence, the notion of neighborhood, orientation and distance, can be used as they are part of the process of spatial reasoning. Then, this spatial conceptual map can be used by the mobile robot to navigate the environment.

The outline of this paper is as follows. Section II describes the human behaviours in the navigation process. In Section III, we mention the relevant aspects in robotic navigation. Section IV presents in detail the components for creating the spatial conceptual map we propose. Some simulation results are shown in Section V. Finally, we give some conclusions and future work in Section VI.

II. HUMAN BASIC NAVIGATION BEHAVIORS

It has been proved that mental imagery is critical for human navigation. However, it remains unclear how this mental representation of the environment, namely a cognitive map, is built related to specific orientation strategies [12], [13]. We gather information by using our sensorial organs and then we build a mental image of the external world. The unconscious conception of our bodies in the space that helps us to interact with our surroundings is called *proprioception*. We need to coordinate our movements in order to know where our body is and what it is doing. This skill has been refined through our lives thanks to a system of constant feedback which has been developed since we were inside our mother’s womb. The sensors give us constant feedback so the movements can be refined until reaching perfection. Each person may adopt alternative strategies while moving along the same well-known route, but it is widely accepted that cognitive maps are a key element for orientation since any target can be reached from any place in the environment. Thus the ability to create a cognitive map is related to the particular ability of performing mental rotations of simple geometric shapes, and the ability to visualizing how we move on a map. In order to navigate successfully in both known and unknown environments, individuals need the ability to become familiar and orient in the environment, this is known as *topographical orientation* [14]. This complex task requires many cognitive skills such as visual perception, memory, attention, and decision-making techniques [15], [16], being mental imagery skills one of the most important for orienting within the environment [15], [3].

When navigating through an indoor environment, humans, contrary to animals, have the understanding of functional and spatial properties of the environment, while interacting safely with it. We make use of labels to share common concepts like the existence of corridors, corners, specific furniture, areas, etc. These concepts are not only labels but semantic expressions that are related to a complete object or to an objective situation. For example, the label “living room” generally is related to a place that has a particular structure and contains objects (furniture) such as couch, center table, tv, etc. Thus, representing the space as “seeing” by humans requires to take into account the way in which we make reference to entities in the space through language.

In general, an artificial agent can use different type of strategies to go from one place to another. However, if these strategies are to be used every time without storing them in a map, it has to learn everything again and again, even if some distances have been previously covered. To this end, the topological information and the navigation based on searching use spatial memory that does not depend of the goal and can be used for route planning independently of the final goal. The memory that does not depend of the final goal is called cognitive map [10] in which the knowledge about

the routes is a form of preprocessed memory. From the field of cognitive psychology and the experimental results in [17], the notion of object’s influence area was born. This notion consists on the idea that people mentally build an “subjective influence area” that surrounds the objects in the environment to be navigated in order to talk about their relative position, distance and orientation. According to this, the influence area is an abstraction of the way objects influence in the vision and perception of people. It allows to reason in a context, evaluate quantitative measures and qualify positions and distances between objects. It also allows to reason in a qualitative manner about space.

III. ROBOTIC NAVIGATION

In order to build internal representations of the environment, robots use its sensors. The sensors can capture information of the objects in the environment that can be used to position the robot in it or to integrate the path the robot has navigated. For a robot, to use an internal representation of the space distribution for navigation, can result in a complex task. As today, there exist several localization systems in robotics that use metric and/or topological maps as internal representations. A metric map considers the space in two dimensions in which the objects are localized with precise coordinates. Metric maps can be created independently to the robot, with a high level of precision according to the type of sensors used. A metric map facilitates the operation of robots. However, to create a metric map to be used by a robot can be a cumbersome task. The time for the acquisition and processing of information could be very high as the robot needs to take measurements constantly of the environment while navigating. A topological map considers the relationships between places and objects. The map is represented as a graph in which the nodes correspond to places/objects and the edges could represent directions or path convenience. Contrary to the metric maps, a topological map does not require models based on precise range measurements, and this is an important advantage upon localizing the robot. However, the precision of using a topological map is not high. A common solution is to use both, a metric and a topological map, in order to get better robot’s pose estimates [18], [19].

There exist a vast amount of research work related to navigation systems for indoor and outdoor robots (for a survey that highlights the more interesting works see DeSouza and Avinash [20]). It is clear that in order to navigate we need perceptual and metrical information from the environment. In robotics, the most common sensors are cameras and laser range finders to obtain visual and geometric information, respectively. However, to incorporate conceptual and cognitive knowledge about the environment into an internal map for navigation purposes is not a trivial task. This knowledge, in terms of geometry of space, perceptual and other metrical information transmitted by the human-like perception of the

world needs a better understanding of the inherent spatial and functional properties, while still being able to safely navigate in it. As such, there has been proposed in the literature a variety of ways to represent this knowledge into maps (metric, topological and conceptual maps) to be used by a mobile robot for self-localization and navigation tasks. Alternatives to map-based navigation strategies are biologically inspired navigation methods (behavior-based) that imitate navigational cues observed in animals. In this research work we adopt a hybrid approach that combines the two approaches, that is, we construct a map based on cognitive-behavioral knowledge as well as conceptual knowledge obtained directly from human while navigating an indoor environment.

IV. CREATING THE SPATIAL CONCEPTUAL MAP

Humans generate mental images that represent the spatial knowledge of the area they are navigating. These mental images are then processed and analyzed in order to generate a cognitive map. Figure 1 shows the navigation process as a comparison between humans and artificial systems and the components involved in the construction of a spatial conceptual map as an analogy of the human cognitive map.

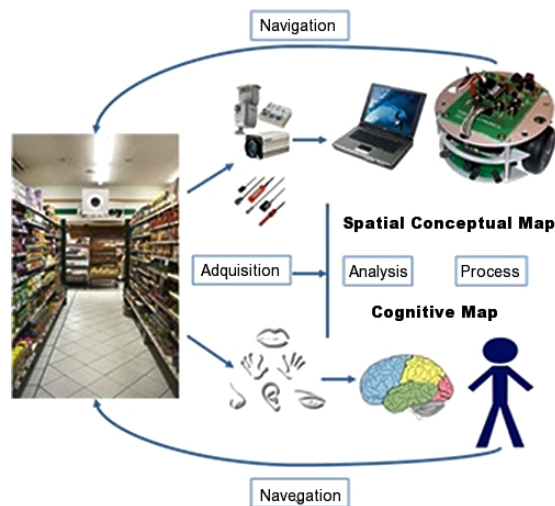


Figure 1. A comparison of the navigation process carried on by humans and artificial agents. The arrows indicate the flow of information.

A cognitive map can function as a navigation problem solver to find routes, relative positions, as well as to describe the location of the subject in a given moment. Thus, the cognitive map is a non-observable physical structure of information that represents the spatial knowledge. The learning process is based on the assimilation of what was captured by our senses into a cognitive map, and the problem solution is a process that extracts the answers to particular questions from the cognitive map. The need of analyzing, processing

and using the information in a cognitive map build by a human is related to the need of generate an analogous representation that allows to manipulate the information using computer algorithms in robotics applications. This representation is known as spatial conceptual map. There exist some work in the literature that use a computerized representation of the cognitive maps for navigation. For example, Moulin and Kettani [17] create a spatial conceptual map to integrate information such as key features in the environment, the free navigable space, route definition and the categorization of the free space elements according to their relationship with the surrounding objects, etc.

There is not an standardized way to build a conceptual map of a given environment. A spatial conceptual map basically must contain representations of salient objects and key features in the environment, virtual connections between the objects in space as well as knowledge of free space to navigate. The key features and salient objects are used by people as landmarks to identify elements or regions in the environment through a defined route in the free space. A spatial conceptual map can also contain information about the area of influence of the objects in the environment. The area of influence is an abstraction of how objects are perceived by people, and it greatly depends on the objects features. It helps in the estimation of the relative positions, distances and orientations of the objects. Also, according to these researchers, the area of influence allows people to perform qualitative reasoning about space.

Our spatial conceptual map uses the elements mentioned above together with the concepts of neighborhood, area of influence and distance.

It is easy to see that, for navigation, the main goal is to have a good representation of the elements of free space in the conceptual map and an easy way to detect them. As in [17], we define two different sets to identify the free space. The first set embraces the salient objects and key characteristics in the environment, whose area of influence is intersected by an element of free space. This means that the element of free space is a neighbor of diverse objects that can be used as reference in the navigation process. The second set includes all elements of free space that intersect with other elements of free space.

The conceptual map we propose in this work seeks to integrate the information that people use to navigate a route in a given environment. We collect this information through an experiment in which a group of persons were asked to cover a given route in a large-scale man-made indoor environment. The main difference with the work presented in [17] is that all elements and routes are defined directly by the persons navigating the environment. Therefore, the elements of free space are defined through the connectivity between nodes, their vicinity with relevant objects or features in the environment. And, it is through the sequence of the connected nodes that the route navigated by each person is

represented. The following section describes the experiments we carried on to build the conceptual map.

A. Description of the experiments

We have designed an experiment that allow us first, to understand the way humans perceive their surroundings when successfully navigate in an indoor man-made environment and second, to register in a natural way, relevant information used by people in navigation tasks. The experiment consisted in a set of 15 navigation tests, where five people participate. The environment was a local shopping centre which was unknown to the people in this experiment. In order to select the route to use in the navigation tests, another person were asked to walk through the environment for five minutes without a defined route and then select one. The route selected and the environment is depicted in Figure 2. Then, we asked to each person to cover a given route in the environment, following the same route three times. At the end of each route, they were asked to close their eyes to focus on the mental image they have from the portion of the environment navigated and then generate a pictorial representation of it. Before, they were instructed to include as much information as possible related to key features, physical objects, free space, abstract areas conformed by physical objects. In addition, they were asked to include in their drawings a rough idea of metric and topological data, as an option. Also, we interviewed each participant asking what were the more relevant characteristics in which they think they focused on in order to navigate the shopping centre and what was the dominant thought during the route. It is important to note that in a spatial conceptual map, the information is not just limited to the information above listed, and in case we can have access to more information, this can be integrated to reinforce the environment description and thus facilitate the navigation task.

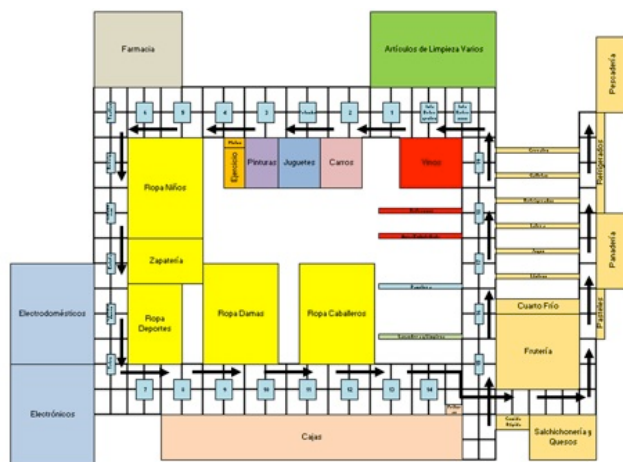


Figure 2. A sketch of the environment navigated in the experiments.

Figure 3 shows a diagram of the experiment indicating the

route navigated by the five participants. All gathered information was used in the spatial conceptual map construction.

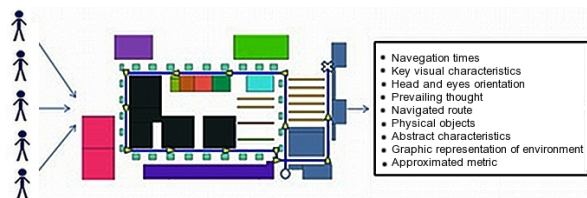


Figure 3. Diagram of the experiment. Five people participate in the navigation tests. The information gathered was used for building the Spatial Conceptual Map.

B. Representing the spatial conceptual map

From the information obtained by the five people through the navigation tests we can conform two types of maps: a metric map containing information about distances that define the location of objects; and a topological map containing the existing relationships (mainly vicinity and connectivity) between the present entities in the space to navigate, such as objects, areas or free space units. As mentioned before, the metric information is obtained in an approximately as people indicate roughly the distances between visualized objects and the traveled length in each segment of the route navigated. This information makes possible to colocate objects in a map and locate from a common referential frame. However, this information only allows knowing the approximated position of the object within the environment, thus, to make the navigation possible for a robotic system, is necessary to consider an average intrinsic referential of the routes navigated by the five subjects that, together with the average extrinsic referential (which is fixed and common among objects) in the environment, allows a continuous update of the robot pose, thus making possible the process of route integration, which, as it was mentioned is one of the main elements in the navigation process.

The metric and topological maps that conform the spatial conceptual map (SCM) are shown in Figure 4. These maps are integrated in order to define the navigation routes, in which the identification of the relevant objects is crucial. An important characteristic of the SCM is that all information in it comes from the participants in the navigation tests. Therefore, it will totally depend on the way the participants perceive the environment, regarding the key features in the navigation process, the salient objects used as reference, or the abstract areas conformed by physical objects (also used as reference) together with the concepts of area of influence, orientation, and neighborhood.

In the SCM, each relevant object has a set of properties, one is its *neighborhood* (see Figure 5). We define the neighborhood of an object in terms of orientation and approximated distance between its neighbors. In the SCM, each physical object must have at least one neighboring

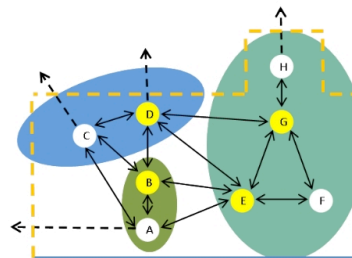
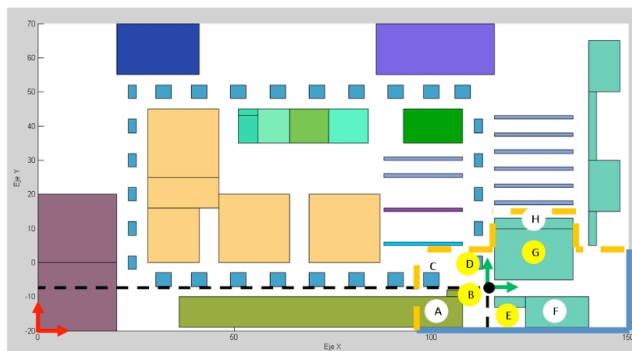


Figure 4. Graphic representation of the integration of metric and topological information. The shaded nodes represent key characteristics in the environment identified by the participants in the navigation tests. It shows how a locality can be defined as a function of nearby objects.

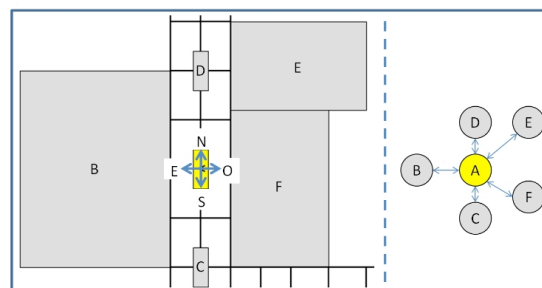


Figure 5. The neighborhood property. The right side shows the topological relationship that a physical object has with its neighbors. The left side shows a metric map generated from the neighborhood information defined in distances and relative orientations between an object and its neighbors.

object (either physical or abstract). This generates in the SCM a strong interrelated structure that complement the approximated metric with the local blocks of qualitative relative information between each of the objects. Thus allowing, by identifying one or more objects in a locality, the inference of an approximate relative robot position to the local objects, and an absolute robot position to the common extrinsic referential for each of the entities in the environment. The knowledge of the relative and absolute robot position together with the real-time identification of key features in the environment, makes possible the navigation process and to correct any errors present in the estimation due to the approximated metric and/or the robot's odometry.

Another important property of the SCM, which allows the existence of one of the three levels in the map, is the area to which an object belongs. We call this the *membership* property, and consists in wrapping all objects with common characteristics (see Figure 6).

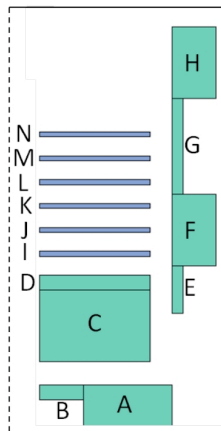


Figure 6. The membership property. The figure shows a portion of the graphical representation of the SCM. It can be identified two set of objects (labeled nodes from A to H and from I to N, in alphabetical order) which have similar characteristics and therefore form part of the same area.

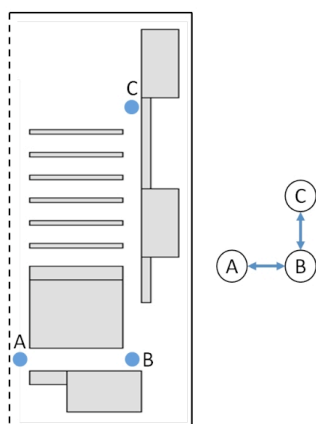


Figure 7. The connectivity property. The left side of the figure shows a portion of the SCM. It can be identified three nodes of free space. The right side shows the topological relationship of the connectivity among the nodes. It can be seen that it is possible to go from node “A” to node “C” going through “B”.

By encapsulating common objects in areas, we strengthen the existing neighborhood interrelations among them by facilitating the manipulation of information in the SCM. Additionally, the recognition process is simpler because we only need to recognize only one or two objects and then know in which area is the robot. Thus, the robot, similar to humans, is navigating using complete areas as reference.

The last property is the *connectivity* property and is used

to manipulate the free space in the SCM. The free space is considered as a set of points in the space, and it is free of obstacles, thus is navigable. This property allows that the free space can be represented as a graph, where each of the nodes represents a point in the free space. The connectivity property dictates if it is possible to go from node “A” to node “C” (see Figure 7). Thus, by knowing the individual connections of each of the nodes conforming the free space, it is possible to generate a network that englobes all nodes and to know if a given route is possible or not. Each of the properties mentioned above facilitate the access and manipulation of the information in the SCM. Moreover, as these properties allow that the elements in different SCMs of the same environment can be related among them, we can identify another property, which integrates all information in one SCM. We call this the *interrelation* property. This property allows the existence of the multilevel structure in the SCM, in which there can be a direct or indirect interrelation between each of the elements in the same level or in different levels. We explain in detail the interrelation between three levels conforming our SCM in the next section.

C. The multi-level structure of our SCM

The three levels of the SCM are structured to follow a hierarchy. The physical objects conform the basic (bottom) level. Once the objects are classified according to their characteristics the next (middle) level is generated, that is, each area is defined exclusively by their objects in it, giving origin to the first interrelation: physical objects with areas. Then, the main (top) level contains all the nodes of free space. These nodes are referenced to nearby physical objects such that the definition of the location of each free space unit is dictated directly by the referenced physical object, and indirectly by the area that object belongs to; thus giving origin to a direct interrelation of physical objects with free space and an indirect one of free space with areas. These interrelations allow to integrate the whole information in only one SCM (see Figure 8).

It is important to note that each level in the SCM is conforming by a set of individual and unrepeatable elements of similar hierarchy. Moreover, each node’s structure has all the necessary information to establish the existing interrelations with the nodes of the same or different levels of the SCM.

The level of *physical objects* is integrated by the existing objects in the navigation space indicated as key elements. These objects can be obstacles or those considered as reference to facilitate the navigation process. Each node representing a physical object contains information such as an identification label, nominal label, area, dimensions, neighbors and its orientation w.r.t. to the object.

The *area* level has the objective of complementing the level of physical objects. The elements that conform this level are of abstract nature and are based on the membership

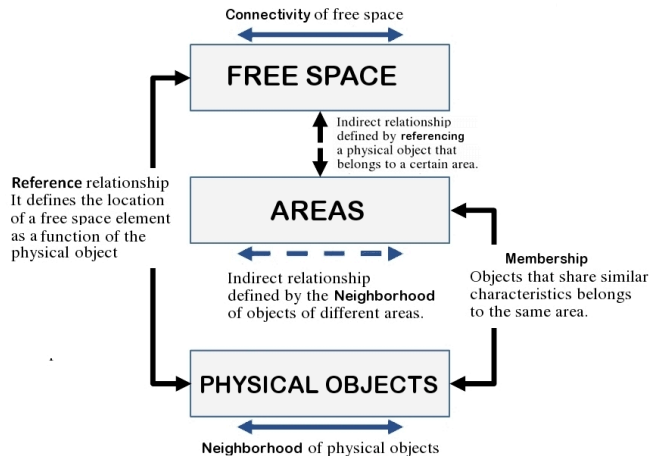


Figure 8. The multi-level structure of the Spatial Conceptual Map.

property that has the level of physical objects. Each of these elements represent a portion of the space, within the environment, that is distinguished by containing physical objects of affine characteristics. The area nodes are generated by the SCM from the level of physical objects. These nodes, similar to the objects nodes, contain information of identification, physical objects in the area, a color associated to the area, etc.

Finally, the *free space* level has the objective of representing the space in the environment where a subject can navigate. Within the SCM, the free space is considered as a set of points in the free space of obstacles and navigable. Those points in the space are the elemental units of free space. Similarly, the free space elements are represented by nodes containing relevant information to the point in the space represented. This information allows registering the position in space, the connectivity with other free space elements and its neighborhood with other nearby physical objects. For our SCM we consider two cases: a) the element of free space is a point in the route, and b) the element of free space is a cross between ways (see Figure 9).

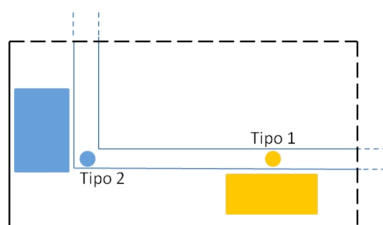


Figure 9. Types of free space in our SCM and its respective objects using as reference.

Thanks to the multilevel structure integrated in an unique SCM, it is possible to have access to all the information

contained in the map from any of its elements. This is due to the existing direct or indirect relationships between the registered elements.

D. Mobile robot navigation: determining the navigation routes

In order to determine a navigation route in a spatial conceptual map, we need to identify the elements of free space and construct a sequence of them. The main topological property of the elements of free space is their adjacency. Each of these elements is defined according to their neighbors (i.e., objects, features or elements of free space) and assigned an unique identification label (α_i). The fragmentation of paths in elements of free space allows defining all possible displacements from any element by using the connectivity relationship between elements. In our case, all the routes in the conceptual map are defined by the persons that navigate previously the environment. It is through the sequence of connected nodes that the route navigated by a person is represented. In a real application, where a mobile robot is navigating the environment using a SCM, the robot pose is estimated from the information gathered through its sensors. Then, the navigation route will be determined by matching what the robot “sees” to what is already registered in the SCM. Previous to the matching process there exist an inherent recognition process which in this work is assumed to be ideal. Figure 10 shows the recognition stage. Given that the nodes of free space in the SCM are referenced by nearby physical objects (salient objects) in the environment, which are already registered in the SCM, it is possible to detect on which free space unit the robot is in a given moment as a function of the recognized objects. However, as this pose estimation could have some errors due to the dimensions of the free space units, we need to compensate these errors by using the robot’s odometry as well. In robotics, it is known that using just the odometers information could result in a high accumulation of errors if long distances are navigated without any other feedback. However, in our case, we only rely on the odometers in very short distances, i.e., along one unit of free space. There will be cases where the detected key features do not correspond to the estimated ones, and therefore a reorientation or relocation of the robot must be done by estimating the free space unit in the SCM that have similar key features. This free space unit is then assigned as the new topologic position for the robot. Figure 11 shows an example of this reorientation stage.

Figure 12 is the final graphical representation of the physical objects registered after the total set of navigation trials. We can conclude that physical objects of greater dimensions tend to be the most relevant for navigation. In relation to the approximated metric of the environment, this was obtained by computing the average of the total number of steps of each subject. We observed that this metric is

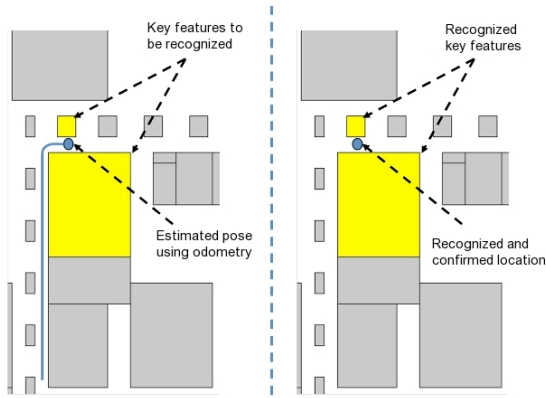


Figure 10. The recognition stage of the environment.

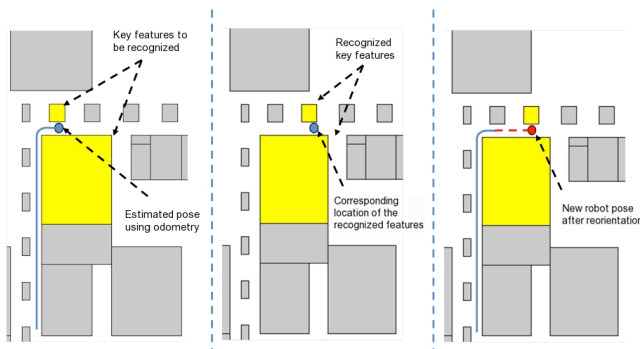


Figure 11. Reorientation.

consistent between the six people since the proportion at each section with respect to the complete route, for the three navigation trials, is similar and with low standard deviation. Therefore, it can be considered that the approximated metric is good enough since it is also congruent with the data obtained during the navigation trials. Table I shows the average steps for each section for the three navigation trials.

Table I
THE AVERAGE STEPS AS THE APPROXIMATED METRIC FOR EACH SECTION IN THE ROUTE NAVIGATION.

	Average of steps
Section 1	64.00
Section 2	85.00
Section 3	49.67
Section 4	112.00
Section 5	56.00
Total in route	366.00

V. SIMULATION RESULTS

At this point, from any physical man-made indoor environment, our model is validated through simulation. We use the final graphical representation, which englobes the gathered information of the 15 navigation tests carried on in

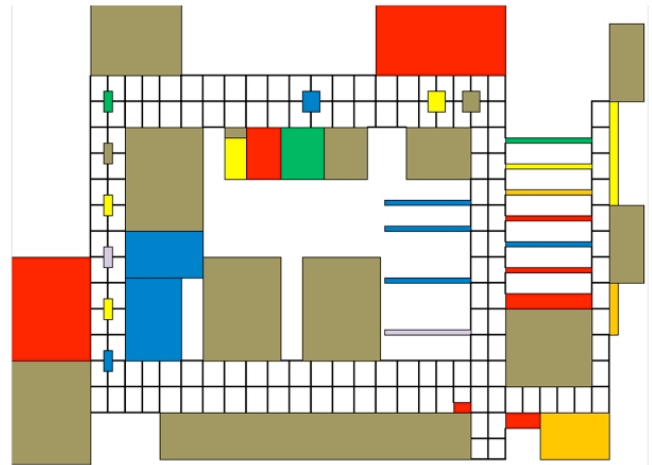


Figure 12. Final graphical representation of the navigation trials. The color of objects (boxes) indicate if they were seen only by 1 person (yellow), 2 (blue), 3 (red), 4 (green), or all subjects (brown).

the shopping centre. We simulate the cinematics of a point robot in a bidimensional space, without considering changes in orientation. This in order to simplify the robot's cinematic model. Thus, the robot pose in the space is defined by:

$$q(t) = (x(t), y(t)), \quad (1)$$

where $q(t)$ is the robot pose at time t , $x(t)$ and $y(t)$ are the coordinates of the robot in the axis X and Y , respectively. The robot's pose at time i is given by:

$$q_i = (x_i, y_i). \quad (2)$$

The change of the robot's pose in a time interval Δt_i , can be calculated as:

$$\Delta t_i = t_i - t_{i-1}, \Delta q_i = q_i - q_{i-1}. \quad (3)$$

From the above equations, we can compute the velocity of the point robot for the time interval Δt_i by:

$$v_i = \frac{\Delta q_i}{\Delta t_i}, \quad (4)$$

For the simulation, the physical objects considered in the map (Figure 13) are colored according to their corresponding area. The free space is defined by the route established in the navigation tests. As it is assumed that the visual recognition of the relevant characteristics in the environment is always correct, the integration of the route navigated in our simulation is free of errors. However, what it is relevant to note here is the fact that the model works by using as a reference only an approximated metric of the environment and the topological information of the spatial conceptual map. Moreover, in a real application, following the route indicated would strongly depend on the correct recognition of the key characteristics in the environment described in the spatial conceptual map.

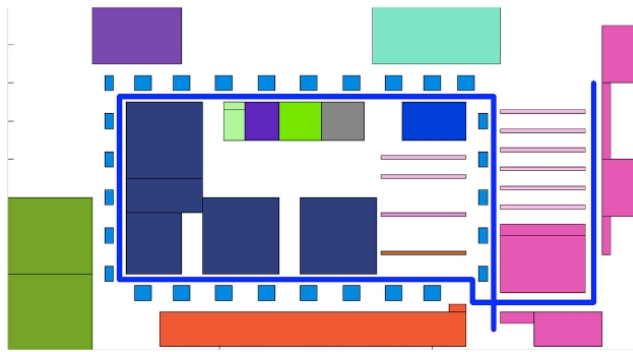


Figure 13. Graphical representation of the route navigation for the simulation. The blue line on the free space is the route.

VI. CONCLUSION AND FUTURE WORK

Mobile robot navigation is generally based only on the information acquired by the robot’s sensors. However, we have observed that sensors have great limitations in terms of coverage capabilities, quality in the measurements and also factors such as elevated acquisition times and costs. Current research trends are being focused on the study of the cognitive behaviors of humans navigation and how conceptual maps are created.

In general, humans do not have exact knowledge of the metric of the environment they navigate. They navigate by constructing a topological hierarchy of the free space according to specific characteristics observed in the environment that are more relevant than others.

In this work, we have created a model based in a conceptual map that considers human navigation behaviors in close indoor environments. Our preliminary results have shown that this map can be used by a mobile robot to facilitate its navigation and eliminate the need of using sensors for capturing exact metric information of the environment. The information contained in the conceptual map is enough to estimate the robot pose and orientation if visual landmarks are correctly matched.

Future work involves the implementation of our spatial conceptual model in a real robotic platform. For this, it is necessary to integrate a robust recognition model of the key visual features.

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