Qualitative Spatio-Temporal Representation and Reasoning Framework for RISE mobile robot's operator training planning

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Abstract

In this paper we proposed new methodology for RISE (Risky Intervention and Surveillance Environment) mobile robot's operator training planning. For this task Qualitative Spatio-Temporal Representation and Reasoning Framework called Semantic Simulation Engine is used. The core concept is connected with development of Mobile Spatial Assistance System capable of building a semantic model of the environment based on observations. The goal is to support operator's training planning by using information gathered from real tasks execution. This can drastically increase the effectiveness of the training process by providing realistic scenarios without the need for time-consuming development of complex and sophisticated artificial environments.

Keywords: semantic model, robotic system, operator training, qualitative representation and reasoning

Introduction

In the paper the framework for RISE (Risky Intervention and Environmental Surveillance) mobile robot's operator training planning is presented. The basic idea behind the framework is to provide software tools for mobile robot simulation. Created simulations may then be used in operator training. To achieve realistic rigid body simulation and realistic rendering NVIDIA PhysX engine and OGRE (Open Graphic Rendering Engine) are used. To provide realistic visual representation of the environment we use CAD models. The compatibility between modeling tools, such as SolidWorks, an the framework is assured by using COLLADA format. The simulator has motion models of several types of robots such as caterpillar or wheeled. The simulated robot can be operated from real control station.

The main feature of presented framework is the idea of automatically generated semantic model of the environment, in a way so that the model could easily be used for operator training. We believe that in the near future it will be possible to model complex training scenarios based on robot's observation of real task execution. The work is related with Spatial Assistance System (SAS)[1]. For this paper our focus is on Mobile Spatial Assistance System (MSAS) that is the agent for gathering information and creating semantic model of the environment. The model can be used for designing training levels in virtual environment, that can be used for operator's examination.

The paper is organized as follows: the next section QSTRR (Qualitative Spatio-Temporal Representation and Reasoning) Framework demonstrates the ontological approach to semantic modeling used in training planning, section named Training Design explains the integration issues with existing training platform, final section Conclusions and Future Work points out the advantages of proposed approach and direction of future research.

QSTRR (Qualitative Spatio-Temporal Representation and Reasoning) Framework for training planning

Work[2] is a good overview of computer simulators of unmanned vehicles. In [3] a comparison of modern real-time physics simulation systems is given, along with qualitative evaluation of number of free publicly available physics engines. Apart from that, several frameworks are available that can, partially, support mobile robot's simulation examples being: USARSim [4] [5] [6], Stage, Gazebo [7], Webots [8] and MRDS [9] [10]. Interesting simulator classification system is proposed in [11]. The system provides means for grading existing simulators on the basis of their functionality. An interesting simulation engine - the Search and Rescue Game Environment (SARGE), which is a distributed multi-player robot operator training game, is described in [12]. Unfortunately presented systems do not provide means for creating semantic models from information gathered during real task execution. Our aim is for Mobile Spatial Assistant System to explore the environment and generate it's semantic model. Afterwards we can define semantic events related to specific training task. After this steps training planning is complete.

Ontology of training

The concept of using Spatio-Temporal Representation and Reasoning, in automatically generated semantic models of the environment for robot operator training, is a fresh approach. In our framework internal information sharing is accomplished by encoding domain knowledge using a standard vocabulary based on an ontology. An example of such approach is a declarative Spatial Reasoning Framework (SRF) [13] capable of representing and reasoning in a high-level, qualitative way based on spatial knowledge about the world. Ontology, as a representation vocabulary, proposed in this paper is dedicated for the domain of physical/functional entities in real structured environment. An ontology (O) is composed of several entities: { a set of concepts (C), a set of relations (R), a set of axioms (A) (e.g. transitivity, reflexivity, symmetry of relations), a concepts' hierarchy (CH), a relations' hierarchy (RH), a set of spatio-temporal events (Est) }. what can be formulated as following definition:

$$O = \{C, R, A, CH, RH, Est\}$$

An ontology is supposed to support reasoning mechanisms. Concept is defined as a primitive spatial entity described by a shape (S), composed of polygons in 3D space, associated with a semantic label (SL). Shape is perhaps one of the most important characteristics of an object, and particularly difficult to describe qualitatively. Ontology distinguishes two different types of attributes that can be assigned to a concept, quantitative (Aqn) and qualitative (Aql). Five values of qualitative attribute (entity function) are listed: {real physical object, empty space, functional space, operational space, range space}. Functional, operational and range spaces are connected with spatial artifacts, more information can be found in [1], [14], [15]. Quantitative attributes are connected with physical properties of spatial entities and are as follows: {location, mass, center of mass, moment of inertia (how resistant is the object to changing the orientation about an axis), material (friction, restitution)}. Therefore, the definition of the concept (C) can be formulated:

$$C = \{S, Aqn, Aql, SL\}$$

The set of relations (R) is composed of quantitative and qualitative spatial connections. For topological spatial relations (qualitative) the Region Connected Calculus (RCC) [16] is proposed. RCC is a formalism for spatial reasoning that takes regions of space (shapes) instead of points of classical geometry as primitives. One particular prominent reasoning system is a system of topological relations called RCC-8 [17] (the relations of RCC-8 calculus and conceptual neighborhood is shown on figure 1), in which the ontology includes eight different topological relations between two regions (in our case shapes): {disconnected (DC), externally connected (EC), partial overlap (PO), equal (EQ), tangential proper part (TPP) and its inverse (TPPi), non-tangential proper part (NTPP) and its inverse (NTPPi)}. Quantitative spatial relations are a way to constrain entities movement relative to each other. Ontology defines following constraints: {origins locked, orientations locked; origins locked, orientations free; free rotation around one axis; sliding}. Quantitative attributes and relations can be used to build a quantitative model in COLLADA (COLLAborative Design Activity) format. COLLADA is used as an interchange file format for interactive 3D applications. Qualitative attributes and relations can be used, for example, to build a qualitative model for Spatial Reasoning Framework (SRF) [13].

An important aspect and, at the same time, difficult to implement is qualitative spatio-temporal representation. Ontology should provide mechanism of building world models, that assume spatio-temporal relations in different time intervals (in other words: world models that can integrate changes), for representing the knowledge used for spatiotemporal reasoning. Chosen temporal representation takes temporal intervals as a primitive [18], therefore ontology defines qualitative spatio-temporal events (Est) related with topological spatial relations TSR_{RCC-8}: { onEnter (DC->EC->PO), onLeave (PO->EC->DC), onStartInside (PO->TPP->NTPP), onStopInside (NTPP->TPP->PO)}. These four qualitative spatio-temporal events can be used to represent most important relations between two concepts in different intervals of time. Spatio-temporal events are also associated with time stamp, therefore we can define Est as:

$$Est_T=\{C_A, C_B, TSR_{RCC-8}, T\}$$

where: C_A,C_B concepts, TSR_{RCC-8} topological spatio-temporal relations using RCC-8, T timestamp. Ontology defines a TASK as a set of spatio-temporal events connected via temporal relations Est_T:

$$TASK = \{Est_{T1}, Est_{T2}, Est_{T3}, \ldots Est_{TN}\}, T1<T2<T3<\ldots<TN$$

MISSION is defined as set of pairs - independent tasks related with a goal assigned quantitatively an amount of points.

$$MISSION = \{ (TASK_1, GOAL_1), (TASK_2, GOAL_2), (TASK_3, GOAL_3), \ldots , (TASK_N, GOAL_N)\}$$

TRAINING is defined as a directed graph where nodes are defined as pairs (MISSION, tasks' sum of points) and edges correspond to the conditions for advancing into the next MISSIONS checked using the amount of points acquired during previous tasks' execution. To store the instances of ontology-based training elements (defined on the conceptual level) an instance base (IB^O) is defined:

$$IB^O = \{I^O_C , I^O_R , I^O_{Est}, I^O_{TASK}, I^O_{MISSION}, I^O_{TRAINING} \}$$

where: I^O_C contains instances of concepts C, I^O_R contains instances of relations R, I^O_{Est} contains instances of spatio-temporal events E_{st}, I^O_{TASK} contains instances of training tasks, $I^O_{MISSION}$

contains instances of missions, $I^{O}_{TRAINING}$ contains instance of training. Semantic model of the training is defined as a pair:

$$SM_{TRAINING} = \{O, I_B^{O}\}$$

where: O is an ontology and I_B^{O} is an instance base related to ontology O. Ontology is known a-priori but instance base is being updated during training planning process.

Conceptualization

An important part of the framework is development of semantic object identification and transformation into concepts with accordance to the ontology presented in previous section. Instead of wall, door, ceiling and door identification proposed in [21] we focus on human detection and Delaunay triangulation [22] for complex planar 3D shapes modeling.

Human detection

The method used for human detection we use is Histogram of Oriented Gradients (HOG) [19]. We chose it because it proved to be effective in detecting objects of characteristic shapes(humanoid shape in case of people detection). For the purpose of basic framework development we use the OpenCV library package [20]. In the final version we want to use a GPU supported version of the algorithm. For the conceptualization purpose we decided to use the default detection descriptor provided be OpenCV. In preliminary experiments it proved to be reasonably robust achieving up to 90 percent positive detections. To get the images necessary for detection we use the KINECT device. It was chosen because of good video quality and most importantly, automatic stabilization of images, which is extremely important for data acquisition during motion. For the purpose of detection, information from both the RBG camera and depth camera are used. HOG provided potential areas of detection and ,based on depth information, rough size of detected object is calculated. This allows to filter most of the false positives, as commonly they are much smaller or much larger than average human. Figure 2 demonstrates the result: detected human and visualization of automatically generated concept.

Wall detection

Apart from wall, door, ceiling and door identification proposed in [21] we proposed a new approach that uses Delaunay triangulation [22] for complex 3D shapes modeling. It provides one of the possible solutions for extracting triangles from the given projected 3D cloud of points onto a plane. Triangulation of a planar set of points connects them by edges in such a way that no edges intersect each other. The assumption is that no edges can be added that break this condition. Delaunay triangulation maximizes minimal angle of all the triangles in the triangulation. Thus it tends to produce least possible amount of thin triangles which is beneficial for our application. We expect, that solid large obstacles such as walls will be represented as large triangles, which will allow to minimize the computation effort for further 3D RCC8 analyses. There is a number of algorithms for building Delaunay triangulation and corresponding Voronoi subdivisions. For basic framework purpose we are using implementation coming with the OpenCV library [23]. This implementation provides a sufficient performance for most practical purposes where the number of nodes is not too high.

Robot path in INDOOR environment (room detection)

We demonstrate an illustrative example of automatic semantic model generation performed by mobile assistant during INDOOR environment exploration. The 3D data were collected in

Royal Military Academy (Brussels, Belgium) building with the prototype of MSAS (Mobile Spatial Assistance System). The goal is to provide semantic model of a room based on proposed ontology, where each concept is connected with a shape. Figure 4 shows an example of this approach. Room is composed of several shapes in relation PO (Partially Overlapped) to neighboring shapes. Each shape has assigned semantic label describing its function or a role in the environment, for example door shape is an operational shape. If there is a semantic connectivity between two neighboring doors via empty spaces in relation PO, we consider that this set of shapes can be labeled as a room-concept. A room-concept can be used as a training environment.

Training design

After automatically generating semantic models of an INDOOR environment (previous section) we are able to plan the training using developed software tools that integrate semantic model of a robot with the semantic model of the environment. More details can be found in[24].

Semantic model of a robot

Semantic model of a robot is shown in figure 5. The model is a composition of concepts: real robot parts connected via quantitative relations describing joints, cameras and lights that are modeled by shapes with qualitative attribute: range space. Such semantic model may be used in training simulation. Based on spatio-temporal reasoning we can observe possible mistakes of the operator, for example an intersection between robot's arm and robot's chassis will be marked with negative points.

Semantic model of an environment

Example semantic models of an OUTDOOR and INDOOR environments are shown in figures 6 and 7. These semantic models compose of crucial concepts needed to perform a mission, that is hazardous material transportation from given location into defined location of neutralization. Hazardous material detection by operator is monitored based on PO (Partailly Overlap) qualitative relationship, and spatio-temporal event onEnter between operation shape: camera and physical shape: hazardous material. The success or failure of the mission is decided based on the spatio-temporal event onEnter between physical shape: hazardous material and empty space: location of neutralization. Operator is punished each time when the shape: hazardous material is in qualitative relation PO (Partially Overlap) with defined concepts: real physical shapes.

Conclusion and future work

In this paper we proposed new methodology for RISE (Risky Intervention and Surveillance Environment) mobile robot's operator training planning. The planning process is performed using Qualitative Spatio-Temporal Representation and Reasoning Framework called Semantic Simulation Engine. The core concept is related to the development of a Mobile Spatial Assistance System that can build a semantic model of a training based on environment's observation, which is considered as the main advantage of proposed approach. We believe that in near future such approach will replace SoA techniques as it will be possible to model the real task scenarios based on robot' observation. Our mobile assistant serves the informational and computational functionality of spatial assistance system that is intended to provide intelligent spatial decision-making capabilities for training design purpose. The goal is to support operator's training planning by using information derived from real task execution. This can drastically improve the training process by providing realistic scenarios without the need of time-consuming manual development of complex and sophisticated virtual artificial environments.

Acknowledgement

The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement n°284747.

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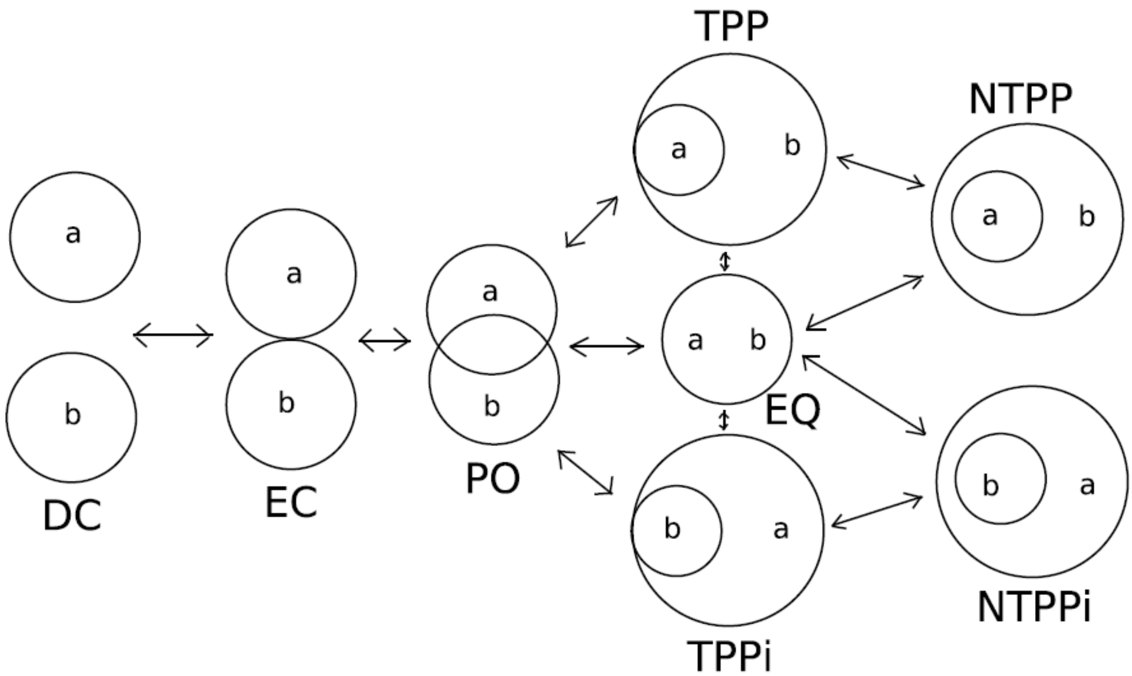

Figure 1: The relations of RCC-8 calculus (conceptual neighborhood).

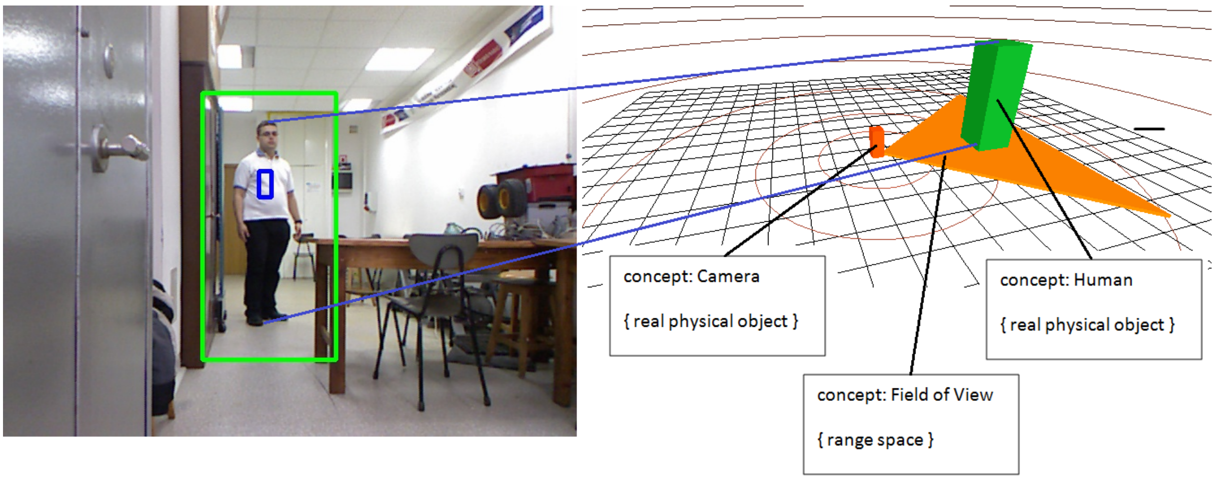

Figure 2: Conceptualization of human detected by the mobile robot equipped with KINECT sensor.

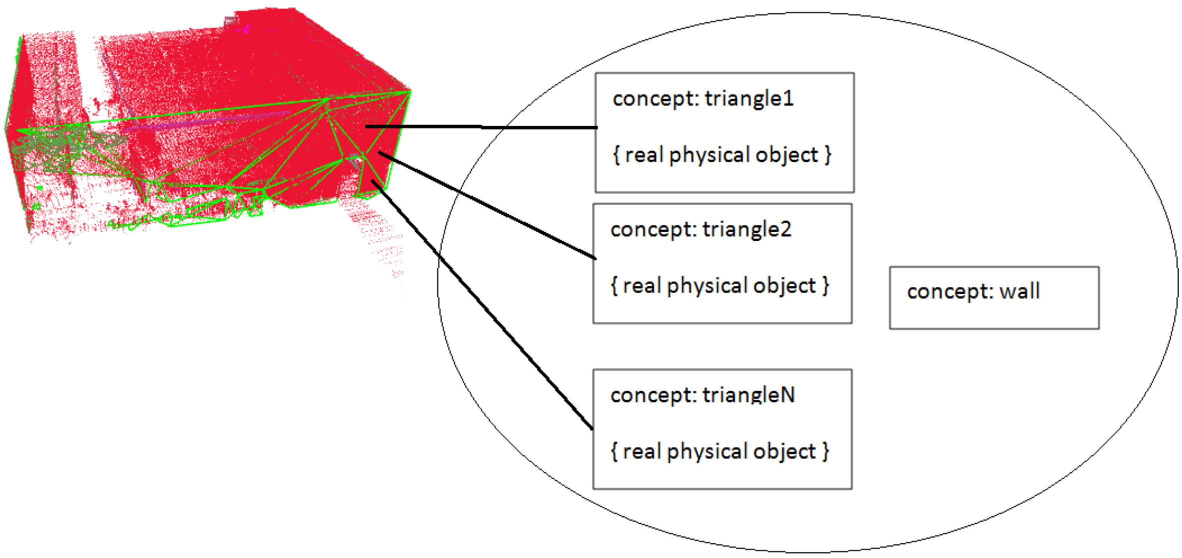

Figure 3: Extracted triangles for given 3D cloud of points using Delaunay triangulation technique. The concept of wall is a set of concepts: triangles.

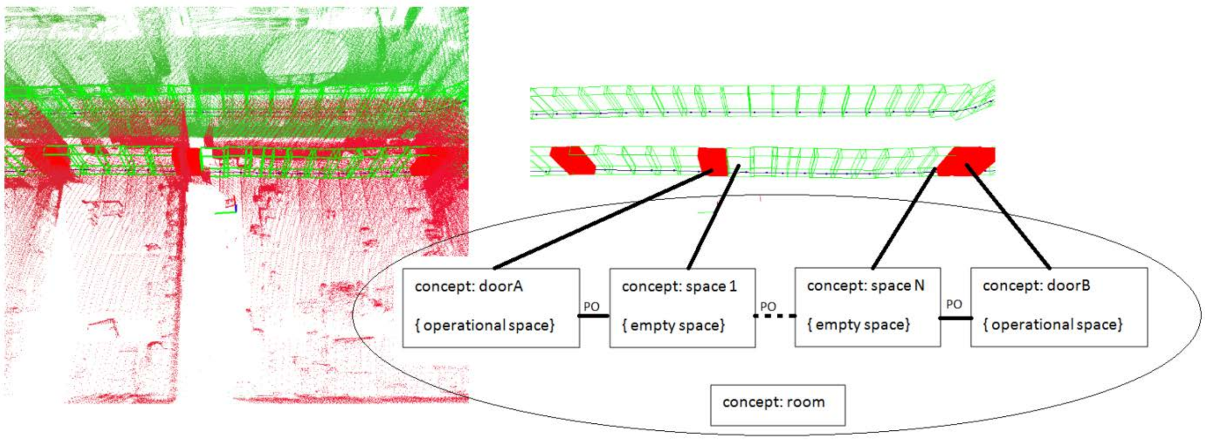

Figure 4: Semantic model of a room automatically build from 3D cloud of points using qualitative representation. PO - RCC8 relationship Partially Overlap.

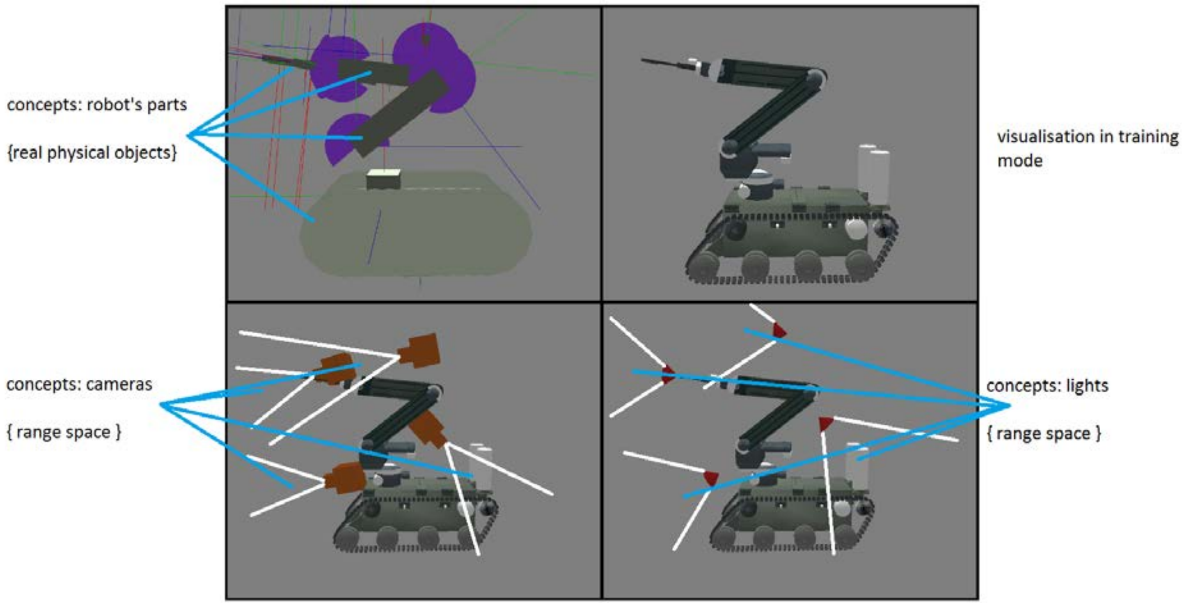

Figure 5: Semantic model of a robot.

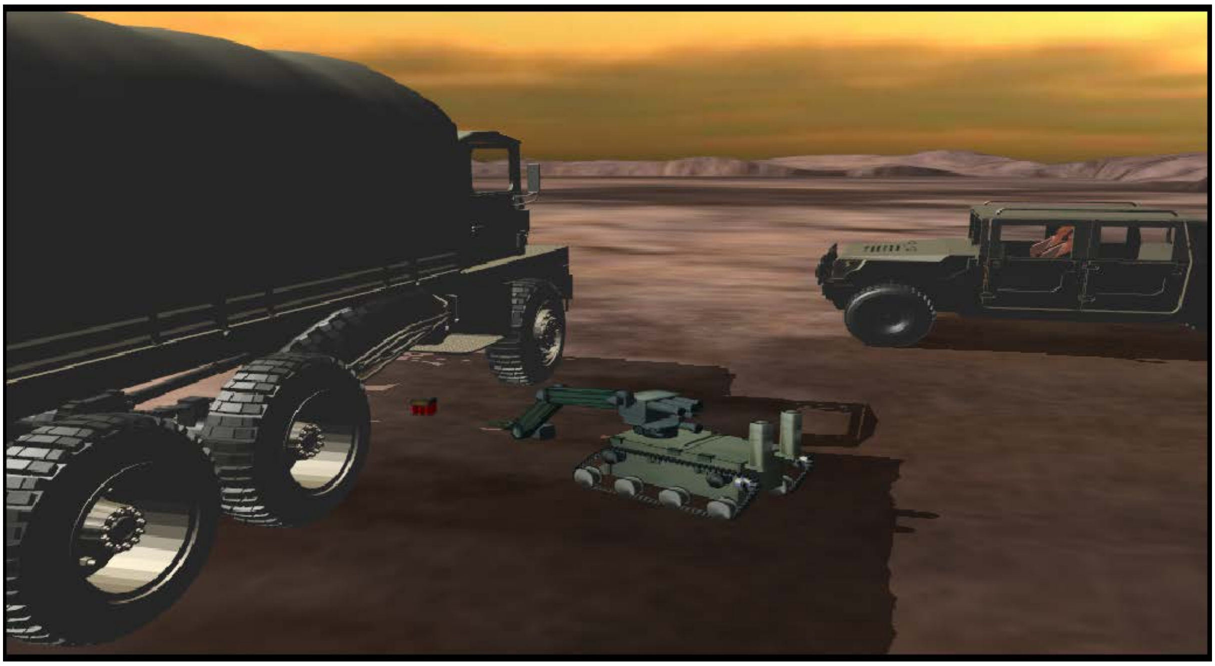

Figure 6: Visualization of a semantic model of a mission in OUTDOOR environment.

Figure 7. Visualization of a semantic model of a mission in INDOOR environment.