Inter-individual Variations in Swarm Robotics with the Case Study of Kilobots

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***Abstract*—Inter-individual differences are studied in natural systems, such as fish, bees, and humans, as they contribute to the complexity of both individual and collective behaviors. However, individuality in artificial systems, specifically in robotic swarms, is undervalued or even overlooked. Agent-specific deviations from the norm in swarm robotics are usually understood as mere noise that can be minimized, for example, by calibration, or regulated by feedback control. We observe that robots have consistent deviations and argue that awareness and knowledge of these can be exploited to serve a task. We use Kilobots as our case study.**

***Index Terms*—Inter-individual Variations, Swarm Robotics, Heterogeneity, Complex Systems**

I. Introduction

While in artificial swarms, such as swarm robotics, heterogeneity in software and hardware is only appreciated since recently, the concept is widely recognized in studies of natural (complex) systems, such as fish schools, animal groups, and humans. Diversity plays a significant role in the complexity of collective systems. The interplay of diversity and complexity in collectives is relevant in a variety of disciplines, such as physics, biology, economics, social science, and neuroscience, indicating a possible generality of the subject. According to [1], three different types of diversity are distinguished as: "*variation within* a type, differences *across* types, differences *between* communities." We focus on the first type of diversity, aka inter-individual variation, in this paper. From a number of studies, we know that the complexity of system behaviors can stem from diversity [1]. Fish are a well-studied species in this regard. For example, [2] studied fish and the development of differences in their left-side body muscles compared to those of the right-side. They report that the "righty" fish are more likely to be hooked on the right side of their mouth. Also, [3] studied the asymmetric development of muscles in fish.

Different from natural systems, the inter-individual variations in artificial systems are often overlooked. As mentioned above, we study the first type of diversity [1]. However, other types have recently received attention, for example, the diversity in the composition of the population, that is, having different robotic platforms (species) within a collective [4], [5]. In this paper, we focus on inner-platform inter-individual differences, the so-called quasi-homogeneity [6]. We even focus narrower, by excluding controllable or programmable variations (software heterogeneity); for example, robots with different control software, specialized in different tasks as by [7]. But rather we explore the intrinsic variations, that come naturally with the embodiment of robots and are an inseparable part of these systems.

In most studies, the system behavior that emerges from the agent-agent, and agent-environment interactions is already complex, so that assuming a homogeneous system is sufficient [8]. The simplifying assumption of homogeneity in artificial systems, and in particular swarm robotics, improves tractability. We divide such assumptions into two main groups: noise and error. For the first group, individuality is seen as agents being deviated from the collective *norm*. To deal with this matter in the modeling, one increases the variation of the noise to the extent that it covers the inter-individual variation, resulting in an increase of (aleatoric) uncertainty in the model [9], which is indeed due to the (epistemic) uncertainties of the system that is seemingly unknown to the observer. We highlight the possibility to extract information from this "noise" that can be exploited and help us predict the behavior of the system more accurately. We use the example of heading bias for Kilobots [10] to elaborate upon the concept. We argue that individual robots show persistent non-zero bias whose time correlation is infinitely large, which makes the noise assumption questionable. Another engineering solution followed by the noise assumption is the attempt to calibrate robot sensors and motors. Although it reduces variations, the effect is only temporary and often deteriorates over time. Calibrated robots eventually get decalibrated and deviate from the norm again. We ask: what is the acceptable extent to which an engineer should be concerned about the decalibration of robots? For the example of the heading bias of Kilobots in an optimization task, we show that the deviations from the ideal robot do not necessarily result in a performance decrease, but rather counter-intuitively enhance it in certain cases.

The second approach is the regulation of deviations by control feedback [11]. By interpreting deviations from the

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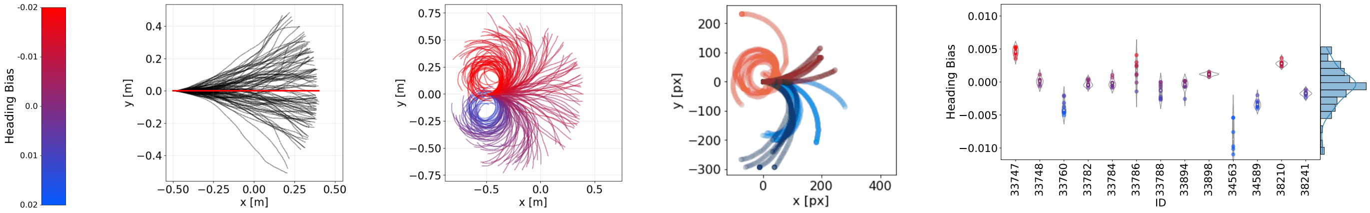


(a) (b) (c) (d) (e)

Fig. 1: Trajectories of robots moving on a straight line (b,c are in a simulation, d is real robot experiment). a) The color map of heading bias (used only in figures c, e). b) The red line is the trajectory of 100 ideal, identical robots without noise. The black lines are different realizations of the trajectories of identical robots with Gaussian noise. c) The trajectories of heterogeneous robots with noise. d) 4 Kilobots moving on a supposedly straight line for 4 independent repetitions starting at (0,0). Each color corresponds to a distinct robot. e) Mean heading bias (over time) for each experiment grouped by robot ID, showing the individuality of heading bias for Kilobots. The right histogram is the ensemble distribution if we remove the dimension of individuality.

desired behavior as an "error", which is meant to be regulated by the control system, the robot constantly tries to modulate its natural deviations and to minimize the error. This requires a feedback signal to form a closed loop [12]. However, in minimal swarm robots with simple noisy perceptions, and stochastic actuators the feedback solution is either expensive or impossible. We ask: should we treat individuality as noise, or a bug and hence try to solve it? Or is it rather a feature that the individual (or the collective) can exploit? Nature has shown a great ability to increase diversity, and to find a way to take advantage of it. Given that most of the swarm robotic systems are bio-inspired, it seems even mildly ironic to ignore or even *fix* this feature.

II. Heterogeneity in Motion

In this section, we study how robots with heterogeneous motor abilities perform tasks differently. First, we model the motion of a differential-wheel robot and describe the effect of heading bias on its motion in simulation. Second, we report the data we analyzed from real Kilobot experiments, where robots are supposed to walk in a straight line.

A. Model

Variations in actuation abilities among agents lead to different movement dynamics. We model a robot moving with speed of $|v|$ in a 2-dimensional (x, y) space with a heading angle of θ using these equations of motion:

$$\begin{bmatrix} \dot{x}^i \\ \dot{y}^i \end{bmatrix} = (|v^i| + \eta_v) \begin{bmatrix} \cos(\theta^i) \\ \sin(\theta^i) \end{bmatrix}, \qquad \dot{\theta}^i = \omega^i + \eta_\omega \tag{1}$$

For the case of Kilobots, [13] reported "strong inter-individual variations" for linear speed and measured the variance of speed distribution (or equivalently η_v) for *calibrated* Kilobots. We focus on the rotational motion and heterogeneity in the heading bias of Kilobots.

B. Heterogeneity in Heading Bias

Here we provide simple measurements of individuality in robots. To measure the heterogeneity in heading bias, here we only consider the simple straightforward motion as an ideal motion, where the desired rotational velocity is zero ($\omega^i_{\text{des}} = 0$). We conducted experiments with real Kilobots and in simulation using ARGoS simulator. We program robots to move in a straight line and log their position. For real robot experiments, we record videos and post-process the video frames using an object detection algorithm from OpenCV library [14]. For simulation, we use the Kilobot extension of ARGoS [13] and modified it by adding the heading bias.

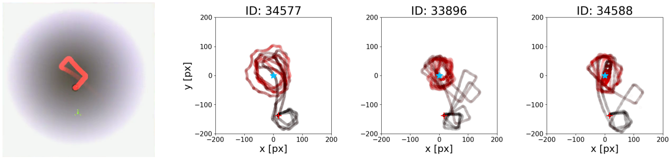
If we choose to reduce the heading bias heterogeneity to mere noise, we assume the following stochastic differential equation for the turning rate of each individual i:

$$\dot{\theta}^i = \eta_\omega, \qquad \eta_\omega \sim \mathcal{N}(\mu, \sigma^2). \tag{2}$$

Notice that statistical properties of $\eta_\omega(\mu, \sigma)$ are without index i as they are meant as a population-wide one-fits-all model. To show the trajectories from this type of model, we modified the simulator by adding Gaussian noise $\mathcal{N}$ to the nominal speed of each motor. The result of such model is a correlated random walk (Fig. 1-b) that does not qualitatively cover all trajectories we observe in real robot experiments (Fig. 1-d). The assumption of a one-fits-all noise model results in a mismatch between model and reality. Fitting the data of real robots to this model, we get a joint (ensemble) distribution for heading bias with mean close to zero ($\mu \approx 0$) and relatively large variance (see far-right, rotated histogram in Fig. 1-e). This is similar to the distribution of speeds ($|v|$) reported in [13]. With this model, we get a high variance (seemingly aleatoric uncertainty), that is indeed reducible only if we consider the individuality of robots as we do next. If we allow each robot its individual (Gaussian) noise model, we get:

$$\dot{\theta}^i = \eta^i_\omega, \qquad \eta^i_\omega \sim \mathcal{N}(\mu^i, (\sigma^i)^2). \tag{3}$$

The added dimension (raised index i) to the parameter space enables us to model the individuality of each robot, which



(a) (b) (c) (d)

Fig. 2: Phototaxis with real Kilobots. a) A snapshot of one robot (same as in c) doing the deterministic phototaxis ($P_{\mathrm{R}} = 1.0$) around the center of the source, with the decaying red trace of its trajectory by post-processing the video. b-d) Trajectories of 3 robots with different heading biases, each showing 3 separate repetitions from the same initial point (red plus). The light source is located at the center (blue star).

leads to lower aleatoric uncertainty. We show the distribution of heading bias for each robot in Fig. 1-e. The data confirms our reasoning as robots have persistent, non-zero heading biases that are individual-specific. The consistency of heading bias for each robot suggests a strong inter-agent variation among Kilobots. Furthermore, these intra-individual variations are on average smaller than the ensemble variance ($\sigma^i < \sigma$).

To simulate the heading bias, we add a deterministic off-balancing term to the left and right motor speeds. This non-zero rotational velocity generates circular trajectories. We illustrated the results of the simulations as a proof of concept in Fig. 1-c. We get trajectories of robots in simulation that have a similar curvature to their real robot experiments, which was not possible even by increasing the variance of the zero-mean noise in Eq. 2.

C. Development of Individuality over Time

The development of individuality in natural systems has already been linked to a variety of factors, such as environmental, social, and behavioral reasons. For artificial systems, the source of such developments in hardware individualities can be traced down to aging of mechanical components, such as fatigue; undergoing a major disturbance, such as damage; or simply the change in the energy source, to name but a handful of causes. For the heading bias of Kilobots in particular, we observe that over the time of experiments, robots that initially are well-calibrated lose their calibration. This de-calibration process is another reason why individuality emerges in synthetic systems and why calibration is not a lasting solution. Different platforms most likely have different timescales for losing their calibration.

III. Phototaxis as an Example Scenario

Phototaxis is a spatial sample-based optimization algorithm that maximizes the objective reward for the robot, which, in our case, is the light intensity distributed in a convex shape. It is an example behavior showing how simple organisms approach the center of an attractive light source [15], [16]. The algorithm is simple enough to be implemented on minimal robots, such as Kilobots. Our phototaxis algorithm is different from the random search explained in [17] and the collective phototaxis as in [18]. Our more greedy algorithm boils down to the following procedure: if the intensity of the light sample gets closer to the objective intensity, the robot keeps going forward, otherwise, it turns. The robot stops if it gets close enough to the center of the source. The algorithm to decide which direction to turn to is determined by one parameter P_{R} which is the probability to turn to the right (and $P_{\mathrm{L}} = 1 - P_{\mathrm{R}}$). To study how this parameter affects the performance of Kilobots, we consider three different configurations:

(asymmetric) deterministic turn to the right ($P_{\mathrm{R}} = 1.0$), symmetric stochastic turns (to the left and right) ($P_{\mathrm{R}} = 0.5$), and asymmetric stochastic turns ($P_{\mathrm{R}} = 0.25$).

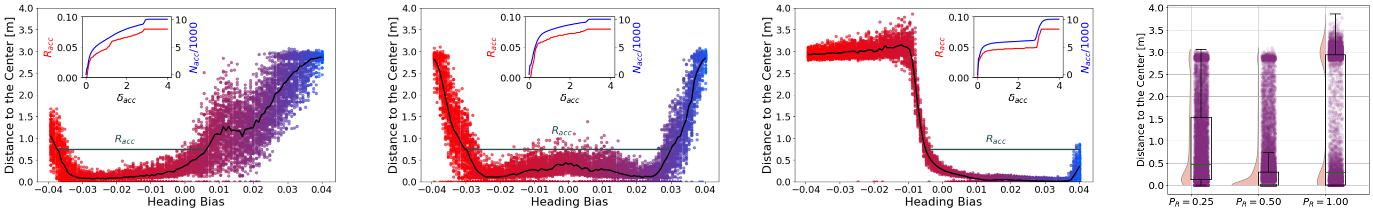
A. Phototaxis for Real Kilobots

Our real robot experiments prove that despite the simplicity of the algorithm and heterogeneity in motion, Kilobots can locate and exploit the center of the light source. Our experiments with real robots (see Fig. 2) for the first algorithm suggest that robots have different performances (in approaching the source center). With $P_{\mathrm{R}} = 1.0$, a robot with a left heading bias (Fig. 2-b) has a lower performance compared to the other robots that have either negligible (Fig. 2-c) or obvious right heading biases (Fig. 2-d). In some cases, too strong left-biased robots failed to get closer to the center and left the area of interest.

B. Phototaxis for Kilobots in Simulation

To study the effect of heading bias on the performance of phototaxis for Kilobots, we conduct experiments in ARGoS with the modified simulator. We test 100 simulated robots with heading biases uniformly distributed in the range of $[-0.04, 0.04]$. Each robot executes the phototaxis algorithm, for 100 independent Monte Carlo simulations.

We consider the distance of the robot to the center of the source for the performance metric as cost and calculate the average over the last 100 data points. We illustrate the results for each trial as a point in Fig. 3. As expected, the robots vary greatly in their phototaxis performance. This variation in the performance would have been otherwise ignored when assuming homogeneous robots. A key finding is that assumed "perfect" robots without bias are outperformed by "non-calibrated" robots (see Fig. 3-b, heading bias of ± 0.023). This relates to our observation with real robots in Fig. 2. To elaborate more on the optimality of non-zero bias robots, let us assume an evolutionary optimization algorithm that modifies the configuration of a robot (heading bias) over generations for a given fixed phototaxis parameter, e.g. $P_{\mathrm{R}} = 0.5$. The fact that the stable optimal heading biases are located at non-zero would cause the evolutionary algorithm to incline toward more biased configurations and select them more often over generations. The attraction points depend on where to start the evolutionary optimization. For each of $P_{\mathrm{R}} = 0.25, 0.5$ there are two separate optimums, one with a positive and the other with a negative heading bias. It confirms that calling individuality a *bug* or a flaw (with negative impacts) is not always true. Nonetheless, there are also other scenarios, where being biased causes harm in an asymmetric manner, for example, having an



(a) $P_{\mathrm{R}} = 0.25$ (b) $P_{\mathrm{R}} = 0.5$ (c) $P_{\mathrm{R}} = 1.0$ (d)

Fig. 3: Performance of robots with different heading biases in doing phototaxis with different parameters in simulation. a-c) A dot represents the performance of each robot at each simulation trial and is color-coded based on its heading bias. The black line shows the mean value over 100 Monte Carlo repetitions. The inset plots show R_{acc} (red) and N_{acc} (blue) vs thresholds δ_{acc}. d) The ensemble distribution of all robots together (the light pink violin plot) by removing the individuality dimension. The black box plot shows the quantiles and the green line is the mean of all data points, each is shown by a purple dot.

asymmetric chance of being hooked on one side compared to the other for a "righty" fish [2].

In addition, we compare the performance of different algorithms. Each algorithm favors a specific range of heading biases. For the deterministic algorithm (Fig. 3-c), where robots always turn to the right ($P_{\mathrm{R}} = 1.0$), the algorithm favors the right-biased robots more than the others. In comparison, for the algorithm with a higher chance to turn to the left ($P_{\mathrm{R}} = 0.25$, Fig. 3-a) the left-biased robots achieve higher rewards (lower cost). To highlight the effect of heterogeneity of heading bias in optimization tasks we imagine a learning problem, where robots are supposed to learn the optimal value of P_{R}. Given the results we provided here, it is predictable that robots with non-identical heading biases converge to different optimal parameters. A left-biased robot would pick a lower P_{R} compared to a right-biased robot. In that light, we argue that tuning one parameter for all robots by only optimizing the performance of a single robot with a specific feature (e.g., a non-biased robot) might not be the best practice.

Another important point is the extent of acceptable "uncalibratedness"; that is the range of heading bias within which robots perform reasonably well (R_{acc}). To quantify R_{acc} we define a threshold (δ_{acc}) for the performance, below which the criterion is satisfied. We show the acceptable range for $\delta_{\mathrm{acc}} = 0.75\mathrm{m}$ in Fig. 3-a-c with the green horizontal line. Another similar performance metric can be measured for the number of experiments (dots) whose performance is below the threshold, we call this metric N_{acc}. We illustrated the performance metrics versus thresholds in the inset plots. We also compared the three algorithms in terms of the acceptable range (and number) versus the threshold. The most efficient algorithm as of this metric depends significantly on where we set our threshold. Apart from performance comparison among algorithms, the acceptable range proposes freedom from calibrations. From an engineering point of view, having less necessity for calibrating robots would reduce the required effort, energy, and cost to maintain such systems.

On the contrary, if we ignore individuality, we get a joint distribution of performance for all robots (see Fig. 3-d.) Following this simplified interpretation we may draw conclusions that are either inaccurate, or not generally valid. For example, the mean performance (denoted by the green line) represents a higher performance for $P_{\mathrm{R}} = 0.5$. However, this may not hold for all robots. Also, the heavy upper tail for $P_{\mathrm{R}} = 1.0$ cannot be explained unless we look through the second dimension, which is individuality.

IV. Conclusion

Inspired by studies on natural systems and the complex behavior caused by inter-individual variations, we attempt to shed some light on the concept of (intrinsic) individuality in swarm robotics. We found that this type of heterogeneity in robot systems in general, and swarm robots in particular, are often overlooked. We argue that robots have agent-specific persistent features, that are characteristic parts of them. These natural differences are either assumed to be "noise" or error and hence provoke solutions like calibration (as an offline solution) or regulation using feedback control (as an online solution). We argue that there is some useful information in the variations which can be exploited to make more accurate models and hence predictions. We also showed that robots develop individuality over the course of experiments, and thus calibration is not always a lasting solution. Also, regulating the errors comes with the price of a feedback signal, which is usually too costly for minimal swarm robots.
Furthermore, dropping heterogeneity as a dimension of the problem space will lead to increased uncertainty in the model. We observe, report, and measure the heterogeneity in motion, and in particular the heading bias of real Kilobots, and show that the robots have agent-specific, persistent, non-zero mean biases. With the accurate model for heterogeneity in heading bias, we scaled up our studies and showed how different robots vary in their performance. Our results prove that calling inter-individual variations a bug or a flaw is not always true. Our results show a counter-intuitive comparison of the perfect and biased robots, with the perfect robot being outperformed by biased ones in some tasks. Besides, the new perspective opens space for new insights to be gained from these complex systems.

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