

# Communication and Localization Networks in Swarm-Intelligent Systems

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**Abstract**—This paper discusses the role of communication and localization as enabling technologies of swarm-intelligent systems. In this work swarm-intelligence is understood as an evolving capability of decentralized, self-organized systems whose elements are collectively able to coordinate and synchronize their actions towards fulfilling a common goal. In order to share their observations of the environment, processing results or internal states, a swarm's elements form a dynamic communication network. Additionally, the swarm elements form a second network, consisting of measurements for determining their relative positions. The paper discusses the fundamental differences between these two networks and illustrates the applicability of the swarm-intelligence perspective in several application fields.

**Index Terms**—swarm intelligence, sensor networks, position determination, communications.

## I. INTRODUCTION

Swarm Intelligence is both a very old and a very new concept. Whereas animals such as birds, ants, fish, or honeybees have been realizing the concept of swarm intelligence successfully for eons, the concept has only recently started its career in engineering for solving challenging problems in the areas of aviation, space exploration and intelligent traffic systems. In the technical realm, swarm intelligence is an artificial intelligence technique based around the analysis and synthesis of collective behavior in decentralized, self-organized systems. Particular attractiveness of applying the concept to technology arises from its promise to result in adaptive, robust and cost-efficient systems.

In general, research on swarm-intelligent systems provides an insightful and generalizing perspective to other current research topics, such as grid computing or wireless sensor networks. From this perspective, many other systems can be seen as instances of swarm-intelligent systems that implement subsets of a full-fledged swarm-intelligent system's features.

In the following (section II) we will briefly point at the importance and some issues of communication for swarm-

intelligent systems. In section III we will discuss the determination of swarm elements' location. The underlying principles for distance measurements are described in III-A. These measurements are the essential input for forming localization networks which are illustrated in III-B. We will then outline the use of swarm-intelligent systems in some application areas (section IV) and conclude (section V) with our view on the current and future challenges and chances of swarm-intelligent systems.

## II. COMMUNICATION

Communication enables swarm elements to share measurement data or results of computations and to coordinate and synchronize their actions towards fulfilling a common goal. It is therefore an essential functionality of every swarm element that is supposed to contribute to the evolving decentralized intelligence. The properties of the application scenario, e.g. the spatial spread and mobility of swarm elements, the intensity of the information flow, or the power-constraints of the swarm elements determine the conditions under which their communication subsystems have to function. The specific application of a swarm-intelligent system and its processing strategies result in specific requirements pertaining to the physical layer, such as radio resource allocation e.g. of spectrum or power, channel coding and modulation schemes, and higher layers, such as multi-hop and ad-hoc routing, addressing, store-and-forward mechanisms, or pre-fetching.

Being closely related to sensor networks, the large body of work on sensor networks (see [1], [2]) can often be used as a basis for the communication problems in swarm-intelligent systems. In contrast to many "pure" sensor networks, a swarm can actively steer some of its elements towards positions where they enable a more efficient or balanced routing of communication.

Knowledge about the swarm elements' relative position is predicted to enable significant efficiency gains in the communication between these elements. Two aspects con-

tribute to these efficiency gains: Firstly, the determination and distribution of routing information between mobile swarm-elements can consume a significant amount of communication capacity when the network topology changes frequently. Depending on the number of swarm elements and their mobility this can consume the entire communication and/or computation capacity, thereby rendering communication impossible. Knowledge about the elements' positions can be used to limit the search space and the amount of routing information to be distributed among swarm elements.

Secondly, directive antennas in combination with knowledge about swarm elements' positions and attitudes can be used to steer the power of radio transmissions and receiving antennas, thereby reducing both interference and the necessary power at the transmitter.

### III. LOCATION DETERMINATION

Awareness of the swarm elements of their relative positions is essential for achieving swarm-intelligent behavior. In some applications additional knowledge about a swarm's absolute position is required.

Although there are different scenarios (e.g. in terms of spatial spread, mobility, available power or spectral bandwidth) and requirements (e.g. with respect to accuracy, timeliness) for location determination of swarm-intelligent systems, only few underlying principles span the space of technical solutions to this task. While applications often require positions estimations as accurate as usually achieved by surveying techniques, i.e. in the range of few centimeters or even less, we found that the problem is usually more difficult in swarm-intelligent systems. Firstly, a swarm's topology may change very dynamically; secondly, in contrast to equipment used in surveying, swarm elements are not capable of measuring angles in the scenarios we investigated (UAVs, rovers, underwater vehicles,...). Therefore, swarm elements have to determine their relative positions from deriving distances by time-of-flight measurements of radio and/or acoustic waves.

#### A. Measurement of Distances

An elementary problem in determining the relative positions of swarm elements is measuring the distance  $d$  between two swarm elements  $E_A$  and  $E_B$  (see Fig. 1).

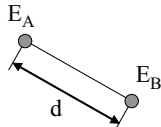


Fig. 1. Two nodes  $E_A$  and  $E_B$  are separated by a distance  $d$ .

Several protocols exist to cooperatively measure this distance. All are based on the transmission of signals with known velocity of propagation  $c$ .

The most straightforward Protocol A is illustrated in Fig. 2 and requires element  $E_A$  to transmit a signal at time  $t_1$ . The signal can either be time-stamped or the time can remain stored at  $E_A$ . When  $E_A$  receives the signal, it records the time  $t'_2 = t_2 + \Delta t_{A,B}$ , where  $\Delta t_{A,B}$  denotes the offset between the two clocks of  $E_A$  and  $E_B$ . If both clocks at  $E_A$  and  $E_B$  were perfectly synchronized, the clock offset  $\Delta t_{A,B}$  would be zero and the distance could be easily computed, since  $d = \tau_1 \cdot c$ , and  $\tau_1$  would be  $t'_2 - t_1$ . Unfortunately, the drift of quartz oscillators is a stochastic process and any offset  $\Delta t_{A,B}$  between the two clocks directly translates to an error  $e = \Delta t_{A,B} \cdot c$ . If electromagnetic waves are used, an error as small as 1 microsecond, would result in an error of almost 300 meters. However, Protocol A can be used when the clock offsets are treated as unknown variables that can be solved for in an overall solution for the relative positions and the clock offsets. Fig. 3 illustrates Protocol B, which does

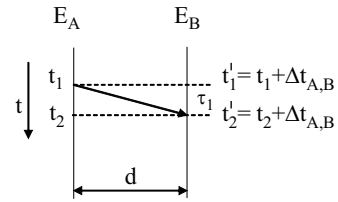


Fig. 2. The space-time diagram illustrates Protocol A: Element  $E_A$  transmits a signal at when its clock shows  $t_1$ . The signal is received by  $E_B$  after the duration  $\tau_1$  of the propagation. At this time  $E_B$ 's clock shows  $t'_2 = t_2 + \Delta t_{A,B}$ , where  $\Delta t_{A,B}$  denotes the offset between the two clocks of  $E_A$  and  $E_B$ .

not require any synchronization of clocks. Again a signal is transmitted by  $E_A$ . Upon reception of the signal  $E_B$  sends itself a signal to  $E_A$ . The total duration of the process can be timed with the clock at  $E_A$ . If the delay  $\tau_2$  at  $E_A$  is constant and known, we can compute the distance  $d = (t_2 - t_1 - \tau_2)/2 \cdot c$ . An elegant solution is

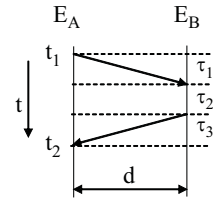


Fig. 3. Protocol B: Element  $E_A$  transmits a signal at time  $t_1$ . The signal is received by  $E_B$  after the duration  $\tau_1$  of the propagation. After a processing delay  $\tau_2$  element  $E_B$  sends back a signal to  $E_A$ . This signal is also subject to a propagation delay  $\tau_3$  and received by  $E_A$  at time  $t_2$ .

Protocol C, as illustrated in Fig. 4. Two signals  $s_1$  and  $s_2$  with velocities of propagation  $c_1$  and  $c_2$ , where  $c_1 \gg c_2$  are transmitted by  $E_A$ . In a well-known example, signal  $s_1$  is an electromagnetic wave and  $s_2$  is an acoustic wave [5]. Reception of the two signals happens at times  $t'_2$  and

$t'_3$ , respectively. Both times are measured by the clock of  $E_B$ , without any need for synchronization. Hence, we can compute the distance  $d = (t'_3 - t'_2)/(1/c_2 - 1/c_1)$  or use the approximation  $d = (t'_3 - t'_2) \cdot c_2$  if  $c_1 \gg c_2$ .

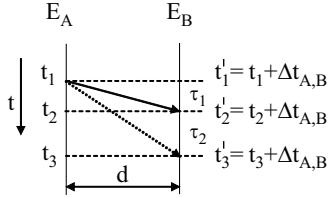


Fig. 4. Protocol C: When its clock shows  $t_1$ , element  $E_A$  transmits two signals  $s_1$  and  $s_2$  with velocities of propagation  $c_1$  and  $c_2$ , where  $c_1 \gg c_2$ .  $E_B$  receives signal  $s_1$  after propagation delay  $\tau_1$  when its clock shows  $t'_1$ . After an additional delay  $\tau_2$ ,  $E_B$  receives signal  $s_2$  when its clock shows  $t'_3$ .

### B. Localization Network

Let  $N$  denote the number of swarm elements and let  $D$  denote the dimensionality of the space in which the swarm elements are spread. Since we need  $D$  coordinates to describe the position of an individual swarm element, the total number of unknowns  $n_u$  scales linearly with  $N$ . Whenever no outer orientation of the overall swarm is required, we can choose an arbitrary swarm element as origin and set its coordinates to an arbitrary value (e.g. zero), thereby reducing the number of unknowns by  $D$ .

$$n_u = (N - 1) \cdot D \quad (1)$$

Under the assumption that all swarm elements are in range of each other, all  $N$  elements can measure distances to the  $N - 1$  other elements of the swarm. Hence, the maximum number of independent measurements scales quadratically with  $N$ . Under the assumption that only one independent measurement of the distance between each two elements is available (two measurements along the same line between two elements produce dependent errors)  $n_m$  independent measurements are available.

$$n_m = \frac{N \cdot (N - 1)}{2} \quad (2)$$

The minimum swarm size  $N_{\min}$  to solve for all coordinates of the swarm elements can be easily derived from equations 1 and 2. Since  $n_m \geq n_u$  is a necessary condition to solve for all unknowns,  $N_{\min} = 2 \cdot D$ . Accordingly, a swarm of size 4 would be capable of determining the relative positions of its elements in a two-dimensional scenario. An interesting mode of operation is to relocate a subset of a swarm's elements to new positions that are chosen by some random process (e.g. swarm elements carried by air or liquid flows and again docking to the ground after some time), while the remaining elements maintain their positions. If the number of unchanged coordinates plus the number of measurements to the relocated element is equal

to or exceeds the total number of coordinates, the positions of the relocated elements can be determined. In order to determine a spatial map of some physical quantity (e.g. the concentration of some chemical substance), repeated execution of this procedure leads to arbitrarily fine-grained spatial sampling of the quantity. Even without any external reference one can often derive useful information from such spatially sampled data (an analogy is a picture taken by a camera. Despite lacking measured data about the outer orientation of the camera, a picture often contains valuable information).

Most scenarios do not incorporate a fully meshed network of all swarm elements. Instead, the range of distance measurements is generally shorter than the overall extension of the swarm. Fig. 5 shows an example of a resulting graph.

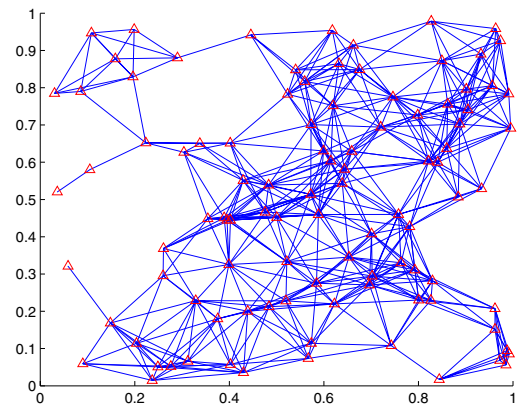


Fig. 5. A swarm of 100 elements with positions (red triangles) randomly drawn from a two-dimensional uniform distribution over a quadratic area  $[0..1] \times [0..1]$ . The graph's edges show that the two elements at the edges are in range of each other. The maximum range for this simulation has been set to 0.15.

While the resulting network would be sufficient to connect all swarm elements for communication purposes, it is not well suited for determining the relative position of all its elements, since the location of at least three elements (see far left, center) cannot be determined. In contrast, Fig. 6 shows the swarm elements at the same positions and the resulting graph if the range of the measurement is doubled. All elements are sufficiently connected and their relative positions can be determined. The ranges for communication and distance measuring are not necessarily identical. Accordingly, two graphs are typically necessary to describe a swarm's networks at any given time.

## IV. APPLICATION DOMAINS

In general, the concept of swarm intelligence provides fresh solutions to many scientific and engineering problems in which spatially extended phenomena or processes exist that are measured or influenced by sensors or actuators. Examples of such problems arise in airborne sensors (mini-UAVs), intelligent traffic systems (vehicles,

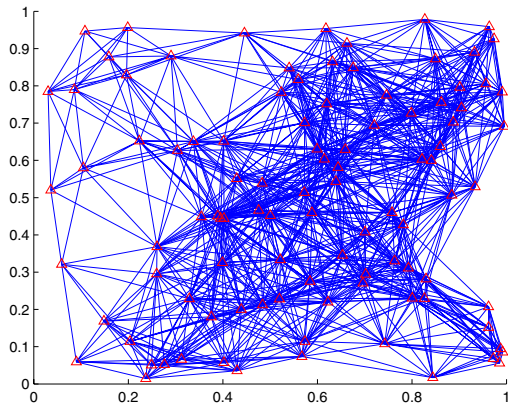


Fig. 6. A swarm of 100 elements with positions (red triangles) randomly drawn from a two-dimensional uniform distribution over a quadratic area  $[0..1] \times [0..1]$ . The graph's edges show that the two elements at the edges are in range of each other. The maximum range for this simulation has been set to 0.3.

humans), early warning systems for natural and man-made hazards (seismic sensors, buoys, drifters, satellites) or in exploration and prospecting for deposits of oil, gas or minerals (trucks/sensors for reflective seismology), where swarm elements may be in space, in the air, on land, at sea or even underwater. Most interestingly, the concept of swarm intelligence finds its application even in current considerations in future space missions to Moon and Mars (rovers, landers, gliders and orbiters).

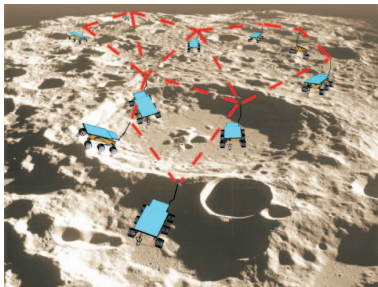


Fig. 7. Illustration of a swarm of rovers on Moon's surface.

Of particular immediate interest are colonies of intelligent robots on the Moon's surface. The specific research problems include approaches to the scientific exploration of the Moon's surface, knowledge/information sharing between/among robots, collaborative learning, fault diagnosis and repair (possibly autonomous repair), collaborative robot/astronaut activities and dynamic sensor-webs including formation and operation. Most of the applications involve complex problems such as dynamic re-grouping of a swarm's elements into subgroups to support dynamic distributed problem-solving and require advanced algorithms for data fusion and joint/decentralized intelligence. Among the relevant issues for understanding and solving these problems are formal

modelling of a swarm to support dynamic behavior analysis and emergent behavior prediction and/or analysis.

## V. CONCLUSION

Swarm elements typically act as both sensors and actors, are very mobile and interact in dynamically changing roles and relations to other swarm elements. To some extent this can be seen as distributed computing and grid computing paradigms applied to systems that interact with the physical world. While even for these domains the communication between hosts is sometimes a relevant bottleneck, communication capacity is likely to be a much scarcer resource in a swarm-intelligent system. We should therefore keep communication aspects in mind when developing (distributed) algorithms for swarm intelligence, since these algorithms may have crucial influence on the communication load. Whereas bad strategies may render a swarm's task unfeasible, due to congestion of its communication links, "good" strategies may significantly extend a swarm's lifetime by saving its energy resources. Complex swarm-intelligent behavior is fascinating to observe in nature, simulation or laboratory setups. It remains a challenging task to develop swarm-intelligent systems that will leave the lab and contribute to solving real-world problems or, at one day even go beyond earth, as far as to Moon or Mars.

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