

From SLAM to Situational Awareness: Challenges and Survey

Hriday Bavle, Jose Luis Sanchez-Lopez, Eduardo F. Schmidt, Holger Voos

Abstract—The knowledge that an intelligent and autonomous mobile robot has and is able to acquire of itself and the environment, namely the situation, limits its reasoning, decision-making, and execution skills to efficiently and safely perform complex missions. Situational awareness is a basic capability of humans that has been deeply studied in fields like Psychology, Military, Aerospace, Education, etc., but it has barely been considered in robotics, which has focused on ideas such as sensing, perception, sensor fusion, state estimation, localization and mapping, spatial AI, etc. In our research, we connected the broad multidisciplinary existing knowledge on situational awareness with its counterpart in mobile robotics. In this paper, we survey the state-of-the-art robotics algorithms, we analyze the situational awareness aspects that have been covered by them, and we discuss their missing points. We found out that the existing robotics algorithms are still missing manifold important aspects of situational awareness. As a consequence, we conclude that these missing features are limiting the performance of robotic situational awareness, and further research is needed to overcome this challenge. We see this as an opportunity, and provide our vision for future research on robotic situational awareness.

Index Terms—Situational Awareness, Simultaneous Localization and Mapping (SLAM), Semantic SLAM, Localization, Scene Modeling, Mobile Robots, Aerial Robots, Ground Robots.

I. INTRODUCTION

Robotics industry is experiencing an exponential growth embarking newer technological advancements as well as applications. Mobile robots especially have gained interest from the industry due to their capabilities to replace or aid humans in repetitive or dangerous applications. Some applications where mobile robots are widely being used consist of industrial inspection, underground mine inspections, surveillance, emergency rescue operations, reconnaissance, petrochemical applications, industrial automation, construction, entertainment, museum guides, personal services, intervention in extreme environments, transportation, medical care etc.

Mobile robots can be operated in a manual teleoperation mode, a semi-autonomous mode with a constant human intervention in the loop, and an intelligent autonomous mode

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in which the robot can perform the entire pre-programmed mission and execute it based on its own understanding of the environment. The autonomous mode is the most desirable mode as it requires minimum human intervention thus reducing the costs as well as increasing productivity. But unlike traditional robots working in industrial settings, where the world is designed around them, mobile robots operate in dynamic, unstructured and cluttered environments, thus autonomous mobile robots need to continuously acquire a complete situational awareness, by observing it, understanding it, and projecting into the future the possible options; taking decisions by reasoning into these options, and finally ensuring that they are properly executed (see Fig. 1).

In this paper we would like to delve into two important research question faced by the robotics community:

(1) *Do mobile robots understand and reason the situation around them the similar manner as humans?*

(2) *How far are we from achieving completely autonomous mobile robots with superior intelligence as humans?*

Situational awareness is a holistic concept widely studied in fields in the fields like Psychology, Military, Aerospace, Education, etc., [1] but it has barely been considered in robotics, which has focused on independent research ideas such as sensing, perception, sensor fusion, state estimation, localization and mapping, spatial AI, etc as can be seen from Fig. 2. Endsley's works [2] formally defined in the 90s situational awareness as “*the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future*”, which remains valid till date and could be applied to mobile robotics categorizing the situational awareness into three levels:

The **perception of the situation** consists of the acquisition of different kinds of information of the situation, both exteroceptive (i.e. of the surroundings, such as visual light intensity or distance) and proprioceptive (i.e. of the internal values of the robot, such as velocity or temperature). Sensors provide measurements that are transformed by perception mechanisms (e.g. the pixel values of an acquired image are distorted by the camera gain, perceiving the colors differently as they are in reality). The use of multiple sensor modalities is essential to perceive complementary information of the situation (e.g. acceleration of the robot, visual light intensity of the environment), and to compensate for low-performance in different situations (e.g. dark rooms, light-transparent materials)

The **comprehension of the situation** extends to, not only the understanding of the perceived information at present, considering the particularities of the perception mechanisms,

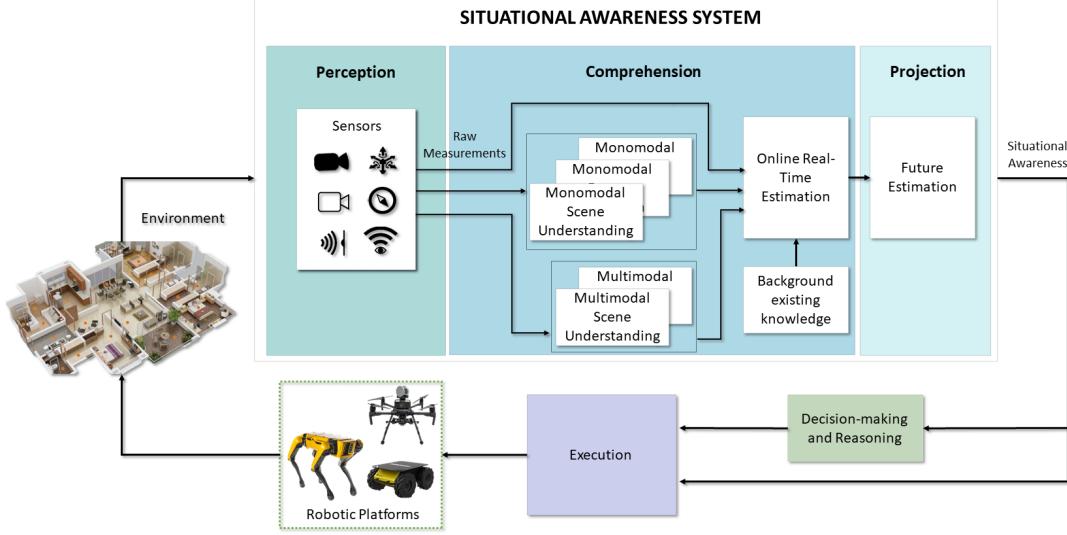


Fig. 1: Generic software architecture for autonomous mobile robots with connection between different components.

but also, building a long-term model of the situation that includes the information acquired in the past. The understanding of the situation covers different abstractions that are included in this model, such as geometric (e.g. shape of the objects), semantic (e.g. type of the objects), hierarchical, topological, and dynamic relationships (e.g. relationships between the objects), or stochastic information (e.g. to include uncertainty). The comprehension of the situation is affected by mechanisms, such as attention, that are controlled by the decision-making and control processes (e.g. looking for a particular object in a room vs. getting a global overview of a room).

The **projection of the situation** into the future is essential for the decision-making processes and is related to the level of comprehension achieved. The deeper the level of comprehension, the better the projection is. For example, the projection model of the position of a robot can be better estimated if its current velocity is known. Moreover, if the robot is accurately aware of its current situation, e.g., if it's navigating in an empty corridor, it is more likely to maintain its velocity than if the environment has dynamic agents, as it will need to slow down to effectively navigate through the agents.

The main goal of this paper is to review the current state-of-the-art methods for perception, state estimation, localization, mapping for mobile robots and study their incorporation into the subsections of perception, comprehension and projection as one broad field of situational awareness for mobile robots, in order to address the research questions posed above. We divide the paper into the following manner, where Sect. II presents the current sensor technologies and its limitations used on-board mobile robots. Sect. III reviews the current literature regarding scene understanding, as well as localization and scene modeling for mobile robots. While Sect. IV reviews the literature regarding the projection of situation, Sect. V and Sect. VI discusses and concludes the paper with scope of the

future works for intelligent mobile robots.

II. SITUATIONAL PERCEPTION

The recent advances in sensing technology have made available a large number of sensors that are used on-board mobile robots, as they come with a small form factor (small size, weight, and reduced power consumption). Almost every robotic platform is already integrated with basic sensor suite, such as *Inertial Measurement Units (IMU)*; *Magnetometers*; *Barometers*; or *Global Navigation Satellite Systems (GNSS)*, as well as their higher-precision variants, such as *Real-Time Kinematic* or *Differential GNSS*. Sensors such as *IMU* which can measure the attitude, angular velocities and linear accelerations, are cheap and lightweight which make them ideal to run on-board for any robotic platform. Though the performance of these sensors can degrade overtime due to the accumulation of errors coming from white Gaussian noise [3]. Magnetometers are generally integrated within an *IMU* sensor, measuring the accurate heading of the robotics platform relative to the earth's magnetic field. The sensor measurements from a magnetometer though, can be corrupted in environments with constant magnetic field interfering with the earth magnetic field. While, barometers measure the altitude changes through measured pressure changes, they suffer from bias and random noise in its measurements in indoor environments due to ground/ceiling effects [4]. *GNSS* sensor when used with high precision variants such as *RTK* provide reliable position measurements of the robotic platforms, though these sensors can work only in outdoor uncluttered environments [5].

Cameras are the most prominent exteroceptive sensors used in robotics, since they provide a high range (but complex) of information with a small form factor and a quite affordable cost. *RGB cameras* (e.g. monocular), and especially those with additional depth information (e.g. *stereo*, *RGBD cameras*) are, by far, the most dominant sensors used in robotics. These

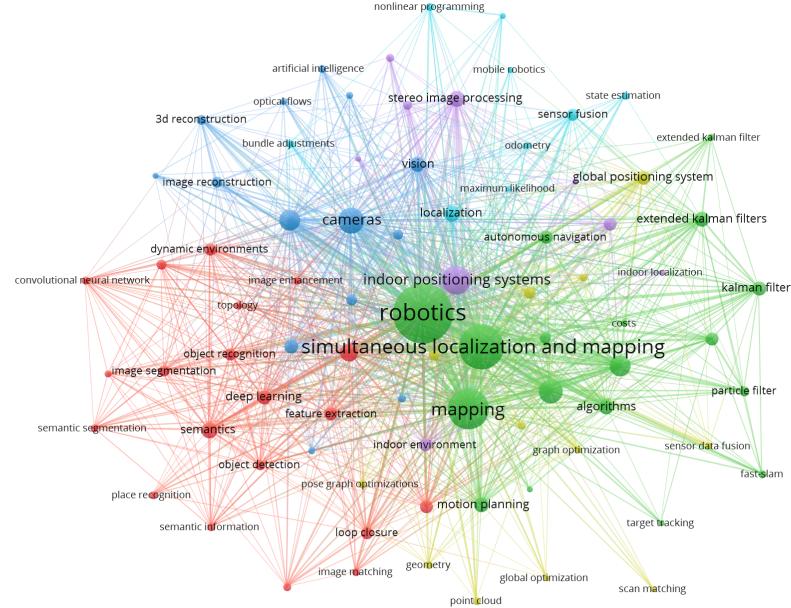


Fig. 2: Scopus database from 2015-2021 covering the research in *Robotics* and *Simultaneous Localization and Mapping (SLAM)*. All the works have focused on independent research areas which could be efficiently encompassed in one field of *Situational Awareness* for robots.

cameras suffer from the disadvantages of motion blur in presence of rapid motion of the robots and the perception quality can be degraded in presence of changing lighting conditions of the environment. Cameras providing other modalities of information, such as *Event cameras* like *Dynamic Vision Sensor (DVS)* [6], *DAVIS* [7] and *ATIS* [8], overcome these limitations by encoding pixel intensity changes rather than the capturing them at a fixed rate as in case of the *RGB* cameras, thus providing a very high dynamic range as well as no motion blur during rapid motions. However, since the provided information is asynchronous in nature i.e data will only be provided in case of particular events, to perceive entire information from the environment these sensors usually need to be combined with the traditional *RGB* based cameras [9].

Ranging sensors, such as small factor solid-state lidars or ultrasound sensors, are the second most dominant group of employed exteroceptive sensors. *1D lidars* and *ultrasound sensors* are used mainly in aerial robots to measure their flight altitude, but only measure limited information of their environments. *2D and 3D lidars* accurately perceive the information of the environment in 360° and the newer technological advancements have resulted in reduction of their size and weight, though challenge still remains in utilizing these sensors on-board small sized robotic platforms as well as the higher acquisition costs of these sensors.

A perfect sensor does not exist for robotic platforms and thus has motivated the use of multiple sensor modalities, essential to perceive complementary information of the situation (e.g. acceleration of the robot, visual light intensity of the environment), and to compensate for low performance in different

situations (e.g. dark rooms, light-transparent materials). Until now the choice of sensors and design of sensors for mobile robots depends on the robotic platform and the application rather than a use of common versatile and modular sensor suite for a precise perception of the elements in a given situation around the robot, to achieve situational awareness for mobile robotic systems to same extent as humans.

III. SITUATIONAL COMPREHENSION

The comprehension of the situation is by far the most challenging goal and, despite being deeply studied, it is still in its infancy [11]. Situational comprehension encompassing broad research areas could be sub-divided into two main components *A. Scene Understanding* and *B. Localization and Scene Modeling*.

A. Scene Understanding

Some research works focus on transforming the complex raw measurements provided by the sensors, into more tractable information with different levels of abstraction, i.e. feature extraction for an accurate scene understanding, without really building a complex long-term model of the situation. Scene understanding based on the sensor modalities can be divided into two main categories.

1) *Mono-Modal Scene Understanding*: These algorithms utilize single sensor source to extract useful information from the environment, with the two major sensor modalities used in robotics, *vision based sensors* and *range based sensors*.

Vision based scene understanding started with early works of Viola and Jones [12] presenting an object based detector



Fig. 3: Deep learning based computer vision algorithms for mono-modal scene understanding [10].

mainly for face detection using harr-like features along with Adaboost feature classification. Following works for visual detection and classification tasks such as [13], [14], [15], [16], [17] which utilized well known image features like *SIFT* [18], *SURF* [19], *HOG* [20], etc, along with *Support Vector Machines (SVMs)* [21] based classifiers. These methods focused to extract only a handful of useful information from environment such as pedestrians, cars, bicycles etc, and degraded in performance in presence of difficult lighting conditions and occlusions.

With the evolution of the deep learning era, recent algorithms utilizing *Convolutional Neural Networks* presented in the literature are not only capable of extracting the scene information robustly in presence of different lighting conditions and occlusions, but also able to classify the entire scene. In computer vision, different types of deep learning based methods exist based on the type of extracted scene information. Algorithms such as *Mask-RCNN* [22], *RetinaNet* [23], *TensorMask* [24], *TridentNet* [25], *Yolo* [26] perform detection and classification of several object instances, they either provide a bounding box around the object or perform a pixel wise segmentation for each object instances. Algorithms such as [27], [28], [29], [30], [31] perform semantic segmentation on the entire image space, being able to extract all relevant information from the scene. Whereas [32] and [33], perform panoptic segmentation over the entire image which not only classifies all the object categories but also sub-classifies each object category based on its specific instance.

To overcome the limitations of the visible spectrum in absence of light, thermal infrared sensors have been researched for scene understanding. Earlier methods such as [34] utilized thermal shape descriptors along with adaboost classifier to identify humans in night time images, whereas newer methods [35] and [36] utilize deep *CNNs* on thermal images for identifying different objects in the scene such as humans, bikes and cars. Though research in the field of event based cameras for scene understanding is not yet broad, some works such as [37] present an approach for dynamic object detection and tracking using the event streams, whereas [38] present an asynchronous *CNN* for detecting and classifying objects in realtime. *Ev-SegNet* [39] provide one of the first semantic segmentation pipeline based on event only information.

Range based scene understanding methods with earlier

works such as [40], [41] present object detection algorithm for range images from 3D lidar using an *SVM* for object classification, whereas authors in [42] utilize range information to identify terrain around the robot along with the objects and use *SVMs* to classify each category. Nowadays, deep learning is also playing a fundamental role in scene understanding using range information, with some techniques utilizing *CNN* classifications over range images whereas others apply *CNNs* directly on the point cloud information. Approaches such as *PointNet* [43], *PointNet++* [44], *TangentConvolutions* [45], *DOPS* [46], *RandLA-Net* [47], perform convolutions directly over the 3D pointcloud data in order to semantically label the pointcloud measurements. *Rangenet++* [48], [49], *SqueezeSeg* [50], *SqueezeSegv2* [51] project the 3D pointcloud information onto 2D range based images for performing the scene understanding tasks. These methods exploit the fact that the traditional *CNN* based algorithms can be directly applied to the range images without utilizing customized convolution operators on 3D point cloud data.

All the above mentioned mono-modal scene understanding methods irrespective of their modality have an inherent limitation of sensor failures and are often required to be complemented with other sensor modalities for improved performance.

2) *Multi-Modal Scene Understanding*: Fusion of multiple sensors for scene understanding allows the algorithms to increase their accuracy by observing and characterizing the same environment quantity but with different sensor modalities [52]. Algorithms combining *RGB* and depth information have been widely researched due to the easy availability of the sensors publishing *RBGD* information. Gonzalez et al. [53] study and present the improvement of fusion of multiple sensor modalities (*RGB* and depth images), multiple image cues as well as multiple image viewpoints for object detection. Whereas authors in [54] combine the 2D segmentation, 3D geometry and contextual information between the objects in order to classify scene and identify the objects inside it. *RBGD* information has also been widely used by algorithms classifying and estimating the pose of objects in a clutter using *CNNs*. These methods are mainly utilized for object manipulations using robotic manipulators which are placed on static platforms or on mobile robots. Several methods to this end exist, for example [55], *PoseCNN* [56], *DenseFusion*

[57], [58], [59].

Alldieck et al. [61] fuse *RGB* and thermal images from a video stream using a contextual information to access the quality of each image stream to accurately fuse the information from the two sensors. Whereas, methods such as *MFNet* [62], *RTFNet* [63], *PST900* [64], *FuseSeg* [65] combine the potential of *RGB* images along with thermal images using *CNN* architectures for semantic segmentation of outdoor scenes, providing accurate segmentation results even in presence of degraded lighting conditions. Authors of *ECFFNet* [66], perform the fusion of *RGB* and thermal images at feature level, which provides a complementary information effectively improving the object detection in different lighting conditions. Authors in [67] and [68] perform a fusion of *RGB*, depth and thermal camera computing descriptors in all the three image spaces and fusing them in a weighted average manner for efficient human detection.

Dubeau et al. [69] fuse the information from an *RGB* and depth sensor with an event based camera cascading the output of a deep NN based on event frames with the output from a deep NN for *RGBD* frames for robust pose tracking of high speed moving objects. *ISSAFE* [70] combine event based *CNN* with an *RGB* based *CNN* using an attention mechanism to perform semantic segmentation of a scene, utilizing the event based information to stabilize the semantic segmentation in presence of high speed object motions.

To improve the scene understanding using 3D point cloud data, methods have been presented which combine scene understanding information extracted over *RGB* images with their 3D point cloud data to accurately identify and localize the objects in the scene. *Frustum PointNets* [60] perform 2D detections over *RGB* images which are projected to a 3D viewing frustum from which the corresponding 3D points are obtained, to which a *PointNet* [43] is applied for object instance segmentation and an amodal bounding box regression is performed. Methods such as *AVOD* [71], [72] extract features from both *RGB* and 3D pointclouds projected to birds eye view and fuse them together to provide 3D bounding boxes for several object categories. *MV3D* [73] extract features from *RGB* images and 3D point cloud data from front view as well as birds eye view to fuse them together in ROI-pooling, predicting the bounding boxes as well as the object class. *PointFusion* [74] design a *RGB* and 3D point cloud fusion architecture which is not scene and object specific and can work with multiple sensors providing depth.

Scene understanding algorithms only provide the representation of the environment at a given time instant, and mostly discard the previous information not creating a long-term map of the environment, this extracted knowledge can thus be transferred to the subsequent layer of *localization and scene modeling*.

B. Localization and Scene Modeling

A greater challenge consists of building a long-term multi-abstraction model of the situation including the past information, as even small errors not taken into account at a particular time instant can cause the high divergence of the

state of the robot as well as the map estimate over time. To simplify the explanation, we divide this section into three subsections namely 1. *Localization only* 2. *Localization with Scene Modeling* 3. *Scene Modeling only*.

1) *Localization only*: Localization component is responsible for estimating the state of the robot directly using the sensor measurements from single/multiple sources and/or the inference provided by the *scene understanding* component (see Sect. III-A). While some localization algorithms only use sensor information in real-time for estimating the state of the robot, some algorithms localize the robot inside a pre-generated map of the environment. Early methods estimated the state of the robot based on filtering based sensor fusion techniques such as an *Extended Kalman Filter (EKF)*, *Unscented Kalman Filter (UKF)* and *Monte Carlo Localization (MCL)*. Methods such as [75], [76] use an *MCL* providing a probabilistic hypothesis of the state of the robot directly using the range measurements from a range sensor. Authors in [77] perform a *UKF* based fusion of several sensor measurements such as gyroscopes, accelerometers and wheel encoders to estimate the motion of the robot. Kong et al. [78] and Teslic et al. [79] perform *EKF* based fusion of odometry from robot wheel encoders and measurements from a pre-built map of line segments to estimate the robot state, whereas Chen et al. [80] use a pre-built map of corner features. Authors in [81] present both *EKF* and *MCL* based approach for estimating the pose of the robot using wheel odometry measurements and a sparse pre-built map of visual markers detected from an *RGBD* camera, while authors in [82] present a similar approach using ultrasound distance measurements with respect to a ultrasonic transmitters.

Earlier localization methods suffer from limitations due to simplified mathematical models subject to several assumptions. Newer methods, try to improve these limitations by providing mathematical improvements over the earlier methods and account for delayed measurements between different sensors, such as the *EKF* developed by Lynen et al. [83] and an *EKF* developed by Sanchez-Lopez et al. [84], which compensates for time delayed measurements in an iterative nature for quick convergence to the real state. Moore and Stouch in [85] present an *EKF/UKF* algorithm well known in the robotics community, which can take an arbitrary number of heterogeneous sensor measurements for estimation of the robot state. Authors in [86] use an improved version of kalman filter called the *error state kalman filter* which uses measurements from *RTK GPS*, *lidar* and *IMU* for robust state estimation. Liu et al. [87] present a *Multi-Innovation UKF (MI-UKF)*, which utilizes a history of innovations in the update stage to improve the accuracy of the state estimate, it fuses *IMU*, *encoder* and *GPS* data and estimates the slip error components of the robot.

Localization of robots using *Moving Horizon Estimation (MHE)* has also been studied in the literature where methods such as [88] fuse *wheel odometry* and *lidar* measurements using an *MHE* scheme to estimate the state of the robot claiming robustness over the outliers in the lidar measurements. Liu et al. in [89] and Dubois et al. in [90] study a *multi-rate MHE* sensor fusion algorithm to account for sensor measurements obtained at different sampling rates.

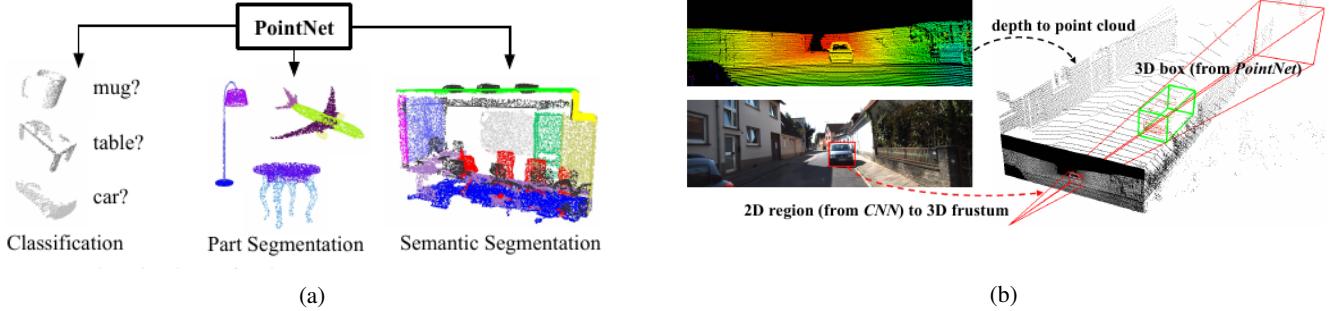


Fig. 4: Mono-modal and multi-modal scene understanding algorithms, (a) *PointNet* algorithm [43] using only lidar measurements (b) *Frustrum PointNets* algorithm [60] combining *RGB* and lidar measurements improving the accuracy of *PointNet*.

Osman et al. [91] present a generic *MHE* based sensor fusion framework for multiple sensors with different sampling rates, compensating for missed measurement, outlier rejection and satisfying real time requirements.

Recently, localization of mobile robots using *factor graph* based approaches has also been extensively studied as they have potential to provide higher accuracy due to the fact that factor graphs can encode either the entire previous state of the robot or upto a fixed amount a recent states (fixed-lag smoothing), capable of handling different sensor measurements in terms of non-linearities and varying frequencies in an optimal and intuitive manner (see Fig. 5). Ranganathan et al. [92] present one of the first graph based approaches using square root *fixed-lag smoother* [93], for fusing information from *odometry*, *visual* and *GPS* sensors, whereas Indelman et al. [94] present an improved fusion based on incremental smoothing approach *iSAM2* [95] fusing *IMU*, *GPS* and *stereo visual* measurements. Methods presented by Merfels et al. [96], [97] utilize sliding window factor graphs for estimating the state of the robot fusing several wheel odometry sources along with global pose sources. Mascaro et al. [98] also present a sliding window factor graph fusing *visual odometry* information, *IMU* and *GPS* information to estimate the drift between the local odometry frame with respect to the global frame, instead of directly estimating the robot state. Qin et al. in [99] present a generic factor graph based framework for fusing several sensors, where each sensor serves as a factor connected with the state of robot, easily adding them to the optimization problem. Li et al. [100] propose a graph based sensor fusion framework for fusing *Stereo Visual Inertial Navigation System (S-VINS)* with *multi-GNSS* data in a semi-tightly coupled manner, where the *S-VINS* output is fed as an initial input to the position estimate from the *GNSS* system in challenging *GNSS* deprived environments, thus improving the overall global pose estimate of the robot.

The *localization only* algorithms as seen in Fig. 5 do not simultaneously create a map of the environment limiting their environmental knowledge which has lead to the research of several *localization with scene modeling* algorithms described in the following subsection.

2) *Localization with Scene Modeling*: This section covers the approaches which not only localize the robot given the sensor measurements but also simultaneously estimate the

map of the environment i.e model the scene in which the robot navigates. These approaches are commonly known as *Simultaneous Localization and Mapping (SLAM)*, which is one of the widely researched topics in the robotics industry [11], as it enables a robot with capability of scene modeling without the requirement of prior maps and in applications where prior maps cannot be obtained easily. Vision and lidar sensors are the two main *exteroceptive* sensors used in *SLAM* for map modeling. As in case of *localization only* methods, *SLAM* can be performed using single sensor modality or using information from different sensor modalities and combining it with scene information extracted from the *scene understanding* component (Sect. III-A). *SLAM* algorithms have a subset of algorithms that do not maintain the entire map of the environment and do not perform stages of *loop closure* called as *odometry estimation algorithms*, where *Visual Odometry (VO)* becomes a subset of *Visual SLAM (VSLAM)* and *lidar odometry* a subset of *lidar SLAM*.

a) *SLAM using Filtering Techniques*: Earlier *SLAM* approaches like [101], [102], [103] utilized *EKFs* for estimating the robot pose simultaneously adding/updating the landmarks observed by the robots, but these methods were quickly discarded as their computational complexity increased with the number of landmarks and they did not efficiently handle non-linearities in the measurements [104]. *FastSLAM 1.0* and *FastSLAM 2.0* [105] were proposed as improvements to the *EKF-SLAM* which combined particle filters for calculating the trajectory of the robot with individual *EKFs* for landmark estimation. These techniques also suffered from the limitations of sample degeneracy when sampling the proposal distribution as well as the problems with particle depletion.

b) *SLAM using Factor Graphs: Modern SLAM* as described in [11], has moved to a more robust and intuitive representation of the state of the robot along with the sensor measurements as well as the environmental map to create factor graphs as presented in [108], [109], [110], [93], [95]. *Factor SLAM*, based on the type of map used for the environmental representation and optimization can be divided into the *Metric SLAM* and *Metric-Semantic SLAM*.

Metric SLAM: Metric map encodes the understanding of the scene at geometric level (e.g. lines, points, planes) which is utilized by a *SLAM* algorithm to model the environment.

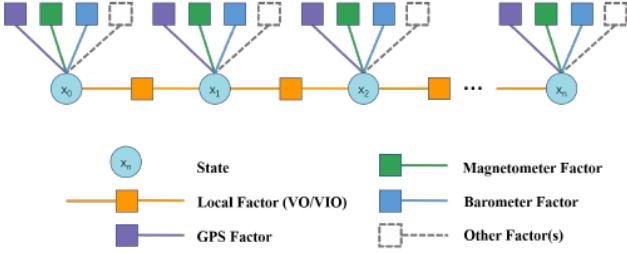


Fig. 5: Localization factor graph used for estimating the robot state fusing multiple sensor measurements [99].

Parallel Tracking and Mapping (PTAM) is one of the first feature based monocular algorithm which split the tracking of the camera in one thread and the mapping of the keypoints in another, performing batch optimization for optimizing both the camera trajectory and the mapped 3D points. Similar extensions to the *PTAM* framework are *ORB-SLAM* [111], *REMODE* [112] creating a semi-dense 3D geometric map of the environment while estimating the camera trajectory. As an alternative to feature based methods, direct methods use the entire image intensity values instead of image features to track the camera trajectory even in feature-less environments such as semi-dense direct *VO* called *DSO* [113] and *LDSO* [114] improving the *DSO* by adding loop closure into the optimization pipeline, whereas *LSD-SLAM* [115], *DPPTAM* [116], *DSM* [117] perform a direct monocular *SLAM* tracking camera trajectory along with building a semi-dense model of the environment. Methods have also been presented which combine the advantages of both feature based and intensity based methods such as *SVO* [118] performing high speed semi-direct *VO* and *Loosely coupled Semi-Direct SLAM* [119] utilizing image intensity values for optimizing the local structure and image features for optimizing the keyframe poses. *MagicVO* [120] and *DeepVO* [121] study end-to-end pipelines of monocular *VO* not requiring complex formulations and calculation for several stages such as feature extraction, matching etc, keeping the *VO* implementation concise and intuitive. All these presented monocular methods suffer from a major limitation of not being able to estimate the true metric scale of the environment as well as not being able to accurately track presence of pure/high speed rotational motions of the robot.

To overcome these limitations, monocular cameras are combined with other sensors, with works on monocular *visual-inertial odometry (VIO)*, using a monocular camera synchronized with an *IMU*, such as *OKVIS* [122], *SVO-Multi* [123], *VINS-mono* [124], *SVO+GTSAM* [125], *VI-DSO* [126], *BASALT* [127]. Delmerico et al. in [128] have benchmarked all the open-source *VIO* algorithms to compare their performance on computationally demanding embedded systems. Methods such as *VINS-fusion* [129], *ORB-SLAM2* [106] (see Fig. 6a) provide a complete framework capable of performing either *monocular*, *stereo* and *RGBD odometry/SLAM* or fusing these sensors with *IMU* data improving the overall tracking accuracy of the algorithms. *ORB-SLAM3* [130] presents improvement over *ORB-SLAM2* performing even multi-map *SLAM* using

different visual sensors along with an *IMU*.

Methods have been presented which perform thermal inertial odometry for performing autonomous missions using robots in visually challenging environments such as [131], [132], [133], [134]. Authors in *TI-SLAM* [135], not only perform thermal inertial odometry but also provide complete *SLAM* backend with thermal descriptors for loop closure detections. Muegler et al. [136] present the a continuous-time integration of event cameras with *IMU* measurements, improving by almost a factor of four the accuracy over event only *EVO* [137]. *Ultimate SLAM* [138] combines *RGB* cameras with event cameras along with *IMU* information to provide a robust *SLAM* system in high speed camera motions.

Lidar odometry and SLAM for creating metric maps has been widely researched in robotics to create metric maps of the environment such as *Cartographer* [139], *Hector-SLAM* [140] performing a complete *SLAM* using 2D lidar measurements and *LOAM* [141] providing a *parallel lidar odometry and mapping* technique to simultaneously compute the lidar velocity while creating accurate 3D maps of the environment. To further improve the accuracy, techniques have been presented which combine *vision* and *lidar* measurement as in *Lidar-Monocular Visual Odometry (LIMO)* [142], *LVI-SLAM* [143] combining robust monocular image tracking with precise depth estimates from lidar measurements for motion estimation. Methods like *LIRO* [144], *VIRAL-SLAM* [145], couple additional measurements like *Ultra Wide Band (UWB)* with visual and *IMU* sensors for robust pose estimation and map building. Methods like *HDL-SLAM* [146], *LIO-SLAM* [147] tightly couple along with *IMU*, *Lidar* and *GPS* measurements, for globally consistent maps.

While great progress has been demonstrated using *metric SLAM* techniques, one of the major limitations of these methods is the lack of information extracted from the metric representation such as, (1) *No semantic knowledge of the environment*, (2) *Inefficiency in identifying static and moving objects*, and (3) *Inefficiency in distinguishing different object instances*.

Metric-Semantic SLAM: As explained in the Section. III-A, the advancements in *scene understanding* techniques have enabled a higher-level understanding of the environments around the robot, leading to the evolution of *metric-semantic SLAM* overcoming the limitations of traditional *metric SLAM* enabling the robot with the capabilities of human-level reasoning. Several approaches to address these solutions have been explored.

Object-based Metric-Semantic SLAM build a map of the instances of the different detected object classes on the given input measurements. The pioneer works *SLAM++* [148], [149] create a graph using camera pose measurements and the objects detected from previously stored database to jointly optimize the camera and the object poses. Following these methods, many object-based *metric-semantic SLAM* techniques have been presented such as [150], [151], [152], [153], [154], [155], [156], [157] not requiring a previously stored database and jointly optimizing over camera poses, 3D geometric landmarks as well as the semantic object landmarks.

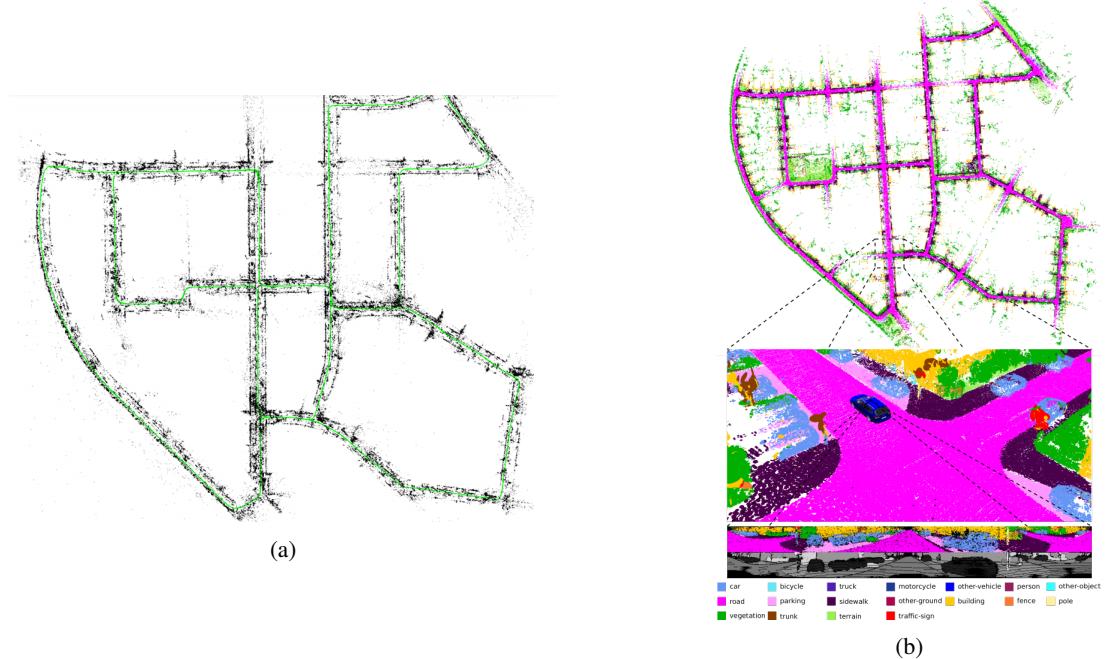


Fig. 6: (a) 3D feature map of the environment created using *ORB-SLAM2* [106] (b) The same environment represented with a 3D semantic map using *SUMA++* [107] providing a richer information to better understand the environment around the robot.

SA-LOAM [158] utilize semantically segmented 3D lidar measurements for generating a semantic graph for robust loop closures. The main sources of inaccuracies of these techniques are due to extreme dependence on the existence of objects, as well as (1) *uncertainty in object detection*, (2) *partial views of the objects which are still not handled efficiently* (3) *no consideration of topological relationship between the objects*. Moreover, most of the previously presented approaches are unable to handle dynamic objects. Research works on adding dynamic objects to the graph such as *VDO-SLAM* [159], *RDMO-SLAM* [160] reduce the influence of the dynamic objects on the optimized graph. Nevertheless, they are still unable to handle complex dynamic environments, and only generate a sparse map without topological relationships between these dynamic elements.

SLAM with Metric-Semantic map augments the output metric map given by SLAM algorithms with semantic information provided by *scene understanding* algorithms, as [162], *SemanticFusion* [163], *Kimera* [164], *Voxblox++* [165]. These methods assume a static environment around the robot, thus the quality of the *metric-semantic map* of the environment can degrade in presence of common moving objects in the environment. Another limitation of these methods is that they do not utilize useful semantic information from the environment to improve the estimation of the pose of the robot as well as the map quality.

SLAM with semantics to filter dynamic objects utilize the available semantic information of the input images provided by the *scene understanding* module, only to filter bad-conditioned objects (i.e. moving objects) from images given to the SLAM algorithms, as [166] for image based, or *SUMA++* [107] (see Fig. 6b) for lidar based. Although these methods increase the accuracy of the *SLAM* system by filtering moving objects,

they neglect the rest of the semantic information from the environment to improve the estimation of the pose of the robot as well as the map quality.

3) *Scene Modeling only*: This section covers the recent works which focus only on complex high-level representation of the environment. Most of these methods assume the *SLAM* problem to be solved and focus only on the scene representation. An ideal environmental representation must be efficient with respect to the amount of resources required, capable of providing plausible estimation of regions not directly observed, and flexible enough to perform reasonably well in new environments without any major adaptations. The utilization of *SDF-based models* in robotics is not new. It has been demonstrated in works such as [167] and [168], which propose a framework for creating globally consistent volumetric maps that is lightweight enough to run on computationally constrained platforms, and demonstrate that the resulting representation can be used for localization. These approaches represent the environment as a collection of overlapping *SDF* submaps, and maintain global consistency by aligning this submap collection. A major limitation of *SDF*, however, is that they can only represent watertight surfaces, i.e., surfaces that divide the space into inside and outside [169]. *Implicit Neural Representations (INR)* (sometimes also referred to as coordinate-based representations) are a novel way to parameterize signals of all kinds, even environments parameterized as 3D points clouds, voxels or meshes. With this in mind, *Scene Representation Networks (SRNs)* [170] are proposed as a continuous scene representation that encode both geometry and appearance, and can be trained without any 3D supervision. It is shown that *SRNs* generalizes well across scenes, can learn geometry and appearance priors, and are useful for novel view synthesis, few-shot reconstruction,

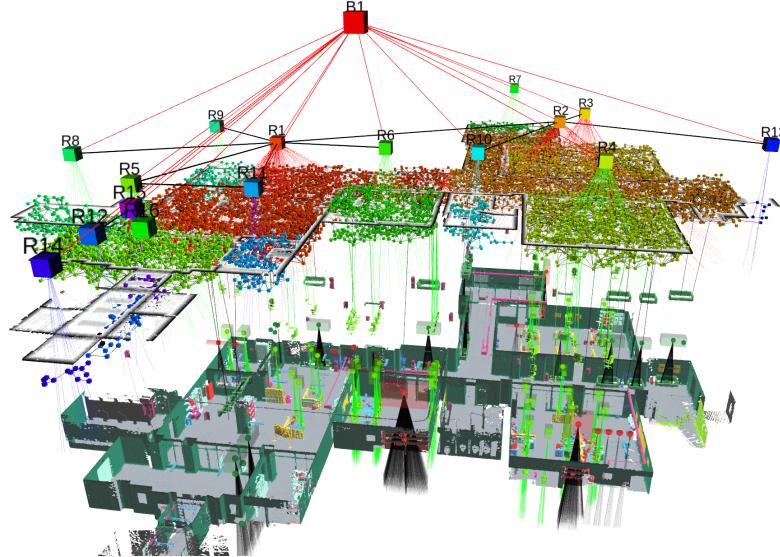


Fig. 7: *Dynamic Scene Graph (DSG)* [161] generating multi-layer abstraction of the environment.

joint shape and appearance interpolation, and unsupervised discovery of a non-rigid models. Similarly, [171], [172] focus on improving the rendering efficiency of *NRF* that are not based on *SDFs* targeting real-time rendering of 3D shapes. In [173], a new approach is presented which is capable of modeling signals with fine details, and accurately capturing not only the signal, but also its spatial and temporal derivatives. This approach, which is based on the utilization of periodic activation functions, demonstrates that the resulting neural networks, referred to as *sinusoidal representation networks (SIRENs)*, are well suited for representing complex signals, including 3D scenes. Although *INR* has shown promising results in terms of scene representations the presented methods are still at very early stages to be able to model entire 3D scenes which could be eventually used not only for planning but also improving the pose uncertainty of the robots. Though research works [174] have already started in this direction, where *INR* is utilized in the *SLAM* tracking pipeline, research is still required for this methods to produce plausible accuracy compared to the current *SLAM* techniques in the literature.

Similarly, *scene graphs* have also been researched to represent a scene, such as [175] and [176], which build a model of the environment, including not only metric and semantic information but also basic topological relationships between the objects of the environment. They are capable of constructing an environmental graph spanning an entire building including the semantics on objects (class, material, shape), rooms, etc. as well as the topological relationships between these entities. However, these methods are executed offline and require a known 3D mesh of the building with the registered *RGB* images to generate the *3D scene graphs*. Consequently, they can only work in static environments. *Dynamic scene graphs (DSG)* (Fig. 7) are an extension of the aforementioned *scene graphs* to include dynamic elements (e.g. humans) of the environment. Rosinol et al. [161] present a cutting-edge algorithm to autonomously build a *DSG* using the *Kimera VIO* [164]. Although these results are promising, their

main drawback is that the *DSG* is build offline, the *VIO* first builds a 3D mesh based semantic map that is then fed to the dynamic scene generator. Consequently, the *SLAM* does not take advantage of these topological relationships to improve its accuracy. Besides, except for the humans, the rest of the topological relationships are considered purely static (e.g. the chairs will never move).

IV. SITUATIONAL PROJECTION

In robotics, the projection of the situation is essential for reasoning and execution, e.g. our work [177]. It has mostly focused on the prediction of the future state of the robot by using a dynamic model, e.g. our work [84]; while most of the works assume a static time-invariant environment (see Sect. 1.2.2). Some recent works, such as our work [157], or [161], [178] have incorporated dynamic models on some elements of the environment, such as persons or vehicles, putting, at to a certain extent, some attention to the uncertainty of the motion. Nevertheless, it is clear that the projection of the situation has been greatly omitted and remains an open challenge, with multiple open research questions, e.g. the projection of movable objects with topological relationships.

V. DISCUSSIONS

In the previously presented sections we perform a thorough review of the state-of-the-art techniques presented by the scientific community to improve the overall intelligence of autonomous robotic systems. It can be seen that the presented approaches until now have mostly followed a bottom up approach i.e., based on the available sensors solve the accuracy of the algorithms, rather than a top down approach i.e., based on a given situation find the accurate algorithmic solutions. Importing the knowledge from the psychology to robotics, we have propose a situational awareness pipeline for autonomous mobile robotic systems, which could be easily sub-divided into three main sections of perception, comprehension and

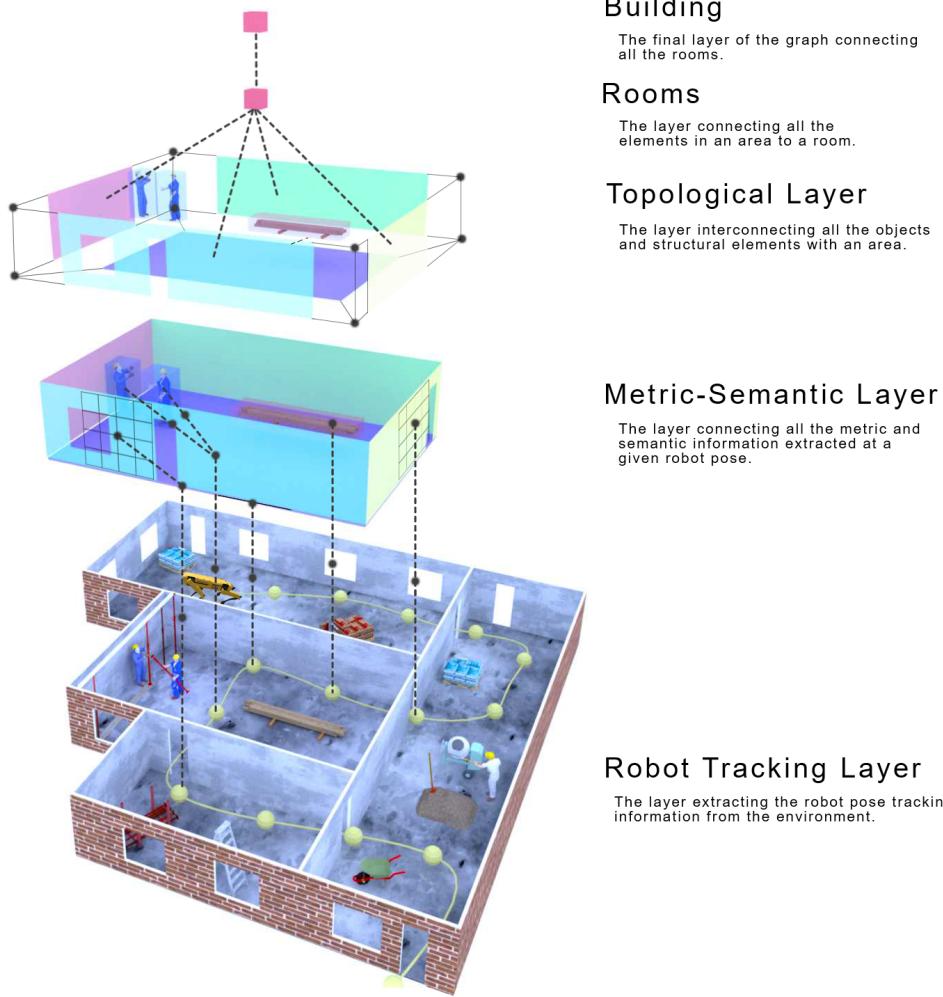


Fig. 8: Proposed *Situational Scene Graph (SSG)*. The graph is divided into three sub-layers namely, the tracking layer which tracks the sensor measurements as it creates a local keyframe map containing its respective sensor measurements. The metric-semantic layer which creates a metric-semantic map using the local keyframes. The topological layer consisting of the topological connections between the different elements in a given area. And finally the rooms layers which connect at a higher level the elements within a room along with the building layer connecting all the rooms.

the projection. Based on our survey we address the research questions posed earlier:

(1) *Do mobile robots understand and reason the situation around them the similar manner as humans?* Through the provided literature review we show that all the current approaches perfectly fit in each of the given sub-category and after analysis, we find that there still exists a gap to be filled between the presented approaches to provide a complete situational awareness for robotic systems in order for the robots to understand and reason the similar manner as human beings. To this end we propose a complete Situational Awareness framework for robotic systems, which as per our mentioned conventions would be divided into 3 sub-sections, mainly 1. *Perception layer* which would consist of a multi-modal, scalable and modular sensor suite for accurately perceiving the environment, 2. *Comprehension layer* represented in the form of a *Situational Scene Graph (SSG)* (Fig. 8) which as an extension to the *DSG* [161] would tightly couple methods

from *scene understanding, localization, scene modeling*, to not only improve the robot pose uncertainty in the environment but also to represent the scene in a robust and human interpretable manner. And finally 3. *Projection layer* which would utilize the SSG to build on-top additional environmental models for their projection in the future utilized by the reasoning and decision making algorithms of the mobile robot.

(2) *How far are we from achieving completely autonomous mobile robots with superior intelligence as humans?* The literature review depicts the advancements in AI playing a significant role in improving the overall understanding of situation for the robot but work still needs to be done to create a standard modular and versatile sensor suite for the mobile robots for robust working of the *scene understanding* algorithms irrespective of the situational challenges, as well as integrating these algorithms efficiently in the scene modeling frameworks. Through the situational awareness perspective we believe the hardware as well as the different algorithmic

implementations could be tightly coupled together in the different layers of the situational awareness pipeline which can steer for faster achievement of superior mobile robots similar to humans.

VI. CONCLUSION

In this paper, we argue that situational awareness is a basic capability of humans that has been studied in several different fields but in robotics has barely been taken into account for robotic systems which has focused on ideas in a diversified manner such as sensing, perception, localization, mapping etc. To this end, we provide a thorough literature review of the state-of-the-art techniques for improving the robotic intelligence and re-organize them in a more structured and layered format of perception, comprehension and projection. We argue that after analyses of these algorithms a situational awareness perspective can steer for a faster achievement of robots with superior intelligence as humans. Thus, as an immediate line of future work, we propose a *Situational Awareness* framework consisting of the three layers namely; *perception*, *comprehension*, *projection*, and a *Situational Scene Graph* (Fig. 8) within its *comprehension* layer to better represent a scene as well as the robots uncertainty in it.

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