

# **PYTHEAS: an Integrated Robotic System with Autonomous Navigation Capabilities**

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## **Abstract**

In this paper we present PYTHEAS, an integrated robotic software system that supports autonomous navigation capabilities. These include localization, workspace mapping, path planning and tracking, and obstacle avoidance. PYTHEAS enables mapping of an unknown indoor environment by exploiting sensory information extracted from a laser scanner. Based on this acquired environment representation, the system is able to navigate autonomously in the mapped workspace, avoiding at the same time dynamic obstacles, such as moving persons or other objects. The developed competences are coupled in an integrated system, which can be controlled through a user-friendly interface over the web. Experimental results demonstrate the ability of the developed system to map complicated environments and support navigation in dynamic worlds.

# 1. Introduction

PYTHEAS is an integrated system, which provides the ability to a user to remotely control a robotic platform in order to (a) map an unknown environment and, (b) effectively navigate in it, avoiding dynamic obstacles. Mapping is the procedure of extracting information from the physical environment by exploiting sensory information and transforming it to an appropriate internal representation. The accuracy of a map depends crucially on accurately localizing the robot within the map. Therefore, estimating and constantly updating the robot's position, is an important issue in map building. Assuming that the robot has an abstract description of the environment (a map) and that it knows its current position and the position of its goal, the robot must define a path leading to the goal that is optimal under certain criteria. The output of this path planning procedure could be a set of sub-goal positions that have to be reached by the robot in a second phase, called plan execution. Path planning relies on static models of the environment and, therefore, may fail to function if unpredictable obstacles block the robot's path. Hence, autonomous mobile robots have to constantly perceive their environments and re-plan dynamically in order to achieve their missions. The above tasks constitute very important issues in the field of mobile robotics and many techniques have been proposed to address them.

Recent research has produced two fundamental paradigms for modeling indoor robot environments, the metric paradigm (grid- or feature-based) and the topological paradigm. Feature-based maps employ appropriate features (usually line segments) to construct a model of the workspace. They are typically used in conjunction with continuous state (e.g. Kalman filter-based) approaches for robot localization [1]. Discrete [5,6] state approaches employ grid-based models, such as the occupancy grids proposed by Moravec and Elfes [2], representing an environment by evenly spaced (2D) cells. Each grid cell may, for example, indicate the presence of an object in the corresponding region of the environment. In such approaches, Markov models are usually employed

to represent the uncertainty in robot's position [5,6]. Topological approaches represent robot environments by graphs, as initially proposed by Kuipers, Byun, Mataric and others [3,4].

Given a representation of the environment (map), path planning techniques are used to construct paths that assume a starting position and lead to desired target locations. A large variety of methods have been proposed, that are special solutions for specific strategic tasks, machines and types of environments. A notable fraction of this work is either theoretic or has been tested only in simulations and additional work has to be done in order to test whether these methods operate satisfactorily with real robots. According to Latombe [8], all path planning methods can be categorized as "Roadmap Methods", "Cell Decomposition Methods" and "Artificial Potential Field Approaches". More recent methods take into consideration different types of uncertainties, such as uncertainty of sensory data, uncertainty of kinematics and of map information/localization, leading to stochastic approaches in path planning [8,15].

The motion planning approaches are usually unable to cope with the dynamics of real-world workspaces and a number of reactive approaches have been proposed to overcome this limitation. The dynamic window approach [9,10] is an example of a reactive collision avoidance strategy based on sequences of circular arcs. The Virtual Force Field method (VFF) [11], relies on the integration of two concepts, certainty grids for obstacle representations and potential fields for navigation, and enables continuous motion of the robot without stopping in front of obstacles. The Vector Field Histogram method (VFH) [12] is an extension of the VFF and uses a two-dimensional Cartesian histogram grid as a world model, which is updated continuously with range data.

The PYTHEAS system is an integration of various methods based on the approaches mentioned above. The underlying model in our system is a discrete state model, implying appropriate localization and environment representation approaches. Regarding environment mapping, dense maps (grid-based) are employed as the internal workspace representation. Dense (metric) maps are relatively easy to build, represent and maintain even for complex environments.

Laser readings are integrated over time, to yield a single consistent map according to a probabilistic model. Our approach for position tracking (localization) follows the Markovian paradigm; it constitutes a variation of a method proposed by Thrun [7,13]. Odometry readings are not used as a source of information because they usually become unreliable in the long run. Instead, the motion commands are employed to provide information about the next position of the robot.

For the task of path planning, the initial grid-based map is transformed to a topological one. As part of this transformation, a triangulation procedure is used to find a set of control points, in order to cover the free space of the map. In this way, the problem of finding a path between current and goal position is turned into a shortest path graph-searching problem. The employed approach exhibits small computational overhead, because the majority of computations are performed off-line. The motion planning method is a combination of "navigating under uncertainty" approaches since it uses probabilistic models on the grid-based map to track the robot's position and of "Roadmap Planners" because of the use of intermediate points in a topological version of the map. In order to dynamically avoid objects that block the path of the robot towards the goal position, the VFH algorithm is selected, because it results in smooth and continuous motion during obstacle avoidance. The high-level control of the system is facilitated through a web user interface that can issue commands to the robot even from a remote location over the network.

The integrated system PYTHEAS consists of the above-described, independent components, which can also be used separately. In this context, it is possible to replace a certain component of the system without having to alter any other component. Moreover, PYTHEAS is a complete system, which totally handles mapping and navigation in an unknown environment, relieving the user from low-level commands. An important feature of PYTHEAS is that it can be remotely controlled over the web, with an easy to use interface.

The PYTHEAS system can be used in a variety of possible applications. The ability of web control allows the system to be used in applications that require remote control of the system, such

as remote “representative” of the user in exhibition areas, trade shows, etc. PYTHEAS may also be employed in order to achieve navigation in hazardous environments, such as high radiation areas. Furthermore, a robot using PYTHEAS could play the role of a moving visual surveillance system. Especially, with the use of a panoramic camera, a large field of view is provided at all times. Since mapping is an independent module, PYTHEAS can also be used to map unknown indoor environments. Last but not least, it can offer services to people with special needs, since it can be used to control a wheelchair’s motion.

In the following section, the PYTHEAS system is described in detail. In section 3, experimental results are presented. The paper concludes with a discussion in section 4.

## **2. The Navigation System PYTHEAS**

PYTHEAS is an integrated robot navigation system that permits a user to control a mobile robot over the web. It consists of three modules. The first module serves the need for mapping an unknown environment while the second is responsible for planning a path in this environment and avoiding obstacles during the execution of the path. In both modules, there is the need for the robot to estimate its position within the environment (localization). PYTHEAS assumes a discrete, probabilistic model for representing the robot’s state as well as the environment. This leads to probabilistic formulas for updating state (localization) estimates that obey the well-known Markov (independence) assumption [14]. The final module offers to the user an interface for communicating with the entire system. The following sections, describe each module in detail. Moreover aspects of their integration to the complete system are also presented.

### **2.1 Mapping**

This module constructs a map of an unknown workspace in order to use it later for navigational purposes. The metric maps considered here are discrete, two-dimensional occupancy grids. Each

grid-cell  $\langle x,y \rangle$  in a map is associated with a value that measures the subjective belief that this cell is occupied by an obstacle. Occupancy values are determined based on sensor (laser) readings. Map building is an iterative procedure; each robot movement command initiates a new step, which is divided into the following four parts.

In the first part, the robot picks up a laser reading, which returns the distance of the robot from every obstacle in the front field of view. The employed laser scanner can observe the half-plane in front of the robot, using a 180 reading sweep with angular accuracy of  $1^\circ$ . These readings are then translated into a local map. Let  $m^{(t)}$  be the sensor reading (measurement) taken at time  $t$ .  $P(\text{occ}_{x,y} | m^{(t)})$  is the probability that a grid cell  $\langle x,y \rangle$  is occupied conditioned on the sensor reading  $m^{(t)}$ , ranging from 0 to 1, which correspond to empty and occupied space, respectively. The desired probability after  $T$  sensor readings,  $P(\text{occ}_{x,y} | m^{(1)}, \dots, m^{(T)})$  is computed as follows [7]:

$$P(\text{occ}_{x,y} | m^{(1)}, \dots, m^{(T)}) = 1 - \left( 1 + \frac{P(\text{occ}_{x,y} | m^{(1)})}{1 - P(\text{occ}_{x,y} | m^{(1)})} \prod_{t=2}^T \frac{P(\text{occ}_{x,y} | m^{(t)})}{1 - P(\text{occ}_{x,y} | m^{(t)})} \right)^{-1} \quad (1)$$

Equation (1) computes the probability that cell  $\langle x,y \rangle$  is occupied taking into consideration all sensor measurements  $m^{(1)}, \dots, m^{(T)}$ . In other words, it integrates sensor measurements over time to estimate the overall probability of a cell being occupied. For the construction of the map, the midpoint algorithm is used for every laser beam in order to find the grid-cells best approximating the beam's line equation. For the cell corresponding to the laser reading we raise the probability of being occupied by setting  $P(\text{occ}_{x,y} | m^{(t)})$  close to 1. For every other cell on the line with distance less than the laser reading, we lower it, by setting  $P(\text{occ}_{x,y} | m^{(t)})$  close to 0. In this way, a local probability map is constructed.

In the second part, the position of the robot has to be estimated. For that purpose, the localizer procedure, explained later in section 2.2, is invoked with arguments the previous position of the robot, the movement instruction and the sensory readings.

In the third part, after having estimated the robot's position, we integrate the local map, to the global map, as shown in Fig. 1. The size of global map is changing dynamically, allowing thus the robot to explore very large areas. Eventually (fourth part), the local map, the so far created global map and the position-orientation of the robot are being communicated to the interface, facilitating the on-line evaluation of the mapping results by the user.

## 2.2 Localization

To navigate reliably in indoor environments, a mobile robot must know where it is, i.e. it must be capable of localizing itself. Our approach is effectively a discrete, probabilistic localizer with some additional elaborations. Let the state of the robot at time  $t$  be  $s_t = \langle x_t, y_t, \theta_t \rangle$ . Let also the sensory measurements at time  $t$  be  $m^{(t)}$  and the motion command  $c^{(t)}$  (the command that resulted in the transition  $s_{t-1} \rightarrow s_t$ ). Markovian modeling of state estimation results in the following probabilistic, recursive formulas for localization [14].

$$P(s_t | c^{(t)}) = \alpha \int P(s_t | c^{(t)}, s_{t-1}) P(s_{t-1} | c^{(0)}, \dots, c^{(t-1)}) ds_{t-1} \quad (2)$$

$$P(s_t | m^{(t)}) = \gamma P(m^{(t)} | s_t) P(s_t | m^{(0)}, \dots, m^{(t-1)}) \quad (3)$$

where  $\alpha$  and  $\gamma$  are scaling factors to ensure that the computed probabilities sum up to unity. The above two formulas give rise to respective methods for estimation of the robot's state (localization).

In the first method, which stems from eq. (2), we consider a paralleloplane in the robot's configuration space and we displace the probabilities from the previous call of localization accordingly, effectively computing the probability  $P(s_t | c^{(t)}, s_{t-1})$ . Hence, the motion command is employed in order to decrease the uncertainty about the robot's position. In this way, we completely

ignore the odometry sensor of the robot, which, for a number of reasons such as the morphology of the ground, may return erroneous measurements.

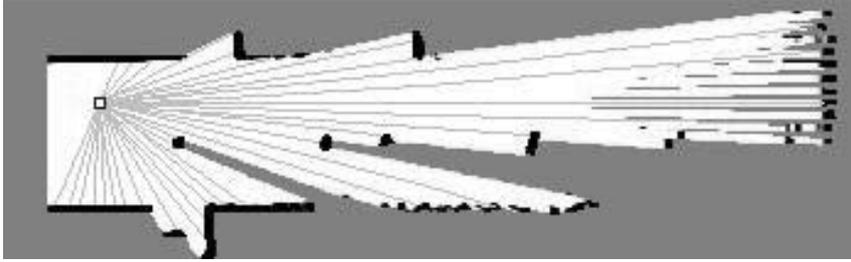
The second method stems from eq. (3) and computes state probabilities using sensory measurements. The probability  $P(m^{(t)} | s_t)$  needed for that is computed using the correlation between the measurements and the distances from the obstacles based on the current map. For every point in the search space  $\langle x, y, \theta \rangle$  we define the vector  $l(\langle x, y, \theta \rangle)$  which stores the 180 measurements that the laser sensor would have returned if the robot was on position  $\langle x, y, \theta \rangle$  and the map was accurate. The method computes the sum of the 180 differences between the actual laser measurement and  $l(\langle x, y, \theta \rangle)[i]$ , which is then converted to probability (the smaller the value of this result, the greater the probability) and assigned to  $P(m^{(t)} | s_t)$ .

Besides the above two described methods, a further method is used which exploits *wall orientation*. This method is based on the fact that in indoor environments, walls are either parallel or form right angles. First, we assume that we only have one line segment constructed from the laser readings with a starting point corresponding to the first reading and an end point to the last one. The algorithm searches for the point that has the greatest distance from the assumed line segment and splits the line in two. The algorithm is recursive and terminates when the distance of every reading from a line falls below a threshold or the number of lines exceeds a limit. Based on the assumption for the walls, the robot's angle is recalculated. The variation from Thrun's approach is that we assign weights to each wall according to the number of successive readings that compose the wall.

The values calculated from these three methods are normalized. We assign a weight for each method taking under consideration several experimental results and we update the probabilities according to:

$$J = \frac{W_{corr} P(s_t | m^{(t)}) + W_{move} P(s_t | c^{(t)}) + W_{wall} wall[x, y, \theta]}{W_{corr} + W_{move} + W_{wall}} \quad (4)$$

where  $W_{corr}$  is the weight of the correlation method,  $W_{wall}$  is the weight of the wall orientation method and  $W_{move}$  is the weight of the probabilities displacement. Finally, we calculate the maximum value of the J table which corresponds to the  $\langle x, y, \theta \rangle$  point returned by localization. Figure 1 shows an example of how laser readings match the profile of the environment during concurrent localization and mapping.



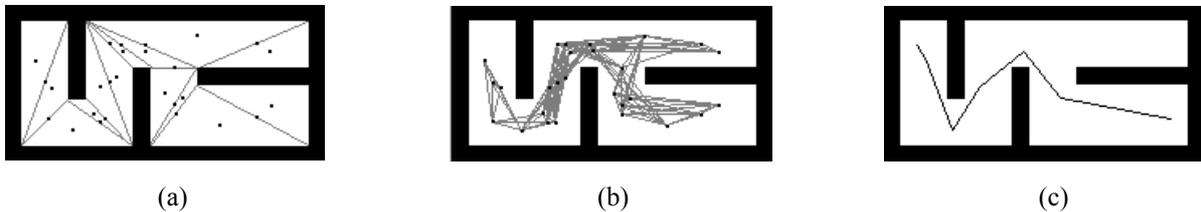
**Figure 1.** *Matching of the laser readings with global map.*

### 2.3 Global path planner

The planner takes as input a grid-based map, a starting point and a goal point and it returns the shortest, non-occluded path from the starting to the goal point. Initially the grid-based map is thresholded and cells with high probability are considered obstacles. A smoothing operation on the grid-based map is performed using the morphological operators opening and closing. Subsequently, the borders of the free space and of all the obstacles are found and their polygonal approximation is computed. As a result, the free space is modeled as a non-convex polygon with holes. A triangulation procedure is then employed in order to fully cover the free space with a dense population of points, which are the mass centers and the middle points of triangle edges.

In the next step a graph is created, using as nodes the output of the triangulation procedure. In this graph, two nodes are connected to each other if a line segment, which is not occluded by obstacles, can connect their corresponding points in the map. The weight of a possible connection between two nodes is the distance between their corresponding points in the map. After the creation of the graph, the Warshal algorithm [16] computes the shortest path between any two nodes in the graph. The complexity of this algorithm is  $O(n^3)$ , but it is called only once as an off-line procedure. Then, the problem of finding the shortest path from a random point to another is transformed to connecting these points to the existing graph and using the results of the Warshal algorithm.

The map positions that correspond to the nodes of the graph, which form the path from the initial to the target position, consist a set of control points. These points are intermediate targets passed to the obstacle avoider in order to reach the final destination. Figure 2 shows an example of the performance of the basic steps in a simple, synthetic map.



**Figure 2:** Global planner (a) Triangulated map including the centers of mass of the extracted triangles and the midpoints of the triangle's sides, (b) the connectivity graph and (c) the shortest path computed between two points.

## 2.4 Obstacle Avoidance

This part of the navigation software system is based on the Vector Field Histogram (VFH) algorithm [12]. Its main purpose is to execute the plan provided by the path-planning module, and simultaneously, to enable the robot to react properly in the presence of dynamic obstacles. As long

as VFH is active, the robot is forced to navigate along the planned path until the desired target is reached. During robot's detours due to obstacles, its speed is optimally adjusted.

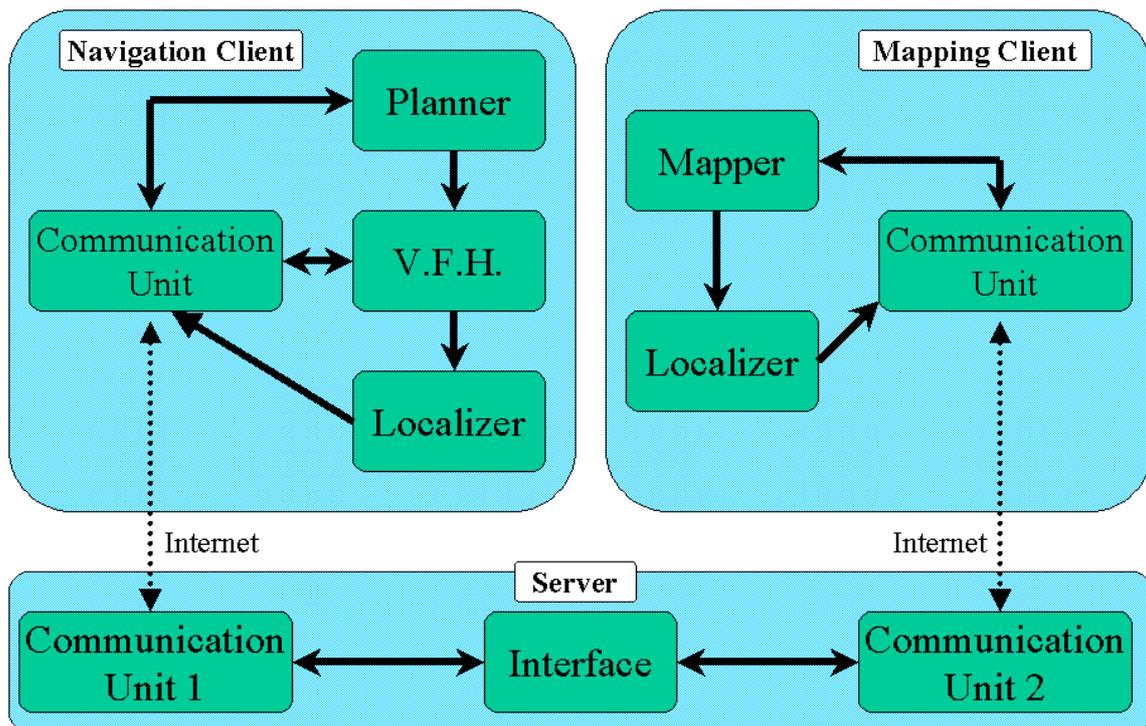
VFH uses as input the robot's laser readings and creates a two-dimensional grid-based local map, as described in section 2.1. Abrupt edges into the map are smoothed out and are then divided in sectors. Tempering each sector's grid values creates the corresponding sector repulsive values. They are named as Polar Obstacle Densities (PODs), and determine a quantum Cartesian object force histogram. All values in the object force histogram below a predefined threshold are considered as non-obstacle areas. The histogram is converted into a polar one, named Vector Histogram, which contains sector valleys that must be wide enough so as to be safe for the robot to pass through them. These valleys comprise a set of possible local steering directions. Taking into consideration the target course and the specified directions, a safe traveling drift relative to the robot, is determined (see Fig. 3). Based on the information from the global map and the localizer, it is converted into a global traveling direction, and an optimal steering speed is defined.



**Figure 3:** (a) A sample 2D grid-based local map computed from laser readings. White color corresponds to free space, black color corresponds to obstacles and gray color corresponds to lack of information. (b) The vector histogram created from Fig 5(a). Light gray sector defines a non-safe (narrow) space and the dark gray sector defines a safe (wide) space. Although the target direction is along line 1, PYTHEAS will follow the direction along line 2.

## 2.5 Integration

PYTHEAS consists of mapping and navigation modules, which run autonomously. The user coordinates both procedures; therefore another system module is always working on a user host, since the user operates the system through the web. The overall module interconnection is shown in Fig. 4.



**Figure 4:** Overview of the integration architecture.

In the present version, the user interface module acts as a server, while the other two modules are its clients. Communication is implemented with two separate sockets, one for each client. The client-server communication supports either predefined or event driven message exchange procedures. For each client, a communication unit (COM) is assigned. In the case of the navigation client, COM receives user commands to reach certain target positions or command to suspend

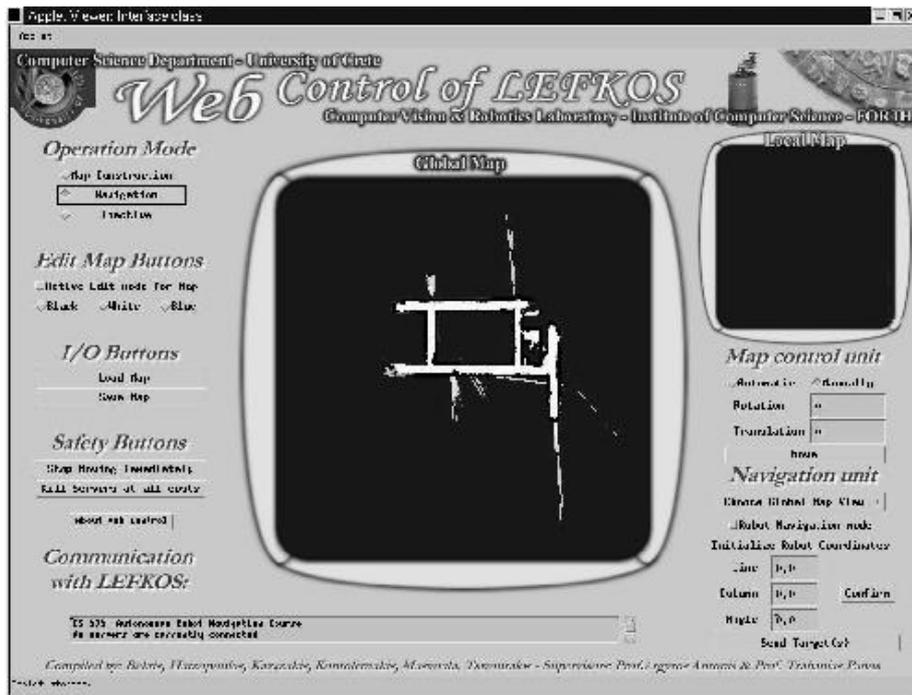
operation. It then transmits the messages to the navigation module. In the case of the mapping client, COM receives movement commands from the user and transmits them to the mapping module. Furthermore, all client modules can call COM functions to send information to the user interface.

Whenever the planner is called to design a new path, it finds a set of control points that form a path trajectory to the target position. Then it calls the VFH to reach each one of them. VFH calls the Localizer periodically to retrieve the current position of the robot and the control returns to the planner if a control point is reached or a time limit is exceeded. On the other hand, mapping calls its localizer routines to retrieve the robot position, whenever a specific motion command has ended, or periodically, if mapping is autonomous.

## **2.6 User Interface**

The interface developed for the navigation system PYTHEAS offers the ability to the user to control map construction and navigation. A snapshot of this interface during operation (workspace mapping), is shown in Fig. 5. The programming language used for developing the interface is Java 1.2 and the communication with the rest of the system is based on sockets.

During map construction, one can either instruct the robot to automatically create a map or to manually control the robot's movement. During execution of this phase, the user can switch between these two modes of operation. For easing experimentation and for aesthetic purposes, a map-editing tool is also attached to the interface. The "Global Map" window shows the evolution of the map building procedure and the "Local Map" window informs about the robot's laser measurements in its current position. After this phase has ended the user can save the map in the robot's file system.



**Figure 5:** The user interface.

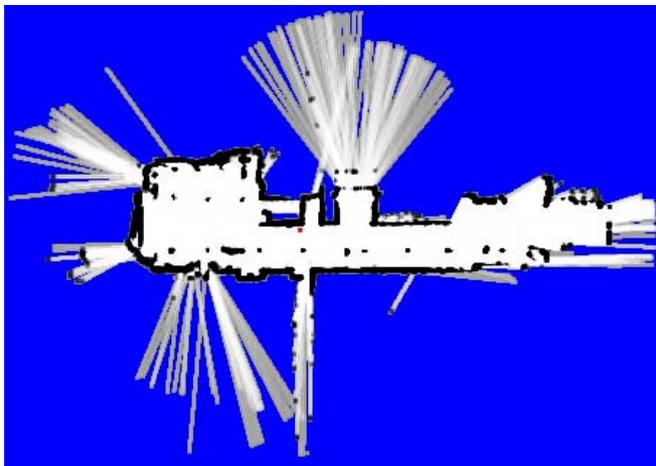
In the navigation mode, the user selects initially whether to use the map currently loaded in the system area or to load another one. Available to the user are many intermediate results of the navigation module, such as the polygonal approximation of the map borders and all the available paths between the intermediate targets. After the user has defined the robot's position, direction and targets, either by clicking on the map or by filling the appropriate fields, the execution of the specified paths initiates. It should be noted that a text field continuously informs the user about the state of the communication between the interface and the rest of the system. It also offers guidance for an efficient control of the PYTHEAS system.

### 3. Experimental Results

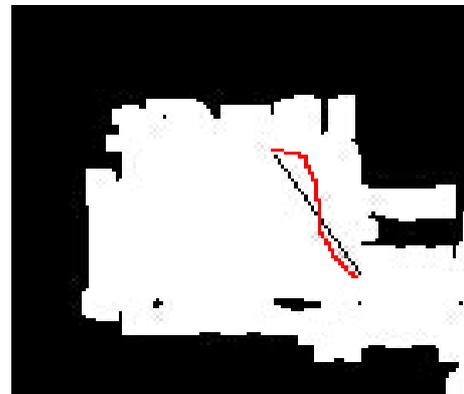
The proposed navigation system has been implemented on Lefkos, an iRobot-B21r mobile robotic platform available at the Computer Vision and Robotics Laboratory of ICS-FORTH. Several experiments were conducted in order to assess the performance of the integrated system, which

have confirmed its appropriateness for indoor mapping and navigation. A sample experiment is reported here for illustrative purposes.

Figure 6(a) shows the map constructed for the ground level of the main building of FORTH. Figure 6(b) shows a detail of the map where a simple path (straight line in black color) connects an initial position and a target one. Because of obstacles (moving persons), the robot finally followed the winding path shown in red color. Snapshots of this navigation session are presented in Fig. 7.



(a)



(b)

**Figure 6:** (a) Map constructed for the ground level of ICS FORTH (b) Detail of the map where the black line depicts an original motion plan between two positions in the map and the red line depicts the path followed by the robot in order to avoid obstacles.

## 4. Discussion

This paper has presented PYTHEAS, an integrated robotic system capable of acquiring maps of the environment autonomously and using them for navigating in the workspace. PYTHEAS is the integration of a number of state-of-the-art techniques in autonomous robot navigation, coupled together under a user-friendly interface that enables a user to remotely control it. The experimental

results from extensive testing are very promising. Future research and development activities will address issues related to the expansion of the capabilities of PYTHEAS.



**Figure 7:** Snapshots from a navigation session. The maneuvers that the robot performs in order to avoid moving obstacles in space can be observed in this experiment.

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