Emergence of Communication Through Artificial Evolution in an Orientation Consensus Task in Swarm Robotics

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Abstract. The emergence of communication through evolutionary computation in a swarm of initially non-communicative robots is a highly complex research topic that has vastly captured the attention in the swarm robotics field. In this paper, we empirically study the emergence of communication as a result of an evolutionary algorithm in a swarm of simulated robots with the objective of solving an orientation consensus problem. Specifically, the consensus is reached provided that the heading orientations of the robots point into the same direction. The robots are controlled by Continuous-Time Recurrent Neural Networks whose parameters are evolved using a genetic algorithm. Once evolution is concluded, we assess the performance and scalability of the swarm behavior and the type of communication that emerged. The study is accomplished by means of an statistical analysis of the communication variables produced in a sample of 50 independent simulations. The conducted analysis suggests that the emerged communication is situated, meaning that both the message content and its associated context about the environment are informative and useful in the communication. Very interestingly, the environment context is the only piece of information actually relevant for reaching the consensus. On the contrary, the abstract message content is crucial for drastically reducing the rotation speed of the robots after the orientation consensus is achieved.

Keywords: Swarm Robotics · Orientation Consensus · Evolutionary Robotics · Emergence of Communication

1 Introduction

In Swarm Robotics (SR) [15], multiple simple and homogeneous robots interact and coordinate locally to solve cooperative problems. From the simple behaviors of each robot and their local and decentralized interactions can emerge utterly complex collective behaviors. A great exponent is the emergence of communication in a swarm of initially non-communicative agents. Generally, the emergence of communication in swarm robotics is explored along with the field of

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Evolutionary Robotics [11]. Multiple studies have investigated from an empirical perspective the emergence and origins of communication in swarm robotics using evolutionary algorithms (see e.g. [2,12,20]). According to [18], there are two main types of emergent communication. *Abstract Communication* [2,9,20] is a type of communication in which only the message content carries information. The environmental context associated to the message is either not processed or not relevant in the emerged communication. In contrast, *Situated Communication* [7,8,17] refers to communication scenarios in which both the message content and its corresponding environmental context carry information within the communication. Environmental context can be, for instance, the signal strength or the direction from where the message was received.

In this paper, we study the emergence of communication in simulated swarms of robots in an orientation consensus problem, in which all the robots in the swarm have to point to the same direction. The robot's controller is a Continuous-Time Recurrent Neural Network whose parameters are evolved using a genetic algorithm. We use the minimal IR-based communication system proposed in [17] as the communication system that the agents can use to complete the task. At the beginning of the evolution, the behavior of the robots is non-communicative. At some point in evolution, the semantics of the communication and their respective processing should emerge as a useful aspect of the robot's behavior for reaching the orientation consensus. An exhaustive post-evolution statistical analysis is accomplished using multiple independent simulations, with the aim of discovering the type of semantics that emerged as a result of the artificial evolution.

The structure of this document is as follows. Section 2 provides an overview of previous works available in the literature related to the orientation consensus task. Section 3 describes the main building blocks used in the experiment. Additionally, Sect. 4 presents the orientation consensus experiment and Sect. 5 shows the results and the emerged communication once evolution is ended. Finally, Sect. 6 concludes the paper.

2 Related Work

Orientation consensus is an important cooperative task as it is one of the pillars of flocking behaviors according to Reynolds' rules [14]. Therefore, the problem of heading alignment has been principally studied and assessed in the context of flocking experiments. Heading alignment is addressed in [21] for a self-organized flocking in swarms of mobile robots using a virtual heading sensor. Each robot senses its own orientation with respect to the North reference, using a digital compass, and broadcasts it to its neighborhood. In [5], the authors propose heading alignment behavior in which a only subset of robots, called informed, are aware of a common objective direction. Informed agents communicate the goal direction to its neighboring robots while uninformed agents relay the average incoming message from its vicinity. Robots correctly achieve alignment with their heading pointing to the goal direction. The swarm members know an absolute reference throughout measuring the light intensity emitted by a light source. In a more recent work, the authors of [13] successfully evolve neural controllers for flocking behaviors. Their fitness is composed by cohesion, separation and alignment terms. Focusing on alignment, robots have an alignment sensor that measures its orientation relative to the average orientation of its neighborhood. In [8], an evolutionary algorithm optimizes the parameters of a recurrent neural network. The emerged behavior was a situated communication because it did not harness the message information itself but the physical conditions of the communication. The orientation consensus is not only a highly relevant behavior in terrestrial swarms of robots but also in underwater environments (see e.g. [16, 19]), where the coordinated navigation must be precise and robust.

3 Materials and Methods

3.1 The Robots and the Communication System

In this paper, we solve the orientation consensus problem using a simulated swarm of static robots placed in a flat square arena. The set of robots is denoted as $\mathcal{R}$. As navigation is not required, robots are seen as static point particles, represented by a position $\mathbf{x}_r$ and a heading orientation θ_r. Even though robots cannot move, they are able to rotate along their center of mass in order to alter their heading orientation.

The robots can communicate and cooperate among them to solve the proposed task by using the communication system proposed in [17]. It is an IR-based minimal communication system with a local and constrained communication range of 80 cm. Using this system, the robots can only perceive a single message at each time step of the simulations from one of four possible discretized orientations. The received information not only comprises the abstract message content but also the relevant context information about the environment (e.g. the signal strength of the received signal or the orientation from where it was sensed). The robot's controller, which is fed by both the received message and its associated context, elaborates a new two-dimensional message to be broadcasted using the communication transmitter. Before sending the message, it is subject to a quantization mapping that converts the raw message into one symbol in the set $\mathcal{C}$ defined in Eq. 1.

$$\mathcal{C} = \left\{0, \frac{1}{K-1}, \ldots, \frac{K-2}{K-1}, 1\right\}^M \tag{1}$$

where M is the dimension of the transmitted message. In this paper, we fix the values of $M = 2$ and $K = 4$, leading to 16 possible two-dimensional symbols.

At the reception side, a message from another robot can be perceived from one of 4 possible IR receivers located at different orientations of the robot perimeter. Thus, the robot can know the relative orientation from where the message was received among the discretized values in the set $\{\theta_r, \theta_r + \pi/2, \theta_r + \pi, \theta_r + 3\pi/2\}$. The communication system of the robots can be either in *send mode*, transmitting their own created message, or in *relay mode*, by emitting a copy of the message received from other robots. This communication state can be controlled by the robot through the binary signal $MODE$. If this signal is 1 then the robots enters the *send mode*. Otherwise, the robot is in *relay mode* provided that $MODE$ is zero.

3.2 Continuous-Time Recurrent Neural Networks

We use a Continuous-Time Recurrent Neural Network (CTRNN) [1] as the model to control the robot actions. CTRNNs are artificial neural networks with feedback connections that operate in continuous time. The employed neuron model is the rate model [3] whose single neuron dynamics are defined in Eqs. 2 and 3.

$$\left.\begin{aligned} \tau_m \frac{\partial v_k(t)}{\partial t} &= -v_k(t) + I_k(t) \\ u_k(t) &= f_k\left(v_k(t) + \beta_k\right) \end{aligned}\right\} \tag{2}$$

Equation 2 depicts the single neuron's voltage ($v_k(t)$) and activation ($u_k(t)$) dynamics. β_k and $f_k(\cdot)$ are the neuron's bias and activation function, respectively. In addition, τ_m is the neurons time constant. $I_k(t)$ is the total current fed to the neuron's soma which is calculated as in Eq. 3,

$$I_k(t) = \sum_{i \in \mathcal{N}_k} w_{ki} u_i(t) + \sum_{j \in \mathcal{N}_k^{\phi}} w_{kj}^{\phi} \phi_j(t) \tag{3}$$

where w_{ki} is the weight of the synapse connecting pre-synaptic neuron i with post-synaptic neuron k and w_{kj}^{ϕ} denotes the weight of the synapse between the j-th input and neuron k. $\phi_j(t)$ is the j-th input signal being fed to the CTRNN and $\mathcal{N}_k$ and $\mathcal{N}_k^{\phi}$ are the sets respectively comprising the pre-synaptic neurons and pre-synaptic inputs to neuron k.

3.3 Genetic Algorithm

A Genetic Algorithm (GA) [6] is used to evolve the parameters of the CTRNN models that define the behavior of the agents. GA is a biologically inspired population based optimization algorithm that mimics how natural selection and survival of the fittest processes work in nature. A population of candidate solutions, namely individuals, genotypes or chromosomes, are updated with the aim of maximizing some performance score defined by a fitness function. Using the evaluated fitness value associated to each genotype, a set of genetic operators are sequentially applied to the overall population in order to generate the population of the next generation or iteration of the GA. In this paper, we use a Gaussian mutation operator that applies a Gaussian noise with a given standard deviation to the real-valued genes with a small probability of mutation. Additionally, the tournament selection [10] is used as the operator to choose which genotypes are used as parents to create the new generation. Finally, the BLX-α operator [4] is the crossover method.

4 The Experiment

4.1 Description of the Experiment

We address the problem of orientation consensus in swarms of robots. By orientation consensus we refer to the task in which all the robots in the swarm have to point to the same direction. Thereafter, the orientations of all robots $\theta_r(t)$ must converge to the same value for reaching the best performance. For this aim, the swarm of robots is static, so that the positions of the agents are fixed during the simulations. The robots can only modify their heading orientations by means of rotation movements, either clockwise or counterclockwise, at an angular speed modulated by their corresponding neural controller. Robots do not have access to any absolute sensing reference, such a light source or a compass, that would utterly ease the orientation consensus achievement. Agents must infer the orientation of their neighbors relative to its own orientation merely using the minimal communication system exposed in Sect. 3.1, which makes it a challenging experiment.

At the beginning of each simulation, the positions $\mathbf{x}_r$ are randomly sampled with a random spatial graph initialization that guarantees that there are no isolated nodes. Heading orientations are also randomly initialized. During evolution, every simulation is executed 600 time steps with swarms of 10 robots.

4.2 Fitness Function

The fitness function is composed by two terms that are merged in a multiplicative way. The fitness score of a single agent r at time step t is shown in Eq. 4.

$$f(t,r) = \left(1 - \frac{\min\{2\pi - |\theta_r(t) - \overline{\theta}(t)|, |\theta_r(t) - \overline{\theta}(t)|\}}{\pi}\right) \cdot (1 - |a_{wr}(t)|) \qquad (4)$$

where the first term measures the orientation deviation or misalignment of the robot with respect to the mean orientation of the swarm formulated in Eq. 5.

$$\overline{\theta}(t) = \arg\left(\sum_{r \in \mathcal{R}} e^{j\theta_r(t)}\right) \qquad (5)$$

Thereafter, the first term in the product of Eq. 4 will linearly increase as the orientation of the robot r tends to the mean orientation of the swarm. The maximum value of this term corresponds to the scenario in which the orientation consensus is reached. The second part of the fitness function rewards robots for reducing their rotation velocity. The partial fitness of this term will rise as the absolute value a_{wr}, which is the signal that controls the speed and sense of rotation, is diminished.

The function $f(t,r)$ computes the fitness for one robot and at an specific time instant. Therefore, to obtain the total fitness score resulting from an evaluation of T time steps and a swarm of R robots, Eq. 6 is applied.

$$F_{tot} = \frac{1}{RT} \sum_{t=1}^{T} \sum_{r \in \mathcal{R}} f(t, r) \tag{6}$$

4.3 Neural Controller

Figure 1 shows the CTRNN architecture that defines the behavior of the robots. It is composed by the input layer of dimension 7, two hidden layers, called H_1 and H_2, of 10 neurons and the output ensemble with 4 neurons. Even though it is not shown in the figure for the sake of simplifying the diagram, there are some synapses joining the output layer with H_1. These feedback connections are chosen randomly only once at the beginning of evolution and are the same for all the population genotypes. The total amount of these backward connections is 12, which is a 30% of the maximum number of connections between these two layers.

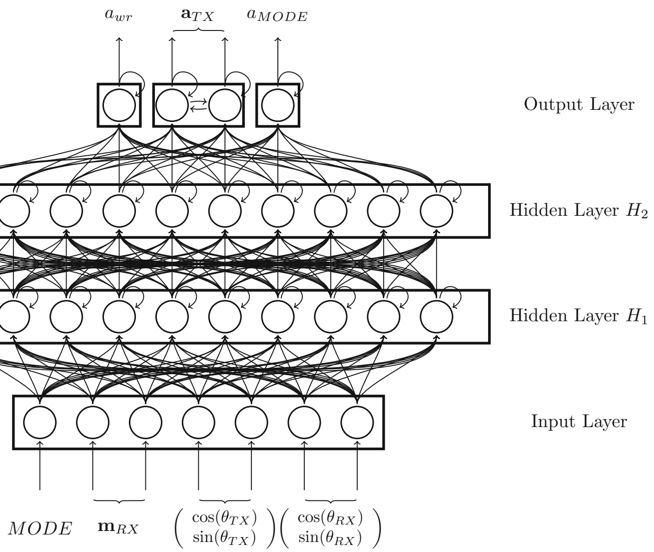
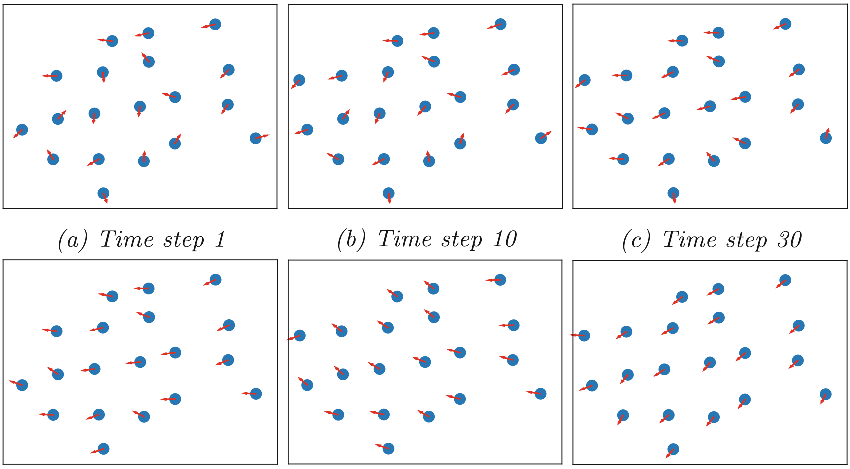


Fig. 1. CTRNN architecture used for controlling the robots. Even though it is not shown in the figure for the sake of simplifying the diagram, there are some synapses joining the output layer with H_1. These feedback connections are chosen randomly only once at the beginning of evolution and are the same for all the population genotypes.

The input layer comprises the relevant signals from the communication receiver of the robot. $\mathbf{m}_{RX}$ is the two-dimensional vector that contains the received message from the agent's neighborhood at the current time step. Additionally, $MODE$ is the binary signal, described in Sect. 3.1, that decides the operation mode of the communication system of the robot. θ_{TX} and θ_{RX} are the discretized orientations from where the message was transmitted and received, respectively, which are relative to the corresponding heading orientations of the sender and the listener robots. The output neurons are split into three layers. Firstly, $a_{MODE} \in [0, 1]$ is the signal used to generate the new state of $MODE$. It is subject to a post-processing step that converts it to a value of 0 or 1 by using a Heaviside or step function. Additionally, $\mathbf{a}_{TX} \in [0, 1]^2$ is the new message to be broadcasted if $MODE = 1$. $a_{wr} \in [-1, 1]$ is the signal that directly controls the speed and sense of the rotation of the robots. The activation function of all the neurons is the sigmoid function, except for the output neuron generating the signal a_{wr}, that employs the hyperbolic tangent function.

The genetic algorithm evolution lasts 1000 generations and the population is composed of 100 individuals. Among these 100 individuals, the 2 best performing genotypes are directly selected as elites every generation. It evaluates in 5 independent trials or simulations the fitness of each individual in order to slightly reduce the variance of the estimation. The probability of mutating a CTRNN parameter is 0.05 while the probability of recombining two genotypes to produce two children individuals is 0.9. A tournament selection is used with a tournament size of 3 and a value of $\alpha = 0.5$ is used in the BLX-α crossover. The genetic algorithm evolves the weights, neuron biases and membrane time constants of the CTRNN. These parameters are bounded as follows: $w_{ij} \in [-5, 5]$, $\beta_i \in [-2, 2]$ and $\tau_i \in [0.3, 32]$, for any neurons i and j.



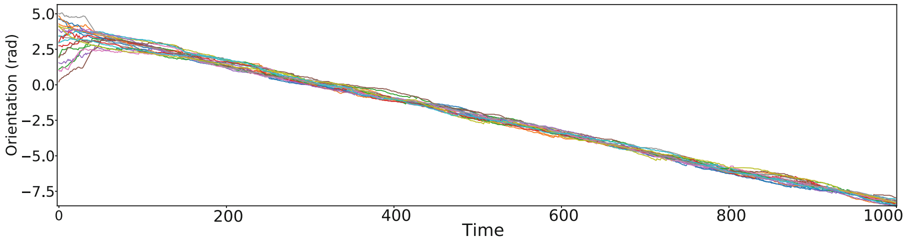
(a) Time step 1 *(b) Time step 10* *(c) Time step 30*

(d) Time step 50 *(e) Time step 100* *(f) Time step 500*

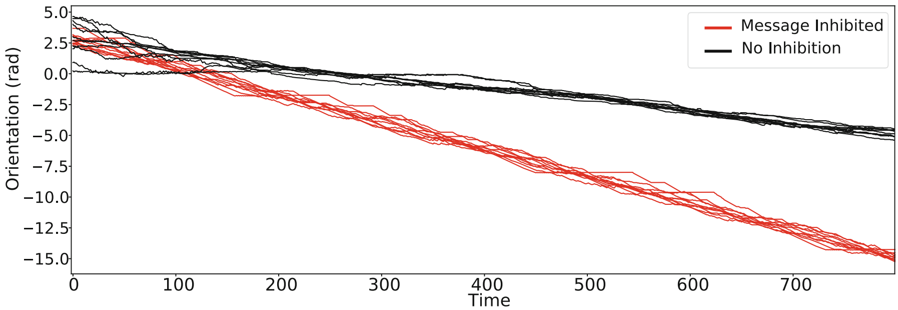
Fig. 2. Frames of a simulation of the orientation consensus experiment. Blue dots depict the robots in the swarm and red arrows show the orientations of the agents. (Color figure online)

5 Results

The evolved agents successfully solve the task of orientation consensus as it can be observed in Fig. 2, where snapshots of the simulation at different time steps are sketched. Blue balls represent the robots in the swarm and red arrows illustrate their heading orientations. The swarm of robots successfully reaches the orientation consensus at time step 100. For further time instants the consensus is correctly maintained, albeit some slight variations of the consensus value can be noticed.



(a)



(b)

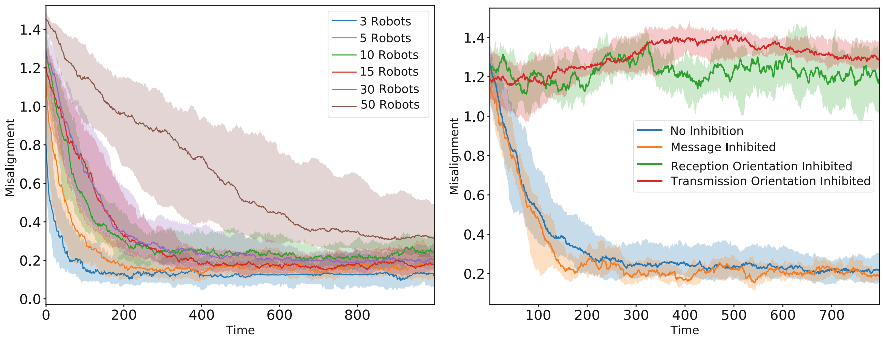
Fig. 3. (a) Temporal evolution of the orientation of the robots in a simulation with swarm size of 20. Each curve corresponds to the orientation of one of the agents. (b) Temporal evolution of the orientation of the robots in a simulation with any communication variable inhibited (black) and with the message content inhibited (red). Curves in each color represent the orientations of the robots in the swarm in the corresponding simulation conditions. In both figures, the orientation range of $[0, 2\pi)$ is extended to the set of real numbers merely for visualization purposes. (Color figure online)

Figure 3a displays an example of the results in a simulation with 20 robots. Each curve represents the evolution of the orientation of the robots. After a transient period of about 100 time steps, the robots tend to reach the orientation consensus by matching their heading direction with the orientation of its neighborhood. Even though consensus is approximately fulfilled, robots still rotate with very low angular speed in order to preserve orientation agreement. This residual rotation can be observed in the figure as the slope in the orientations of the robots, albeit this slope is merely about 0.01 radians per time step.

We now assess the scalability of the evolved system. For this aim, we introduce the misalignment metric defined as in Eq. 7,

$$M_\theta(t) = \frac{1}{R} \sum_{r \in \mathcal{R}} \min \left\{ |\theta_r(t) - \overline{\theta}(t)|, 2\pi - |\theta_r(t) - \overline{\theta}(t)| \right\} \tag{7}$$

which essentially measures the mean orientation deviation of each robot with respect to the mean orientation of the swarm. The optimal value of this metric is zero, corresponding to a perfect heading orientation consensus. The mean orientation $\overline{\theta}$ was already formulated in Eq. 5.



(a) Scalability Assessment *(b) Stimuli Inhibition*

Fig. 4. Temporal evolution of the misalignment metric (see Eq. 7) distribution using 50 simulation trials and diverse swarm sizes. The darker curves represent the median of the misalignment using all 50 collected samples. Alternatively, the clearer areas indicate, at each time instant, the first and third and quantiles. In (a), the scalability of the system is assessed by increasing the swarm size from 3 robots up to 50 robots. On the contrary, (b) studies the relevance of each controller input related to the communication. Each curve represents the evolution of the orientation misalignment when a different signal inhibited or nullified.

Unlike the results shown in Fig. 3a, that uniquely represent one sample that could be biased, for the scalability evaluation we use a sample of 50 independent simulations. Thereafter, Fig. 4a illustrates the performance with diverse swarm sizes and using the 50 samples to build each curve. At each time instant, the darker curves denote the median value of the misalignment metric across the 50 simulations. Moreover, the shadow areas are delimited by the first and third quantiles. As the swarm size increases, the time elapsed before convergence to the consensus is increased. Additionally, the convergence value or steady state misalignment slightly grows as the swarm size scales. However, the consensus is approximately fulfilled even in the worst case scenario of 50 robots and considering the sparsity and low connectivity degree of the swarm due to the local and constrained IR communication.

The emerged communication semantics are also analysed. Figure 4b shows the misalignment evolution when different variables are inhibited or nullified. The deletion of $\mathbf{m}_{RX}$, θ_{RX} and θ_{TX} are considered and compared to the results without inhibition. The state of the communication (variable $MODE$) was not studied because we observed that all the robots remain always in the *send mode*. The curves in the figure indicate that θ_{RX} and θ_{TX} are both crucial for solving the problem. On the contrary, the inhibition of $\mathbf{m}_{RX}$ leads to an equivalent misalignment evolution compared to the normal conditions. Therefore, apparently, this fact suggests that the message content by itself is not relevant for reaching the orientation consensus.

However, Fig. 3b provides a different perspective that refutes the previous statement. It compares the temporal evolution of the orientation for a single simulation. Black curves represent the heading orientations of the robots in the trial with normal conditions and, alternatively, red curves depict simulations with $\mathbf{m}_{RX}$ nullified. Even though the inhibition of the message content is not significantly relevant for the consensus itself, it is clearly used for the reduction of the rotation speed of the robots once consensus is reached. This property is not reflected in the misalignment metric and, thus, Fig. 4b incorrectly categorizes $\mathbf{m}_{RX}$ as an irrelevant signal.

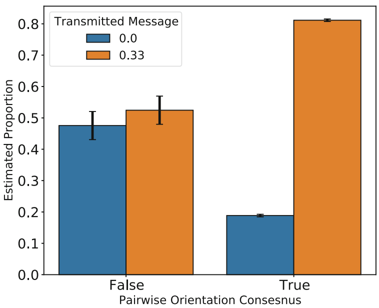


Fig. 5. Proportion estimates and 95% confidence intervals of the times each symbol is transmitted conditioned to the status of pairwise communication.

To conclude the post-analysis of the emerged communication, Fig. 5 deepens into the semantics or meanings of the transmitted symbols. It depicts the estimate of the proportion of times that a robot sends each symbol message when pairwise orientation consensus between sender and listener robots is fulfilled. The CTRNN only generates the symbols $(0, 0)$ and $(0.33, 0.33)$ among the 16 available symbols and, thus, only those symbols are shown in the figure. In addition to the point estimates, the plot additionally illustrates the confidence intervals with 95% of confidence level and using the results from 50 independent trials. When pairwise orientation consensus is reached, the symbol 0.33 is mostly generated. Alternatively, when robots are not aligned, there is not a statistically significant difference in the proportion of times that each symbol is generated. This information matches with the observations of Fig. 3b, indicating the relevance of the message once the consensus is achieved.

6 Conclusions

In this paper we studied the emergence of communication in swarm robotics in an orientation consensus problem. The simulated static robots, that are controlled by CTRNN neural networks evolved using a genetic algorithm, must coordinate with the goal of pointing into the same direction. The simulated robots can use the minimal IR-based communication system previously proposed in [17] for solving the proposed task. After the artificial evolution, a statistical analysis was carried out to assess the performance, scalability and emergent communication of the swarm of robots. The results demonstrate that the robots correctly reach the desired orientation consensus with low error and good scalability. Moreover, the assessment suggests that the emergent communication is a situated communication in which both the pure message and the environmental context are highly relevant. Specifically, the context is the only critical information for reaching the consensus itself. Nonetheless, even though the message seems to be irrelevant for the consensus achievement, it is highly important for the reduction of the rotation speed once the consensus is fulfilled.

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