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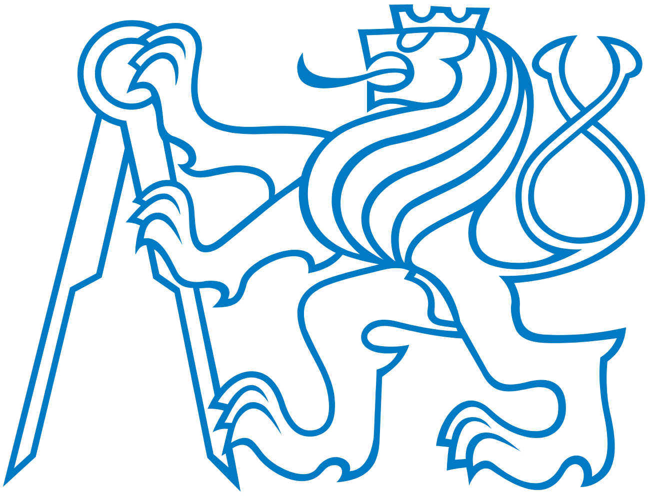

DOCTORAL THESIS STATEMENT

CZECH TECHNICAL UNIVERSITY IN PRAGUE
FACULTY OF ELECTRICAL ENGINEERING
DEPARTMENT OF CYBERNETICS
GERSTNER LABORATORY

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ROBOT MAPPING FOR LARGE ENVIRONMENTS

Ph.D. Programme: Electrical Engineering and Information Technology
Branch of study: Artificial Intelligence and Biocybernetics

Doctoral thesis statement for obtaining the academic title of "Doctor",
abbrevieted to "Ph.D."

Prague, May, 2011

The doctoral thesis was produced in combined manner of Ph.D. study at the Department of Cybernetics of the Faculty of Electrical Engineering of the CTU in Prague

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1 Introduction

Nowadays, robots are quickly moving from the laboratories and factories into households, offices, and streets. Therefore, the aim of this thesis is to allow a mobile robot to operate autonomously in large every-day environment. To achieve this, the robot has to sense the environment, construct a representation of the environment, store it in an appropriate data structure, reason over stored spatial knowledge, and perform the actions to fulfill given goals. Therefore the thesis focuses on finding the suitable representation of the spatial knowledge about the surrounding environment. Two sources of inspiration are used: the cognitive theories, how the humans and animals represent the spatial knowledge, and existing implementations of robotic maps, which are the robotic representation of the spatial knowledge.

The robot needs the mechanism, how to build the map (inner representation of the knowledge about the environment) autonomously. Therefore, the algorithm for autonomous exploration of the unknown environment will be proposed in the thesis.

As the information gathered during the exploration are subject to errors, the mechanism for handling the uncertain information is requested. The reasoning algorithm will be proposed in the thesis. It has to process the uncertain information with the aim to diminish the uncertainty and to deduce the new information for the actual knowledge.

The main goals of this thesis are :

1. To perform a study of the currently used representations of the spatial knowledge.
2. To propose a scalable probabilistic representation of the space - a map which is able to represent diverse types of environments, indoor as well as outdoor and deal with the uncertainty.
3. To propose a method of an autonomous exploration without necessity of the environment modification.
4. To propose a method for reasoning about uncertain spatial knowledge.
5. To implement and integrate the proposed methods into a unified mapping framework.
6. To verify the proposed methods in realistic environments and conditions.

2 Related works

The spatial knowledge representation proposed in this thesis takes inspiration from two sources. First source are cognitive theories of humans or animals mental representation of the environment, which was called cognitive maps by E. Tolman in [40]. All evidence suggests, that the human cognitive map represents a space quite differently from a printed map, which has a single global frame of reference. The widely used developmental theory of cognitive maps is based on children's cognitive maps development, mainly build on Piaget theory [32], and recognizes three stages of the development: (1) landmarks, (2) route map and (3) survey map.

The first comprehensive computational model of the human cognitive map is a TOUR model introduced by Kuipers in his PhD thesis [18]. The TOUR model [19] was strongly inspired by Kevin Lynch's seminal book, The Image of the City [25], and by studies of the development of children's spatial knowledge [32]. The computational model called PLAN

(Prototypes, Locations and Associative Networks) [6] is also build on the top of the developmental theory. This model treats the landmarks as the category of the objects, called prototypes, rather than a single unique object. Then stores these in associative networks, which provides the route map. The prototypes are grouped into the locations, which are connected again into the network which represents the survey map. Yeap, in his computational model [43], focuses on a problem how the information perceived directly from sensors are used to compute a cognitive map. Yeap builds his computational model on the Marr's theory [28] of vision.

The robotic map representations are the second source of inspiration. The metric and topological maps are two main paradigms in robotics. A metric map represents the environment as collected positions of relevant landmarks, features and object with respect to a single metric frame of reference i.e. a global coordinate system [39], [23], [33]. During the process of building a metric map is necessary to determine the position of a robot in a global frame of reference. When the environment is a large-scale space, then a localization becomes an important issue. Therefore the localization and map building is tightly coupled and solved simultaneously as problem of Simultaneous localisation and mapping (SLAM) or concurrent mapping and localisation (CLM) [36], [38], [30], [5].

Metric maps excel in solving of some low-level problems encountered in robotics [21], [22], reduce a pose error in small-scale space, but the drift in the odometry makes the global consistency of the map difficult to maintain in large environments.

As a consequence, metric maps can not easily handle large cyclical environments once the position has drifted excessively. Mapping and planning in very large metric maps can be time consuming. Metrical maps also suffer from the lack of a good interface for higher-level symbolic problem solvers.

A topological maps [35], [29], [5] are connected with the cognitive maps theories and generally represent spatial knowledge as a graph, describing locations and object of interest as vertices and their spatial relations as edges. The basic concept outlined in the TOUR model has been refined into the Spatial Semantic Hierarchy (SSH)[20]. The SSH treats observations gathered during exploration as the fundamental source of experience for building a cognitive map of large-scale space. Kortenkamp in [16] implements cognitive map theory PLAN (Prototypes, Location and Associative Networks) and calls his implementation RPLAN - Robot PLAN. RPLAN uses the integration of sonar and vision through two theoretical concepts, gateways and scenes.

Hybrid maps [17], [41], [3], [7] combine metric and topological approaches to support advantages and suppress disadvantages of both. The known hybrid approaches combine the metric and topological approaches in three ways: (1) Single global metrical map is augmented with the topological structures. (2) Vertices of the global topological map are augmented with local metric maps. (3) Global metric map is divided into parts and this parts are connected in graph-like structure. Regarding the approaches, it seems suitable to have a hybrid approach based on a global topological map for the representation of the environment.

The process of exploration can be understood as a process of autonomous navigation of a mobile robot in an unknown environment in order to build a model of the environment. An exploration algorithm can be defined as an iterative procedure consisting of a selection of a new goal (exploration strategy) and a navigation to this goal. Such an algorithm is terminated whenever the defined condition (mission objective) is fulfilled.

The frontier-based exploration [42] is widely used for metric maps.

The topological exploration of the environment can be seen as the graph search. Many of the graph exploration algorithms rely on the unique labeling of the vertices or edges. These approaches are not suitable for the robotic exploration at all, or require to put the artificial landmarks into the environment to produce such a labeling. Second group of algorithms use movable markers [10], [34], [1] to allow robot distinguish the vertices from each other. It puts the hard requirements on the robot hardware which must be able to put the marker into the environment, recognize it and recollect it later back. The approaches not using the markers [27] rely on the keeping the collection of possible hypotheses about the world consistent with the experienced data.

The uncertainty can be handled in different manners. The symbolic approaches are focused in this thesis and different extensions of symbolic logic are discussed. The term *probabilistic logic* was firstly used in [31] by Nils Nilsson and describes a semantic generalization of a logic in which the truth values of sentences are probability values. The possibilistic logic [8], [9] handles propositional or first-order logic sentences weighted by a real number, which is a lower bound of a necessity or possibility measure as used by Zadeh [45]. The fuzzy logic [2] is based on fuzzy sets introduced by Zadeh in [44]. The subjective logic [11] operates on the base of Dempster-Shafer belief theory [37] and contains standard logical operators extended with some non-standard operators [12], [15], [14], [13] which specifically depend on belief ownership.

The applicability of the aforementioned logic approaches are compared with respect to the application in the robotic mapping. The propositions about the world are typically evaluated as true or false and the uncertainty arises from the errors of the measurements and sensing. Therefore, the advantage of the *fuzzy logic*, the ability to express vague proposition, is not crucial for this work .

It is assumed, the knowledge about the real world can be logically inconsistent, as the knowledge is build from the uncertain data. Therefore, this assumption excludes the *probabilistic logic* from the selection as this supposes the logically consistent set of propositions.

The choice can be done between the *possibilistic logic* and the *subjective logic*. As the *subjective logic* provides richer representation of uncertainty and new operators, the *subjective logic* is used in the thesis.

3 Proposed Spatial Representation

The spatial representation proposed in this thesis is based on the cognitive theories of the human spatial knowledge. The main structure is a topological map, a directed graph $G = (V, E)$ which consists of vertices V and edges E, likewise existing robotic implementation of topological maps. The vertices stand for places in the environment whereas the edges represents navigation paths. The vertex represent the point of interest or the significant place in the environment. Typically vertices are placed to the points, where robot can take a decision.

This classical representation is extended by explicit association of the procedural knowledge with the graph elements, where the procedural knowledge is that information, which is necessary to know how to get from one place to another or how to distinguish one place from another.

The edge procedural knowledge is an input for one of the navigating algorithms, describing how to traverse along edge $e = (v_s, v_t)$ from the starting place v_s to the target place v_t. It is expected, the procedural knowledge describes a deterministic behavior.

The information stored in the vertex descriptors are used to localize the robot inside the local frame of reference and to distinguish the vertices from each other. The vertex is not requested to be uniquely distinguish by its description from others. The pairwise similarity $s_A(v_i, v_j)$ of two vertices is computed by a matching algorithm A from the set of matching algorithms, which compares a specific descriptors of the involved vertices.

The metric maps can be joined to the vertex and/or edge as an additional information. Each vertex or edge can carry multiple different descriptors with further additional information as area, length, curvature, relative position, and so on.

All the knowledge can be augmented by the measure representing the uncertainty of the knowledge. Stored information is transformable in human understandable form and can be used in communication with human.

The advantages of the proposed map in the form of the annotated graph are summarized in this section.

The main advantage over a current topological approaches is the rich descriptor of the edge in contrast to the simple link representing only the connection between the places. It allows to use a complex navigating algorithms, which needs the detailed description of the path. This description is learned during the traverse along the edge first time and then reused.

Next advantage of the proposed approach over the current hybrid approaches is the possibility to have multiple metric maps related to one place. The different maps produced by different sensors or different algorithms are assigned to the same vertex, and represent the same physical location. For example, one place is represented by an occupancy grid from sonars, and a feature map generated from camera and a point map from a laser scanner, all at hand and aligned.

The proposed rich representation allows to have a one map for an environment with a parts of a different type. For example, it is possible to have a map a university campus, where the areal of the campus with insides of the building is stored in one representation. It is not necessary to split it to different maps for each building and then switching between them. The robot is able to navigate fluently from indoor to outdoor and back.

Also it is possible to have a one map for different types of robots. The robot equipped with the camera share the map with the robot equipped with the laser range-finder. The same definition of the vertices and edges, representing the same physical places and paths, but different algorithms for navigation and localization. This is not possible in the classical metric representation.

The representation with the incorporated uncertainty in form of opinions from subjective logic increase the robustness and reliability of the representation. As the representation is augmented with the reasoning procedure, the missing information is deduce from the current uncertain information. The resulting uncertainty indicates if the current information is convenient enough to make the required conclusion, or, it is necessary to gain more information.

4 Reasoning

The map can be understood as a knowledge base, the set of proposition about the environment, and robot-environment interaction. The reasoning module takes uncertain knowledge stored in the map and infers the new information based on predefined set of rules. It is also capable to generate the most consistent hypothesis explaining given set of observation.

Suppose, there is a propositional language L describing the environment, supplemented by the tautology $\top$ and contradiction $\perp$. The set of propositions will be finite, as the world is assumed to be limited and closed. Let Ω_L denotes the set of worlds that corresponds the interpretations of L. Let consider an actual world, denoted as ω_0, i.e., a world that corresponds to the actual state of environment. The robot does not know which world in a set of possible worlds is the actual world.

The robot's actual knowledge about the actual world can be encoded in set of propositions K. The set Ω_K is set of worlds considered as possible by the robot in the actual situation. If the robot knows the truth status of every propositions of interest, then it would know, which world is ω_0.

The subjective logic is used, as the information gathered from the environment is uncertain and cannot be expressed by classical logic propositions. The true value of the proposition p is expressed by an opinion $\mathcal{O}(p)$. The opinion $\mathcal{O}$ has four components: believe b, disbelieve d, uncertainty u and atomicity a.

Used algorithms provide the propositions with values from interval $[0, 1]$ or $[0, \infty]$. The value is converted into the form of an opinion with assumption that the value expresses the probability expectation. As there is no evidence to prefer to belief or disbelief, the uncertainty will be maximized during the conversion. The parameters for the conversion are acquired using machine learning techniques from training sets of annotated vertices.

Multiple algorithms can provide opinions about the single proposition. The consensus operator $\oplus$ is used for the fusion of the algorithms' results.

In subjective logic, Jøsang defines the conditional deduction in conformity with the probability calculus. It means, the conditional probabilities are necessary to know to deduce the consequent Q. As these conditional probabilities are not known, there is given a novel definition of the Modus Ponens in the thesis. It can be expressed as discounting the opinion about the rule $P \to Q$ by the opinion about the antecedent P:

$$\mathcal{O}(Q) = \mathcal{O}(P) \otimes \mathcal{O}(P \to Q),$$

where $\otimes$ is a operator discounting.

Moreover, a loop closing procedure is proposed in the thesis. The loop closing is a process of finding the correct correspondences in a experienced set of observations gathered during the exploration. The observations are converted into the list of propositions about the environment with the opinions K_E. This propositions are in a form of similarity of the vertices and edges. The algorithm deduced the knowledge about the loop-closing $K_E, R \vdash K_C$ from the experienced knowledge K_E and the set of rules R, where the set of the rules is the knowledge about the properties of the environment converted into the form of the logical proposition with the opinions about the validity for a given environment.

5 Exploration

During the exploration, the robot gains the information about the actual world, adds the propositions to K, and reduces the size of Ω_K. In the case when $|\Omega_K| = 1$, the robot knows the actual world and the exploration ends.

There are two algorithms proposed in the thesis: First algorithm uses one not-movable marker placed at the starting place, called *base vertex*, and second algorithm uses the reasoning procedure to close the loops in the environment instead of the marker.

The algorithm consists of two phases: exploration and merging.

In the *exploration phase*, the robot moves through the environment and makes its own map $G_M = (V_M, E_M)$ of the world. As the robot cannot distinguish particular vertices from each other, it is unable to close loops in environment and every visited vertex must be handled as unvisited one until the robot proves the contrary. During the exploration phase, one place in the environment might be represented by more vertices in the map. This inconsistency is reduced in the *merging phase*.

The first algorithm uses the marked *base vertex* for the loop closing detection. When the robot revisits the *base vertex*, the actual vertex is merged with the *base vertex* and all edges incident with the them are checked. If there are two or more same edges, they are merged and their ends vertices are merged as well. The information propagates through the whole map.

The marker-less exploration strategy relies on the loop-closing algorithm. Whenever the algorithm enters the vertex, checks if this vertex is already stored in the map. The loop-closing algorithm is called and the information about the environment stored in knowledge base is refined on. If there exist pairs of vertices with similarity higher than given threshold, the merging phase is called. The edges with the similarity higher than the threshold are also merged.

The exploration algorithm ends, when the map contains no unexplored edge.

6 Framework Integration

The proposed spatial knowledge representation introduces the procedural knowledge as a crucial property. The procedural knowledge is split into two parts, the algorithms and the data. The data are stored directly in the map. The algorithms are stored as libraries or executable programs separately.

These algorithms work with different sensors and robotic platforms, but all of them are used with a single environment representation. The unified approach to handle them and communicate with them is necessary. Therefore, all the algorithms for localization, navigation along with reasoning and map representation are incorporated into one framework called Large Maps Framework (LaMa).

The LaMa framework is build as a modular system and therefore allows to easily incorporate new algorithms into it. Mechanisms for modules coordination and cooperation are incorporated into the LaMa framework and therefore the individual modules need no specific mechanism for these interactions.

The framework consists of several backbone parts: Map, Executor and Jockeys. The Map holds gathered information about the environment and provides interfaces for writing, modifying and reading data.

6.1 Executor

The Executor module provides abstraction for higher level planning, hides the implementation details, and enables handling all types of map elements in unified way. Also, it enables coordination and cooperation of navigating, learning and localizing algorithms encapsulated as modules called Jockeys.

According to requested action, the Executor calls a specific Jockey. If there are more suitable Jockeys, the one with the best expected performance is chosen. The Executor supervises the behavior of the executed Jockey and if the Jockey fails, tries to substitute the requested behavior by executing another Jockey with similar functionality.

6.2 Jockeys

It is necessary to have the unified access to all the algorithmic parts of procedural knowledge, which need direct access to the robot hardware or work with raw data gathered from the robot hardware. Therefore, these algorithms were designed as an independent modules called *Jockeys* as they are 'riding' the robot. According these functionalities of the algorithms, three different types of modules are defined : Navigating Jockey, Learning Jockey and Localizing Jockey. For each type of Jockey is defined the specific interface in form of communication protocol.

The Navigating Jockey guides the robot along the edges of the specific type and has two different subtypes: Memory-less and Memory-based.

The Memory-less Jockey uses a reactive navigating strategy, which computes the control commands directly from the sensory input. Main advantage of reactive navigating is the ability to traverse an unknown edges and discovery new vertices, therefore it is used mainly during the exploration of the environment.

The Memory-based Jockey needs the data part of the procedural knowledge related to the edge in advance. This information (edge descriptor) is acquired by the coupled Learning Jockey. The Memory-based navigation can be more precise and repeatable than the reactive one, can determine the failure of the navigation, and can provide the measure of similarity of the appropriate edges.

The Learning Jockey creates new possibility to traverse the edge with different navigating strategy alongside to the actually used. This Jockey gathers information while a robot is driven by a Navigating Jockey and the gathered procedural knowledge is stored in the edge descriptor. The edge descriptor is utilized by Memory-based Navigating Jockey later on.

The Localizing Jockey is able to distinguish vertices of the specific type from each other and compare the actual vertex with other vertices stored already in the map. It gives the results in form of probabilities to be in some of the previously visited vertices. This behavior is used for global localization and loop-closing. In addition, the robot position in the vertex local frame of reference can be estimated, if the descriptor is in the form of the metric map.

7 Experiments

The set of experiments were performed to verify the functionality and performance of the proposed mapping framework. The experiments were performed in three types of environments: Simulated, Indoor and Outdoor. The selected results are described here.

The results of the marker-less exploration in the simulated environment are depicted in Figure 1. The simulated environment (Fig. 1a) and resulting map with closed loops (Fig. 1c) are shown. The map (Fig 1d) was produced with the exploration algorithm, when only the similarity of the vertices was used, instead of the reasoning loop-closing procedure which incorporates the knowledge contained in the edges.

The localization results are shown (in Fig. 1b) in form of the receiver operating characteristic (ROC), which is a graphical plot of the sensitivity, or true positive rate, vs. false positive rate for a binary classifier system as its discrimination threshold is varied. The localization is here seen as a classification of the pairs of the vertices into two classes, positive, if the two vertices represents the same physical place, and negative otherwise.

The results of localization algorithms based on Fast Fourier transformation (FFT), normalized cross-correlation (NCC), integral invariants [26], tangent space [24], and scan line [4] are depicted in the figure. Notice the algorithm denoted as *consensus*. It is a localization algorithm computed from localizing algorithms FFT and NCC converted into the form of opinions and fused using the consensus operator from the subjective logic. The classification of this *consensus* classifier is better, as it combines the localizing algorithms sensitive to different errors in sensory data and these errors are compensated.

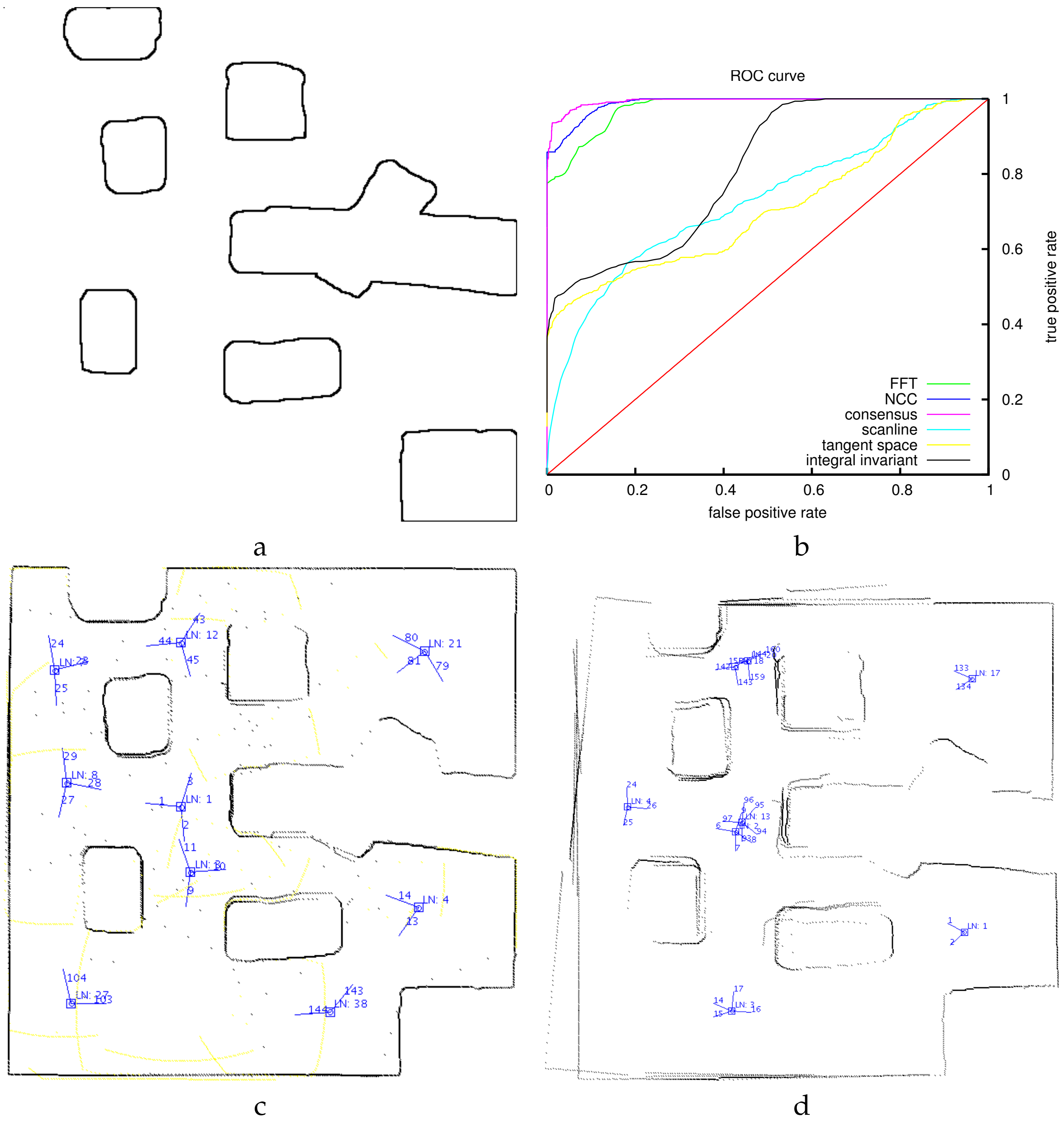

Figure 1: Simulated environment Cave (a). Results of localizing algorithms (ROC) (b). Map gathered with loop closed using reasoning algorithm (c) and not using reasoning algorithm (d).

The map of the botanical garden Albertov can be seen on Figure 2. Position of the vertices where taken from GPS receiver, nevertheless GPS data was not used by the algorithm at all. The size of the working environment of the robot was reduced by blocking some of the paths and robot considers these blocked paths as dead-ends and in the map are represents as self-loop. The marker-less exploration strategy was used. It has to be pointed out, that the used environment contains vertices almost undistinguishable and whole loop-closing algorithm must rely only on similarity of edges only. Note, that all existing loops were correctly closed.

Figure 2: Outdoor environment - botanical garden, Albertov, Prague

8 Contribution

The following section recapitulates the contribution of the thesis. In comparison with existing topological maps, the proposed representation brings a following main achievements:

- Paths in an environment are represented as edges in a map. This representation contains a procedural knowledge (how to traverse the edge) in contrast to previously used simple edge representation in the sense of connection or existence of route. The procedural knowledge representation is necessary to utilize various navigational algorithms not only reactive ones, but also the algorithms relaying on the previously learned information. The each edge can hold more than one procedure to navigate from the starting point to the destination. It allows to select the most reliable navigational algorithm or the most suitable for current conditions, state of the environment and the robot itself.

- The proposed modular concept of Jockeys - algorithms for navigation, learning and localization allows to utilize multiple senors and algorithms concurrently. This approach allows to use a single map for representing heterogeneous environment consisting from a wide range of vertex and edge types.

- The concept of Learning and Memory-base Navigating Jockey brings a qualitatively improvement into the area of topological mapping. The flexibility and reactivity of the navigation method is required during the exploration of the environment and the map learning as the robot needs to move autonomously through the unknown environment. On the other hand, the repeatability and rigidity is requested during the navigation using the map.

  It is not possible to fulfill this antagonistic requirements in nowadays topological mapping system. To solve this problem in the proposed framework, the pairs of Learning and Memory-based Navigating Jockeys are introduced. The classical reactive navigation is used during the exploration of an unknown environment, but simultaneously one or more Learning Jockeys are running. These Jockeys memorize the trajectory, and store the data necessary for traverse of the edge - the procedural knowledge. Whenever there is a request to traverse already learned edge, the appropriate Memory-based Jockey is called. If there exists more than one procedural knowledge, the best navigating algorithm can be chosen according to a-priori computed or observed performance for a particular edge. The behavior of Memory-based Jockeys is deterministic, also they are able to recognize and report the failure in contrast to reactive Memory-less Navigating Jockeys.

- The uncertainty representation using the subjective logic brings the power of the symbolic reasoning with the uncertain propositions. The advantage of the subjective logic is shown in the combining the information from different localizing modules into one opinion about the position of the robot. Also the proposed symbolic description of the environment properties and usage of this feature is shown in the loop-closing during the exploration. The used representation of uncertainty allows the extension of the representation by the non-deterministic behavior of navigation algorithms.

9 Conclusion

This work addresses the problem of robotic mapping of an unknown large-scale environment. The proposed map representation is based on the cognitive theories of the human spatial knowledge. The methods for localization, navigation, reasoning and exploration together with the map proposed representation are incorporated into modular framework called Large Maps Framework (LaMa). This LaMa framework is considered as a knowledge base allowing to handle and utilize spatial knowledge of various environment in a unified way.

The experimental verification of the proposed methods shows, that the framework is able to handle indoor as well as outdoor environments in the scale of hundreds of meters and perfectly operate in them later on. The automated exploration of unknown environment can be seamlessly extend with a human assisted exploration. The performance of navigation is improved using the pairs of Learning and Memory-based Navigating Jockeys.

The established principles proposed in the thesis are successfully exploited in the European projects from *Symbiotic Evolutionary Robot Organisms* (Symbrion) founded by FET Proactive Intiative: pervasive adaptation and *Robotic Evolutionary Self-Programming and Self-Assembling Organisms* (Replicator) founded by Cognitive Systems, Interaction and Robotics. The partial implementation of the LaMa framework was previously used in the Robotour competition. Our team wins this competition in years 2008 and 2009.

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Resumé

Cílem této disertační práce je umožnit autonomní provoz mobilního robotu v běžném a rozlehlém prostředí. K tomu robot potřebuje vnitřní reprezentaci prostředí, schopnost uvažovat o prostředí a akcích a provádět akce tak, aby byl schopen plnit zadané úkoly. Mimo to, je nezbytné, aby robot byl schopen získávat informace o okolí samostatně. Robot musí umět reprezentovat a pracovat s neurčitostí, neboť informace jsou pořízeny ze senzorů, jejichž měření je zatíženo chybou, omezeným dosahem i rozlišením a tedy neurčité.

Práce se zaměřuje na nalezení vhodné reprezentace prostorových znalostí o okolním prostředí. Jako inspirace slouží kognitivní teorie lidské reprezentace prostředí a existující přístupy k reprezentaci robotických map. Navržená reprezentace je rozšířením stávajících topologických map, které prostředí reprezentují jako graf, kde vrcholy grafu popisují význačná místa v prostředí a hrany cesty mezi nimi. Navržená reprezentace přidává k prvkům grafu procedurální znalost, která uchovává popis jak rozpoznat jeden vrchol od druhého a jak se navigovat podél hrany od počátečního vrcholu ke konečnému. Každý prvek grafu může mít přiřazenou celou řadu různých popisů, může být popsán také lokálními metrickými mapami. Toto rozšíření umožňuje použít komplexní navigační a lokalizační algoritmy, které v klasických topologických mapách není možné použít. Pro navigaci je možné použít takové algoritmy, které vyžadují znalost celé cesty předem. V takovém případě se pro nalezení popisu procedurální znalosti příslušné hrany použije učící algoritmus.

V této práci je navržený odvozovací mechanizmus (uvažování), který je schopen pracovat s neurčitými znalostmi o prostředí. Jeho cílem je kombinovat neurčité znalosti tak, aby se míra neurčitosti snížila, a vyvozovat nové znalosti ze znalostní báze a pravidel. Odvozovací mechanizmus je postaven na subjektivní logice, která rozšiřuje vlastnosti symbolické logiky o vyjádření a práci s neurčitostí a náhodností. Subjektivní logiku rozšiřuje o vlastní návrh výpočtu Modus Ponens a tento výpočet je pak využit v nově navrženém algoritmu uzavírání smyček.

Algoritmus autonomní explorace prostředí umožňuje robotu samostatně budovat model prostředí. V práci jsou navrženy dva explorační algoritmy. První z nich vyžaduje pro svou práci umístění značky na jedno místo v prostředí, nazývané základna. Tato značka je použita pro uzavírání smyček. Druhý algoritmus nahrazuje značku použitím algoritmu uzavírání smyček zmíněný výše.

Navržená reprezentace prostředí, explorační a uvažovací algoritmy jsou spolu se sadou navigačních a lokalizačních algoritmů integrovány do jediného mapovacího modulárního systému. Navržený modulární systém odděluje reprezentaci znalostí, spolu s uvažovacím algoritmem, od konkrétních senzorů, aktuátorů a algoritmů pracujících s konkrétním robotickým zařízením. Přístup vyšších, abstraktnějších vrstev k nižším vrstvám řídí výkonný modul. Toto modulární řešení spolu se zmíněným oddělením umožňuje zároveň používat více různých navigačních a lokalizačních algoritmů současně, i pokud používají různé senzory. Přidání nového algoritmu nebo senzoru je snadné a neovlivní funkčnost stávajícího systému ani použitelnost dříve vytvořených map.

Provedené experimenty ověřují funkčnost navržených přístupů. Mimo jiné ukazují, že navržená reprezentace prostředí je schopna uchovávat informace o různých typech prostředí (vnitřích i venkovních), bez potřeby jakékoliv úpravy a že robot je schopen získat tuto reprezentaci samostatně.

Hlavní přínosy této práce jsou: zahrnutí procedurální znalosti do popisu prostředí, modulární přístup, který umožňuje získat detailní popis prostředí z různých pohledů současně, koncept využití dvojice algoritmů, z nichž první vytvoří detailní popis hrany a druhý pak zajišťuje spolehlivou a opakovatelnou navigaci a využití subjektivní logiky k popisu neurčitosti spolu s algoritmy pro práci s neurčitými znalostmi a odvozování nových.