AGH University of Science and Technology
Computer Science Laboratory
Department of Automatics
Al. Mickiewicza 30
30-059 Kraków, POLAND

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Konrad Kułakowski
AGH University of Science and Technology
Department of Automatics
Kraków, POLAND
kkulak@agh.edu.pl

Abdel-Illah Mouaddib
Université de Caen Basse-Normandie,
BP 5186 Computer Science Department
14032 Caen Cedex, France
mouaddib@info.unicaen.fr

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Contact us at: `mszpyrka@agh.edu.pl`

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Konrad Kułakowski
AGH University of Science and Technology
Department of Automatics
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Abdel-Illah Mouaddib
Université de Caen Basse-Normandie,
BP 5186 Computer Science Department
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`mouaddib@info.unicaen.fr`

Abstract. In the recent years the role of artificial intelligence in robotics has become more and more important. Teams of contemporary robots are not only tools in hands of humans, but the tasks that are entrusted them frequently require high level of autonomy in the choice of optimal means, tools and methods. To achieve their goals, robots must understand the environment in which they operate. They must be situation aware. Unfortunately, the notion of situation awareness is usually defined in the context of humans not robots. Thus, in this paper the intuitive definition of situation awareness for possibly autonomous robots and robot teams is given. The extension of the discussion on situation awareness is a literature survey in the field of distributed robotics that gathers selected topics connected with situation awareness.

Keywords: situation awareness, probabilistic distributed robotics,

1 Introduction

1.1 Distributed robotics

Distributed robotics [33], sometimes referred to as collective robotics [53] or cooperative robotics [5] is dynamically growing, and a vast research branch deals with multi-robot systems. Such systems are interesting for several reasons [5, 53]:

- some problems might be solved more effectively using many robots working in parallel,
- systems based on many robots are more robust and fault tolerant,
- building several simple, universal robots might be cheaper than constructing a single, powerful robot solving one specific problem,
- the theory of multi-robot systems may take benefits from other scientific disciplines such as multi-agent systems [30], social sciences and live sciences, and therefore it may contribute to the development of many theories going beyond the generally understood idea of computer science.

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There are several definitions of a multi-robot system. For instance, Verret [53] defines a *multi-robot systems* as having the ability to cooperate, communicate and coordinate, as well as awareness (in the sense that one robot is aware of the others), whilst Cao et al. [5] give the prominence to the cooperative aspect of *multi-robot systems*. *Distributed robotics*, as discussed in [33], seems to be the most capacious notion, since it captures a wide range of *multi-robot systems* including e.g. *cellular robot systems* [14] and architectures for multi-robot cooperation like ACTRESS [32]. Thus, for the purposes of this paper, the notion *distributed robotics* has been adopted as a synonym for the generally understood *multi-robot systems* problem area.

In her work Parker [33] has identified several important problem areas concerning *distributed robotics*. The major ones are:

- Biologic models and their influence on multi-robot systems
- Multi-robot communication
- Architectures, Task Planning and Control
- Localisation, Mapping and Exploration
- Object Transport and Manipulation
- Motion Coordination

Some problems are natural extensions of the research into single-robot systems, however multi-robot systems also pose completely new challenges to researchers e.g. formation and marching problems or multi-robot communication [5]. Additionally, multi-robot localisation and map making seem to be very interesting. In this context, *probabilistic robotics* in particular seems to be very promising [51, 29]. The algorithms developed according to the probabilistic paradigm are able to handle uncertainty in the system, thus they are able to take into account the imperfection of the world.

1.2 Probabilistic robotics

In fact *probabilistic robotics* is now a separate fields of research that helps to manage different kinds of uncertainties that computer-controlled devices called robots may face during their work [50]. There are three main sources of uncertainty in robotics.

The first one is connected with the nature of sensors - the appliances that allow the robot to perceive the environment. Sensors are limited in their perception. Several factors such as range, resolution, sampling frequency and measurement method etc., may decide about the usefulness or uselessness of the given sensor (e.g. a camera may be useless in a completely dark room). Moreover, sensors measurements are usually subject to different kinds of noise. Thus, the information about the environment comes to the robot with some error which has to be taken into account by algorithms using the measured values.

Another source of uncertainty is introduced by the robots' actuators. The result of an action performed by the robot may be far from ideal, because of mechanism imprecision, such as unforeseen environmental conditions, move trajectory approximations etc.

The third important cause of uncertainty in robotics is the robot environment itself. When it is highly dynamic, complex and contains many objects, it is often also highly unpredictable. E.g. angry crowd or car racing.

Besides the three reasons of randomness mentioned above, the robots' software might also be the cause of uncertainty. The impreciseness of the internal world representation as well as approximation of calculations may also lead to the random robot behavior.

In this context, the situation awareness of robots seems to be very interesting. Decision making, planning, cooperation, move coordination and even successful communication between robots require appropriate situation judgement. To achieve that, the processing of signals from different

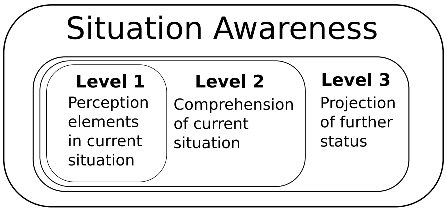

Figure 1: The three levels of situation awareness according to Endsley.

sensors placed on different robots, is indispensable. Due to the possibly high volume of data, their inhomogeneity and different noise characteristics of measurements coming from different data sources, the questions "how far can the robot may be situation aware?" is still waiting for a definitive answer.

1.3 Organisation of the paper

In the first section of this paper distributed and probabilistic robotics and map making are discussed. In particular, some intuition about situation awareness in the context of probabilistic robotics is given, and the notion of localisation awareness is introduced.

The second section is devoted to some aspects of situation awareness, whilst the third section contains brief review of various methods that might be considered as situation aware when focusing on multi-robot localisation and multi-robot mapping.

2 Situation awareness

Situation awareness is not a computer science or mathematical notion. Of course, it is not even a precise definition of existing phenomenon, however, despite these drawbacks in many situations people find it important and useful. The first time when the significance of situation awareness (SA) was explicitly identified was during World War I. At that time it was discovered that gaining awareness of the enemy, before the enemy gained similar awareness, and defined methods that allow such awareness to be gained are important [46]. Further research brings other applications of (SA). Woods [54] analyzes the psychology of human behavior in complex systems. There are some effort connected with decision making, including human like (naturalistic) approach [57, 22], as well as more formal approaches (e.g. using neural networks) [3]. The key concept behind the notion of SA relies on naming the difference between the actual state of the world and the state of the world as it is perceived by the operator [54]. When the gap between these two states is small, we may claim that the situation awareness of the operator is high. In spite of the fact, that the key idea is simple, defining the situation awareness is not simple. There are a lot of different definitions of situation awareness. Brenton and Rousseau [4] identified over 20 different SA definitions. Some of them give the prominence of SA as a state, whilst others exhibit the process nature of situation awareness [4, 2]. Some are very specific, and others try to be more general [4].

The most influential definition of SA comes from Endsley [11] and can be summarized 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 feature". In this approach, three levels of situation awareness are defined (Fig. 1).

The first, and the most basic level of SA focuses on perception of the environment, recognition of basic objects and simple information processing. The second level addresses the problem of comprehension of the current situation. It usually relies on grouping simple objects, signals and variables into more complex structures providing the operator (human/intelligent system) with deeper insight into the current situation. For example, combining information about flight time, distance and the available, fuel provides pilots of aircraft with crucial information about the flight. The third level of SA is connected with the ability to project the future of the elements in the environments. The correctness of predictions depends on results provided by two previous levels. In other words, situation awareness is rather a kind of high level description of how the system should process the information rather than a definition of the system state [4].

Besides the general Endsley's definition, situation awareness is frequently discussed in the context of group of individuals. Here, the two complementary definitions can be found: *Team SA* and *Shared SA*. The first notion (*Team SA*) is defined as "the degree to which every team member possesses the SA required for his or her responsibilities", whilst the second one (*Shared SA*) is given as "the degree to which team members possess the same SA on shared SA requirements" [10, 12]. Along the definitions of SA for team operations also an appropriate *Team SA Model* has been proposed. It consists of four elements such as:

- *Team SA Requirements* - information about which knowledge has to be shared among a team members,
- *Team SA Devices* - appliances for storing information,
- *Team SA Mechanisms* - information about the way in which different team members become "situation aware",
- *Team SA Processes* - information about engagement of different team members into sharing SA processes.

In practical applications it is convenient to use notion *Measurement of SA*. Due to the complex nature of situation awareness itself, defining its measurement is not an easy task. For this reason there is no one unique way to make a SA measurement. Instead, there are several techniques such as SAGAT *(Situation Awareness Global Assessment Technique)* or SART *(Situation Awareness Rating Technique)* [10]. Most of the metrics based on these and others techniques to SA estimation are specific to the problem domain e.g. SA assessment in air traffic may require to prepare a bunch of specific questions that have to be answered by air crew etc.

2.1 Situation awareness and robotics

The idea of SA came to robotics from human sciences, so it is not directly connected with robots. This may explain why situation awareness in robotics usually appears in the context of mixed man-machine teams and man-machine cooperation. The example of that kind of problem might be *Search and Rescue Robotics (SAR Robotics)* or *USAR Robotics (Urban Search and Rescue Robotics)* [31]. In general, a USAR problem involves localizing and helping victims of different kinds of disasters, such as building collapses, fires etc. Usually members of USAR teams are well-trained, professionally-skilled people. Unfortunately, sometimes the situation in the place of accident is too dangerous to send a human there. It creates a need to use robots, which might be sent in to the dangerous terrain in order to localize and help the victims. Usually robots used in USAR are completely controlled by human operators. Methods that help to increase the level of situation awareness among operators of robots are a very important part of research conducted into the USAR problems [6, 45, 18]. It has been proved by experiment that rescue teams with high situation awareness operators are 9 times more likely to find victims than rescue teams with low situation awareness operators [19]. Originally the term SA was defined for humans [9], however there is some effort to extend the definition of SA to non-human beings. The work [1] may serve as an example becasue Adams defines the situation awareness of an unmanned vehicle. Sometimes situation awareness is not explicitly defined. An example of work where SA is given implicitly is the CUSAS system (The Consolidated Undersea Situational Awareness System) [16].

2.2 Situation awareness in probabilistic robotics

Since situation awareness is usually defined in the context of humans, it may be asked whether it is reasonable or even possible to use the notion of SA for (possibly autonomous) robots. The literature sources describing SA phenomenon in the context of autonomous robots are very limited, and they do not seem to form one consistent theory. Thus, the authors of the report decided to briefly define SA in the light of probabilistic robotics, hence extend the notion of SA to a substantial set of autonomous robotic constructions.

The principal idea behind the probabilistic robotics relies on the observation that there is a difference between the actual state of the world and the state as it is perceived by the robot [50]. It is interesting, that a similar idea is at the heart of the model of situation awareness [54]. The main difference relies on the fact that probabilistic robotics does not use terms such as comprehension or understanding, which are inherently connected with the description of the human mind and states of its awareness. On the other hand, the first level of SA (according to Fig. 1) should provide "*perception elements of the environment*" [11], but this is exactly what probabilistic robotics does. From this observation arises the intuition that *probabilistic robotics* may serve (in the limited sense of course) as a source of formal models of *situation awareness*. That intuition creates the ground for considering some aspects of probabilistic robotics in the context of *situation awareness*.
Following that intuition, *the robot might be called situation aware if it is able to cope with the difference between the state of the actual world and the state of its internal world representation. The more adequate conclusions the robot is able to draw knowing that difference, the greater situation awareness it has*. The two previous sentences create in fact an intuitive definition of situation awareness for robotics purposes. This informal definition will accompany us through the rest of the paper.

2.3 Global situation awareness

The intuitive definition proposed in the previous section concerns one single possibly autonomous robot. Thus, there is a need to extend that definition for multi-robot systems. We would say that a multi-robot system has *global situation awareness* (GSA) if it is able to cope as a whole with the difference between the actual state of the real world and the state of the world as it is perceived by the robots. In that context every team member may have *local situation awareness*, understood in the same way as in the previous section.

3 Distributed robotics – localisation and mapping problem survey

The definition of GSA allows us to discuss SA in the context of distributed robotics. Of course, the question arises as to whether such systems that fit the GSA definition exist and if so, what are they? We claim that they really exist, however they probably have never been discussed in such a context. Hence, in this section the selected problems of distributed robotics, which fit the GSA definition, are briefly reviewed.

3.1 Distributed robotics and GSA

Among different benchmark problems in distributed robotics [5, 33, 53] there are two which seem to be the most explicitly exposed to the different kinds of sensor measurement errors. These are:

- multi-robot localisation
- multi-robot map construction

In the first case, multi-robot systems on the basis of the sensor measurements have to estimate the positions of all their members. The difference between the actual position and the estimated position determines the level of GSA of the system. In the case of the mapping problem, a team of robots has to create the map of its environment. The difference between the actual environment and the map representing the internal robot's projection of the environment concerns GSA. The better the map the robots team is able to create the more GSA it may have. Very often both problems of multi-robot localisation and multi-robot map construction have to be solved at the same time. Robots building a map have to know where they are. Such a problem is referred to in the literature as the SLAM (Simultaneous localisation and Mapping) or just mapping problem.

At first glance *the mapping problem* might not seem to be difficult. That is because a good architect or an experienced land surveyor is able to make a map of a given building or terrain with high precision relatively quickly. That is true, but they also know which landmarks are important, they are able to spot such landmarks quickly, they do not have a problem with localisation and even when they do the measurements with error, they probably realized the problem quickly. Why is it so? Probably because seasoned architects and land surveyors have high *situation awareness*. Much higher, of course, than the robots have, although we do not have a conceptual apparatus to compare the SA of human beings and robots.

For the moment, *the mapping problem* is difficult. Even if robot teams have some partial, initial, abstract map, they have to improve it by adding newly captured information. This involves finding an adequate common map representation, making reliable updates of such a map, determining spatial knowledge granularity and defining spatial knowledge processing as well as solving many other minor problems, such as inter-robots communication.

Thrun [49] points out five key problems of mapping in robotics. They are:

- measurement error accumulation – current measurement error affects the way future sensor measurements are interpreted.
- map complexity, dimensionality – entities that are mapped usually are described by many factors.
- correspondence problem – usually it is difficult to be sure that two different measurements separated in time concern the same physical phenomenon.
- dynamically changing environment – the problem is so hard, that the majority of solutions assume a static environment.
- exploration strategy – both localisation and mapping tasks are conducted during an environment exploration. So a well-defined, robust exploration strategy might be vital for the success of the whole system.

In fact all of them, maybe except *map complexity*, also affect *the localisation problem*. In the case of multi-robot systems the issue is even worse because the problems mentioned before become more complex and difficult, completely new problems arise. Some of these are:

- distributed or centralized – the person who constructs the multi-robot system has to define what functionality is inherent to every individual robot, and what has to be common for all the robots, and which system's element will be responsible for the common parts of the system.
- coordination and cooperation – solving this issue impacts exploration strategy, localisation accuracy and mapping quality etc.
- computation complexity and scalability – the question how the system will behave if the number of robots increases frequently remains unanswered.
- communication – since the system has to be prepared for at least temporary communication problems that may happen in apriori unknown environment, a well-designed communication scheme might be crucial for assumed goals to be completed by the system.

In response to the mapping problem several techniques have been developed. Thrun [49] enumerates the eight most important algorithms. These are:

- Kalman filtering,
- Lu/Milios method,
- EM (expectation maximization algorithm)
- Incremental maximal likelihood
- Hybrid
- Occupancy grid
- Multi-planar Maps
- Dogma

Some of them also have theirs multi-robot versions. There are several factors e.g. type of map representation, uncertainty representation and convergence etc., that characterize all of the mentioned techniques. Since this review is designed as a brief record of recent works in the topic rather than a comprehensive study of the *localisation* and *mapping problem* for further reference please use [49, 50, 51, 53, 35].

3.2 Multi-robot localisation

The localisation problem has been described in many places [30, 42, 47]. The goal in the case of single robot and multi-robot systems is similar. To figure out the position of itself with respect to the places of interest. In case of many robots operating within the confines of one system, the position of the whole system consists of the positions of single robots. Usually these robots are able to detect each other, thus, besides their individual position, their mutual location also has to be estimated. Of course the estimated location usually has some level of inaccuracy. Thus, very often the localisation problem and the methods that help to solve it are discussed in the context of probabilistic robotics and, as a result, fit our intuitive definition of (global) situation awareness.

An example of a probabilistic approach to multi-robot localisation is the work of Fox at al. [13]. In this work Fox proposes an efficient probabilistic approach to the multi-robot localisation problem based on Markov localisation [50]. Robot positions are represented as a set of samples, or *particles*, which is transformed into a density function using *density trees*. Performed experiments prove that multi-robot localisation, making use of robot detection gives better results (smaller errors) than single-robot localisation. Thus, following the introduced definition of situation awareness, thanks to cooperative work, a team of robots may achieve a higher level of SA than the robots operating separately. Authors also point out several questions that are left unanswered, e.g. false-positive detection of other robots, exploiting negative detection (i.e. not seeing another robot also might be informative) etc.

Another example of multi-robot localisation comes from Roumeliotis and Bekey [37]. In this approach, every time the robots meet each other they update their localisation data. Authors start their consideration from the remark that the simple combination of positioning information between two robots would not work. That is because after the first information exchange, the further behaviour of these robots is correlated, so this correlation has to be taken into account. This observation leads to the definition of appropriate cross-correlation terms used for constructing a *distributed Kalman filter* describing the whole of the system. Experimental results prove that using the proposed approach allows the reduction of covariance connected with the model, and therefore decreases the uncertainty of position and orientation estimates. More information about this approach as well as an extensive description of experiments can be found in [38]. Further results as regards the model proposed by

Roumeliotis might be found in [39, 40]. In their work [24] Mourikis and Roumeliotis introduce analytical expressions for the upper bound of the robot team's expected positioning uncertainty. This bound is determined as a function of covariance of sensor noise and the eigenvalues of RPMG *(Relative Position Measurement Graph)*. They prove that changes in the topology of RPMG does not impact on localisation performance.
The original work of Roumeliotis and Bekey [37] inspired other research. Parker et al. [34, 36, 21] proposed multi-robot localisation coming from the idea of Kalman filtering shown in [37] and based on EKF formalism.

In the case of a team of inhomogeneous robots various types of sensors are used by different robots, and as a result the captured data requires different processing time. This creates space for discussing optimal resource allocation in group of robots. This problem is studied by Mourikis and Roumeliotis in [27]. For a description of the system they used EKF *(Extended Kalman Filter)* formalism that leads to the well known non-linear *Riccatti differential equation* as regards the system covariance calculations.

In the context of multi-robot mapping, since measurements of the environment depend on the robots' poses, the problem of robots pose estimation might be interesting in itself. This problem is studied by Zhou and Roumeliotis in [55, 56]. They present efficient algorithms for solving the relative pose estimation problem. In their model they use a team of robots, where every robot is equipped with one odometric sensor for measuring its position and range sensor (e.g. sonar) to measure the distance to each other.

Probabilistic methods are also used for cooperative estimation of robots' state. Thorsten et al. [41] describe a state estimation module for a single robot cooperating with others. This module is responsible mainly for self-localisation of the robot and tracking the position of moving objects in the robot environment. They propose their own algorithms for localisation which in some aspects resembles Kalman filtering. Aside from odometric measures, robots use vision analysis from a camera subsystem.

An interesting concept (earlier than the works of e.g. Thrun and Roumeliotis works) comes from Kurazume and Nagata [20]. Their proposed approach relies on dividing the whole group of robots into two teams. When the first team is moving the second remains stationary and acts as a landmark. After a while the roles are changed. In their works, the authors provide variance and covariance estimation for positioning errors. Theoretical results are confirmed by simulation experiments.

There are also some non-probabilistic methods that try to solve the localisation problem. An example of this approach might be LOST (localisation-Space Trails) system [52]. The system is designed to allow a team of robots to navigate between points of interest using trails built of landmarks. Because the system does not use advanced probabilistic formalism, the trails computation might be fast and the whole system is claimed to be scalable. It also suffers from some limitations, of which the major one seems to be the fact that the absolute localisation accuracy is determined by the size and complexity environment not by LOST itself. It is worth remembering that, in the case of KF based algorithms, the accuracy grows in every subsequent step of computation, and does not depend on the environment.

3.3 Distributed Map construction

Distributed map construction is a topic closely related to multi-robot localisation. The crucial aspect for map construction is answering the question: *where have I been?*, whilst the localisation brings the answer to the question: *where am I?* [30]. It is impossible to create an accurate map if the robots do not know where they are, thus very often map construction is conducted together with localisation. In the literature the problem of simultaneous localisation and mapping is called SLAM. However, sometimes it is useful to assume that the position is known and to focus only on the map construction algorithm.

An example of early work focusing purely on the multi-robot mapping problem is the algorithm MAP proposed by Singh and Fujimura [44]. In this approach the move space is represented in the form of an occupancy grid map [8, 23]. The algorithm makes use of seven procedures described in the article. After every move a single robot computes a partial map update according to the algorithm, and sends the map update to other robots.

An interesting probabilistic mapping algorithm comes from Thrun [48]. The presented approach combines two techniques: the maximum likelihood map and Monte Carlo localizer with particle representation. The algorithm works for a single robot as well as for a group of robots. In the multi-robot approach every robot holds its own pose estimations, whilst the occupancy grid map is shared. Thanks to extending the algorithm for a multi-robots team, an almost the linear speedup in map construction could be achieved. I.e. using N robots compared with using a single robot shortens the mapping time N-times. Later on in the article a 3D-mapping technique for indoor environments is presented.

The map building in populated environments is considered by Haehnel et al. [15]. In this approach the robot's environment is populated by people. Such moving obstacles introduce additional measurement errors, thus the system has to filter out these errors from the map. To do so, every person is detected and tracked with the help of SJPDAFs (Sample-based Joint Probabilistic Data Association Filters). Then the tracking data are combined with the mapping data and a consistent map is computing. Experimental results prove the method's effectiveness in 2D and 3D cases.

Coordination between different robots in their SLAM task is the subject of the work presented by Simmons et al. [43]. Every robot during exploration calculates the maximum likelihood estimate of its position (localisation), the maximum likelihood estimate of different objects in the environment (mapping) and the posterior density of its actual location. The one central mapper module combines maps coming from different robots into one central map. The exploration strategy for different robots might vary, and depends on the central mapper module. The exploration tasks are assigned to the robots following a simple greed algorithm maximizing the total expected utility. It has been proved in experiments that, in general, as the number of robots grows the mapping time of the whole system drops, however, there are some interesting exceptions to that rule. Namely, it has been observed that in the given obstacle free environment the mapping time for three cooperating robots is longer than for a two-robot team. One possible explanation is the increase in sensor noise level because of the increase number of robots.

An interesting example of the use of a manifold map representation in multi-robot mapping is given by Howard et al. [17]. The manifold is discretized by dividing it into a set of overlapping patches, each of which defines some local euclidian space. Over the set of patches a relation that gathers all the local coordinate systems into one global map is defined. The relation is not given explicitly, but it has to be gradually created by the cooperating robots. The authors defined an algorithm that allows partial manifolds from different robots to be merged. To find a set of projected poses a maximal likelihood estimation technique is used. Performed experiments prove the usefulness of the given representation. In their work, the authors also identify a few major drawbacks of their, approach such as poor scalability (in terms of size of team) and sensitivity to communication failures (because of centralized architecture).

The majority of multi-robot systems are designed for indoor environment mapping. One of the rare examples of the outdoor multi-robot mapping systems comes from Madhavan et al. [21]. In the presented system the authors use a distributed EKF localisation scheme. The terrain mapping algorithm relies on merging maps provided by each member of the robot team. The elevation gradient is determined by fusing differential GPS altitude information with inclinometer readings. During the experiments a two-robot team was used. Although the system is based on a decentralized computation scheme it is not clear how vulnerable it is to increases in the team size.

In the case of EKF based cooperative localisation and mapping there is a possibility to predict the quality of the process. The analytical upper bound for the positioning accuracy is given by Mourikis [25, 28, 26].

Besides probabilistic methods that are used for solving the localisation problem, some researches use non-probabilistic algorithms. One example is the landmark-based matching algorithm proposed by Dedeoglu and Sukhatme [7]. The presented algorithm assumes that every robot when creating its own partial map collects some landmarks. Thus it should be possible to build one global map upon the partial maps by pairwise matching landmarks coming from different robots.

4 Survey summary and open questions

The goal of this section is to discuss situation awareness in the context of distributed robotics, and review these multi-robotics research areas that may have something in common with SA. Of course, neither situation awareness nor distributed robotics have been entirely discussed, and many topics have been left untouched. First of all, it should be noticed that the situation awareness as defined in this paper may be a much more capacious notion than covered by the survey literature. That is because, in general, the environment as well as communication and interaction with it may vary between different systems. If we e.g. assume that in the environment of our robot there are other unknown robots, this forces us to take into consideration another, new source of uncertainty. Such systems can also be considered as situation aware, however, this time SA comes with a slightly different flavour than before. It is clear that there are many more examples of systems that fit the intuitive definition of SA.

Discussion about situation awareness in the context of robotics naturally concerns the probabilistic aspects of robotics. That is because in probabilistic robotics the difference between the state of the actual world and the world perception is extremely important. Every single measurement error may impact the next measurement estimates and calculations. Thus, for a dozen or so years, effort in probabilistic robotics has been put into creating such methods which allow the measurement errors to be handled, i.e. the methods that allow the robots' situation awareness to increase. Although much research into both fields; single-robot and multi-robots; has already been conducted, there are still some open issues that require further effort and research. In this context multi-robot systems in particular seem to be interesting since the single-robot systems and the general problems are discussed in many sources [49, 50].

For the purpose of this article two mainstream topics of probabilistic robotics have been selected. These are multi-robot localisation and multi-robot mapping. In recent years, several papers in these areas have been published [35, 36, 38, 39, 48], however, some questions seem to be still either left unclear or passed over.

For certain, one of those issues is solution scalability and computation efficiency. Many algorithms require advanced mathematical calculations that may have exponential complexity, so probably scaling the solution up to the higher number of robots might be hard. Unfortunately in a number of works that problem has not been well discussed. Many experiments have been led using relatively small teams of robots (2 - 3 robots), and it is not clear how the presented algorithms behave in case of a higher number of robots.

Other interesting question are also connected with the size of the robot team. For instance, none of the reviewed articles discuss the problem of the optimal number of robots depending on the kind of topology of the explored environment, kind of robot sensors etc. Some remarks regarding the problem with growing numbers of robots in obstacles free environment might be found in Simmons et al. [43]. The authors suggest that decreases in the speed of mapping can be caused by the mutual interference of sensors placed on different robots, however, there are no further studies on that topic.

In all the reviewed papers, wheeled robots have been examined. Obviously that is because wheels and, as a result, odometry measurements are important sources of information about the position and pose of robots. However, it is interesting whether it is possible to obtain similar position information with the help of legged robots. How could a team of legged robots cope with the measurements errors?

Almost all multi-robot systems available in the literature assume that the environment is static, structured and of limited size. localisation and mapping in dynamic, unstructured and large environments still seem to pose a challenge for researchers.

Thrun, in his review [49], points out the problem of the difference between the vast amount of knowledge about the environments possessed by humans and relatively the little knowledge about the same environment possessed by robots. Thus humans much better understand the environment than the robots and, consequently, humans are much more situation aware. For this reason we believe that working on increasing the situation awareness of robots might bring measurable benefits. Moreover, working on SA may open probabilistic robotics to new application areas, especially those connected with man-robot cooperation like e.g. the lifelong existence of robots with humans at theirs homes.

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