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A Categorization of Simultaneous Localization
and Mapping Knowledge for Mobile Robots

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*Dedicado a mis padres y hermanos,
quienes fueron el soporte ideal durante
estos años de estudio.*

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Resumen

Los robots autónomos están desempeñando un papel importante en las actividades académicas, tecnológicas y científicas. Por lo tanto, su comportamiento se está volviendo más complejo. Las principales tareas de los robots autónomos incluyen el mapeo de un entorno y la localización de sí mismos. Estas tareas comprenden el problema de la Localización y Mapeo Simultáneo (SLAM). La representación del conocimiento SLAM (por ejemplo, las características de los robots, la información del medio ambiente, el mapeo y la información de localización), con un modelo estándar y bien definido, proporciona la base para desarrollar soluciones eficientes e interoperables. Sin embargo, hasta donde sabemos, no existe una clasificación común de esos conocimientos. Muchos trabajos existentes basados en la Web Semántica, han formulado ontologías para modelar información relacionada sólo con algunos aspectos del SLAM, sin un estándar. En este trabajo, proponemos una categorización del conocimiento manejado en el SLAM, basado en las ontologías existentes y los principios del SLAM. También clasificamos ontologías recientes y populares de acuerdo a las categorías propuestas y resaltamos las lecciones a aprender de las ontologías existentes. Evidenciando la necesidad de desarrollar una ontología completa para representar la información de SLAM en los robots móviles.

Palabras clave: Ontologías, SLAM, Web Semántica, Robots móviles

Abstract

Autonomous robots are playing important roles in academic, technological, and scientific activities. Thus, their behavior is getting more complex. The main tasks of autonomous robots include mapping an environment and localize themselves. These tasks comprise the Simultaneous Localization and Mapping (SLAM) problem. Representation of the SLAM knowledge (e.g., robot characteristics, environment information, mapping and location information), with a standard and well-defined model, provides the base to develop efficient and interoperable solutions. However, as far as we know, there is not a common classification of such knowledge. Many existing works based on Semantic Web, have formulated ontologies to model information related to only some SLAM aspects, without a standard arrangement. In this work, we propose a categorization of the knowledge managed in SLAM, based on existing ontologies and SLAM principles. We also classify recent and popular ontologies according to our proposed categories and highlight the lessons to learn from existing solutions. Showing the necessity to develop a complete SLAM ontology in mobile robots.

Keywords: Ontologies, SLAM, Semantic Web, Mobile Robots

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Capítulo 1

Introduction

Nowadays, autonomous robots are everywhere and they are playing important roles in every day life activities, as well as for academic, technological, and scientific applications [Coeckelbergh et al., 2016, Ingrand and Ghallab, 2017]. The main tasks of autonomous robots are mapping an environment and localize themselves. These tasks conform the Simultaneous Localization and Mapping (SLAM) problem. Thus, SLAM, deals with the necessity of building a map of the environment, while simultaneously determining the location of the robot within this map. In general, building maps of unknown environments is based on information captured by a range of sensors, such as lasers or sonars, while robot location needs more information coming from other types of devices (e.g., GPS). Due to the evolution of mobile technologies and sensors, the complexity of the behaviors that robots are expected to perform is growing. Naturally, this trend involves the use of increasingly complex knowledge. It includes understanding SLAM as a continuous and dynamic process because of the physical world that the robot explores is in constant change. Also, the change of the world that we refers includes: (i) uncertainty about the robots' position and landmarks' position, and (ii) the request for multirobots and collaboration between human and robots (e.g., rescue tasks in inaccessible places for humans, large tasks that cannot be performed by just one robot or a single robot's type).

In the other hand, Semantic Web is a collaborative effort led by the World Wide Web Consortium [Berners-Lee, 1994] result of the work of a large number of participants among industrial and research partners. It is based on the use of RDF [Klyne and Carroll, 2006], which integrates a wide variety of applications through the use of XML [Bray et al., 2000] for syntax and the use of URLs [Berners-Lee et al., 1994] for identification. Then, in order to extend the limited expressiveness of RDF Schema [Brickley et al., 2014], a more expressive Web Ontology Language (OWL) [Antoniou G., 2004] has been defined by W3C. Semantic Web serves as a bridge to the knowledge that is on the Web. The Semantic Web is not linked to a specific area but it is involved transversally in all of the knowledge categories.

To gain more benefits of having information organized by meaning, the use of ontologies appears as a powerful tool. In computer science, ontologies are formal models to represent information, that enable the description of objects, properties, and relationships among such objects in a knowledge domain. Ontologies are particularly important

to provide machines with knowledge representation and reasoning capabilities to solve a task, as well as to perform semantic interoperability among systems.

1.1. Motivation and Context

A common way to organize knowledge in the SW is using web ontologies. With them, we can express the knowledge acquired by a robot. In computer science, ontologies are formal tools that enable the description of objects, properties and relationships among such objects in a knowledge domain [Prestes et al., 2013]. The description is explicit, meaning that all the information is formally defined in the ontology. In this definition lies one of the basic strengths of ontologies, as being explicit means they can be understood (and therefore used) by both machines and men.

Another bennefit of using ontologies is the interoperability [Fortes, 2013] among robots who solves the problem of SLAM with differents tecniques or sensors, but still can save and share the acquired knowledge with the same ontology. Using transformations, defined in the ontology, a robot that uses some polar coordinate system could share knowledge with another robot that uses a Cartesian one. Even a flying drone that uses a 3D coordinate system could share the location of features with a land robot that uses a spatial scenario with 2 dimensions.

In this context, formulate SLAM ontologies contributes positively in two communities (Robotics and Semantic Web). That is why since November 2011 Ontologies for Robotics and Automation Working Group (ORA WG) [Prestes et al., 2013] is actively working with industry, academia, and government organizations to develop a set of ontologies and an associated modeling methodology to be used as a standard in Robotics and Automation (R&A).

1.2. Problem Statement

Even though, SLAM is an area that is well researched and has reached a high level of maturity where progress is currently being made [García-Fernández et al., 2019, Leitinger et al., 2019, Demim et al., 2018], there is still a lack of standardization to represent such information and the knowledge needed to propose efficient and interoperable solutions. In this context, the need for a standard and well-defined model for capturing the knowledge managed by SLAM algorithms, becomes evident. According to the work of [Burroughes and Gao, 2016], ontologies are the best way to organize knowledge since they are a mixture of first-order logic (FOL) and a model based on characteristics.

As far as we know, there is not a common classification of such knowledge. In fact, many existing works based on Semantic Web, have formulated ontologies to model information related to some SLAM aspects, without a standard and common arrangement. Hence, there are few ontologies that can be considered complete solutions to the SLAM problem.

Furthermore, in the current state of the art of SLAM ontologies, it is clear that a lot of work is done only in the final result, as if SLAM were a static process. By considering the SLAM process as something static, we are modeling the knowledge acquired only partially. For this reason, it is important to understand SLAM as a continuous process with the presence of uncertainty. For this reason, in order to develop a complete ontology, we have to start considering not only the result but to examine characteristics inherent to the dynamicity of the process such as uncertainty, for example, the uncertainty of the robot pose generated by the inaccuracy of its physical movements and the position of the landmarks founded in the robot's path.

1.3. Objective

Model and develop SLAM-UP, an ontology to model the uncertainty in robot pose and landmarks positioning in order to enrich the existing modeling of SLAM knowledge.

1.3.1. Specific objectives

1. Propose a categorization of the knowledge managed in the SLAM problem, based on existing ontologies and SLAM principles, in particularly, for mobile robots.
2. Analyze the features currently admitted for the actual ontologies whose model robot pose, including (position and orientation).
3. Analyze and study the advances already developed in landmark positioning.
4. Develop an ontology that manages the uncertainty of robot pose and landmark position.

1.4. Organization of the thesis

The remainder of this thesis is structured as follows. Chapter 2 describes some studies related to our work and the most important concepts of SLAM. There is also a review of the work that has modeled the knowledge of SLAM up to date. As there is no taxonomy already defined to classify these works, a categorization has been proposed according to the sub-problems that SLAM has to solve.

In Chapter 3, there is the whole process of modeling and developing SLAM-UP. It is explained which requirements the ontology must satisfy, as well as the main concepts that will be extracted from existing ontologies. Additionally, it is described how the validation process will be.

In Chapter 4 we present the implementation of SLAM-UP, describing the resources and relationships that have been added. The experiments performed and the results obtained in the validation are also presented. Finally, in Chapter 5, general conclusions of this work and future works are presented.

Capítulo 2

Background

2.1. SLAM Principles: Preliminaries

SLAM is a well-known problem by which a mobile robot must construct a map of a specific environment and simultaneously identify its own position within this map [Durrant-Whyte and Bailey, 2006]. A SLAM solution is mostly based on the identification of some representative objects in the environment, called landmarks. Landmarks are static objects, that can be used to identify places or zones in the environment. An efficient and consistent solution for SLAM requires to combine the robot pose and every landmark's position (considering time information) in a unique state. The state must be updated on every robot observation, considering that it includes certain uncertainty [Durrant-Whyte and Bailey, 2006]. There exist three kinds of maps that can be constructed, either in 2D and 3D mapping, in a solution of the SLAM problem: (i) join pose-feature maps; (ii) pose-only maps; and (iii) feature-only maps. A pose-feature map is a map obtained from the feature-based SLAM, which consists of the landmarks and robots positions. A pose-only map is a map obtained from the pose-graph SLAM, consisting of relative positions among the robot poses. A feature-only map is obtained from a decoupled SLAM (D-SLAM) and considers all landmarks features [Zhao et al., 2019]. Building an accurate map, along with performing precise localization of robots is a non easy problem [Guclu and Can, 2019], that demands a variety of information. Thus, when a developer or researcher implements a solution for the SLAM problem, it is important to know what information must be stored. The information that is available and could be stored is mainly related to: (i) the map itself; (ii) the robot pose; (iii) semantic and features of the workspace; (iv) changes of poses and landmarks features on time; (v) data representing uncertainty; and (vi) some information related to the kind of solution is implemented [Bailey and Durrant-Whyte, 2006, Durrant-Whyte and Bailey, 2006].

A representation of the map itself is, of course, the main information that must be stored. It includes geographical information about all the environment with landmarks correlation. It is important to storage features representing the shape and position of landmarks. Also, it is important to consider that this information comes from an estimation and this estimation can change on time. Finally, it is important to consider and storage specific domain information of the environment, either if it is obtained for each landmark

or for zones in the environment.

Robot pose is another important information to count on, because the problem is about localization while mapping an environment. It is important to include kinematic information of the robot to understand its pose and the space it holds. Also, for understanding how the map is estimated, and possibly improving that estimation, it is important to store sensory information and the robot trajectory. Robot trajectory is relevant for some kinds of SLAM problems, like active SLAM, which considers the capability of mobile robots to generate on-time trajectories to maximize the accuracy of the generated map and the localization of robots [Carrillo et al., 2012].

Beliefs about the map and positions of objects will change every time; then, it is important to store these changes including the information of moving objects. These beliefs changing will bring uncertainty that must be represented, quantified, and stored at each time. Stored uncertainty will bring the level of confidence associated to the estimation of robot poses and mapping [Rodríguez-Arévalo et al., 2018]. If the solution is a large scale one, it could include sub-mapping and delayed mapping, then it is important to store correlated sub-maps and relative correlations of positions, shapes, and poses.

According to these SLAM principles, some works have proposed to partially model the information managed in SLAM applications, by using ontologies. To address this limitation, we propose a categorization of such as knowledge, considering all aspects of SLAM. In the next section, we describe our proposed categorization.

2.2. Ontologies for SLAM

It is obvious that in a SLAM scenario, there exist different types of information and knowledge that are managed, considering the description of the capabilities, characteristics, behaviours of robots, as well as environmental and specific domain information.

In order to correctly categorize the knowledge in SLAM, it is important to consider that: (1) SLAM is a problem that must be solved by autonomous robots; (2) a SLAM solution is a continuous solution; thus, the problem is not completely solved after some time; that means that while the robot is working, it must map the environment and locate itself; (3) since a solution to SLAM is continuous in time, then robots will always have some uncertainty about the correctness of the mapping process and also about its location; (4) the mapping process and the robot's location estimation depend on the correctness about beliefs of shapes and location of landmarks; (5) the location of a robot depends also of its physical structure, defined by its kinematics; (6) it is important to consider that the main goal of autonomous robots is to act in real world, that means, to act in dynamic environments with possibly moving objects (passive or active) that must affect the process of mapping and location; (7) in order to improve the robot capabilities of self-location while mapping an environment, it is important to manage information and knowledge about physical and semantic characteristics of landmarks in the environment; and (8) information and knowledge about the environment depend on the dimension of the perception of the robot (2D or 3D) and also in the specific domain of application of the robotic solution is implemented.

Hence, based on these considerations, our proposed classification considers the following fields of SLAM knowledge: (i) robot information; (ii) environment mapping; (iii) timely information; and (iv) workspace. We detail each category as follows.

1. **Robot Information:** It is related to the information that conceptualize the main characteristics of the robot, physical and structural capacities. It mainly considers:
 - a) **Robot kinematic information:** It is related to robots' degrees of freedom, degree of mobility, among others. This information is important for modeling the actions that the robot can perform, that in turns allows to consider the navigation of the robot in the space it is discovering.
 - b) **Robot sensory information:** Another relevant field is to model what the robot perceives through its sensors.
 - c) **Robot pose information:** It is important to consider information related to the location of the robot; position and orientation related to its degrees of freedom.
 - d) **Robot trajectory information:** For mobile robots, which is the focus on this work, it is necessary to model information of the trajectory.
 - e) **Robot position uncertainty:** In the context of SLAM, there is an uncertainty related to a set of positions where the robot could be. Then, it is important to model actual positions, as well as this uncertainty, as possible positions.
2. **Environment mapping:** This category includes information generated directly by the tasks of mapping and localization. Thus, it considers:
 - a) **Geographical information:** Mapping is a basic requirement for autonomous robots; they must be capable of creating an accurate and in-depth characterization of the surrounding. Hence, it is essential to model the geographical information of the terrain in which they are. Autonomous robots can conceptualize single scenes like offices or multiple scenes like departments.
 - b) **Landmark basic information (position):** It refers to the information related to the presence of other objects in the environment, that are not the robot, and the position of these objects on the map being built during the SLAM.
 - c) **Landmark shape information:** Besides the information related to the landmark position, in some scenarios it is also useful to know the shape it has or if it is a complex landmark. In some SLAM scenarios, the ability of decomposing landmarks into simpler parts, can be useful.
 - d) **Landmark position uncertainty:** In addition to the uncertainty of robot position, the uncertainty of the position of landmarks can be considered. That means to model possible positions and actual positions of objects used as landmarks.
3. **Timely Information:** Dynamic environments can change over the time. Thus, it is important to model:
 - a) **Time information of robots and objects:** In particular, it is considered the information related to poses and positions of robots and objects during the time.

- b) **Mobile objects:** It relates the knowledge of objects that can be present or not at specific moments in time. In other words, it matters objects with respect to time.
- 4. **Workspace:** This category of information is related to general characteristics that describe the work space in which the SLAM solution is applied. It considers:
 - a) **Dimensions of mapping and localization:** It refers whether the mapping and localization is modeled in two or three dimensions.
 - b) **Specific domain information:** If the SLAM solution is used in particular applications, it is important to model high level knowledge of the environment that surrounds the robot and the specific domain in which the SLAM is applied. Examples of specific entities or objects that can be modeled could be related to a restaurant (for a restaurant service domain), an office (for a rescue application), or planets (for an automatic search domain).

In order to demonstrate the suitability and completeness of our categorization, we perform a comparative analysis of existing ontologies and evaluate which information is modeled on each one. Additionally, we report: (i) the *Application Scope* in which the SLAM problem was applied (e.g., service, rescue, automatic search); this refers to the context of applicability of the ontology being analyzed; and (ii) the *Origin Ontology (Based on)*, if the ontology has been based on an older ontology or on a more general level, such as an Upper ontology. In the next section, we present such comparative analysis.

2.3. SLAM ontologies classification: A Review

This section describes, according to our categorization, how some ontologies model SLAM specific information, in order to know which are the most developed fields and which are still missing.

2.3.1. Robot Information

Before a robot can describe and know its surroundings, it needs to know what it can do, which are its physical, structural, and functional capabilities. In this section, we describe ontologies that are mainly focused on those aspects, however some of them also take into account some aspects related to the environment, mapping, and specific domain knowledge. In the following, we describe ontologies that model the knowledge of each aspect considered in this category.

a) Robot kinematic information:

Even though the RoboEarth ontology [Riazuelo et al., 2015] main focus is to model concepts and relationships among objects and maps, it is the best one we found that provides a good kinematic robot model and robot's motion capabilities model (e.g., it can

tology is the management of uncertainty, that could be caused by hallucinated objects detection, limited observability and sensor noise. ROSPlan [Cashmore et al., 2015] manages both sources of information (i.e., sensors in the environment and in the robot) to locate valve panels and valves. These objects are important for the case study of the work. Most considered ontologies model information received from the sensors in the robot. Some of these ontologies have a whole ontology only for sensors, as is the case of SUMO [Eid et al., 2007] and the ontology proposed by Burroughes and Gao [Burroughes and Gao, 2016].

Other ontologies model sensory information, even it is not their main objective, such as: (i) RoboEarth ontology [Riazuelo et al., 2015], (ii) the ontology of SEMAP, a framework for semantic maps representation in spatial databases, proposed by Deeken et al., in [Deeken et al., 2018]; (iii) the ontology proposed by Wu et al., in [Wu et al., 2014]; (iv) the ontology used in OMRKF (Ontology-based Multi-layered Robot Knowledge Framework) [Suh et al., 2007]; (v) based on OMRKF, the knowledge framework OUR-K [Lim et al., 2011] is presented to be used for service robots, (vi) OASys ontology, that treats sensors as a type of device; it is developed for Unmanned Aerial Vehicles (UAV) and Unmanned Ground Vehicles (UGV); and (vii) Robot Ontology, where the structural characteristics are captured when the robot is defined; one of this characteristics is related to sensors (e.g., camera, Temperature Sensor, GPS, SONAR, Audio).

c) Robot pose information:

Robot position can be absolute or relative. For the first case, a robot is positioned at a global spacial coordinate (e.g., (x, y) if its workspace is \mathbb{R}^2), while in the second case, the robot is positioned considering the position of a landmark in the environment (e.g., the robot is *behind* the "wall", where *behind* means a conical region centred on the "wall" and pointing backward). In the absolute case, works like: (i) Burroughes and Gao's proposal [Burroughes and Gao, 2016], that with its Topological Map Ontology and Simple Map Ontology can represent an absolute position; (ii) SUMO [Eid et al., 2007], which we assume it models absolute positions, in a coordinate system, because in one application in which it is tested, it is possible to model car positions in a New York map; and (iii) the ontology presented by Wu et al., in [Wu et al., 2014], which uses a Bayes algorithm for a reliable position of the robot in spatial semantic hybrid map building; it is a more accurate way of modeling robot position. On the other hand, works able to represent relative positions are: (i) RoboEarth [Riazuelo et al., 2015]; (ii) the work of Fortes-Rey [Fortes, 2013], that can represent both absolute and relative positions; (iii) POS Ontology [Carbonera et al., 2013], which complements Core Ontology and expands SUMO, by specifying the main concepts and their relationships, and underlying the notions of pose, orientation, and position; additionally, POS allows the description of postures, orientations, and positions, in a coordinated system; in this way it is possible to model quantitatively and qualitatively orientations and positions; and (iv) the ontology proposed by Deeken et al., in [Deeken et al., 2018] for semantic maps in spatial databases, whose mapping approach consists on obtaining absolute geometric data from the environment to model objects and their relative spatial relationships.

There are proposals that do not generate a metric map as a result of their SLAM stage, in contrast they generate a graph where each node represents a possible place

or position where the robot can be. The Knowledge Base ontology of ROSPlan framework [Cashmore et al., 2015], uses the structural similarities between many robotics planning domains. For example, in the case study presented authors represent the areas, where an Autonomous Underwater Vehicle (AUV) can move, showing with points its possible locations (waypoints). In a similar way of [Cashmore et al., 2015], KNOW-ROB [Tenorth and Beetz, 2009] models robot pose in a list of places where the robot could be, using the RobotPlace entity; and the ontology proposed by Hotz et al., in [Hotz et al., 2012], which combines two spatial reasoning calculi, RCC-8 and CDC, with ontological representations of maps for service robots for a restaurant. There are also ontologies which combine different maps like OUR-K ontology [Lim et al., 2011], that combines semantic, topological, and metrics maps to describe *Spaces*; and the ontology for multi-layered conceptual maps proposed by Martinez et al., in [Mozos et al., 2007] and the one proposed by Li et al., in [Li et al., 2013], which represent metric, navigation, topological, and conceptual maps.

d) Robot trajectory information:

Considering that a trajectory is a sequence of positions in a given time, an ontology has to model time to properly model trajectories. Two ontologies comply with this temporal characteristic, the one proposed by Burroughes and Gao [Burroughes and Gao, 2016] and the proposal of Fortes-Rey [Fortes, 2013]. The first one has a module called Process Ontology related to Temporal Ontology (see Figure 2.1). Instead, Fortes-Rey proposes a relationship, called *posAtTime*, that allows to relate a robot to a position and timing. Then, it is possible to describe the trajectory of a robot.

e) Robot position uncertainty:

Only two ontologies were found that conceive uncertainty. KNOW ROB ontology [Tenorth and Beetz, 2009]. This ontology considers the actions of robots are unreliable and inaccurate. Also the ontology for Spatial Semantic Hybrid map building proposed by Wu et al., in [Wu et al., 2014], which is able to represent the most probable position where the robot can be.

f) Discussion:

Table 2.1 summarizes the inclusion of the five topics, related to robot information, in the analyzed ontologies. As it is shown in Table 2.1, almost all ontologies model basic robot information, such as kinematic, sensory, and pose. This kind of information is most focused on the result of SLAM solution: maps and robot's locations. However, trajectory and position uncertainty information, which are focused on "the process to obtain" maps and locations, are not very considered.

Trajectory is most related to specific types of SLAM solutions, like Active SLAM and position uncertainty is specific information related to the process of solving SLAM. Then, we can conclude that the majority of ontologies intend to represent the result of SLAM

solutions, i.e., a map and a robot located on it. Although, in the field of autonomous mobile robots, they must be “always” exploring new environments to resolve the SLAM problem, considering more than the basic information could enrich the knowledge managed and open new frontiers to expand the SLAM application.

2.3.2. Environment mapping

SLAM deals with the ability of autonomous robots to localize themselves in a map/plan and construct the map (outdoor use) or the floor plan (indoor use). To do so, geographical information, as well as, information related to landmarks present in the explored space, are needed to keep. In this section, we describe ontologies able to model such kind of information.

a) Geographical information:

In this category of information, RoboEarth ontology [Riazuelo et al., 2015] is the most outstanding. This is reflected in its ability to model the location of objects with respect to the robot, the geometry of the scene, as well as the relationships and concepts between objects and maps.

There are other ontologies that model geographic information in a general way. This is the case of: (i) Space Ontology [Belouaer et al., 2010], which is a spatial knowledge representation complemented with a reasoning system, able to model and manage the space (e.g., hierarchical organizations, spatial entities); (ii) the ontology proposed by Burroughes and Gao [Burroughes and Gao, 2016] has two modules related to geographic information: the Simple Map Ontology and the Topological Map Ontology; and (iii) the ontology proposed by Hotz et al., [Hotz et al., 2012], which describes an environment as a topological graph and separates overlapped and reachable rooms.

Instead of using topology maps, other form to describe an environment is to jointly use metric maps, navigation maps, topological maps, and semantic maps. This is the case of: (i) OUR-K ontology [Lim et al., 2011], which has a Knowledge Class, specifically to handle spatial notions as metric and topological map; (ii) the ontology presented by Li et al., in [Li et al., 2013], which shows how the interaction with an intelligent wheelchair is done by combining multi-layered maps; (iii) the proposal of Martinez et al., in [Mozos et al., 2007], which defines topological areas, defined as an ontological instance of the type Area, in the conceptual map of the ontology (iv) OMRKF ontology, in which *Rooms* are defined as *Spaces*; (v) the ontology proposed by Deeken et al., in [Deeken et al., 2018], which models rooms with objects associated with them; (vi) CORA [Prestes et al., 2013], POS [Carbonera et al., 2013], and the work of Fortes-Rey [Fortes, 2013], which have been inspired by the general concepts of SUMO [Eid et al., 2007]; they share concepts such as *Region* and *Environment*.

Finally, there are ontologies that do not describe the environment as a space where there are objects, but build an environment from the objects. This is the case of the work of Wang and Chen [Wang and Chen, 2011] and the one proposed by Wu et al., [Wu et al., 2014].

Name	Ref	Kinematic	Sensory	Pose	Trayectory	Position
		Inf.	Inf.	Inf.	Inf.	Uncertainty
Robot Ontology, 2005	[Schlenoff and Messina, 2005]	X	X	-	-	-
Burroughes and Gao, 2017	[Burroughes and Gao, 2016]	X	X	X	X	-
OASys, 2012	[Paull et al., 2012]	X	X	-	-	-
Fortes-Rey, 2013	[Fortes, 2013]	X	-	X	X	-
Core Ontology, 2013	[Prestes et al., 2013]	X	-	-	-	-
POS, 2013	[Carbonera et al., 2013]	X	-	X	-	-
SUMO, 2007	[Eid et al., 2007]	-	X	X	-	-
Hotz et al., 2012	[Hotz et al., 2012]	-	-	X	-	-
RoboEarth, 2015	[Riazuelo et al., 2015]	X	X	X	-	-
OUR-K, 2011	[Lim et al., 2011]	X	X	X	-	-
Martinez et al., 2007	[Mozos et al., 2007]	-	-	X	-	-
ROSPlan, 2015	[Cashmore et al., 2015]	-	X	X	-	-
KNOW ROB, 2012	[Tenorth and Beetz, 2009]	X	X	X	-	X
Li et al., 2013	[Li et al., 2013]	-	-	X	-	-
OMRKF, 2007	[Suh et al., 2007]	-	X	-	-	-
Wu et al., 2014	[Wu et al., 2014]	-	X	X	-	X
Deeken et al., 2018	[Deeken et al., 2018]	-	X	X	-	-

Cuadro 2.1: Ontologies related to Robot Information

b) Landmark basic information:

When we refer to modeling the basic information of landmarks, we have considered two criteria: (i) the capability of modeling an object other than the robot on the map; and (ii) the capability of modeling the position of this object with respect to the map. Almost all ontologies have defined the entity *Object* or *Artifact* to describe landmarks. The work presented by Burroughes and Gao [Burroughes and Gao, 2016] has a whole ontology dedicated to modeling *Objects*. CORA [Prestes et al., 2013], POS [Carbonera et al., 2013], and the work of Fortes-Rey [Fortes, 2013], which are extensions of SUMO [Eid et al., 2007]. RoboEarth ontology [Riazuelo et al., 2015], use the *Object* entity, which is a specialization of the concept *Entity*, that can be either *Abstract* or *Physical*. The ontology proposed by Hotz et al., [Hotz et al., 2012] uses the *TBox* concept to model objects in the environment (such as cup, plate, table, room). The proposal of Martinez et al., in [Mozos et al., 2007] defines a conceptual map that is the link between the communication system used for the dialogue between the robot and the human when they refer to representations of spatial entities, such as instances of *Objects* or *Rooms*, and low-level maps. In a similar way, the proposal of Deeken et al., in [Deeken et al., 2018] has the *ObjectDescription* entity, which defines a generalized model of the spatial characteristics for each class of object.

The ontology proposed by Li et al., in [Li et al., 2013], describes its environment also with the help of a conjunction of metrical, topological, and semantics maps, just as Martinez's work makes use of relationships *has-a*. Thus, it is possible to have relations such as *Building has-a Floor*, *Floor has-a Room*, and *Room* has objects like a *Desk* or a *Book*. This ontology also allows the modeling of relationships between objects *in a Room*, such as *Book on-a Desk*.

RoboEarth ontology [Riazuelo et al., 2015] and OUR-K ontology [Lim et al., 2011] can model compound and simple objects, where each object belongs to a position node, associated to an area in a relative (not absolute) way. The method of representing indoor environment semantic maps for mobile robots proposed by Wang and Chen [Wang and Chen, 2011], is totally different from its predecessors. For this work, the semantics of an environment does not longer begin with identifying and connecting Spatial Regions; instead, it defines a Region based on the objects that compose it. For example, an office can be defined by the presence of a chair, a desk, a room, walls, or other things. This example can be seen graphically in Figure 2.2.

KNOW ROB [Tenorth and Beetz, 2009] and OMRKF [Suh et al., 2007] ontologies model the absolute positions of objects, i.e., with coordinates (x,y,z). The ontology proposed by Wu et al., [Wu et al., 2014] models the name, size, function, color, shape, and other relevant data of features of an object, by using a QR code. In the ROSPlan ontology [Cashmore et al., 2015], with the data of the sensors captured while the plan is executed and after being collated in the ontology, it is possible to define the resources of the type objects and the relations between them.

c) Landmark shape information:

This information about landmarks, is important not only in the process but in the final result. Thus, when considering shape information is possible to obtain a more realis-

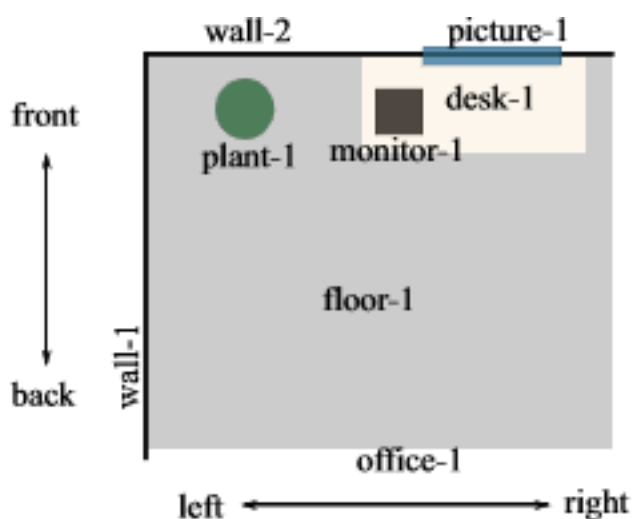


Figura 2.2: An example of an office scene with the ontology proposed by Wang & Chen [Wang and Chen, 2011]

tic an accurate map of the world. From the studied ontologies, only one explicitly models the shape of landmarks, that is the ontology proposed by Wu et al., [Wu et al., 2014]. It includes the shape of the landmark, as well as the size, the color, among other characteristics.

Other ontologies model partially this informations, such as: (i) RoboEarth ontology [Riazuelo et al., 2015], which represents a set of characteristics of the surfaces of the object, with a multi-view geometry; (ii) OUR-K ontology [Lim et al., 2011], it does not specifically analyze the landmark form, however it offers the possibility of decomposing a landmark in other simpler ones; for example a *cup* is composed of a *body* and a *handle* ; and (iii) the one proposed by Wang and Chen [Wang and Chen, 2011], which counts on relations *part-of* and *has-a* to describe more complex landmarks; thus, even though the landmark shape is not described geometrically, it does so structurally.

d) Landmark position uncertainty:

The only ontology that can fully model the uncertainty of landmark positions is the one proposed by Wu et al. [Wu et al., 2014]. To model this uncertainty, this proposal uses the hidden Markov model and a probabilistic approach based on the Bayes algorithm. RoboEarth ontology [Riazuelo et al., 2015] also has an approximation to the probability of positions, because based on where the landmarks are located, the knowledge base deduces possible locations, where the objects could be.

e) Discussion:

Table 2.2 summarizes the inclusion of the four topics, related to environment mapping, in the ontologies analyzed. Most of the ontologies considered model the geographic information and the basic information of the landmarks. Just one of them models infor-

mation related to the shape of landmarks, while only few of them, partially represent this knowledge. Furthermore, similar to the previous section (see Table 2.1), the number of ontologies that model the uncertainty of landmark positions, is very low.

Landmark position uncertainty information is related to the process of solving the SLAM problem; then, the fact that it is not considered enough, ratifies the characteristic of the existing ontologies of only considering the final result of a solution to the problem of SLAM. On the other hand, shape information about landmarks is important not only in the process but in the final result. Thus, when considering shape information is possible to obtain a more realistic and accurate map of the world.

2.3.3. Timely Information

SLAM is a problem solved by mobile robots and can consider dynamic environment. Thus, not only static positions should be modeled. It is important to model the temporary factor that affects both the environment and the robot.

a) Time information of robots and objects:

A diachronic ontology can represent state changes of its concepts through the time. SUMO [Eid et al., 2007] has support for indexing facts over time. In fact, SUMO represents time using *TimeMeasures* classes, that represent positions or intervals in the universal time-line. In a similar way, the ontology proposed by Fortes-Rey [Fortes, 2013], includes the time component in points and regions position measurements. On its side, the ontology proposed by Burroughes and Gao [Burroughes and Gao, 2016] has a complete module to model temporal information (Temporal Ontology). OMRKF [Suh et al., 2007] and OUR-K [Lim et al., 2011] ontologies, present a model based on levels, where one level is Context and the temporal context is considered.

b) Mobile objects:

We can say that the proposal of Burroughes and Gao [Burroughes and Gao, 2016] allows to recognize mobile objects, if we analyze the relationships among the ontologies of Objects and Single Map, with the Temporal Ontology. Also the work of Fortes-Rey [Fortes, 2013] allows to differentiate objects that move from those that do not, since the ontology can represent an object placed in a position at a given time. Ontologies such as RoboEarth [Riazuelo et al., 2015] and OMRKF [Suh et al., 2007] recognize mobile objects from databases, according to their visual characteristics, instead of their temporal characteristics. For example, a bicycle is considered a mobile object because of its shape but not because of its movement.

c) Discussion:

Table 2.3 summarizes ontologies related to temporal information. In the context of mobile robots solving the SLAM problem, it is clear the need of representing dynamic

Name	Ref	Geographical Info	Landmark Basic Info	Landmark Shape Info	Landmark Position Uncertain.
Burroughes and Gao, 2017	[Burroughes and Gao, 2016]	X	X	-	-
Fortes-Rey, 2013	[Fortes, 2013]	X	X	-	-
Core Ontology, 2013	[Prestes et al., 2013]	X	X	-	-
POS, 2013	[Carbonera et al., 2013]	X	X	-	-
SUMO, 2007	[Eid et al., 2007]	X	X	-	-
Hotz et al., 2012	[Hotz et al., 2012]	X	X	-	-
Space Ontology, 2010	[Belouaer et al., 2010]	X	-	-	-
Wang, 2011	[Wang and Chen, 2011]	X	X	X	-
RoboEarth, 2015	[Riazuelo et al., 2015]	X	X	X	X
Martinez et al., 2007	[Mozos et al., 2007]	X	X	-	-
OUR-K, 2011	[Lim et al., 2011]	X	X	X	-
ROSPlan, 2015	[Cashmore et al., 2015]	-	X	-	-
KNOW ROB, 2012	[Tenorth and Beetz, 2009]	-	X	-	-
Li et al., 2013	[Li et al., 2013]	X	X	-	-
OMRKF, 2007	[Suh et al., 2007]	X	X	-	-
Wu et al., 2014	[Wu et al., 2014]	X	X	X	X
Deeken et al., 2018	[Deeken et al., 2018]	X	X	-	-

Cuadro 2.2: Ontologies related to Environment Mapping

Name	Ref	Time Info	Mobile objects
Burroughes and Gao, 2017	[Burroughes and Gao, 2016]	X	X
Fortes-Rey, 2013	[Fortes, 2013]	X	X
RoboEarth, 2015	[Riazuelo et al., 2015]	-	X
SUMO, 2007	[Eid et al., 2007]	X	-
OUR-K, 2011	[Lim et al., 2011]	X	-
OMRKF, 2007	[Suh et al., 2007]	X	X

Cuadro 2.3: Ontologies related to Timely Information

environments, which requires time modeling. As Table 2.3 shows, less than a half of the selected ontologies comply with modeling timely knowledge, mainly with concepts related to temporal information associated to positions and objects. Concerning the modeling of mobile objects, we can notice that although the ontology models basic temporal information, sometimes it is not enough to model dynamic objects in the environment. This is the case of SUMO and OUR-K. On the contrary, RoboEarth, which does not model temporal information, is capable of recognizing moving objects; at least partially (as explained above). Thus, it is important to note, the fact of recognizing and storing information about mobile objects not only refers to a good understanding of the process of solving SLAM, but the quality of mapping. Because in the real world (where robots are intended to work), mobile objects are very common and an accurate mapping must include its recognition and characterization on the map.

2.3.4. Workspace

General characteristics of the work space where the SLAM solution is applied are mainly related to the dimensionality to represent maps and specific semantic knowledge of the domain.

a) Dimensions of mapping and localization:

Some ontologies show that they can model knowledge related to mapping and location in two dimensions such as the work of Fortes-Rey [Fortes, 2013], POS [Carbonera et al., 2013], SUMO [Eid et al., 2007], and OUR-K [Lim et al., 2011].

As expected, more recent ontologies are already able to model information in 3D. The ontology proposed by Burroughes and Gao [Burroughes and Gao, 2016] allows to receive and model information from an external 3D mapping service. The one proposed by Wang and Chen in [Wang and Chen, 2011], defines relationships between objects like, *back*, *right back*, *right front*, *left*, *left back*, *left front*, *below*, and *above*, giving the idea of a cube (3D) as a scenario around the object. The same case is presented in OMRKF [Suh et al., 2007], in the ontology proposed by Li et al., in [Li et al., 2013],

KNOW ROB ontology [Tenorth and Beetz, 2009], and the ontology proposed by Wu et al., in [Wu et al., 2014]. Others ontologies such as RobotEarth [Riazuelo et al., 2015] and the one described by Deeken et al., in [Deeken et al., 2018] model 2D and 3D SLAM.

b) Specific Domain Information:

Once the modeling of information related to the two main SLAM tasks (i.e., mapping and localization), is solved, the next step is regarding the information to detect an object and identify it. It does not only matter identifying objects that exist, but objects that belong to a specific domain. This is the case for the ontology presented by Hotz et al., in [Hotz et al., 2012] and KNOW ROB ontology [Tenorth and Beetz, 2009] that have entities only for restaurants. KNOW ROB was also applied in robotic housework [Pangercic et al., 2012].

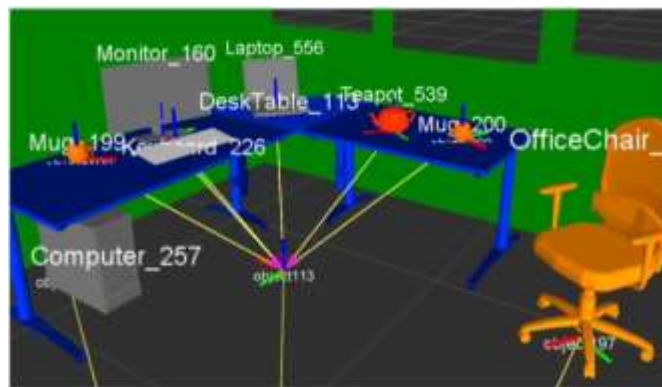


Figura 2.3: Objects on a table according the ontology of Deeken et al., [Deeken et al., 2018].

Another examples are offices modeled by the ontology proposed by Wang and Chen in [Wang and Chen, 2011] (see Figure 2.2) and by the one described by Deeken et al., in [Deeken et al., 2018]. Figure 2.3 shows a *table* in close-up to illustrate how objects on the table are bound to the table's reference frame.

Finally, specific domains less specialized are the indoor environments modeled in: (i) the work proposed by Martinez et al., [Mozos et al., 2007], in which typical indoor environments, such as kitchen, living room, office, and laboratory can be modeled; including also the objects that can be found in them (e.g., blackboards, desks, armchairs, fridges; (ii) OMRKF [Suh et al., 2007], which is also able to model a kitchen and a living room, including objects such as cups, tables, chairs; (iii) the ontology proposed by Li et al., in [Li et al., 2013], which instead models an academic environment, where laboratories, offices, corridors, and computer rooms can be modeled, including objects such as computers and desks; and (iv) RoboEarth [Riazuelo et al., 2015] provides a sub-database of relevant object models that will be needed to fulfill the target task. Thus, its semantic reasoning enhances recognition by reducing the false positive rate and computation.

Name	Ref	Dimensions	Specific Domain Info
Burroughes and Gao, 2017	[Burroughes and Gao, 2016]	3D	-
Fortes-Rey, 2013	[Fortes, 2013]	2D	-
POS, 2013	[Carbonera et al., 2013]	2D	-
SUMO, 2007	[Eid et al., 2007]	2D	-
Hotz et al., 2012	[Hotz et al., 2012]	-	restaurant
Wang and Chen, 2011	[Wang and Chen, 2011]	3D	office
RoboEarth, 2015	[Riazuelo et al., 2015]	2D-3D	models relevant for the task at hand
OUR-K, 2011	[Lim et al., 2011]	2D	-
Martinez et al., 2007	[Mozos et al., 2007]	-	kitchen, living room, office, lab
KNOW ROB, 2012	[Tenorth and Beetz, 2009]	3D	restaurant
Li et al., 2013	[Li et al., 2013]	3D	office, lab
OMRKF, 2007	[Suh et al., 2007]	3D	kitchen, living room
Wu et al., 2014	[Wu et al., 2014]	3D	-
Deeken et al., 2018	[Deeken et al., 2018]	2D-3D	office

Cuadro 2.4: Ontologies related to Workspace

c) Discussion:

Table 2.4 summarizes the inclusion of the relevant ontology features, related to the workspace, for the analyzed ontologies. As for the dimensions that are handled, there is a predominance in 3D. This means that ontologies are looking to model more and more real data. In relation to specific domain information, we note that there is a preference to model indoor environments. These include academic environments such as offices and laboratories. There are also environments that describe the interior of a house, such as a living room or a kitchen. These works present applications of service robots which is an area that is being quite developed in mobile robots, which use ontologies to model the knowledge collected by SLAM.

2.3.5. Summary

Table 2.5 summarize all analyzed ontologies. The ontologies are marked with a cross if they conceptualize the subcategory of the associated column. We identify that some SLAM ontologies do not cover only one category, normally they cover more than one. However, most ontologies consider the first two categories, considering Robot Information and Environment Mapping, while Timely Information and Workspace appear as complement with the others.

SLAM problem is continuous in time; that means that it is desired that an autonomous robot must be solving it all the time, since it works in a real world and it can find new places at any time. We have parsed the importance of representing the timely information into SLAM ontologies, to improve the process of solving SLAM. We consider that the integration of environment mapping information, robot information, and timely information with the positioning uncertainty in robots and landmarks, represent an option to optimize and improve the precision of the results of SLAM solutions.

It is important to develop ontologies for SLAM because more detailed information can take developers to include high level reasoning in autonomous robots in decisions including details of the environment.

Additionally, we consider relevant to know the information relative to: (i) origin ontology, to know if the proposal has a predecessor; in this regard we can note that more than a half ontologies are based on an older ontology such as SUO KIF, KAON, or RCC-8, but also we can find ontologies that have been defined from the scratch as Robot Ontology and OASys; and (ii) the application scope, since there are ontologies for several knowledge areas, not limited to Service or Search and Rescue robots; we find other areas such as AUV and planetary robots.

We finally point out the fact that each aspect considered in our proposed categorization is addressed for at least one of the revised ontologies. This indicates that we have took into consideration the most important knowledge related to the SLAM problem. Also, our knowledge categorization allows to evaluate the completeness of SLAM ontologies and to identify lacks and challenges that can boost future research in this area.

Thus we can note that there is no ontology that models all categories completely. For this reason, we gather the acquired knowledge to model an ontology that satisfies all categories, in other words, that models the entire SLAM process. On the other hand, there are very few ontologies that model important aspects of SLAM, such as uncertainty (Columns 5.1.5 and 5.2.4) and temporality (Column 5.3.1 and 5.3.2). In order that, we are considering both as important topics in the development of the proposed ontology.

Cuadro 2.5: Summary of evaluation of ontologies for SLAM

Name	Ref	Cat 1					Cat 2				Cat 3		Cat 4		Application Scope	Origin Ontology
		5.1.1	5.1.2	5.1.3	5.1.4	5.1.5	5.2.1	5.2.2	5.2.3	5.2.4	5.3.1	5.3.2	5.4.1	5.4.2		
Robot Ontology, 2005	[Schlenoff and Messina, 2005]	X	X	-	-	-	-	-	-	-	-	-	-	-	Rescue and Search	-
Burroughes and Gao, 2017	[Burroughes and Gao, 2016]	X	X	X	X	-	X	X	-	-	X	X	3D	-	Planetary Rovers	[Prestes et al., 2013]
OASys, 2012	[Paull et al., 2012]	X	X	-	-	-	-	-	-	-	-	-	-	-	Autonomous systems	-
Fortes-Rey, 2013	[Fortes, 2013]	X	-	X	X	-	X	X	-	-	X	X	2D	-	Positioning	[Prestes et al., 2013],[Eid et al., 2007],SUO-KIF
Core Ontology, 2013	[Prestes et al., 2013]	X	-	-	-	-	X	X	-	-	-	-	-	-	[Eid et al., 2007], SUO KIF, ALFUS	
POS, 2013	[Carbonera et al., 2013]	X	-	X	-	-	X	X	-	-	-	-	2D	-	Positioning	[Prestes et al., 2013]
SUMO, 2007	[Eid et al., 2007]	-	X	X	-	-	X	X	-	-	X	-	2D	-	-	-
Hotz et al., 2012	[Hotz et al., 2012]	-	-	X	-	-	X	X	-	-	-	-	-	X	Service robot	RCC-8 and CDC
Space Ontology, 2010	[Belouaer et al., 2010]	-	-	-	-	-	X	-	-	-	-	-	-	-	-	RCC
Wang and Chen, 2011	[Wang and Chen, 2011]	-	-	-	-	-	X	X	X	-	-	-	3D	X	indoor mapping	-
RoboEarth, 2015	[Riazuelo et al., 2015]	X	X	X	-	-	X	X	X	X	-	X	2D/3D	X	Service robots	OpenCyc systems
Martinez et al., 2007	[Mozos et al., 2007]	-	-	X	-	-	X	X	-	-	-	-	-	X	Service Robots	-
OUR-K, 2011	[Lim et al., 2011]	X	X	X	-	-	X	X	X	-	X	-	2D	-	Service Robots	KAON
ROSPlan, 2015	[Cashmore et al., 2015]	-	X	X	-	-	-	X	-	-	-	-	-	-	AUV	-
KNOW ROB, 2012	[Tenorth and Beetz, 2009]	X	X	X	-	X	-	X	-	-	-	-	3D	X	Autonomous Robots	Cyc ontology
Li et al., 2013	[Li et al., 2013]	-	-	X	-	-	X	X	-	-	-	-	3D	X	Intelligent Wheelchairs	-
OMRKF, 2007	[Suh et al., 2007]	-	X	-	-	-	X	X	-	-	X	X	3D	X	Service Robots	KAON
Wu et al., 2014	[Wu et al., 2014]	-	X	X	-	X	X	X	X	X	-	-	3D	-	Service Robots	SSH
Deeken et al., 2018	[Deeken et al., 2018]	-	X	X	-	-	X	X	-	-	-	-	2D/3D	X	indoor mapping	-

Capítulo 3

Proposal

In the scientific literature related to SLAM solutions based on ontologies, there are few ontologies that model uncertainty. It is important to consider uncertainty when the knowledge generated by the SLAM process is modelled, because robots that solve this problem move in a dynamic physical environment. The physical world is neither precise nor discrete as is well known

In order to create an ontology that models the knowledge generated by SLAM, we have to consider it as a process instead of just taking the result. We develop an ontology that models the uncertainty of the robot and the positions of the landmarks. To achieve this goal, we select an ontology that models in detail the Robot's pose as the ontology of Fortes-Rey [Fortes, 2013]. Fortes-Rey ontology has been based on Core-Ontology [Prestes et al., 2013] that is the result of the Working Work of ORA, which is an important working group for the development of ontologies for autonomous robots, as mentioned in the introduction of this work. In addition Fortes-Rey ontology has the necessary documentation to attach a module easily in it. Finally, we consider its capacity to model temporary information. Due to the fact that temporality and uncertainty are inherent characteristics of the SLAM process as a process. So it seems to us a good starting point.

After we define the basis ontology, we chose the Markov Logic to model uncertainty in SLAM, because there is a precedent in the state of the art in modeling SLAM knowledge with this logic. Specifically concerning the uncertainty of landmarks in the work of Wu et al [Wu et al., 2014], though it is not its main objective. For our proposal SLAM-UP, we select the SLAM entities that are necessary to model the uncertainty of the robot and landmark position, as well as the necessary relationships between the entities chosen.

Now we summarise the set of requirements that we considered for the development of SLAM-UP.

3.1. Requirements of SLAM-UP

- **Purpose:** The purpose of this ontology is to model the uncertainty of robot position as well as the uncertainty of landmark positions, besides all the knowledge related to the SLAM problem: robot information, environment information, timely information and workspace information. Thus, it is possible to get closer to a complete ontology for SLAM. Considering that SLAM is a process that describes a dynamic environment, where uncertainty is a characteristic that must be considered.
- **Type of Ontology:** it would be a general SLAM ontology, able to describe uncertainty of robots and landmarks positions. However, it should be possible to use this ontology in specific domains for specific SLAM applications (e.g., tourism, restaurant service robotics, spatial discovering).
- **Design Criteria:** to ensure the coherence and quality of SLAM-UP ontology, it is important to pay attention on clarity and extendability for its development.

With these criteria in mind we have designed a process to develop our ontology, SLAM UP, explained below

3.2. SLAM-UP, Ontology Development Flow

To develop this ontology we have 3 phases, as we can see in Fig 3.1. We began with the acquisition of knowledge, followed by the implementation and end with a validation phase. Next, we describe in more detail what each phase consists of.

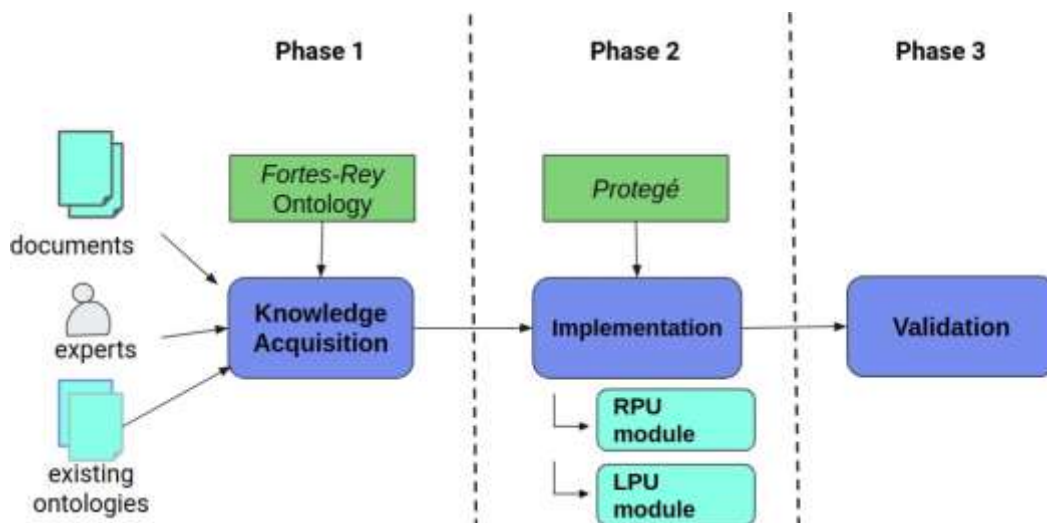


Figura 3.1: Development flow of SLAM-UP

3.3. Knowledge Acquisition

The proposed ontology is made considering different sources such as existing ontologies, related documents and the opinion of experts in domains. The existing ontologies will be reviewed, because the SLAM domain has been previously conceptualized, but with a different purpose than the one of this thesis. These existing ontologies will be selected, evaluated and finally reused partially or totally, in the case that a great affinity is found between what the ontology models and the purpose of this work. Additionally, attention will be paid to the level of granularity (if the existing ontology covers the same level of detail as the developing ontology). The documents considered are surveys, articles or books as a source of information for the ontological elements of SLAM-UP. SLAM and Semantic Web domain experts also act as a possible source for conceptualization, since they provide their terminology, that is, the words and terms of a domain with which they are familiar.

3.4. Implementation

In this phase we will implement two modules: Robot Position Uncertainty (RPU) and Landmark Position Uncertainty (LPU). Those were implemented using OWL, language that is being used as standard for the development of web ontologies. Specifically, we will use it with RDF/XML serialization. We will also use Protegé, which is a free, open-source ontology editor and framework for building intelligent systems. It also has a viewer that allows us to see the ontology developed in the form of a graph. To see how the concepts are related as we formalize them. How this is an ontology developed on the basis of Fortes-Rey's work, we got the source codes and went through an analysis process. Which consists of checking if resources, including their properties, are not incomplete and if the relationships between the resources are not damaged.

3.5. Validation

This phase is based on the surveys of Brank *et al* [J Brank, 2005] and Hlomani and Stacey [Hlomani and Stacey, 2014] that provides us with an overview of how to evaluate and how to compare ontologies. Hlomani and Stacey perceives ontology evaluation to be done in the view of two complementary perspective *Quality* and *Correctness*. The first refers to how the Ontology is structured in terms of lexemes and relationships between entities. As well as the completeness of its definitions in the domain it models. The other perspective seeks to review the *Correctness of Ontology* at the syntactic, architectural and design levels.

On the other hand, Brank proposes to evaluate the ontologies according to the following levels:

- Lexical, vocabulary, or data layer: Evaluation on this level tends to involve comparisons with various sources of data concerning the problem domain.

- Hierarchy or taxonomy: evaluates is-a relations between concepts.
- Other semantic relations: The ontology may contain other relations besides is-a, and these relations may be evaluated separately.
- Context or application level: evaluation looks at how the results of the application are affected by the use of the ontology.
- Syntactic level: for ontologies that have been mostly constructed manually.
- Structure, architecture, design: We want the ontology to meet certain pre-defined design principles or criteria; structural concerns involve the organization of the ontology and its suitability for further development.

Using the first three levels, we get a common way to evaluate ontologies which is comparing the ontology to a "golden standard", this is the case of Measuring Similarity between Ontologies of Alexander Maedche and Steffen Staab [Maedche and Staab, 2002].

A global view of how are related perspectives of Hlomani and Stacey [Hlomani and Stacey, 2014] and levels of Brank [J Brank, 2005] it can be seen in Fig. 3.5. On quality are the fourth upper levels of Brank and on Correctness are the left ones. Also the Fig.3.5 shows the relation of the Maedche and Staab's work [Maedche and Staab, 2002] with the Quality perspective.

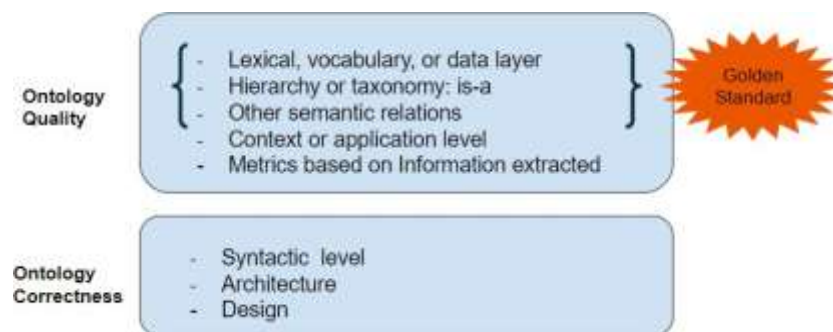


Figura 3.2: Relationship between perspectives of Hlomani and Stacey [Hlomani and Stacey, 2014] and levels of Brank [J Brank, 2005]

Levels of evaluation

We are going to use the levels proposed by Brank [J Brank, 2005] grouping them in the two perspectives of Hlomani and Stacey [Hlomani and Stacey, 2014]. In the Quality we will make the evaluation at linguistic level (string analyze) and at structural level (graph analyse). Related to the Correctness we will check the capacity of modeling the problem through the elicitation of the knowledge of an expert in the area of SLAM.

- **Linguistic Level:** Generally, linguistic analyze relies on their names, labels, comments and some other descriptions. But also the number of resources of the ontology, the

properties of type object and type data of each resource, the number of classes and individuals.

- **Structural Level:** Using directed bipartite graphs to represent ontologies. We will analyze statements (triples) composed of subject, predicate and object. Also we will analyze the principal relationships among triples. In order to evaluate semantically.
- **Domain of Knowledge Level:** The third level of evaluation is the ability to model the SLAM domain specifically in relation to positioning. For this purpose, an expert's knowledge was elicited about the functionalities that a robot should fulfill in order to affirm that it solves the SLAM problem. The expert grouped the questions in 3 subcategories:

1. Self-knowledge:

It is important that the robot can know its location on a map but when it comes to positioning is also relevant to save the pose of the robot because according to that the robot could act differently with its environment, take as an example the robot in Figure 1, its name is komodo and has an arm that can be extended to almost twice its height when the arm is folded. It has to avoid certain obstacles when its arm is stretched out (e.g. a table), which he could ignore if the arm were folded. In addition to the pose, it is important to be

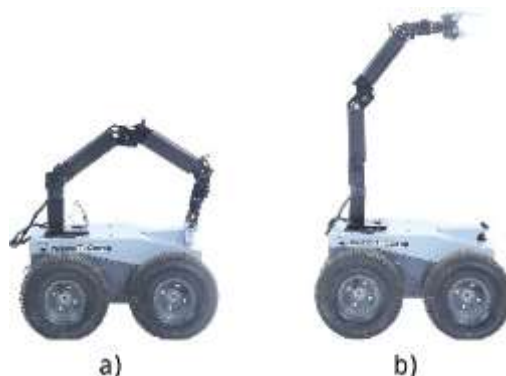


Figura 3.3: Komodo with its arm a) folded and b) stretched out

able to define other characteristics of the robot, including its geometry and the reference systems associated with it. As well as the possibility of passing from one system to another, in order to be able to share the acquired knowledge.

The Ontology :

- a) Allows to represent the pose of a robot?
- b) Stores the geometry of the robot?
- c) Defines a referential system for each link for articulated robots?
- d))Conceptualizes in some way the uncertainty of the position of the robot?
- e) Allow to represent in some way the uncertainty of robot pose?
- f))Allows transformations between referential systems?

2. Environment-knowledge:

The aim here is to evaluate the robot's ability to describe the environment in

which it is located. Although it is known that the names that objects can take may vary according to the environment. What is sought to know is if the ontology is able to define that the robot can recognize other objects (not robots)? This question is what opens up the possibility of a more complex SLAM. Because if the robot is able to differentiate objects from their environment, it has the ability to locate itself either quantitatively or qualitatively with respect to them. In addition, objects could be mobile as in the case of a door, which can be open or closed according to the angle with respect to its point of origin. Or have subareas of interest such as the knob on the door.

The Ontology:

- a) makes it possible to differentiate objects around the robot in terms of their name and characteristics?
- b) can represent the relative position of a robot to the objects around it?
- c) allows to represent the pose of an object in the robot environment?
- d) allows to store sub-objects of interest in larger objects?
- e) allows to know the relative position between objects without being these robots?
- f) model the uncertainty in object position?
- g) represents each object (other than robots) with its own referential system?
- h) registers objects (other than robots) with joints?
- i) allows to store the different poses of an object (which is not a robot) in time?
- j) allows you to store empty spaces and their coordinates?

3. Route-knowledge:

This last group of questions is interested in knowing if the ontology is capable of modeling a path of the robot, this is important because just as it is relevant to record the change of objects in the environment where the robot is, it is even more relevant that the ontology can know if the robot is moving, where it has moved and for how long it has remained in that movement or position.

The Ontology:

- a) Allows to store a path of the robot and query it?
- b) Allows to store the different poses of a robot in time?

Capítulo 4

Experiments and Results

4.1. SLAM-UP Implementation

In order to implement SLAM-UP, we have analyzed the concepts implemented by the Fortes-Rey Ontology which we would henceforth refer to as fr2013. There are some of the concepts implemented by fr2013 that we will use in our proposal. For example, *CartesianPositionRegion* that is the basic unit to model the position of a robot.

```
<!--RobotsAutomation.owl#CartesianPositionRegion -->
<owl:Class rdf:about="&RobotsAutomation;CartesianPositionRegion">
<rdfs:subClassOf rdf:resource="&RobotsAutomation;PositionRegion"/>
  <rdfs:subClassOf>
    <owl:onProperty rdf:resource="&RobotsAutomation;ptsOfPR"/>
    <owl:allValuesFrom rdf:resource="&RobotsAutomation;
      CartesianPositionPoint"/>
  </rdfs:subClassOf>
</owl:Class>
```

As well as the implementation of the concept of *CartesianCoordinateSystem*, an equally important entity to model the pose of a robot in a given environment.

```
<!--RobotsAutomation.owl#CartesianCoordinateSystem -->
<owl:Class rdf:about="&RobotsAutomation;CartesianCoordinateSystem">
<rdfs:subClassOf rdf:resource="&RobotsAutomation;CoordinateSystem"/>
<rdfs:subClassOf>
  <owl:onProperty rdf:resource="&RobotsAutomation;ofCS"/>
  <owl:allValuesFrom rdf:resource="&RobotsAutomation;
    CartesianPositionPoint"/>
</rdfs:subClassOf>
</owl:Class>
```

We use the the WebVOWL [Lohmann et al., 2014] Viewer to ensure the good development of the proposed new ontology (SLAM-UP), as well as to analyze the entities of the base ontology (fr2013). With the help of this viewer we noticed one problem in the base ontology, when we are defining the RPU module, that the main concepts for modeling the *Robot Position Uncertainty* generated two disconnected graphs: one of the Robot model and the second of the Position model, as can be seen in Figures 4.1 and 4.2, respectively.

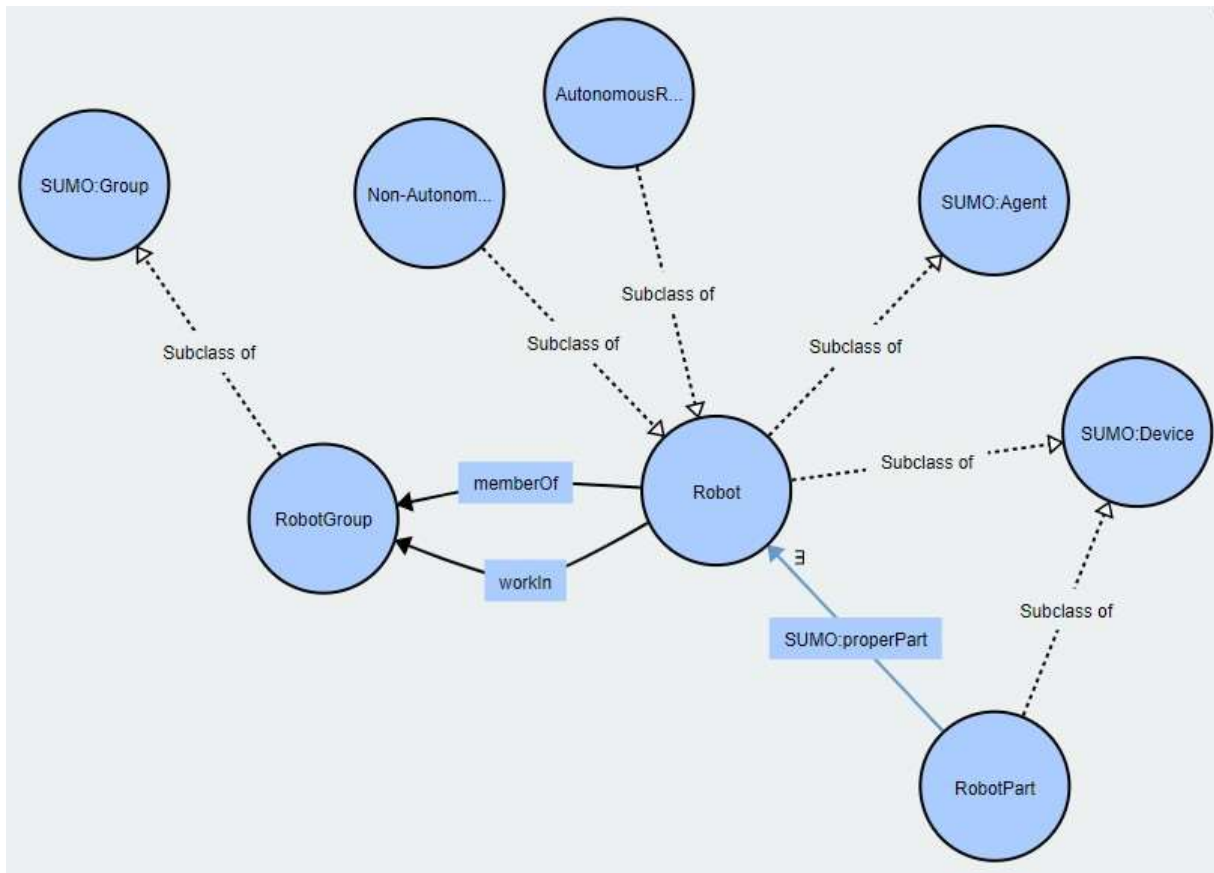


Figura 4.1: Robot graph- Image generate with the WebVOWL [Lohmann et al., 2014]

For this reason we insert a new relationship called **slam-up#has**, which models that a *Robot*, of any type (autonomous, semi-autonomous or non-autonomous), has a *PositionPoint* that can be a *CartesianPositionPoint*. Analogously a *RobotPart* also has a *PositionPoint* associated with it. In the following code, you can see the implementation of this relationship.

```

<!-- slam-up#has -->
<owl:ObjectProperty rdf:about="&RobotsAutomation;has">
<rdf:type rdf:resource="&owl;FunctionalProperty"/>
<rdfs:domain rdf:resource="&RobotsAutomation;Robot"/>
<rdfs:domain rdf:resource="&RobotsAutomation;RobotPart"/>
<rdfs:range rdf:resource="&RobotsAutomation;PositionPoint"/>
</owl:ObjectProperty>

```

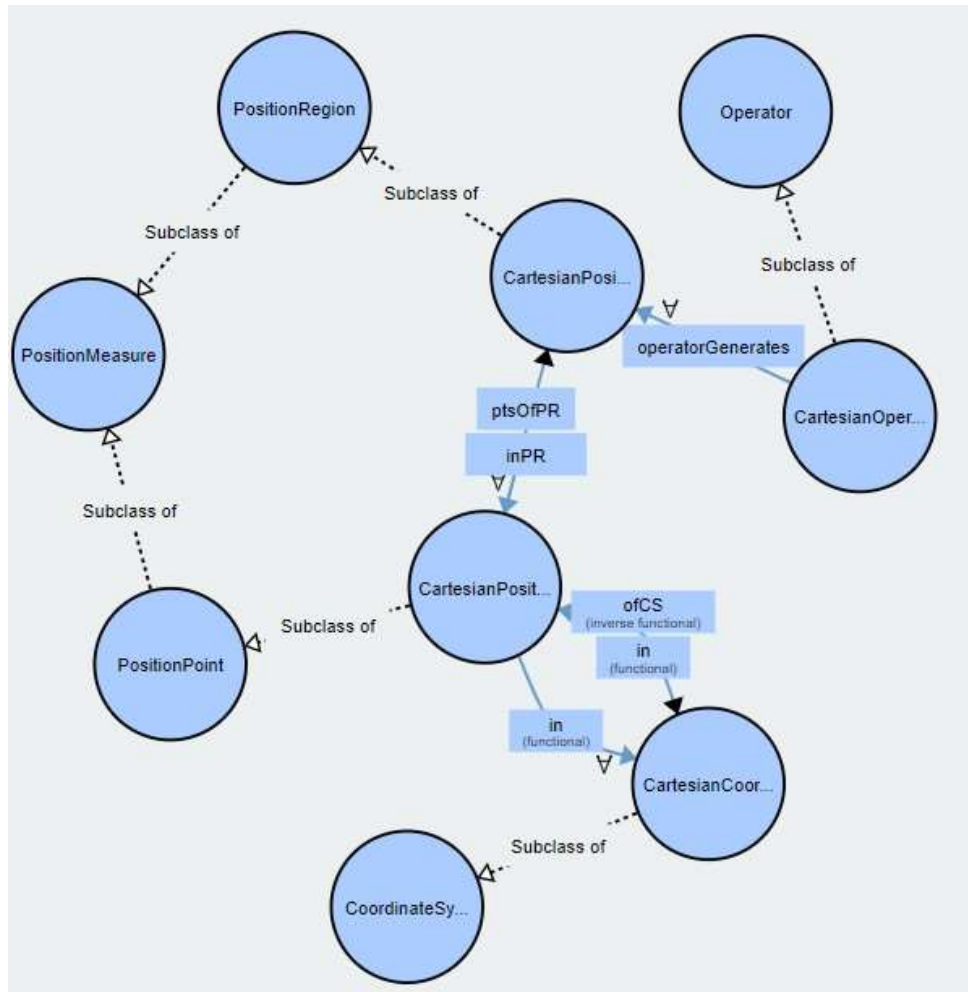


Figura 4.2: Position graph- Image generate with the WebVOWL [Lohmann et al., 2014]

In the same way, we have seen in this example of the inclusion of the **slam-up#has** relationship between *Robot* and *PositionPoint*, and adding several new concept, it is how the expansion of Fortes-Rey Ontology was made to become SLAM-UP. Our SLAM-UP ontology is depicted in Fig. 4.3. In what follows (also in Fig. 4.3), every ontology concept is denoted in the format *< prefix >: < concept_name >*, where prefix is a an abbreviation name of the ontology, and *< concept_name >* is the name of the concept. For example, *cora:Robot* refers to the Robot concept within the Core Ontology, while *slam-up:RobotPose* refers to the RobotPose concept of the SLAM-UP ontology. The list of ontology prefixes that we use in this chapter are as follows.

- **cora:** is a prefix for the Core Ontology for Robots & Automation ontology;
- **fr2013:** is a prefix for the Fortes-Rey ontology (a minimal version of the Fortes-Rey ontology proposed by W3C);
- **slam-up:** is a prefix for the SLAM-UP Ontology (our proposal);

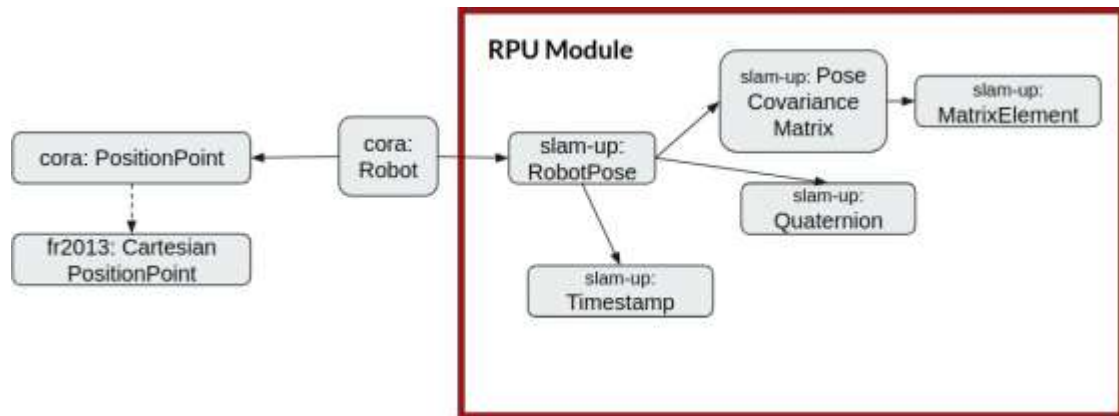


Figura 4.3: Entities developed as now of the SLAM-UP ontology, in the red squares you can see the RPU Module.

The extensions that we have done to the Fortes-Rey ontology to propose SLAM-UP ontology can be categorized into two main modules. The first implemented module is described below.

4.1.1. Robot Position Module

This extension allows SLAM-UP ontology to better model a robot pose. To do this, the `cora:Robot` concept was extended with `slam-up:RobotPose`. This pose is related to a specific time `slam-up:timestamp` through the `fr2013:PosAtTime` relationship of the Fortes-Rey ontology. This `slam-up:RobotPose` also allows to model location, orientation and uncertainty of this position. This is done through relationships that we will formally define.

1. **slam-up:HasPosition**: denoted as hp , is a 2-tuple for matching a robot with its current position, defined as $hp = \langle rp, pp \rangle$, where:
 - rp : is an identifier to a `slam-up:RobotPose` given in IRI format;
 - pp : is an identifier to a `fr2013:CartesianPositionPoint` given in IRI format. It was extended also by adding the component Z, because in Fortes-Rey ontology only have component X and Y.
2. **slam-up:HasOrientation**: denoted as ho , is a 2-tuple for matching a `slam-up:RobotPose` with its current orientation, defined as $ho = \langle rp, q \rangle$, where:
 - rp : is an identifier to a `slam-up:RobotPose` given in IRI format;
 - q : is an identifier to a `slam-up:Quaternion` given in IRI format; this quaternion is a set of four real numbers that represent the orientation of a robot.
3. **slam-up:HasUncertainty**: denoted as hu , is a 2-tuple for matching the `slam-up:RobotPose` with its current uncertainty, defined as $hu = \langle rp, cm \rangle$, where:

- `rp`: is an identifier to a `slam-up:RobotPose` given in IRI format;
- `cm`: is an identifier to a `slam-up:PoseCovarianceMatrix` given in IRI format; this matrix is a set of `slam-up:MatrixElement`. Each `slam-up:MatrixElement` is related to 3 values: `slam-up:row`, `slam-up:column` and element `slam-up:value`.

4.2. Results

In this section we will see the results obtained after the implementation phase. As already mentioned in the chapter of The Proposal, to validate that SLAM-UP ontology meets the requirements and improves the performance of current ontologies that model SLAM, we use this three levels of validation: linguistic, structural and knowledge domain.

4.2.1. Linguistic Level

At this level, two types of OWL entities will be analyzed: prefixes and resources. The prefixes help us to give a context to the indicated entity, to determine its relationship or belonging with a certain vocabulary. Table 4.1 declares the prefix names that are commonly used throughout this specification. IRIs with prefixes `rdf:`, `rdfs:`, `xsd:`, and `owl:` constitute the reserved vocabulary of OWL 2.

Prefix Name	Prefix IRI
<code>rdf:</code>	<code><http://www.w3.org/1999/02/22-rdf-syntax-ns#></code>
<code>rdfs:</code>	<code><http://www.w3.org/2000/01/rdf-schema#></code>
<code>xsd:</code>	<code><http://www.w3.org/2001/XMLSchema#></code>
<code>owl:</code>	<code><http://www.w3.org/2002/07/owl#></code>

Cuadro 4.1: Commonly used prefixes

In Table 4.2 we collect all the prefixes used by the ontologies evaluated. It can also be seen what prefix each ontology uses.

On the other hand, resources are the entities that conceptualize the knowledge of the domain of the ontology in question. The following table shows the number of resources, with their respective object and data properties. Additionally, the number of Classes and Individuals has been considered. Classes then are simply a way of defining meaningful groups into which these resources can be placed - they are classifications [LinkedDataTools, 1999]. Besides in semantic web terms, any resource that we've placed into a class is called an Individual of that Class. An Individual is a resource that has been placed into the Class (or, the classifying group). Individuals are not classes themselves. To better understand these concepts let's look at the following example:

An *IndoorEnvironment* Class, a class for all members of Indoor Environments, into which we could place the *Office1*.

Prefix Name	fr2013	SLAM-UP
rdf:	X	X
rdfs:	X	X
owl:	X	X
xsd:	X	X
RobotsAutomation:	X	X
SUMO:	X	X
xmlns:	X	X
xml:	X	X
slam-up:		X

Cuadro 4.2: Used prefixes in ontologies evaluated

Domain ontologies, as is the case with the two ontologies that we are validating, have the characteristic of having a greater number of Classes than the number of Individuals. This occurs in the opposite way in ontologies of Application. However in our case we decide to populate some individuals to the ontology of SLAM-UP to make some consultations in the third level of validation. In Table 4.3 we see the evaluation of both ontologies at the level of resources, properties, classes and individuals.

	fr2013	SLAM-UP
Resources	62	66
Object Properties	16	20
Data type Properties	2	2
Classes	43	43
Individuals	0	4

Cuadro 4.3: Linguistic Evaluation

Discussion:

After the analysis at the linguistic level, we can see in Table 4.3 that the number of SLAM-UP entities and classes is greater than fr2013. This result is that we expected since SLAM-UP is an extension of Fortes Rey, besides being a consequence of including new entities to model a greater amount of knowledge.

4.2.2. Estructural Level

The structural level is determined through the analysis of built-in properties used in the two ontologies to be evaluated. The built-in properties are RDF , RDFS and

OWL built-in vocabularies used as properties in triples (e.g. `rdf:type`, `rdfs:subClassOf` and `owl:onProperty`).

Table 4.2.2 shows the number of some selected Built-in Properties. As is the case of *subClassOf*, this property is important because it gives us an idea of the interconnection between the Classes of the ontology implemented in both ontologies. In other side, one general piece of information that is consistent about an RDF resource, outside of the URI to uniquely identify it, is the resource or class type. To explicitly define the resource type, you would use the RDF *rdf:type* property. Normally the property *rdf:type* is associated with the same level of granularity as the other properties. However, we will also analyze the use of the property *owl:onProperty*

	fr2013	SLAM-UP
<code>rdfs:subClassOf</code>	66	66
<code>rdf:type</code>	9	9
<code>owl:onProperty</code>	11	15
<code>rdfs:domain</code>	16	20
<code>rdfs:range</code>	16	20

Cuadro 4.4: Estructural Evaluation: Built-in Properties

Discussion:

On a structural level we can note that, in the same way as in the previous level, the number of relations that SLAM-UP has is greater than that of fr2013. This behavior is within the expected results because SLAM-UP is an expansion of an existing ontology and as a consequence of having introduced new entities it is logical that the number of relations increases.

4.2.3. Domain of Knowledge Level

For the third level it has been proposed a set of questions. That will be done through the SPARQL language [Hayes, 2013]. SPARQL is an RDF query language capable of retrieving and manipulating data stored in RDF format, such as our web ontologies. This tool allows the consultation of triple patterns, conjunctions, disjunctions and optional patterns. Below are some of the queries made in SPARQL with the corresponding output:

For answer question:

1a. The Ontology allows to represent the pose of a robot?

In fr2013, a complex query had to be made, since it did not have the "Pose" class defined explicitly, like other positioning ontologies. In this ontology the pose of the robot it can represent with a vector of points with their respective cartesian Ppoints, each one associated with a representative part of the robot.

```

QUERY 1
PREFIX fr2013:
  <http://www.semanticweb.org/ontologies/
    2013/7/RobotsAutomation.owl#>
SELECT ?subject ?dev ?artifact ?ref ?ofCS
WHERE {
fr2013:RobotPart rdfs:subClassOf ?dev .
  ?subject rdfs:subClassOf ?dev .
  ?dev rdfs:subClassOf ?artifact .
  ?artifact rdfs:subClassOf SUMO:Object .
fr2013:ref rdfs:domain ?ref .
fr2013:ofCS rdfs:range ?ofCS .
fr2013:CartesianPositionPoint
rdfs:subClassOf ?ofCS
}

```

Here we are checking that the RobotPart class defined in fr2013 is related to an Object, remember that all Object have an associated Coordinate System. We also consult the ref relationship that models if a CartesianPositionPoint belongs to a Coordinate System.

subject	dev	artifact	ref	ofCS
RobotPart	SUMO:Device	SUMO:Artifact	oordinateSystem	PositionPoint

Cuadro 4.5: Output of Query 1

Once it has been shown that a part of the robot has a Coordinate System associated. In fr2013 we can answer analogously 1c and 1e, taking a link and a sensor as a part of the robot. For 1f, fr2013 have CORA#TransformationFunction, with two domains:

- TransformationMapsFrom
- TransformationMapsTo

The table 4.6 shows that in this category the two ontologies are at the same level, and that they model well the self-knowledge part of the robot. This is a good starting point because to be able to correctly describe the environment that surrounds it, the robot must be able to describe itself first.

In the Table 4.7 it can be seen a clear limitation in the capacity that fr2013 ontology have to model the environment that surrounds them, because although it has inherited from SUMO the Object class and from CORA the definitions of Robots and their types. So it can be inferred that a robot could recognize an object (another robot) with respect to its position. However, it is not possible to define an Object that is not a Robot. Despite we could define the empty space (question 2j) using the PRegion class, present in both ontologies. Considering that a PRegion is composed of points. Also in fr2013 there is the relation :ptsOfPR that has as a domain a PRegion and as a range PPoints. The

Question	fr2013	SLAM-UP
1a	YES	YES
1b	YES	YES
1c	YES	YES
1d	NO	YES
1e	NO	YES
1f	YES	YES

Cuadro 4.6: Self-knowledge questionnaire

Question	fr2013	SLAMP-UP
2a	NO	NO
2b	NO	NO
2c	NO	NO
2d	NO	NO
2e	NO	NO
2f	NO	NO
2g	NO	NO
2h	NO	NO
2i	NO	NO
2j	YES	YES

Cuadro 4.7: Environment-knowledge questionnaire

complement to this relation is :inPR that has a domain PMeasure (that could be a PPoint) and a range PRegion.

As the third group of questions is interested in the modeling of the robot path, it has been seen as convenient to check how is given the relationship between time and position in fr2013. To see this relationship the following consultation was made in fr2013:

```

QUERY 3
PREFIX SUMO:
  <http://www.semanticweb.org/ontologies/
    2013/7/RobotsAutomation.owl#SUMO:>
SELECT  ?measure ?unit
WHERE {
?measure rdfs:subClassOf
SUMO:PhysicalQuantity .
?unit rdfs:subClassOf ?measure

```

}

In the table 4.8 it is possible to see that fr2013 can model the Route-knowledge in the SLAM domain, since the robots can define their position and their poses in relation to time. In this sense SLAM-UP will keep the entities and relations defined by fr2013 to not lose this feature.

Question	fr2013	SLAM-UP
3a	YES	YES
3b	YES	YES

Cuadro 4.8: Route-knowledge questionnaire

A consolidated of the three subcategory of Domain of knowledge can be seen in Table 4.9. For each row is statement the number of questions satisfied by the ontology in the respective column. In the fourth column N_Q is the number of questions for each subcategory. The percent of the last row is relative to the total number of questions in this comparison level.

Subcategory	fr2013	SLAM-UP	N_Q
Self-knowledge	4	6	6
Environment-knowledge	1	1	10
Route-knowledge	2	2	2
Total of Questions satisfied	7 (38.0 %)	9 (50.0 %)	18 (100.0 %)

Cuadro 4.9: Domain of knowledge similarity

Discussion:

After analyzing each of the subcategories of the domain level of knowledge, we came to the conclusion that the ontology proposed SLAM-UP better models the SLAM domain. This improvement can be seen in the first category, where SLAM-UP satisfies 100 % (6/6) of the questions about Robot Information. This is the main contribution of this work, because with the expansion of the RPU module the capacity to model the SLAM problem has been increased to 50 %. This constitutes a 12 % improvement with respect to its base ontology (fr2013) which modeled the SLAM problem with a 38 % effectiveness.

We see a notable deficiency in the second subcategory of knowledge of the environment, since none of the ontologies is able to define objects that are not robots yet. In the third subcategory (Route Knowledge) there is no improvement, since Fortes-Rey's ontology already satisfied 100 % of the questions (3/3). Since SLAM-UP is based on it, the same result is inherited.

Capítulo 5

Conclusions and future works

5.1. Conclusions

In this work, we propose a categorization for the knowledge generated by in SLAM algorithms: (i) robot information, (ii) environment information, (iii) temporal information and (iv) workspace information. Through the analysis of several ontologies that had as, partial or total, objective to model the knowledge of SLAM, we have parsed the importance of representing the timely information into SLAM ontologies, to improve the process of solving SLAM. We consider that the integration of environment mapping information, robot information, and timely information with the positioning uncertainty in robots and landmarks, represent an option to optimize and improve the precision of the results of SLAM solutions.

Based on this categorization, we point out that there is not an ontology fully covering the whole SLAM problem. Additionally we found a gap in the area of uncertainty in relation to the first two categories. This is why it was decided to implement SLAM-UP, wich has two modules, one relative to Robot Position Uncertainty (RPU) and the other of Landmarks Position Uncertainty (LPU).

Fortes-Rey ontology was chosen, due to its detailed robot positioning model, to serve as the basis for our new ontology: SLAM-UP. Until now we have implemented the first module (RPU). After the validation, we see an improvement of 12 % of effectiveness to represent the SLAM problem, with respect to its predecessor. This improvement was on the third level of knowledge domain, which is the most relevant category in our work.

5.2. Future Works

As future work, we are proposing to continue with the implementation of SLAM-UP, with the development of the LPU module. This module will allow modeling not only the Robot Positioning Uncertainty, but also the Landmark Positioning Uncertainty (characteristic objects of the environment). With this we seek to obtain 100 % of the

effectiveness in the capacity to model the SLAM problem.

Although the presented evaluation of the ontology provides a good basis to validate the SLAM-UP, we consider that the ontologies should be tested in the real environments of their application domain. In our case, the environment (known or unknown) that the robot will model. Therefore, we are proposing as a future work to present a practical validation of the new SLAM-UP ontology.

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