Swarm challenges under onboard sensors limitations

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Abstract Localization is an important task in swarm robotics framework. This paper overviews swarm control and localization approaches, concentrating on localization methods under restrictions that are imposed by using inexpensive onboard sensors with the emphasis on swarm formation control applications in urban search and rescue and environment exploration tasks. The goal of the paper is to aid researchers selecting appropriate sensors for these tasks.

1 Introduction

For many years, robotics focused on single-robot strategies to achieve required objectives, while robots were becoming more and more intelligent and reliable. Nowadays, with algorithm development, sensory perception limits are elegantly overcome using different sensory data synergy and sophisticated mathematical data processing methods. Biologically inspired approaches in robotics consider examples of ant and bee colonies, flocking birds and schooling fishes as life evidences of effective multi-agent systems. Moreover, single distinct agents in such systems are not capable of performing any essential tasks alone and only their collaborative behavior guarantees a successful survival of a colony. Under the conditions of highly limited individual agent intelligence, these systems show very high performance, scalability and flexibility as a team. In order to transfer these qualities from the nature to artificial robotic systems, swarm robotics studies intensity grew exponentially in the past decades.

Swarm robotics is a field of research which studies multi-robot systems. Such systems are designed to perform collaborative tasks using multiple agents and communications between them in order to increase overall system efficiency. It is important to note that collective behavior appears in distributed manner, without a centralized control. Robotic swarms are a flexible tool to perform wide range of tasks, including collective exploration [1], flocking [2], foraging [3], hunting [4], collaborative manipulation [5] and relocation [6], and others.

For a long time, mathematical simulations were a major way of swarm algorithms verification and validation. This trend is changing because of computation power increase and flexible programming frameworks appearance. For example, Robot Operating System (ROS) framework bundled with Gazebo simulator gives opportunities to test new methods and algorithms considering most real-world conditions [7]. The ability to verify collective swarm behavior in a simulation is essential because of a high total equipment cost for multiple physical entities of robots. High quality simulations give a chance for swarm robotics to perform various areas of research without a direct purchase of an expensive hardware. Moreover, constant decrease of electronic components cost and size allows researches to construct and test various robot construction designs and algorithms in experiments, proving swarm robotic systems efficiency, effectiveness and usability. This paper pays a special attention to robotic equipment cost-efficiency.

2 Swarm robotics terminology

Swarm robotics started to attract attention of researchers when a single-robot robotics field was already flourishing. As the field is still establishing, even the basic terms of swarm robotics vary from one paper to another and this must be carefully considered by researchers. For example, groups of multiple robots are denoted in various recent studies as:

- Multi-Robot System or MRS [8–11]
- Multi-Agent System or MAS [12–18]
- Swarm Robotics System (Robotic Swarm) or SRS (RS) [1, 3, 4, 19–24]

These terms are often used as synonyms within a same paper [2,25], however, it is worth to note that, strictly speaking, MAS definition spans over non-robotic systems as well, for example, such as people crowds, schooling fishes and bird flocks. Therefore, the third definition, *swarm robotics system*, is used in this paper as more a popular and, in our opinion, a more precise expression.

Formation control is an important swarm robotics task that consists of reaching and keeping a desired robot position by every swarm member robot from its arbitrary initial position. Desired positions are often defined by a 1D, 2D or 3D geometric shape formation, although it is not the only way to create a formation. For instance, a shape may be determined on the fly by a particular obstacle boundaries shape. This task has several sub-tasks, however, there is no common sub-tasks classification: only formation producing and formation tracking sub-tasks are specified in [16], however, formation transformation and its kinds are pointed out additionally in [17]. Yet, we could roughly specify three main sub-tasks of formation control as follows:

- Formation producing, which requires the robots to create a particular desired shape [13, 19, 20, 26]
- Formation tracking, which is a formation shape preserving during locomotion of a swarm as a single structural group [4, 10, 12, 25, 27]
- Formation transformation, which is a controlled formation type or shape evolution in the process of locomotion [17]. In turn, it may take a form of:
  - Arbitrary transformation: a formation type evolution caused by an operator command [9]
  - Obstacle avoidance with a formation: an automatic formation type evolution that occurs in order to avoid swarm robot collisions with static or dynamic obstacles [2, 14]
  - Self-adaptation: a formation type automatically adapts to environment conditions [15]

3 Sensors for a swarm

A precise environment perception is essential for every robot, and different sensors may be employed to perceive different kind of data about robot and its surrounding, which is demanded in order to perform a particular task. These data could be used in further processing and decision making, allowing a robot to dynamically react on inner and outer conditions changes according to its program. Typically, these sensors are treated as an additional equipment mounted on a robot, and therefore it is important to consider sensor's properties before its use: its accuracy and error rate, power and computation needs, data transmission interfaces, its size and cost, etc. Every robot in a group or a swarm should be equipped with a single sensor or a set of sensors, thus, cost-effectiveness becomes crucial in the case of swarm robotics. GPS receivers and laser range finders, typically, are still relatively high-cost devices and their usage in robotic swarms is very limited.

Without attempting to form a complete list of all sensor types that are used in swarm robotics, we overview most popular and important of them in Table 1 and their strong features and potential pitfalls. The table includes cameras, GPS, radio frequency (RF), ultrasound and infrared beacons [10], optical and acoustic sensors [21], chemical sensors (particularly, alcohol sensors [29]) and others.

While for swarm robots low-cost sensors are preferable due to scalability with regard to the swarm size, a number of significant drawbacks should be emphasized. The first one is the lack of measurement accuracy (for infrared and ultrasound sensors) or data resolution (for visual sensors). This forces researchers to deal with imprecise sensory data and adapt their algorithms accordingly. For example, several measurements could be done sequentially to decrease average error value and statistical methods may be applied to reduce noise in the output data. The second drawback is that the manufacturers in order to reduce the total cost of a sensor may exclude some important yet secondary features, e.g., visual sensors may lack an auto-focus feature or RF sensors may lack noise suppression algorithms. The third is that low-cost components usage often increase sensor size, which is crucial for swarms of tiny robots that has rather tight size and power constraints.

Since we focus on perception in urban search and rescue (USAR) field [30], we concentrate on ultrasonic, infrared and visual sensors. In addition, several laser range finders (LRF) examples that were applied by USAR swarm researchers are mentioned - we noted that LRF use in USAR swarms increases due to their significant cost decrease in recent years. Table 2 presents an overview of major sensors that were used in particular robotic studies in recent years with their main properties and price[1] as well as references to the particular swarm robotics studies, which used the device as a part of a robotic system hardware. In order to distinguish surface mountable and out-of-the-box sensors, some sensors appear in the table with an appropriate controller (e.g., Raspberry Pi 3) that is required in order to process sensory data. We excluded GPS, light and acoustic sensors from this table because of their operating drawbacks in indoor environments, which are the target environments for a USAR swarm.

4 Forms of swarm control

One of the key properties of a robotic swarm is its control form. We intentionally avoid terms like "communication graph" [1] or "connected configuration" [11] because there are multiple examples when both sensory interactions and communication links between swarm robots create non–obvious topology, which is sometimes hard to distinguish and classify. For example, leader-following approach implementations may differ in the way of connectivity usage: it could be completely prohibited [12] or it could be preserved with no actual data transmission [15], although both methods clearly utilize leader-following strategy. Therefore, our approach extends swarm control forms classification that was proposed by Oh et.al. in their multi-agent formation control review [16]. Consensus-based topology [44] is also included into this classification due to its difference from other control forms, while its importance is shown in recent studies.

In **leader-follower** control scheme at least one of robots is defined as a leader, while all other robots act as its followers. The leader autonomously preserves its trajectory and the rest of robots follow the leader with some offset. This type of formation may have features like switching leadership [9], special functional followers [12], dynamically changing distance between robots [15] and other, depending on communication scheme between the robots [25, 45].

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[1] The prices were verified in on-line shops at the time we were writing this paper and were valid for March 2018.

Table 1: Sensors list with features that are important for swarm robotics

Sensor type	Features
GPS	Provide global positioning; not effective in indoor environments [12]
Laser range finders	Provide highly precise range data in a wide angle; no distinguishing between objects; decreased performance in outdoor environment due to weather conditions [2]
Visual sensors	Provide large amount of data that requires complicated processing; depend on light conditions [3, 10, 28]
Radio frequency sensors	Provide a wide bandwidth communication channel between robots; weak dependency on environment [20, 21]
Infrared sensors	Provide a narrow bandwidth communication channel between robots; provide distance measurements in close range; [14, 19, 24]
Acoustic sensors	Broadcasting waves [20]
Ultrasound sensors	Provide distance measurements in short and medium range distances; unable to distinguish among obstacle types [3]
Light sensors	Provide data about light intensity [3, 27]
Chemical sensors	Provide data about chemical substance density [29]

In **behavioral** control approach robots follow several predefined behaviors that include cohesion, inter-robot and obstacle collision avoidance [2–4, 10, 21, 27]. In **virtual structure** control scheme an entire swarm behaves as a single object with a particular desired motion. Motions of distinct robots are determined depending on the entire structure motion [46]. In **consensus** control scheme an agreement reaching between robots within a swarm is based on their states and collected data [1, 8, 11, 13, 19, 20, 24].

5 Challenges of localization task

Localization is one of the main tasks for mobile robotics along with mapping and path planning [47]. Localization must be performed as accurate as possible in order to perform locomotion and sensory data gathering in precise and predictive manner. Effectively performed localization of a robotic swarms helps avoiding inter-robot collisions and performing formation control task.

Localization methods could be divided into range-free and range-based localization [19]. **Range-free** class includes methods that do not use distance for localization. Positions are estimated based on the fact of connectivity existence or on indirect properties, e.g., Received Signal Strength (RSS), and are used without further converting them into distance values. This class also includes methods based on pheromones and others, which do not use sensory data to estimate ranges [1, 22, 27, 29].

On the opposite, **range-based** class consists of methods where range measurements serve as a base for further processing and position estimation. Range-based methods allow using a wide range of devices, which in turn dictate the limits of a desired accuracy. Distances could be computed using empirically obtained correlations between distances and sensory data (e.g., RSS values) or special techniques (e.g., time of arrival, TOF, or time difference of arrival, TDOA [21]).

Recent studies [14, 16] classify localization into three types depending on the robots' coordinate frames relations and measured variables (Table 3), and range-based methods play important role in all mentioned localization types, which are classified as follows:

- Position-based: robots get direct measurements of their position relative to a global coordinate system [3, 14, 26, 48]
- Displacement-based: robots actively control displacements of their neighbors relatively to their own local coordinate system. To make a formation, robots' local coordinate systems orientations must be aligned with each other [11, 24]
- Distance-based: desired formation is achieved by tracking inter-robot distances, therefore, local coordinate systems may be oriented in an arbitrary way [4, 8, 10, 12, 19–21, 25]

6 Towards swarm control in urban search and rescue

Urban search and rescue tasks are a forward-looking field of swarm robotics practical application. Natural and technological disasters often bring significant destructions and human rescue teams require broad assistance especially in the first few hours and days after a disaster occurs. Rapidly deployable communication structures, robust and efficient ways of path planning in ruins and urban debris, fast survivors search and buildings inspection are of a high demand in such situations. Thousands of cheap small-sized UAV and UGV robots could serve as a first wave of USAR operation rescue teams, providing detailed information about a

Table 2: Devices list used in robotics researches sorted by their type

Type	Device	Unit price (USD)	Measurement accuracy (cm) or provided resolution	Detection angle (deg)	Minimum detection range (cm)	Maximum detection range (cm)
Ultrasonic	SRF02 [31]	16,8	3	80	15	250
	MB1010 LV-MaxSonar-EZ1 [32]	30,00	3	60	12	390
	328ST160 + 328SR160 [33]	27,00	1	100	10	30
	LPC1768 (Cortex-M3)	60,00				
Infrared	TSKS-5400 + TEFT-4300 [34]	1,80	1	60	0	12
	ATMEGA168	4,00				
	Kingbright APA3010F3C-GX + Kingbright APECVA3010P3BT [35]	1,10	3	120	0	20
	Xmega128A3U	7,00				
	Sharp GP2Y0A02YK [34]	16,00	3	-	12	160
	TCRT1000 [36]	1,00	1	45	1	10
	LPC1768 (Cortex-M3)	60,00				
	782-VSMB1940X01 [19] + 782-TEMD7100X01	1,6	0,1	120	1	10
	556-ATMEGA328P-MU	3,00				
	GP2Y0A41SK0F [23]	10,55	1	-	4	30
	Raspberry Pi 3	35,00				
Visual	OptiTrack Flex 13	999,00	1280 x 1024	H: 56 V: 46	-	-
	OptiTrack OptiHub [37]	300,00				
	Microsoft Kinect [38]	100,10	640 x 480	H: 57 V: 43	40	400
	Microsoft Kinect 2 [39]	550,00	1280 x 960	H: 70 V: 60	50	400
	Asus Xtion PRO LIVE [39]	200,00	1280 x 1024	H: 58 V: 45	80	450
	Intel RealSense D400 Series	150 - 180	1280 x 720	H: 91 V: 66	10	1000
	Intel RealSense SR300 [40]	65,00	1920 x 1080	H: 68 V: 41	20	150
	ZED Stereo Camera [41]	450,00	4416x1242	H: 96 V: 54	50	2000
LRF	Neato XV-11 [42]	159,00	1	360	15	600
	Hokuyo URG-04LX [2]	1040,00	3	240	2	650
	RPLIDAR 360 Laser Scanner [43]	336,00	1	360	20	600

disaster site, people remaining under the ruins and locating zones that are still dangerous for rescue teams (e.g., due to nuclear or chemical pollution, fire or non-stable constructions). While the main task of a swarm within USAR tasks is focused on environment exploration and survivors search, the swarm could also perform various (light) cargo transportation tasks, communication systems replacement, first medical and psychological aid provision to discovered survivors.

In order to be applicable in uncertain GPS-denied environments of partially destroyed buildings robotic swarms require sophisticated methods of control and motion planning. Formation control in such conditions is a complicated task to perform: unpredictable environment, lack of long-range communication and tight time constraints influence swarm behavior. Formation control in such conditions should be considered as only a background task, while robotic swarm should concentrate on simultaneously performing data acquisition and transfer, mapping and path planning. Therefore, formation control algorithms must be highly flexible to adapt swarm behavior to rapidly changing external conditions.

7 Conclusions

Swarm robotics is a rapidly developing field of robotics and its development heavily relies on electronics progress. Robotic swarm agents need relatively small, precise and cost-effective sensory devices. Wide range of available equipment often is a trade-off between these characteristics, therefore, swarm robotics is still a challenging research field. New hardware constructions, continuously enhancing mathematical methods and swarm control topologies are designed to overcome difficulties.

Table 3: Distinctions among position, displacement, and distance-based formation control. *Source*: taken from [16].

	Position-based	Displacement-based	Distance-based
Sensed variables	Positions of agents	Relative positions of neighbors	Relative positions of neighbors
Controlled variables	Positions of agents	Relative positions of neighbors	Inter-agent distances
Coordinate systems	A global coordinate systems	Orientation aligned local coordinate systems	Local coordinate systems
Interaction topology	Usually not required	Connectedness or existence of a spanning tree	Rigidity or persistence

In this paper we briefly overview swarm control and localization approaches, concentrating on localization methods under restrictions that are imposed by using inexpensive on-board sensors. We review sensors that are broadly used in swarm robotics for indoor navigation and exploration while performing urban search and rescue tasks. The goal of the paper was to aid researchers selecting an appropriate set of sensors for these tasks.

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