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Stochastic Approximate Consensus with Samples of Group Average*

Amos Korman[†] and Robin Vacus[‡]

Abstract

Reaching agreement despite noise in communication is a fundamental problem in multi-agent systems. Here we study this problem under an idealized model, where it is assumed that agents can sense the general tendency in the system. More specifically, we consider n agents, each being associated with a real-valued number. In each round, each agent receives a noisy measurement of the average value, and then updates its value, which is in turn perturbed by random drift. We assume that both noises in measurements and drift follow Gaussian distributions. What should be the updating policy of agents if their goal is to minimize the expected deviation of the agents' values from the average value? We prove that a distributed *weighted-average* algorithm optimally minimizes this deviation for each agent, and for any round. Interestingly, this optimality holds even in the *centralized setting*, where a master agent can gather all the agents' measurements and instruct a move to each agent. We find this result surprising since it can be shown that the total measurements obtained by all agents contain strictly more information about the deviation of Agent i from the average value, than the information contained in the measurements obtained by Agent i . Although this information is relevant for Agent i , it is not processed by it when running a weighted-average algorithm. Nevertheless, the weighted-average algorithm is optimal, since by running it, other agents manage to fully process this information in a way that perfectly benefits Agent i . Finally, we also analyze the drift of the center of mass and show that no distributed algorithm can achieve as small of a drift as can be achieved by the best centralized algorithm. In light of this, we also show that the drift associated with our weighted-average algorithm incurs a small overhead over the best possible drift in the centralized setting.

1 Introduction

1.1 Background and Motivation

Reaching agreement, or approximate agreement, is fundamental to many distributed systems, including: computer networks, mobile sensor systems, animal groups, and neural networks [13, 15, 30, 32, 37, 38]. In the natural world, one fascinating example occurs during *cooperative transport* in ants, in which a group of ants join forces to carry a large or heavy food load [17, 18]. While carrying the load, improved consensus on the direction of forces applied by the ants amounts to faster movement of the carried load, since less forces are canceling each other. Another beautiful example concerns flocking birds (or, e.g., schooling fish) that manage to maintain a cohesive direction of movement by constantly aligning their directions of flights [37, 38]. In these contexts, as well as in multiple other contexts, such as during clock synchronization [33, 34], the space in which the approximate agreement process occurs is continuous, measurements are noisy and the output needs to be maintained over time, while being subject to drift.

In several contexts, distributed consensus algorithms can be designed by letting each agent repeatedly execute the following two steps.

1. obtain an estimate regarding the average “opinion” of other agents in the system.
2. shift the “opinion” by a certain extent towards the estimated average.

The first step assumes that agents are somehow able to sense the general behavior of the system. Such an ability may be quite limited in many contexts, but not in all. We shall soon provide several examples for scenarios in which agents are able to measure global parameters of the system, either directly, or indirectly. However, before we list these examples, we would like to stress that the current paper is not concerned with the mechanism behind implementing

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[†]CNRS, located at the French-Israeli Laboratory on Foundations of Computer Science, UMI FILOFOCS, CNRS, UP7, TAU, HUJI, WIS International Joint Research Unit, Tel-Aviv, Israel.

[‡]CNRS, located at the Research Institute on the Foundations of Computer Science (IRIF), Paris, France.

such samples, and instead focuses on optimizing the second step, corresponding to the shifts that should be made after obtaining such samples.

Examples of global parameter samplings. We next provide examples for settings in which agents can sample global parameters. The emphasis is on examples from the biological world. We classify these examples into three categories.

- *Using an external entity as a relay of information.* In several contexts, agents may use an external entity (or a “leader” agent) to gather information from all agents, compute a certain function of it (e.g., the average value), and then communicate this information to all others [39]. Indirectly, this happens, for example, during the process of *cooperative transport*, in which agents physically carry a large or heavy object, as mentioned above. In this process the carried object itself serves as a medium entity through which the global tendency of the group could be sensed by each carrying agent. In the context of ants, for example, the authors of [17, 18, 24, 26] assumed that each ant uses the carried object to sense the sum of the forces exerted by all carrying ants. After measuring this sum (which represents the velocity vector of the carried object), each ant decides whether, and by how much, it should align its force to this measurement. Cooperative transport following a similar approach was also studied in the context of robotics, see, e.g., [5, 40] and the references therein.

Other natural examples include the behavior of a swarm of flying midges [20], and during firefly synchronization [21]. In such swarms, each midge (respectively, firefly) is affected by the acoustic (respectively, visual) field produced by all others. In these examples, the environment plays the role of relaying information regarding the whole group to each agent.

- *Broadcast in clique networks.* Obtaining measurements of the whole system is also relevant for relatively packed systems, so that information from any agent could reach any other agent. In other words, this considers the cases in which the communication is essentially being broadcasted on a clique [11]. In the natural world, the clique abstraction can find relevance in small flocks of birds, or in other small animal groups [9, 35].
- *Well-mixed populations.* The assumption that agents sense global parameters of the system also finds relevance in highly mobile systems. In particular, when the population is well-mixed, the pattern of communication may be captured by a random process, in which the set of neighbors is constantly being replaced by agents chosen uniformly at random. In such cases, sensing the current set of neighbors can serve as a fresh random sample of the global population. This perspective has recently been adopted by multiple works in theoretical computer science (although in contrast to this paper, the typical assumption in these works is that the set of opinions is discrete), see, e.g., [2–4, 6, 7, 10, 14, 16, 19]. For example, in *Majority Dynamics*, each agent pulls the opinions of a few random agents, and changes its opinion to the majority opinion among these samples [2–4, 10, 12, 19]. As such, these protocols can be viewed as being composed of two parts: (1) obtain a noisy sample of the majority opinion in the population based on the opinions of the pulled agents (hence, the noise depends on the distribution of agents and on the number of pulled agents), and (2) align to this majority.

Informally, the problem we study, called *Stochastic Approximate Consensus (SAC)*, considers a group of n agents positioned on the real line, aiming to be located as close as possible to one another. We stress that the setting on the line does not necessarily aim to capture the physical locations of the agents, which may actually be scattered in arbitrary domains (e.g., two or three dimensional Euclidean spaces). Instead, the positions on the line aim to capture the “opinions” of the agents, which, in this preliminary work, are restricted to a one dimensional space. For example, in view of alignment problems, the position of an agent aims to model its direction. When flocks of birds fly, the altitude axis often remains stable, and hence the flight could be viewed as a two-dimensional flight, implying that the direction could be represented as one-dimensional. A similar observation holds in many contexts of two-dimensional navigation, for example, during *cooperative transport* by ants. In view of clock-synchronization [33, 34] or firefly synchronization [21], the position of an agent models its clock (i.e., time), which again can be viewed as a one-dimensional space¹.

Initially, agents’ positions are sampled from a Gaussian distribution around 0. Execution proceeds in discrete rounds, where in each round, each agent receives a noisy measurement of its current deviation from the average position of others. Then, governed by the rules of its algorithm, each agent performs a *move* to re-adjust its position. Subsequently, before the next round begins, the position of each agent is perturbed following random drift. The

¹Depending on the application, the actual domain may be bounded, or periodic. For example, when modeling directions, the domain is $[-\pi, \pi]$ and when modeling clock synchronization, the domain may be $[0, T]$ for some phase duration T . Since we are interested in the cases where agents are more or less aligned, approximating an interval domain with the real line is not expected to reduce the generality of our results.

drift component may model unreliability due to external conditions (e.g., perturbation of direction by wind), or the inability of an agent to precisely adjust itself as it wishes. Both noises in measurements and random drifts are governed by Gaussian distributions. We are mostly interested in the following questions:

- Which re-adjustment rule should agents adopt if their goal is to minimize expected distance of each agent from the average position?
- Could further communication between agents (e.g., by sharing measurements) help?

Importantly, we assume that agents are unaware of the actual value of their current positions, and of the realizations of the random drifts, and instead, must base their movement decisions only on noisy measurements of relative positions. This lack of global “sense of orientation” prevents the implementation of the trivial distributed protocol in which all agents simply move to a predetermined point, say 0.

One trivial algorithm is the “fully responsive” protocol, where in each round, each agent moves all the way to its current measurement of the average position of others. Such a fully responsive protocol was assumed in various models that consider alignment, including in the celebrated flocking model by Vicsek et al. [37]. When drift is large, measurement noise is negligible, and the number of agents is large, this protocol can become highly efficient. However, when measurement noise is non-negligible, it is expected that incorporating past measurements could enhance the cohesion, even though drift may have changed the configuration considerably.

Perhaps the simplest class of algorithms that take such past information into account are *weighted-average* algorithms; By weighing the current position against the measured position in a non-trivial way, such algorithms can potentially exploit the fact that the current position implicitly encodes information from past measurements. Indeed, in a centralized setting, when a single agent aims to estimate a fixed target relying on noisy Gaussian measurements, a weighted-average algorithm is known to be optimal, in the sense that it minimizes the expected distance between the agent and the target [1]. However, here the setting is more complex since it is distributed, and the objective goal is to estimate (and get closer to) the average position, which is a function of the agents decisions.

1.2 The Stochastic Approximate Consensus (SAC) problem

We consider n agents located on the real line \mathbb{R} . Let $I = \{1, \dots, n\}$ be the set of agents. We denote by $\theta_i^{(t)} \in \mathbb{R}$ the position of Agent i at round t , where initially, the position of each agent is chosen independently according to a normal distribution around 0, with variance σ_0^2 , that is, for each Agent i , $\theta_i^{(0)} \sim \mathcal{N}(0, \sigma_0^2)$. As mentioned, we assume that an agent is unaware of the actual value of its current position, and must base its decisions on relative measurements.

Execution proceeds in discrete rounds. At round t , each agent i receives a noisy measurement of the deviation from the current average position of all other agents. Specifically, denote the average of the positions of all agents except i by:

$$\langle \theta_{-i}^{(t)} \rangle = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \theta_j^{(t)}.$$

Let $\bar{\theta}_i^{(t)} = \langle \theta_{-i}^{(t)} \rangle - \theta_i^{(t)}$ denote the *stretch* of Agent i . At any round t , for every $i \in I$, a noisy measurement of the stretch of Agent i is sampled:

$$Y_i^{(t)} = \bar{\theta}_i^{(t)} + N_{m,i}^{(t)}, \tag{1}$$

where $N_{m,i}^{(t)} \sim \mathcal{N}(0, \sigma_m^2)$. In response, Agent i makes a move $d\theta_i^{(t)}$ and may update its memory state (if it has any). Finally, the position of Agent i at the next round is obtained by adding a drift:

$$\theta_i^{(t+1)} = \theta_i^{(t)} + d\theta_i^{(t)} + N_{d,i}^{(t)}, \tag{2}$$

where $N_{d,i}^{(t)} \sim \mathcal{N}(0, \sigma_d^2)$. All random perturbations $(N_{m,i}^{(t)})_{i \in I}$ and $(N_{d,i}^{(t)})_{i \in I}$ are mutually independent, and we assume that $\sigma_m, \sigma_d > 0$.

Definition 1 (Cost). *The cost of Agent i at a given time t is the absolute value of its expected stretch at that time², i.e.,*

$$\mathcal{C}_i^{(t)} := \mathbb{E} \left(\left| \bar{\theta}_i^{(t)} \right| \right).$$

²Another natural cost measure is the expected deviation from the average position of all agents (including the agent), i.e., $\mathcal{C}_i^{(t)'} := \mathbb{E} \left(\left| \frac{1}{n} \sum_{j=1}^n \theta_j^{(t)} - \theta_i^{(t)} \right| \right)$. These two measures are effectively equivalent. Indeed, $\mathcal{C}_i^{(t)'} = \frac{n-1}{n} \mathcal{C}_i^{(t)}$, thus an algorithm minimizing one measure will also minimize the other.

Note that the cost depends on the algorithm used by i but also on the algorithms used by others. As these algorithms will be clear from the context, we typically omit mentioning them in notations.

Definition 2 (Optimality). We say that an algorithm is optimal if, for every $i \in \{1, \dots, n\}$ and every round t , no algorithm can achieve a strictly smaller cost $\mathcal{C}_i^{(t)}$. Note that the definition refers to a very strong notion of optimality — it implies that if Algorithm A is optimal, then for any given round t and for any given Agent i , no algorithm B can achieve better performances for Agent i at round t than the performances guaranteed by A , regardless of what B did in previous rounds.

Definition 3 (Weighted-average algorithms). Perhaps the simplest class of algorithms that one may consider are weighted-average algorithms. Such an algorithm is characterized by a responsiveness parameter $\rho^{(t)}$ for each round t , indicating the weight given to the measurement at that round. Formally, an agent i following the weighted-average algorithm $\mathcal{W}(\rho^{(t)})$ at round t , sets

$$d\theta_i^{(t)} = \rho^{(t)} Y_i^{(t)}. \quad (3)$$

Full communication (or centralized) model. When executing a weighted-average algorithm, an agent bases its decisions solely on its own measurements. A main question we ask is whether, and if so to what extent, can performances be improved if agents could communicate with each other to share their measurements. In order to study the impact of communication, we compare the performances of the best weighted-average algorithm to the performances of the best algorithm in the *full-communication model*, where agents are free to share their measurements with all other agents at no cost. In the case that agents have identities, this setting is essentially equivalent to the following centralized setting: Consider a *master* agent that is external to the system. The master agent receives, at any round t , the stretch measurements of all agents, i.e., the collection $\{Y_j^{(t)}\}_{j=1}^n$, where these measurements are noisy in the same manner as described in Eq. (1). Analyzing these measurements at round t , the master agent then instructs each agent i to move by a quantity $d\theta_i^{(t)}$. After moving, the agents are subject to drift, as described in Eq. (2). Note that the master agent is unable to “see” the positions of the agents, and its information regarding their locations is based only on the measurements it gathers from the agents, and on the movements it instructs. The goal of the master agent is to minimize the maximal cost of agents, where the maximum is over the agents, per round. In particular, an algorithm is said to be optimal in the centralized setting if it satisfies Definition 2.

At a first glance, it may appear that weighted-average algorithms may be sub-optimal in the centralized setting. This is because it can be shown that the measurements made by Agent i contain strictly less information about the agent’s relative position to the average position than the information contained in the collection of all measurements $\{Y_j^{(t)}\}$. Indeed, although the $\{Y_j^{(t)}\}$ measurements are not centered around the stretch $\bar{\theta}_i^{(t)}$ of Agent i , they still contain useful information. For example, it can be shown that

$$-\sum_{\substack{j=1 \\ j \neq i}}^n Y_j^{(t)} = \bar{\theta}_i^{(t)} - \sum_{\substack{j=1 \\ j \neq i}}^n N_{m,j}^{(t)}, \quad (4)$$

thus representing an additional “fresh” estimation of $\bar{\theta}_i^{(t)}$. Therefore, it may appear that in the centralized setting, the stretch of agents could potentially be reduced by letting the master agent process all measurements.

1.3 Our results

We prove that a distributed *weighted-average* algorithm, termed \mathcal{W}^* , optimally minimizes the expected stretch of all agents at all rounds. Specifically, by the strong definition of optimality (Definition 2), for any round t and for any given i , no algorithm can achieve a better cost for Agent i at round t than \mathcal{W}^* . Interestingly, the optimality of this weighted-average algorithm holds even in the centralized (full-communication) model. We find this result surprising since, as mentioned, the total measurements obtained by all agents contain strictly more information about the deviation of any given Agent i from the average value, than the information contained in the measurements obtained by Agent i (Eq. (4)). Although this information is relevant for Agent i , it is not processed by it when running \mathcal{W}^* . Nevertheless, this weighted-average algorithm is optimal, since other agents manage to fully process this information in a way that also benefits Agent i , by shifting the center of mass towards it. Finally, we also analyze the drift of the center of mass, and show that when the number of agents is large, \mathcal{W}^* yields a relatively small drift, yet not the smallest possible.

In order to obtain preliminary understanding, let us first examine the case of two agents operating in a single round, and compare the situation between the centralized and the distributed setting. This simple example is informative since it already demonstrates the aforementioned surprising phenomenon.

1.3.1 Intuition: The case of Two Agents in One round.

Here, we consider a one-round version of our model, in order to gain some intuition. To really limit this example to “one round”, we assume the initial distribution of the stretches to have a very large variance (formally, $\sigma_0^2 \gg \sigma_m^2$). Therefore, we can put aside the Bayesian conflict between the current knowledge about the stretches, and the information contained in the new measurement – and only work with the latter.

When considering two agents, the *stretch* $\bar{\theta}_i$ of Agent $i \in \{1, 2\}$ is simply its relative distance to the other agent. Assume that their positions are initially set to:

$$\begin{cases} \theta_1 = 0 \\ \theta_2 = 1 \end{cases}, \text{ and so by definition, } \begin{cases} \bar{\theta}_1 = +1 \\ \bar{\theta}_2 = -1. \end{cases}$$

Assume further that the respective measurement noises are:

$$\begin{cases} N_{m,1} = 0.1 \\ N_{m,2} = 0.2 \end{cases},$$

and so the measurements of the stretches are:

$$\begin{cases} Y_1 = \bar{\theta}_1 + N_{m,1} = +1.1 \\ Y_2 = \bar{\theta}_2 + N_{m,2} = -0.8. \end{cases} \quad (5)$$

We next compare the situation between the centralized and the distributed settings.

- **Centralized setting.** Here, a central entity gathers both measurements Y_1 and Y_2 , and, based on these measurement, instructs each agent of its next move. Since we assumed the initial distribution of the stretches to have very large variance, the most accurate estimates of the relative stretches between the agents depends only on the measurements:

$$\begin{cases} \hat{\theta}_1^{\text{cent}} = \frac{1}{2}(Y_1 - Y_2) = \frac{+1.9}{2} = +0.95 \\ \hat{\theta}_2^{\text{cent}} = \frac{1}{2}(Y_2 - Y_1) = \frac{-1.9}{2} = -0.95. \end{cases} \quad (6)$$

Recall that the goal of the central entity is to minimize the absolute stretch between the agents. Note that for this purpose, it has a degree of freedom, since, once it moves each of them, shifting both by the same amount would not change their stretch. If the central entity also wishes to minimize the drift of the center of mass, then it should instruct the agents to move towards the estimated center, shifting them by $\hat{\theta}_i/2$ towards each-other. (This type of algorithm will later be called “meet at the center”.) Specifically, the instructed moves would be:

$$\begin{cases} d\theta_1^{\text{cent}} = \frac{1}{2} \hat{\theta}_1^{\text{cent}} = +0.475 \\ d\theta_2^{\text{cent}} = \frac{1}{2} \hat{\theta}_2^{\text{cent}} = -0.475, \end{cases}$$

and so by definition, the new positions of the agents (before drift applies) would be:

$$\begin{cases} \theta_1^{\text{cent}} = \theta_1 + d\theta_1^{\text{cent}} = 0.475 \\ \theta_2^{\text{cent}} = \theta_2 + d\theta_2^{\text{cent}} = 0.525 \end{cases}. \quad (7)$$

As can be seen, the center of mass is unchanged. In fact, this is no coincidence and would be the case for any measurement noises (before drift takes place). Finally, with the new positions, before drift applies, the new relative stretches are:

$$\begin{cases} \bar{\theta}_1^{\text{cent}} = +0.05 \\ \bar{\theta}_2^{\text{cent}} = -0.05 \end{cases}. \quad (8)$$

- **Distributed setting.** In the *distributed* setting, an agent must base its estimate of the stretch on its measurement alone. In this case, we have:

$$\begin{cases} \hat{\theta}_1^{\text{dist}} = Y_1 = +1.1, \\ \hat{\theta}_2^{\text{dist}} = Y_2 = -0.8. \end{cases}$$

Of course, the quality of these estimates is less than in the centralized setting (compare with Eq. (6)). It follows that the “distributed perception” is shifted in the same manner for both agents. That is, both agents think

that the other agent is located $\frac{1}{2}(Y_1 + Y_2)$ to the right of what is estimated by the centralized setting (Eq. (6)). If, for example, $Y_1 + Y_2 > 0$, then the agent on the left thinks that the distance to the other agent is $Y_1 + Y_2$ larger than what it would think in the centralized setting, whereas the agent on the right would think that the distance to the other agent is $Y_1 + Y_2$ smaller than what it would think in the centralized setting. As we shall see, this shift in perceptions will cause the agent on the left to move more distance towards the other agent than it would in centralized setting, whereas the agent on the right would move less distance towards the other agent than it would in centralized setting. Overall, the distance between them would remain the same in both settings.

More precisely, under the distributed setting, in attempting to “meet at the center”, the best that the agents can do is to go half way to their respective estimate of the location of the other agent. That is:

$$\begin{cases} d\theta_1^{\text{dist}} = \frac{1}{2} \hat{\theta}_1^{\text{dist}} = \frac{1}{2} \cdot Y_1 = +0.55 \\ d\theta_2^{\text{dist}} = \frac{1}{2} \hat{\theta}_2^{\text{dist}} = \frac{1}{2} \cdot Y_1 = -0.4 \end{cases},$$

and so by definition, their new locations (before drift applies) would be:

$$\begin{cases} \theta_1^{\prime \text{dist}} = \theta_1 + d\theta_1^{\text{dist}} = 0.55 \\ \theta_2^{\prime \text{dist}} = \theta_2 + d\theta_2^{\text{dist}} = 0.6 \end{cases}, \text{ yielding } \begin{cases} \bar{\theta}_1^{\prime \text{dist}} = +0.05 \\ \bar{\theta}_2^{\prime \text{dist}} = -0.05. \end{cases}$$

Evidently, in contrast to the centralized case (Eq. (7)), here the center of mass moved as a result of the agents movements. Importantly, however, the relative positions of the agents (and therefore, their costs) are identical to the ones obtained in the centralized protocol (Eq. 8). Again, this is no coincidence, and holds for any measurement noises. The reason is, that the two locations of the agents in the distributed setting differ by the same shift, compared to their location in the centralized setting. Indeed, we have:

$$\begin{cases} \theta_1^{\prime \text{dist}} - \theta_1^{\text{cent}} = d\theta_1^{\text{dist}} - d\theta_1^{\text{cent}} = \frac{1}{4}(Y_1 + Y_2) \\ \theta_2^{\prime \text{dist}} - \theta_2^{\text{cent}} = d\theta_2^{\text{dist}} - d\theta_2^{\text{cent}} = \frac{1}{4}(Y_1 + Y_2). \end{cases}$$

This shift, i.e., $\frac{1}{4}(Y_1 + Y_2)$, represents the “mistake” made by distributed agents in attempting to meet at the center, compared with the centralized algorithm. However, since both agents in the distributed setting are shifted by the same quantity compared to their respective positions in the centralized setting, their relative stretch remains the same in both settings.

1.3.2 Weighted-average algorithms with fixed responsiveness.

As a warm-up towards understanding multi-round scenarios, we first investigate weighted-average algorithms in which all agents have the same responsiveness ρ , that furthermore remains fixed throughout the execution (see Eq. (3)). The proof of the following theorem is given in Section 2.

Theorem 1. *Assume that all agents execute $\mathcal{W}(\rho)$, for a fixed $0 \leq \rho \leq 1$. Then for every $i \in \{1, \dots, n\}$ and every $t \in \mathbb{N}$, the stretch $\bar{\theta}_i^{(t)}$ is normally distributed, and*

$$\lim_{t \rightarrow +\infty} \text{Var} \left(\bar{\theta}_i^{(t)} \right) = \frac{\frac{n}{n-1}(\rho^2 \sigma_m^2 + \sigma_d^2)}{1 - (1 - \frac{n}{n-1}\rho)^2},$$

with the convention that $\lim_{t \rightarrow +\infty} \text{Var}(\bar{\theta}_i^{(t)}) = +\infty$ if the denominator $1 - (1 - \frac{n}{n-1}\rho)^2 = 0$.

If all agents run $\mathcal{W}(\rho)$, then the extent to which they are aligned with each other asymptotically is captured by $\text{Var}(\rho) := \lim_{t \rightarrow +\infty} \text{Var} \left(\bar{\theta}_i^{(t)} \right)$. Indeed, for every i , since $\bar{\theta}_i^{(t)}$ is normally distributed, $\lim_{t \rightarrow +\infty} \mathbb{E} \left(\left| \bar{\theta}_i^{(t)} \right| \right) = \sqrt{\frac{2}{\pi} \text{Var}(\rho)}$. The minimal value of this is achieved when taking $\text{argmin}_{\rho} \text{Var}(\rho)$ as the responsiveness parameter. The proof of the following theorem is given in Section 2.

Theorem 2. *The weighted-average algorithm that optimizes group variance among all weighted-average algorithms $\mathcal{W}(\rho)$ (that use the same responsiveness parameter ρ at all rounds) is $\mathcal{W}(\rho^*)$, where*

$$\rho^* = \frac{\sigma_d \sqrt{4\sigma_m^2 + \left(\frac{n}{n-1}\sigma_d\right)^2} - \frac{n}{n-1}\sigma_d^2}{2\sigma_m^2}. \quad (9)$$

When n is large, Eq. (9) becomes $\rho^* \approx \frac{\sigma_d \sqrt{4\sigma_m^2 + \sigma_d^2} - \sigma_d^2}{2\sigma_m^2}$. Note that the role played by the measurement noise is very different than the role played by the drift. For example, if $\sigma_m \gg \sigma_d$, then $\rho^* \approx 0$. However, if $\sigma_m \ll \sigma_d$ then $\rho^* \approx 1$. Interestingly, if $\sigma_m = \sigma_d$ then $\rho^* \approx \frac{\sqrt{5}-1}{2}$, which is highly related to the golden ratio. Moreover, for large n , the minimal $\text{Var}(\rho)$ is

$$\text{Var}(\rho^*) = \frac{1}{2} \sigma_d \left(\sqrt{4\sigma_m^2 + \sigma_d^2} + \sigma_d \right). \quad (10)$$

Note that when the measurements are perfect, i.e., $\sigma_m = 0$, we have $\text{Var}(\rho^*) = \sigma_d^2$, which is the best achievable value that an agent can hope for, since no strategy can overcome the drift-noise.

1.3.3 The impact of communication.

Our next goal is to understand whether, and if so, to what extent, can performances be improved if further communication between agents is allowed. For this purpose, we compare the performances of $\mathcal{W}(\rho^*)$ to the performances of the best algorithm in a centralized (full-communication) setting.

A natural candidate for an optimal algorithm in the centralized setting is the “meet at the center” algorithm. This algorithm first obtains, for each agent, the best possible estimate of the distance from the agent’s position to the average position $\langle \theta \rangle$, based on all measurements, and then instructs the agent to move by this quantity (towards the estimated average position). However, it is not immediate to figure out the distances to the average position, and furthermore, quantify the performances of this algorithm. To this end, we adapt the celebrated Kalman filter tool, commonly used in statistics and control theory [1], to our setting. Solving the Kalman filter system associated with the centralized version of our SAC problem, we obtain an estimate of the relative distance of each agent i from the average position (based on all measurements). To describe these estimates we first define the following.

Definition 4 (Uncertainty). *We inductively define the sequence $(\alpha_t)_{t=0}^\infty$. Let $\alpha_0 = n\sigma_0^2/(n-1)$, and for every t , let*

$$\alpha_{t+1} = \frac{\sigma_m^2 \alpha_t}{\frac{n}{n-1} \alpha_t + \sigma_m^2} + \frac{n}{n-1} \sigma_d^2. \quad (11)$$

The value of α_t aims to represent the variance of the (random) error made when estimating the stretch of the agents at round t . When thinking of n as very large, the formula for α_{t+1} is reminiscent of the resistance formula in electrical circuits, where we add in parallel to the current resistor with resistance α_t a resistor with resistance σ_m^2 (standing for the measurement noise), and another resistor in a series, with resistance σ_d^2 (standing for the drift).

Definition 5 (Optimal weight). *For every integer t , let*

$$\rho_\star^{(t)} = \frac{\alpha_t}{\frac{n}{n-1} \alpha_t + \sigma_m^2}.$$

The value of $\rho_\star^{(t)}$ aims to indicate by how much to weigh the measurements of round t in order to move optimally: if $\sigma_m^2 \ll \alpha_t$, then $\rho_\star^{(t)} \approx 1$, meaning that the agent should entirely rely on the measurement. Conversely, if $\sigma_m^2 \gg \alpha_t$, then $\rho_\star^{(t)} \approx 0$, and the agent should not take the measurement into account.

At each round t , the Kalman filter returns an estimate of the relative distance of each agent i from the average position, which turns out to be

$$\rho_\star^{(t)} \left(\frac{n-1}{n} Y_i^{(t)} - \frac{1}{n} \sum_{j \neq i} Y_j^{(t)} \right).$$

As guaranteed by the properties of the Kalman filter, these estimates minimize the expected sum of square-errors, which can be translated to our desired measure of minimizing the agents’ costs. The “meet at the center” algorithm is given by Algorithm 1 below, and the following theorem stating its optimality is proved in Section 3.5.

Theorem 3. *Algorithm 1 is optimal in the centralized setting.*

Note that in the centralized setting, once we have an optimal algorithm A , we can derive another optimal algorithm B but simply shifting all agents, at each round t , by a fixed quantity λ_t . Indeed, such shifts do not influence the relative positions between the agents. Conversely, we show in Appendix D.1 that all (optimal) deterministic algorithms in the centralized setting are shifts of one another, though, we stress that the shifts λ_t are not necessarily the same for all rounds t .

Algorithm 1: Meet at the center

```
foreach round  $t$  do
    Consider all measurements at round  $t$ ,  $\{Y_j^{(t)} \mid 1 \leq j \leq n\}$ ;
    foreach agent  $i$  do
        Set  $d\theta_i^{(t)} = \rho_\star^{(t)} \left( \frac{n-1}{n} Y_i^{(t)} - \frac{1}{n} \sum_{j \neq i} Y_j^{(t)} \right)$ ;          /* Output an estimate of  $\langle \theta \rangle - \theta_i$  */
    end
end
```

Algorithm 2: The Weighted-average algorithm \mathcal{W}^\star

```
foreach round  $t$  do
    Consider all measurements at round  $t$ ,  $\{Y_j^{(t)} \mid 1 \leq j \leq n\}$ ;
    foreach agent  $i$  do
        Set  $d\theta_i^{(t)} = \rho_\star^{(t)} Y_i^{(t)}$ ;
    end
end
```

In particular, by adding the shift $\lambda_t = \frac{1}{n} \rho_\star^{(t)} \sum_{i=1}^n Y_i^{(t)}$ to the agents in Algorithm 1 (see Appendix D.2) we obtain a weighted-average algorithm, which we term \mathcal{W}^\star .

Since \mathcal{W}^\star is a solution that follows from the Kalman filter estimations, it yields optimal stretches. The proof of the following theorem is given in Section 3.6.

Theorem 4. *The weighted-average algorithm $\mathcal{W}^\star = \mathcal{W}(\rho_\star^{(t)})$ (Algorithm 2) is optimal in the centralized setting.*

In contrast to $\mathcal{W}(\rho^\star)$, Algorithm \mathcal{W}^\star uses a different responsiveness $\rho_\star^{(t)}$ at each round t . We next argue that the sequences (α_t) and $(\rho_\star^{(t)})$ converge. Not surprisingly, at the limit, we recover the optimal responsiveness as stated in Theorem 2. The proof of the following claim is deferred to Appendix B.2.

Claim 1. *The sequence α_t converges to*

$$\alpha_\infty := \frac{1}{2} \left(\sigma_d \sqrt{4\sigma_m^2 + \left(\frac{n}{n-1} \sigma_d \right)^2} + \frac{n}{n-1} \sigma_d^2 \right).$$

Moreover, $\lim_{t \rightarrow +\infty} \rho_\star^{(t)} = \rho_\star$.

1.3.4 Drift of the center of mass.

In this section we analyze the drift of the center of mass. Essentially, we show that with respect to this drift (and in contrast to the measure of stretch as used in Definition 1), there is a gap between the centralized and the distributed settings. Specifically, we first show that the “meet at the center” algorithm (Algorithm 1) is “drift-optimal”, in sense that it achieves the best possible drift among all centralized algorithms that are based on the set of agents’ measurements only. In contrast, we prove that there is no distributed algorithm that can achieve as small of a drift as the one obtained by the “meet at the center” algorithm. Consistent with this result, the (distributed) weighted-average algorithm \mathcal{W}^\star (Algorithm 2) is not “drift-optimal”, yet the overhead it incurs in terms of this drift is relatively small, especially when n is large.

Let us now describe these results in more detail. Denote

$$\Delta_t = \langle \theta^{(t)} \rangle - \langle \theta^{(0)} \rangle.$$

By definition (Eq. (2)), for a given algorithm, the center of mass changes in round t as follows:

$$\langle \theta^{(t+1)} \rangle - \langle \theta^{(t)} \rangle = \frac{1}{n} \sum_{i=1}^n \left(d\theta_i^{(t)} + N_{d,i}^{(t)} \right). \quad (12)$$

The drift of the center of mass after t rounds is therefore

$$\Delta_t = \frac{1}{n} \sum_{s=0}^t \sum_{i=1}^n \left(d\theta_i^{(s)} + N_{d,i}^{(s)} \right) = \frac{1}{n} \sum_{s=0}^t \sum_{i=1}^n d\theta_i^{(s)} + \frac{1}{n} \sum_{s=0}^t \sum_{i=1}^n N_{d,i}^{(s)}.$$

Let us denote $\Delta_t^{\text{inh}} := \frac{1}{n} \sum_{s=0}^t \sum_{i=1}^n N_{d,i}^{(s)}$, and refer to it as *inherent-drift*. Similarly, we write $\Delta_t^{\text{rel}} := \frac{1}{n} \sum_{s=0}^t \sum_{i=1}^n d\theta_i^{(s)}$, and refer to it as *relative-drift*. (The choices of names will be clarified later). With these notations, we have

$$\Delta_t = \Delta_t^{\text{rel}} + \Delta_t^{\text{inh}}. \quad (13)$$

Note that, while Δ_t^{rel} depends on the protocol being used, Δ_t^{inh} has always the same distribution, regardless of the protocol used. However, this fact doesn't necessarily mean that the two variables are independent, since for some protocols, Δ_t^{rel} could, in principle, depend on Δ_t^{inh} . Indeed, under some (non-Gaussian) distributions of drift, it is possible to find a protocol that makes the two variables dependent. However, as the following lemma shows, when the underlying distributions are Gaussian (as assumed in this paper), these two variables are always independent. The proof of the following lemma can be found in Appendix E.

Lemma 1. *For every protocol and for every round t , Δ_t^{inh} and Δ_t^{rel} are independent.*

A direct consequence of Lemma 1 is that

$$\begin{aligned} \mathbb{E}(\Delta_t^2) &= \mathbb{E}(\Delta_t)^2 + \text{Var}(\Delta_t) \\ &= \left(\mathbb{E}(\Delta_t^{\text{inh}}) + \mathbb{E}(\Delta_t^{\text{rel}}) \right)^2 + \text{Var}(\Delta_t^{\text{inh}}) + \text{Var}(\Delta_t^{\text{rel}}) \\ &= \mathbb{E}(\Delta_t^{\text{rel}})^2 + \text{Var}(\Delta_t^{\text{rel}}) + \text{Var}(\Delta_t^{\text{inh}}) \\ &= \mathbb{E}(\Delta_t^{\text{rel}2}) + \text{Var}(\Delta_t^{\text{inh}}) \\ &\geq \text{Var}(\Delta_t^{\text{inh}}), \end{aligned} \quad (14)$$

justifying the choice of the term ‘‘inherent’’. Since $\text{Var}(\Delta_t^{\text{inh}}) = \text{Var}\left(\frac{1}{n} \sum_{s=0}^t \sum_{i=1}^n N_{d,i}^{(s)}\right) = \frac{t+1}{n} \sigma_d^2$, we obtain the following.

Theorem 5. *For every round t and for every protocol in the centralized setting, the drift of the center of mass satisfies*

$$\mathbb{E}(\Delta_t^2) \geq \frac{t+1}{n} \sigma_d^2.$$

This lower bound gives rise to the next definition.

Definition 6. *An algorithm is called drift-optimal, if for every round t , the drift of the center of mass satisfies*

$$\mathbb{E}(\Delta_t^2) = \text{Var}(\Delta_t^{\text{inh}}) = \frac{t+1}{n} \sigma_d^2.$$

Theorem 6. *The ‘‘meet at the center’’ algorithm (Algorithm 1) is drift-optimal.*

Proof. When the agents follow the ‘‘meet at the center’’ centralized algorithm, for every $t \in \mathbb{N}$

$$\frac{1}{n} \sum_{i=1}^n d\theta_i^{(t)} = \frac{1}{n} \sum_{i=1}^n \rho_\star^{(t)} \left(\frac{n-1}{n} Y_i^{(t)} - \frac{1}{n} \sum_{j \neq i} Y_j^{(t)} \right) = \frac{\rho_\star^{(t)}}{n} \left(\frac{n-1}{n} \sum_{i=1}^n Y_i^{(t)} - \frac{1}{n} \sum_{i=1}^n (n-1) \cdot Y_i^{(t)} \right) = 0.$$

Hence, by definition, $\Delta_t^{\text{rel}} = 0$ and by Eq. (14), the drift of the center of mass in round t is limited to Δ_t^{inh} , which concludes the proof of Theorem 6. \square

Next, we argue that although the weighted-average algorithm \mathcal{W}^\star (Algorithm 2) manages to maintain optimal stretches, it is not drift-optimal. Nevertheless, it yields a relatively small drift when n is large.

Theorem 7. *When Algorithm \mathcal{W}^\star is used, the drift of the center of mass satisfies*

$$\mathbb{E}(\Delta_t^2) = \frac{t+1}{n} \sigma_d^2 + \frac{\sum_{s=0}^t \rho_\star^{(s)2}}{n} \sigma_m^2.$$

Proof. When the agents follow the weighted-average algorithm \mathcal{W}^* , we have for every $t \in \mathbb{N}$

$$\frac{1}{n} \sum_{i=1}^n d\theta_i^{(t)} = \frac{1}{n} \sum_{i=1}^n \rho_\star^{(t)} \left(\bar{\theta}_i^{(t)} + N_{m,i}^{(t)} \right) = \frac{1}{n} \sum_{i=1}^n \rho_\star^{(t)} N_{m,i}^{(t)},$$

where the last equality is by Lemma 2. Using Eq. (14), and summing over the rounds $s = 0, \dots, t$, we conclude the proof of Theorem 7. \square

Note that since $\rho_\star^{(s)} \leq 1$, the overhead incurred by Algorithm \mathcal{W}^* is at most $\frac{t+1}{n} \sigma_m^2$.

Finally, we argue that the sub-optimality of Algorithm \mathcal{W}^* (in terms of the drift of the center of mass) is not coincidental. The proof of the following claim is deferred to Appendix D.3.

Claim 2. *No algorithm in the distributed setting can be simultaneously optimal (Definition 2) and drift-optimal (Definition 6).*

1.4 Related works

The Kalman filter algorithm is a prolific tool commonly used in control theory and statistics, with numerous technological applications [1]. This algorithm receives a sequence of noisy measurements, and produces estimates of unknown variables, by estimating a joint probability distribution over the variables for each time step. In this paper, we used the Kalman filter to investigate the centralized setting, where all relative measurements are gathered at one master agent that processes them and instructs agents how to move. Fusing relative measurements of multiple agents is often referred to in the literature as *distributed Kalman filter*, see surveys in [8, 28, 29]. However, there, the typical setting is that each agent invokes a separate Kalman filter to process its measurements, and then the resulted outputs are integrated using communication. Moreover, works in that domain often assume that observations are attained by static observers (i.e., the agents are residing on a fixed underlying graph) and that the measured target is external to the system. In contrast, here we consider a self-organizing system, with mobile agents that measure a target (average position) that is a function of their positions. Closer works to our setting where a group of mobile agents aim to gather together are [23, 36]. However, among the several differences with our paper, these papers assume that there is no drift and that agents communicate their absolute position, rather than their relative position.

A model concerning a group of individuals that aim to estimate an external signal relying on noisy real-valued measurements was studied in [25]. Despite the differences between models, similarly to our paper, the findings in [25] emphasize the effectiveness of performing a weighted-average between the current opinion of the individual and the sample it receives. Nevertheless, we note that in the context of the model in [25], this result is less surprising since it does not involve any drift, and since each individual communicates with only one individual at a round.

Another related self-organization problem is *clock synchronization*, where the goal is to maintain a common notion of time in the absence of a global source of real time. The main difficulty is handling the fact that clocks count time at slightly different rates and that messages arrive with some delays. Variants of this problem were studied in wireless network contexts, mostly by control theoreticians [31, 33, 34]. A common technique uses oscillating models [22, 27].

2 Warm-up proofs

Our goal in this section is to prove Theorems 1 and 2. These theorems assume all agents execute a weighted-average algorithm with the same responsiveness parameter ρ , that furthermore remains fixed throughout the execution (see Eq. (3)). The proofs of all intermediate results can be found in Appendix B.1. We start with the following observation.

Lemma 2. *For any t , and whatever the positions of the agents, we have $\sum_{i=1}^n \bar{\theta}_i^{(t)} = 0$.*

Next, we compute how the stretch $\bar{\theta}_i^{(t)}$ of Agent i changes when all agents perform weighted-average moves with constant responsiveness parameter ρ .

Lemma 3. *Assume that all agents execute $\mathcal{W}(\rho)$, for some $0 \leq \rho \leq 1$. Let $\mathcal{E}_j^{(t)} = \rho N_{m,j}^{(t)} + N_{d,j}^{(t)}$. Then for every $i \in \{1, \dots, n\}$ and every $t \in \mathbb{N}$,*

$$\bar{\theta}_i^{(t+1)} = \left(1 - \frac{n}{n-1} \rho \right) \bar{\theta}_i^{(t)} + \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \mathcal{E}_j^{(t)} - \mathcal{E}_i^{(t)}.$$

Now we can prove that the stretch of each agent is normally distributed at every round, and compute its variance.

Lemma 4. *Assume that all agents execute $\mathcal{W}(\rho)$, for some $0 \leq \rho \leq 1$. Then, for every $i \in \{1, \dots, n\}$ and every $t \in \mathbb{N}$, the stretch $\bar{\theta}_i^{(t)}$ is normally distributed, $\mathbb{E}(\bar{\theta}_i^{(t)}) = 0$, and*

$$\text{Var}(\bar{\theta}_i^{(t+1)}) = \left(1 - \frac{n\rho}{n-1}\right)^2 \text{Var}(\bar{\theta}_i^{(t)}) + \frac{n(\rho^2\sigma_m^2 + \sigma_d^2)}{n-1}.$$

Before proving Theorem 1, we need a small technical result.

Claim 3. *Let $a, b \geq 0$. Consider the sequence $\{u_n\}_{n=0}^\infty$ defined by letting $u_0 \in \mathbb{R}$ and for every integer n , $u_{n+1} = au_n + b$. If $a < 1$, then $\{u_n\}_{n=0}^\infty$ converges and $\lim_{n \rightarrow +\infty} u_n = b/(1-a)$. If $a = 1$, and $b > 0$, then $\lim_{n \rightarrow +\infty} u_n = +\infty$.*

We now show how Theorem 1 follows directly from Lemma 4 and Claim 3.

Proof. First, apply Lemma 4. Hence, by Claim 3, $\text{Var}(\bar{\theta}_i^{(t)})$ converges to the limit as stated. Note that the variance is infinite if 1) the responsiveness is equal to 0, in which case the drift adds up endlessly, or 2) the responsiveness is equal to 1 and $n = 2$, in which case the agents “swap” at each round, producing the same result. This completes the proof of Theorem 1. \square

We next prove Theorem 2.

Proof. Consider the function

$$\text{Var}(\rho) = \frac{\frac{n}{n-1}(\rho^2\sigma_m^2 + \sigma_d^2)}{1 - \left(1 - \frac{n}{n-1}\rho\right)^2} = \frac{\rho^2\sigma_m^2 + \sigma_d^2}{2\rho - \frac{n}{n-1}\rho^2}.$$

Note that this function evaluates to $+\infty$ when $\rho = 0$, or when $\rho = 1$ and $n = 2$. Computing its derivative yields:

$$\text{Var}'(\rho) = \frac{2\rho\sigma_m^2 \left(2\rho - \frac{n}{n-1}\rho^2\right) - (\rho^2\sigma_m^2 + \sigma_d^2) \left(2 - 2\frac{n}{n-1}\rho\right)}{\left(2\rho - \frac{n}{n-1}\rho^2\right)^2}.$$

Hence, $\text{Var}'(\rho) = 0$ if and only if:

$$\rho^2\sigma_m^2 \left(2 - \frac{n}{n-1}\rho\right) - (\rho^2\sigma_m^2 + \sigma_d^2) \left(1 - \frac{n}{n-1}\rho\right) = 0 \iff \rho^2\sigma_m^2 - \sigma_d^2 \left(1 - \frac{n}{n-1}\rho\right) = 0.$$

This equation has a unique solution in the interval $[0, 1]$:

$$\rho = \frac{\sigma_d \sqrt{4\sigma_m^2 + \left(\frac{n}{n-1}\sigma_d\right)^2} - \frac{n}{n-1}\sigma_d^2}{2\sigma_m^2}.$$

Checking that this is a minimum concludes the proof. \square

3 Solving the SAC problem

We denote $\mathcal{N}(\mu, \Sigma)$ the multivariate normal distribution with mean vector $\mu \in \mathbb{R}^n$ and co-variance matrix $\Sigma \in \mathbb{R}^{n \times n}$, and by I the identity matrix. Letting $\mathbf{1}$ be the matrix whose all coefficients are equal to 1, we denote $\mathcal{M}(a, b) = b\mathbf{1} + (a-b)I$, the matrix having diagonal coefficients equal to a , and other coefficients equal to b .

3.1 Rephrasing SAC as a linear filtering problem

The goal of this section is to write Eqs. (1) and (2) in a matricial form. Let

$$\begin{aligned} \bar{\theta}^{(t)} &= \left(\bar{\theta}_1^{(t)}, \dots, \bar{\theta}_n^{(t)}\right), & d\theta^{(t)} &= \left(d\theta_1^{(t)}, \dots, d\theta_n^{(t)}\right), \\ Y^{(t)} &= \left(Y_1^{(t)}, \dots, Y_n^{(t)}\right), \\ N_m^{(t)} &= \left(N_{m,1}^{(t)}, \dots, N_{m,n}^{(t)}\right) & \text{and} & \quad N_d^{(t)} = \left(N_{d,1}^{(t)}, \dots, N_{d,n}^{(t)}\right). \end{aligned}$$

Measurement rule. Recall that, as stated in Eq. (1), the measurement of Agent i at time t is given by $Y_i^{(t)} = \bar{\theta}_i^{(t)} + N_{m,i}^{(t)}$. We simply rewrite this equation as:

$$Y^{(t)} = \bar{\theta}^{(t)} + N_m^{(t)}, \quad (15)$$

where, by definition, $N_m^{(t)} \sim \mathcal{N}(0, \sigma_m^2 I)$.

Update rule. We recall the update equation of the stretch, which follows from Eq. (30):

$$\begin{aligned} \bar{\theta}_i^{(t+1)} &= \bar{\theta}_i^{(t)} - d\theta_i^{(t)} - N_{d,i}^{(t)} + \left(\langle \theta_{-i}^{(t+1)} \rangle - \langle \theta_{-i}^{(t)} \rangle \right) \\ &= \bar{\theta}_i^{(t)} - d\theta_i^{(t)} - N_{d,i}^{(t)} + \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}} \left(d\theta_j^{(t)} + N_{d,j}^{(t)} \right). \end{aligned} \quad (16)$$

We define the matrix

$$M_n = \mathcal{M} \left(-1, \frac{1}{n-1} \right).$$

Let $\tilde{N}_d^{(t)} = M_n N_d^{(t)}$. With these definitions and Eq. (16), Eq. (2) becomes

$$\bar{\theta}^{(t+1)} = \bar{\theta}^{(t)} + M_n d\theta^{(t)} + \tilde{N}_d^{(t)}. \quad (17)$$

By definition, $N_d^{(t)} \sim \mathcal{N}(0, \sigma_d^2 I)$, so by Claim 5, $\tilde{N}_d^{(t)} \sim \mathcal{N}(0, Q)$ where

$$Q = \sigma_d^2 \cdot M_n I M_n^\top = \sigma_d^2 M_n^2.$$

3.2 Applying the Kalman filter

We use the Kalman filter as a tool for analysis purposes of the process. We stress, however, that the Kalman filter is not necessarily applied by any agent.

We define $\hat{\theta}_t$ the estimate of $\theta^{(t)}$ produced by the Kalman filter *after* the measurements at round t were obtained (Eq. (15)) and before the update of round t occurs (Eq. (17)). Let P_t denote the error co-variance matrix associated with this estimate. Specifically,

$$P_t = \mathbb{E} \left[(\theta^{(t)} - \hat{\theta}_t)(\theta^{(t)} - \hat{\theta}_t)^\top \right].$$

We add the superscript “-” to these notations (for example P_t^-), to denote the same quantities *before* the measurement obtained at round t .

So, in a sense, round t can be divided into the following four consecutive time steps: (a) the filter produces an estimation $\hat{\theta}_t^-$ of $\theta^{(t)}$, (b) a new measurement vector $Y^{(t)}$ of $\theta^{(t)}$ is obtained, (c) the filter produces an estimation $\hat{\theta}_t$ of $\theta^{(t)}$ given the new measurement, and (d) $\theta^{(t)}$ is updated to $\theta^{(t+1)}$. Recall that at round 0, i.e., at the initialization stage, the agents are normally distributed around 0. For technical reasons, we define the Kalman filter estimate at round 0 to be zero, that is, $\hat{\theta}_0 = 0$.

Measurement update. In order to produce (c), the filter incorporates the measurement in (b) to the estimation in (a). Specifically, the filter computes the “Kalman gain”:

$$K_t = P_t^- (P_t^- + \sigma_m^2 I)^{-1}. \quad (18)$$

Then, it produces the following estimate, as required in (c):

$$\hat{\theta}_t = \hat{\theta}_t^- + K_t \left(Y^{(t)} - \hat{\theta}_t^- \right). \quad (19)$$

The new error co-variance matrix can then be written as:

$$P_t = (I - K_t) P_t^-. \quad (20)$$

Time update The estimation for (a) for the following round is then given by:

$$\hat{\theta}_{t+1} = \hat{\theta}_t + M_n d\theta^{(t)}. \quad (21)$$

Finally, the new error co-variance matrix that will be used in the Kalman gain corresponding to the $t + 1$ 'th round (Eq. (18)) is:

$$P_{t+1}^- = P_t + \sigma_d^2 \cdot M_n^2. \quad (22)$$

3.3 Optimality

Definition 7. A history \mathcal{H}_t is a realization of all measurements and all moves up to time $(t - 1)$.

The following is a well-known result, see e.g., [1].

Theorem 8. For every round t , every history \mathcal{H}_t and every vector $x \in \mathbb{R}^n$,

$$\sum_{i=1}^n \mathbb{E} \left((\theta_i^{(t)} - \hat{\theta}_{t,i})^2 \mid \mathcal{H}_t \right) \leq \sum_{i=1}^n \mathbb{E} \left((\theta_i^{(t)} - x_i)^2 \mid \mathcal{H}_t \right).$$

In particular, for every round t , every history \mathcal{H}_t , every $i \leq n$ and every scalar $x \in \mathbb{R}$,

$$\mathbb{E} \left((\theta_i^{(t)} - \hat{\theta}_{t,i})^2 \mid \mathcal{H}_t \right) \leq \mathbb{E} \left((\theta_i^{(t)} - x)^2 \mid \mathcal{H}_t \right).$$

Definition 8. We say that an algorithm for the SAC problem is Kalman-perfect if it always produces a sequence of moves $(d\theta^{(t)})_{t \geq 0}$, such that for every integer $t \geq 1$, $\hat{\theta}_t = 0$.

The proof of the following result is provided in Appendix A.

Proposition 1. If there exists a Kalman-perfect algorithm for the SAC problem, then this algorithm is optimal in the centralized setting (in the sense of Definition 2). Moreover, any other optimal (deterministic) algorithm is Kalman-perfect.

3.4 Computing the Kalman gain and the error co-variance matrix

Recall the sequences $(\alpha_t)_{t \geq 0}$ and $(\rho_\star^{(t)})_{t \geq 0}$ introduced in Definitions 4 and 5. This section is dedicated to proving the following lemma, which provides a formula for the error co-variance matrix associated with the estimate $\hat{\theta}_t$, as well as for the Kalman gain.

Lemma 5. For every $t \in \mathbb{N}$,

$$P_t^- = \mathcal{M} \left(\alpha_t, \frac{-\alpha_t}{n-1} \right) = -\alpha_t M_n,$$

and

$$K_t = \frac{-\frac{n-1}{n} \alpha_t M_n}{\frac{n}{n-1} \sigma_m^2 + \alpha_t} = -\rho_\star^{(t)} M_n.$$

Proof. We prove the first part of the claim by induction, and prove that for every round t , the second part of the claim (regarding K_t) follows from the first part (regarding P_t^-).

By Claim 5 (see Appendix C), $P_0^- = \sigma_0^2 M_n^2$. By Claim 6 (see Appendix C),

$$M_n^2 = \mathcal{M} \left(\frac{n}{n-1}, -\frac{n}{(n-1)^2} \right) = \frac{-n}{n-1} M_n.$$

Therefore, $P_0^- = -\frac{n}{n-1} \sigma_0^2 M_n$, and so the first part of the claim holds at round 0 since $\alpha_0 = \frac{n}{n-1} \sigma_0^2$.

Now, let us assume that the first part of the claim holds for some $t \in \mathbb{N}$. It follows that

$$P_t^- + \sigma_m^2 I = \mathcal{M} \left(\alpha_t + \sigma_m^2, \frac{-\alpha_t}{n-1} \right).$$

By Claim 7, since $\sigma_m > 0$, we have

$$(P_t^- + \sigma_m^2 I)^{-1} = \frac{\mathcal{M} \left(\alpha_t + \sigma_m^2 - (n-2) \cdot \frac{\alpha_t}{n-1}, \frac{\alpha_t}{n-1} \right)}{\left(\alpha_t + \sigma_m^2 + \frac{\alpha_t}{n-1} \right) \left(\alpha_t + \sigma_m^2 - (n-1) \cdot \frac{\alpha_t}{n-1} \right)} = \frac{\mathcal{M} \left(\frac{\alpha_t}{n-1} + \sigma_m^2, \frac{\alpha_t}{n-1} \right)}{\sigma_m^2 \left(\frac{n}{n-1} \alpha_t + \sigma_m^2 \right)}.$$

By Claim 6 again, we can compute the ‘‘Kalman gain’’:

$$\begin{aligned}
K_t &= P_t^-(P_t^- + \sigma_m^2 I)^{-1} \\
&= \frac{1}{\sigma_m^2 \left(\frac{n}{n-1} \alpha_t + \sigma_m^2 \right)} \cdot \mathcal{M} \left(\frac{\alpha_t^2}{n-1} + \sigma_m^2 \alpha_t - \frac{(n-1) \cdot \alpha_t^2}{(n-1)^2}, \frac{-\alpha_t^2}{(n-1)^2} - \frac{\sigma_m^2 \alpha_t}{n-1} + \frac{\alpha_t^2}{n-1} - (n-2) \cdot \frac{\alpha_t^2}{(n-1)^2} \right) \\
&= \frac{\mathcal{M} \left(\sigma_m^2 \alpha_t, \frac{-\sigma_m^2 \alpha_t}{n-1} \right)}{\sigma_m^2 \left(\frac{n}{n-1} \alpha_t + \sigma_m^2 \right)} = \frac{-\alpha_t M_n}{\frac{n}{n-1} \alpha_t + \sigma_m^2},
\end{aligned}$$

This proves that the second part of the claim holds at round t . Next, we compute the error co-variance matrix after the measurement:

$$\begin{aligned}
P_t &= (I - K_t) \cdot P_t^- = \frac{\mathcal{M} \left(\frac{\alpha_t}{n-1} + \sigma_m^2, \frac{\alpha_t}{n-1} \right)}{\frac{n}{n-1} \alpha_t + \sigma_m^2} \cdot P_t^- \\
&= \frac{1}{\frac{n}{n-1} \alpha_t + \sigma_m^2} \cdot \mathcal{M} \left(\frac{\alpha_t^2}{n-1} + \sigma_m^2 \alpha_t - (n-1) \cdot \frac{\alpha_t^2}{(n-1)^2}, -\frac{\alpha_t^2}{(n-1)^2} - \frac{\sigma_m^2 \alpha_t}{n-1} + \frac{\alpha_t^2}{n-1} - (n-2) \cdot \frac{\alpha_t^2}{(n-1)^2} \right) \\
&= \frac{\mathcal{M} \left(\sigma_m^2 \alpha_t, \frac{-\sigma_m^2 \alpha_t}{n-1} \right)}{\frac{n}{n-1} \alpha_t + \sigma_m^2} = -\frac{\frac{n-1}{n} \sigma_m^2 \alpha_t}{\alpha_t + \frac{n-1}{n} \sigma_m^2} M_n.
\end{aligned}$$

Eventually, we compute the error co-variance matrix at round $t+1$, before the measurement:

$$P_{t+1}^- = P_t + \sigma_d^2 M_n^2 = P_t - \frac{n}{n-1} \sigma_d^2 M_n.$$

Plugging in the expression of P_t , we get

$$P_{t+1}^- = -\frac{\frac{n-1}{n} \sigma_m^2 \alpha_t}{\alpha_t + \frac{n-1}{n} \sigma_m^2} M_n - \frac{n}{n-1} \sigma_d^2 M_n = -\left(\frac{\frac{n-1}{n} \sigma_m^2 \alpha_t}{\frac{n-1}{n} \sigma_m^2 + \alpha_t} + \frac{n}{n-1} \sigma_d^2 \right) M_n = -\alpha_{t+1} M_n,$$

which concludes the induction proof. \square

3.5 Meet at the center

The goal of this section is to prove that the ‘‘meet at the center’’ centralized algorithm (Algorithm 1) is optimal. We also explain why we refer to it as ‘‘meet at the center’’.

Theorem 3 (restated). *Algorithm 1 is optimal in the centralized setting.*

Proof. Our goal is to prove that Algorithm 1 is Kalman-perfect, that is, that for every integer $t \geq 1$, the Kalman filter associated with the moves produced by Algorithm 1 gives the estimate $\hat{\theta}_t = 0$. This would conclude the proof of the theorem, by Proposition 1.

For this purpose, assume that all agents run Algorithm 1. We prove by induction that for every integer $t \geq 0$, the Kalman filter produces the estimate $\hat{\theta}_t = 0$. This holds at $t = 0$ since we assumed that the Kalman filter estimates 0 at round 0, i.e., $\hat{\theta}_0 = 0$. Next, let us assume that $\hat{\theta}_t = 0$ for some integer $t \geq 0$. We have by definition,

$$\hat{\theta}_{t+1}^- = \hat{\theta}_t + M_n d\theta^{(t)}, \quad (23)$$

and

$$\hat{\theta}_t = \hat{\theta}_t^- + K_t \left(Y^{(t)} - \hat{\theta}_t^- \right) = K_t Y^{(t)}, \quad (24)$$

where the second equality in Eq. (24) is by the induction hypothesis. By Lemma 5, $K_t = -\rho_\star^{(t)} M_n$. Note that, by definition of Algorithm 1, $d\theta^{(t)} = -\frac{n-1}{n} \rho_\star^{(t)} M_n Y^{(t)} = \frac{n-1}{n} \hat{\theta}_t$. Finally, by the aforementioned equations, we rewrite Eq. (23) as:

$$\hat{\theta}_{t+1}^- = \left(I + \frac{n-1}{n} M_n \right) \hat{\theta}_t = \left(I + \frac{n-1}{n} M_n \right) K_t Y^{(t)} = -\left(M_n + \frac{n-1}{n} M_n^2 \right) \rho_\star^{(t)} Y^{(t)}.$$

Since $M_n^2 = \frac{-n}{n-1} M_n$, we have $\hat{\theta}_{t+1}^- = 0$. This concludes the induction, and completes the proof of the theorem. \square

Next, we wish to explain why we refer to Algorithm 1 as the “meet at the center” algorithm. Let $i \in \{1, \dots, n\}$. Since $\hat{\theta}_{t,i}$ is produced by the Kalman filter, it is the optimal estimate of the stretch $\bar{\theta}_i^{(t)}$ of Agent i , given the previous measurements and moves. Next, recall that $\langle \theta^t \rangle$ denotes the average position of all agents, and that $\langle \theta^t \rangle - \theta_i^{(t)} = \frac{n-1}{n} \bar{\theta}_i^{(t)}$. Therefore, $d\theta_i^{(t)} = \frac{n-1}{n} \hat{\theta}_{t,i}$ is the optimal estimate of $\langle \theta^t \rangle - \theta_i^{(t)}$ (given the previous measurements and moves). Consequently, instructing Agent i to move by $d\theta_i^{(t)}$, would make this agent be located as close as possible to the average position. This observation justifies that Algorithm 1 consists in “meet at the center”.

3.6 The weighted-average algorithm \mathcal{W}^* is optimal in the centralized setting

The goal of this section is to prove Theorem 4.

Theorem 4 (restated). *The weighted-average algorithm \mathcal{W}^* is optimal in the centralized setting.*

Proof. (The proof follows the same line of arguments as the proof of Theorem 3.) Our goal is to prove that Algorithm \mathcal{W}^* is Kalman-perfect, that is, for every integer $t \geq 1$, the Kalman filter associated with the moves produced by Algorithm \mathcal{W}^* gives the estimate $\hat{\theta}_t = 0$. This would conclude the proof of the theorem, by Proposition 1.

For this purpose, assume that all agents run Algorithm \mathcal{W}^* . We prove by induction that for every integer $t \geq 0$, the Kalman filter produces the estimate $\hat{\theta}_t = 0$.

The base case, where $t = 0$, holds since we assumed that the Kalman filter estimates zero at round zero, i.e., $\hat{\theta}_0 = 0$. Next, let us assume that $\hat{\theta}_t = 0$ for some integer $t \geq 0$, and consider $t + 1$. We have by definition,

$$\hat{\theta}_{t+1} = \hat{\theta}_t + M_n d\theta^{(t)}, \quad (25)$$

and

$$\hat{\theta}_t = \hat{\theta}_t + K_t (Y^{(t)} - \hat{\theta}_t) = K_t Y^{(t)}, \quad (26)$$

where the second equality in Eq. (26) is by induction hypothesis. By Lemma 5, $K_t = -\rho_\star^{(t)} M_n$. Hence, Eq. (25) rewrites

$$\hat{\theta}_{t+1} = M_n \left(-\rho_\star^{(t)} Y^{(t)} + d\theta^{(t)} \right).$$

Finally, by the definition of \mathcal{W}^* , we have $d\theta^{(t)} = \rho_\star^{(t)} Y^{(t)}$, so $\hat{\theta}_{t+1} = 0$, concluding the induction step. \square

4 Discussion and Future Work

We introduced the *SAC* problem, aiming to study basic algorithmic aspects that govern approximate agreement processes in unreliable stochastic environments, while relying on measurements of the overall group tendency. We proposed a weighted-average algorithm, termed \mathcal{W}^* , and proved that it achieves optimal stretches, that is, it minimizes the expected distance of each agent from the center of mass of others, at each round. In fact, the optimality of \mathcal{W}^* holds also in the full-communication (or centralized) model, where communication of internal states is unrestricted. Algorithm \mathcal{W}^* is based on having a different responsiveness parameter that is applied by each agent at each round. We also find the optimal weighted-average algorithm among the ones that use the same responsiveness at all times. In contrast to \mathcal{W}^* that minimizes the expected stretch at every round separately, this algorithm becomes optimal only at steady-state.

In our setting, the cost of an individual is defined as its expected distance from the average position of other agents. Minimizing this quantity is equivalent to minimizing the expected distance from the average position of all agents (see Footnote 2). Another interesting measure is the expected *diameter* of the group, defined as the maximal distance between any two agents, at steady state. It would not come as a surprise if Algorithm \mathcal{W}^* would turn out to be optimal also with respect to this measure, however, analyzing its expected diameter would require handling further dependencies between agents, and therefore remains for future work.

It would also be interesting to see how our work could be extended to scenarios in which each agent can observe a subset of randomly chosen agents at each round. As mentioned in the introduction, averaging the values of the agents in such a subset can serve as a noisy sample of average value in the population. However, in contrast to our model, the noise in this sample is not fixed, and depends on the distribution of values in the population and on the size of the sampled subset. In many cases, one can expect that sampling a subset containing a logarithmic number of agents could suffice to obtain a relatively good sample of the population. We find this encouraging towards generalizing our work to such scenarios.

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APPENDIX

A Proof of Proposition 1

Proposition 1 is a direct consequence of the following result.

Lemma 6. Fix $i \in \{1, \dots, n\}$ and an integer $t \geq 1$, and consider a history \mathcal{H}_t such that the Kalman filter produces $\hat{\theta}_{t,i} = 0$ on \mathcal{H}_t . Let $d\vartheta^{(t-1)}$ be an alternative move for the agents at round $(t-1)$, and consider history \mathcal{H}'_t obtained from \mathcal{H}_t by replacing $d\theta^{(t-1)}$ by $d\vartheta^{(t-1)}$. Then,

$$\mathbb{E} \left(\theta_i^{(t)2} \mid \mathcal{H}'_t \right) \geq \mathbb{E} \left(\theta_i^{(t)2} \mid \mathcal{H}_t \right).$$

Proof. Let c be the i th coordinate of the vector $M_n(d\theta^{(t)} - d\vartheta^{(t)})$. By Eq. (2), c is the difference between the position of Agent i in the beginning of round t if it moves by $d\theta^{(t)}$ instead of moving by $d\vartheta^{(t)}$ (conditioning on having the same drift at the end of round $t-1$). In other words,

$$\mathbb{E} \left(\theta_i^{(t)2} \mid \mathcal{H}'_t \right) = \mathbb{E} \left((\theta_i^{(t)} - c)^2 \mid \mathcal{H}_t \right). \quad (27)$$

By Theorem 8,

$$\mathbb{E} \left((\theta_i^{(t)} - c)^2 \mid \mathcal{H}_t \right) \geq \mathbb{E} \left((\theta_i^{(t)} - \hat{\theta}_{t,i})^2 \mid \mathcal{H}_t \right). \quad (28)$$

By assumption, $\hat{\theta}_{t,i} = 0$, so

$$\mathbb{E} \left((\theta_i^{(t)} - \hat{\theta}_{t,i})^2 \mid \mathcal{H}_t \right) = \mathbb{E} \left(\theta_i^{(t)2} \mid \mathcal{H}_t \right). \quad (29)$$

Combining Equations (27), (28) and (29) establishes the result. \square

B More Results Regarding Weighted-Average Algorithms

B.1 An optimal weighted-average algorithm (at steady state)

Lemma 2 (restated). For any t , and whatever the positions of the agents, we have $\sum_{i=1}^n \bar{\theta}_i^{(t)} = 0$.

Proof.

$$\sum_{i=1}^n \bar{\theta}_i^{(t)} = \sum_{i=1}^n \left(\langle \theta_{-i}^{(t)} \rangle - \theta_i^{(t)} \right) = \frac{1}{n-1} \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \theta_j^{(t)} - \sum_{i=1}^n \theta_i^{(t)} = \frac{1}{n-1} \cdot (n-1) \sum_{i=1}^n \theta_i^{(t)} - \sum_{i=1}^n \theta_i^{(t)} = 0.$$

\square

Lemma 3 (restated). Assume that all agents execute $\mathcal{W}(\rho)$, for some $0 \leq \rho \leq 1$. Let

$$\mathcal{E}_j^{(t)} = \rho N_{m,j}^{(t)} + N_{d,j}^{(t)}.$$

Then for every $i \in \{1, \dots, n\}$ and every $t \in \mathbb{N}$,

$$\bar{\theta}_i^{(t+1)} = \left(1 - \frac{n}{n-1} \rho \right) \bar{\theta}_i^{(t)} + \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \mathcal{E}_j^{(t)} - \mathcal{E}_i^{(t)}.$$

Proof. The stretch of Agent i at round $t+1$ is given by:

$$\begin{aligned} \bar{\theta}_i^{(t+1)} &= \langle \theta_{-i}^{(t+1)} \rangle - \theta_i^{(t+1)} \\ &= \langle \theta_{-i}^{(t+1)} \rangle - \left(\theta_i^{(t)} + d\theta_i^{(t)} + N_{d,i}^{(t)} \right) \\ &= \left(\langle \theta_{-i}^{(t+1)} \rangle - \langle \theta_{-i}^{(t)} \rangle \right) + \left(\langle \theta_{-i}^{(t)} \rangle - \theta_i^{(t)} \right) - d\theta_i^{(t)} - N_{d,i}^{(t)} \\ &= \left(\langle \theta_{-i}^{(t+1)} \rangle - \langle \theta_{-i}^{(t)} \rangle \right) + \bar{\theta}_i^{(t)} - d\theta_i^{(t)} - N_{d,i}^{(t)}, \end{aligned} \quad (30)$$

where the first equality is by definition, and the second equality is a consequence of (2). Let us break down the first term:

$$\langle \theta_{-i}^{(t+1)} \rangle - \langle \theta_{-i}^{(t)} \rangle = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \left(d\theta_j^{(t)} + N_{d,j}^{(t)} \right) = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \left(\rho \left(\bar{\theta}_j^{(t)} + N_{m,j}^{(t)} \right) + N_{d,j}^{(t)} \right),$$

where the second equality is because

$$d\theta_j^{(t)} = \rho Y_j^{(t)} = \rho \left(\bar{\theta}_j^{(t)} + N_{m,j}^{(t)} \right).$$

By Lemma 2, $\sum_{\substack{j=1 \\ j \neq i}}^n \bar{\theta}_j^{(t)} = -\bar{\theta}_i^{(t)}$, so we can rewrite the last equation as

$$\langle \theta_{-i}^{(t+1)} \rangle - \langle \theta_{-i}^{(t)} \rangle = \frac{-\rho}{n-1} \bar{\theta}_i^{(t)} + \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \left(\rho N_{m,j}^{(t)} + N_{d,j}^{(t)} \right) = \frac{-\rho}{n-1} \bar{\theta}_i^{(t)} + \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \mathcal{E}_j^{(t)}. \quad (31)$$

Plugging Eq. (31) into Eq. (30) gives

$$\bar{\theta}_i^{(t+1)} = \left(1 - \frac{\rho}{n-1} \right) \bar{\theta}_i^{(t)} + \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \mathcal{E}_j^{(t)} - d\theta_i^{(t)} - N_{d,i}^{(t)}. \quad (32)$$

By assumption, $d\theta_i^{(t)} = \rho Y_i^{(t)} = \rho \left(\bar{\theta}_i^{(t)} + N_{m,i}^{(t)} \right)$. Plugging this expression into Eq. (32) gives the result. \square

Lemma 4 (restated). *Assume that all agents execute $\mathcal{W}(\rho)$, for some $\leq \rho \leq 1$. Then, for every $i \in \{1, \dots, n\}$ and every $t \in \mathbb{N}$, the stretch $\bar{\theta}_i^{(t)}$ is normally distributed. Moreover, $\mathbb{E} \left(\bar{\theta}_i^{(t)} \right) = 0$, and*

$$\text{Var} \left(\bar{\theta}_i^{(t+1)} \right) = \left(1 - \frac{n\rho}{n-1} \right)^2 \text{Var} \left(\bar{\theta}_i^{(t)} \right) + \frac{n(\rho^2 \sigma_m^2 + \sigma_d^2)}{n-1}.$$

Proof. We prove that the stretch is normally distributed with mean 0 by induction on t . By construction, for every i , $\bar{\theta}_i^{(0)}$ is normally distributed with mean 0. Let us assume that $\bar{\theta}_i^{(t)}$ is normally distributed with mean 0 for some round t , and consider round $t+1$. Recall that Lemma 3 gives

$$\bar{\theta}_i^{(t+1)} = \left(1 - \frac{n}{n-1} \rho \right) \bar{\theta}_i^{(t)} + \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \mathcal{E}_j^{(t)} - \mathcal{E}_i^{(t)}. \quad (33)$$

Since by definition, for every j , $\mathcal{E}_j^{(t)}$ is normally distributed around 0, and by induction $\bar{\theta}_i^{(t)}$ is normally distributed around 0, then $\bar{\theta}_i^{(t+1)}$ is also normally distributed around 0. This concludes the induction.

Moreover, note that $\text{Var} \left(\mathcal{E}_j^{(t)} \right) = \rho^2 \sigma_m^2 + \sigma_d^2$, so

$$\text{Var} \left(\frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \mathcal{E}_j^{(t)} - \mathcal{E}_i^{(t)} \right) = \frac{1}{(n-1)^2} \sum_{\substack{j=1 \\ j \neq i}}^n \text{Var} \left(\mathcal{E}_j^{(t)} \right) + \text{Var} \left(\mathcal{E}_i^{(t)} \right) = \frac{n}{n-1} (\rho^2 \sigma_m^2 + \sigma_d^2).$$

Hence, by Eq. (33),

$$\text{Var} \left(\bar{\theta}_i^{(t+1)} \right) = \left(1 - \frac{n\rho}{n-1} \right)^2 \text{Var} \left(\bar{\theta}_i^{(t)} \right) + \frac{n(\rho^2 \sigma_m^2 + \sigma_d^2)}{n-1},$$

which concludes the proof. \square

Claim 3 (restated). *Let $a, b \geq 0$. Consider the sequence $\{u_n\}_{n=0}^\infty$ defined by letting $u_0 \in \mathbb{R}$ and for every integer n , $u_{n+1} = au_n + b$. If $a < 1$, then $\{u_n\}_{n=0}^\infty$ converges and $\lim_{n \rightarrow +\infty} u_n = b/(1-a)$. If $a = 1$, and $b > 0$, then $\lim_{n \rightarrow +\infty} u_n = +\infty$.*

Proof. First, consider the case that $a < 1$. Let $\lambda = b/(a - 1)$. Consider the sequence defined by $v_n = u_n + \lambda$. We have

$$\begin{aligned} v_{n+1} &= u_{n+1} + \lambda = au_n + b + \lambda \\ &= au_n + (a - 1)\lambda + \lambda \\ &= au_n + a\lambda = a(u_n + \lambda) = av_n. \end{aligned}$$

Since $0 \leq a < 1$, $\lim_{n \rightarrow +\infty} v_n = 0$, and so $\lim_{n \rightarrow +\infty} u_n = -\lambda = b/(1 - a)$.

Now, if $a = 1$, then we have for every $n \in \mathbb{N}$, $u_n = u_0 + nb$. If $b > 0$ then $\lim_{n \rightarrow +\infty} u_n = +\infty$. \square

B.2 The asymptotic behavior of \mathcal{W}^*

The goal of this section is to prove Claim 1.

Claim 1 (restated). *The sequence α_t converges to*

$$\alpha_\infty := \frac{1}{2} \left(\sigma_d \sqrt{4\sigma_m^2 + \left(\frac{n}{n-1} \sigma_d \right)^2} + \frac{n}{n-1} \sigma_d^2 \right).$$

Moreover, $\lim_{t \rightarrow +\infty} \rho_\star^{(t)} = \rho_\star$.

Proof. For $a, b > 0$, define $f_{a,b} : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ such that $f_{a,b}(x) = a \frac{x}{x+a} + b$. Solving $f_{a,b}(\ell) = \ell$ on \mathbb{R}^+ gives $\ell = \frac{1}{2} \left(\sqrt{b} \sqrt{4a+b} + b \right)$. For every $x \in \mathbb{R}^+$:

$$f_{a,b}(x) - f_{a,b}(\ell) = a \left(\frac{x}{x+a} - \frac{\ell}{\ell+a} \right) = a \cdot \frac{x(\ell+a) - \ell(x+a)}{(x+a)(\ell+a)} = a^2 \frac{x - \ell}{(x+a)(\ell+a)}.$$

Thus, and since $x \geq 0$,

$$|f_{a,b}(x) - f_{a,b}(\ell)| = \left| a^2 \frac{x - \ell}{(x+a)(\ell+a)} \right| \leq \frac{a^2}{a(a+\ell)} |x - \ell| = \frac{a}{a+\ell} |x - \ell|. \quad (34)$$

Claim 4. *Let $(u_t)_{t \in \mathbb{N}}$ be a sequence defined by $u_0 \in \mathbb{R}^+$ and for every integer t , $u_{t+1} = f_{a,b}(u_t)$. Then, (u_t) converges, and $\lim_{t \rightarrow \infty} u_t = \ell$.*

Proof. Let $k = \frac{a}{a+\ell}$. Since $a, b > 0$ then $\ell > 0$, and so $k < 1$. Let us show by induction that for every t , $|u_t - \ell| \leq k^t \cdot |u_0 - \ell|$. This equality is trivial for $t = 0$. Assuming that it holds for some $t \in \mathbb{N}$, we have

$$\begin{aligned} |u_{t+1} - \ell| &= |f_{a,b}(u_t) - f_{a,b}(\ell)| \quad (\text{definition of } u_t \text{ and } \ell) \\ &\leq k \cdot |u_t - \ell| \quad (\text{by Eq.(34)}) \\ &\leq k^{t+1} \cdot |u_0 - \ell|, \quad (\text{induction hypothesis}) \end{aligned}$$

concluding the induction. Since $k < 1$, it implies that $\lim_{t \rightarrow \infty} |u_t - \ell| = 0$, and so $\lim_{t \rightarrow \infty} u_t = \ell$. \square

Applying Claim 4 to $(\alpha_t)_{t \in \mathbb{N}}$ with $a = \frac{n-1}{n} \sigma_m^2$ and $b = \frac{n}{n-1} \sigma_d^2$ gives $\lim_{t \rightarrow \infty} \alpha_t = \alpha_\infty$, as stated.

Next, we show that $\lim_{t \rightarrow \infty} \rho_\star^{(t)} = \rho_\star$. By letting t tend to $+\infty$ in Definition 4, we obtain

$$\alpha_\infty = \frac{\frac{n-1}{n} \sigma_m^2 \alpha_\infty}{\frac{n-1}{n} \sigma_m^2 + \alpha_\infty} + \frac{n}{n-1} \sigma_d^2. \quad (35)$$

Doing the same in Definition 5, we get

$$\lim_{t \rightarrow +\infty} \rho_\star^{(t)} = \frac{\frac{n-1}{n} \alpha_\infty}{\frac{n-1}{n} \sigma_m^2 + \alpha_\infty} = \frac{1}{\sigma_m^2} \frac{\frac{n-1}{n} \sigma_m^2 \alpha_\infty}{\frac{n-1}{n} \sigma_m^2 + \alpha_\infty}.$$

By Eq. (35), this gives

$$\lim_{t \rightarrow +\infty} \rho_\star^{(t)} = \frac{1}{\sigma_m^2} \left(\alpha_\infty - \frac{n}{n-1} \sigma_d^2 \right).$$

Plugging in the expression of α_∞ mentioned in the Lemma, we find that

$$\lim_{t \rightarrow +\infty} \rho_\star^{(t)} = \frac{\sigma_d \sqrt{4\sigma_m^2 + \left(\frac{n}{n-1}\sigma_d\right)^2} - \frac{n}{n-1}\sigma_d^2}{2\sigma_m^2} = \rho_\star,$$

which establishes the proof. \square

C Useful linear algebra claims

We first recall the following well-known property.

Claim 5. *If $X \sim \mathcal{N}(\mu, \Sigma)$, then for every $c \in \mathbb{R}^n$ and $B \in \mathbb{R}^{n \times n}$, $c + BX \sim \mathcal{N}(c + B\mu, B\Sigma B^\top)$.*

In addition, we give two useful results about matrices of the form $\mathcal{M}(a, b)$.

Claim 6. *For every $a, b, a', b' \in \mathbb{R}$,*

$$\mathcal{M}(a, b)\mathcal{M}(a', b') = \mathcal{M}(aa' + (n-1)bb', ab' + a'b + (n-2)bb').$$

In particular, $\mathcal{M}(a, b)\mathcal{M}(a', b') = \mathcal{M}(a', b')\mathcal{M}(a, b)$.

Claim 7. *For every $a, b \in \mathbb{R}$ such that $a \neq b$ and $a \neq -(n-1)b$, the matrix $\mathcal{M}(a, b)$ is invertible, and*

$$\mathcal{M}(a, b)^{-1} = \frac{\mathcal{M}(a + (n-2)b, -b)}{(a-b)(a + (n-1)b)}.$$

Proof. Note that $\mathbb{1}^2 = n\mathbb{1}$. Let $A = \mathcal{M}(a, b)$. We have

$$\begin{aligned} A^2 &= (b\mathbb{1} + (a-b)I)^2 \\ &= b^2\mathbb{1}^2 + 2b(a-b)\mathbb{1} + (a-b)^2I \\ &= (nb + 2(a-b))(b\mathbb{1}) + (a-b)^2I \\ &= (2a + (n-2)b)(b\mathbb{1} + (a-b)I) \\ &\quad - (nb + 2(a-b))(a-b)I + (a-b)^2I \\ &= (2a + (n-2)b)A + (a-b)(-nb - 2(a-b) \\ &\quad + (a-b))I \\ &= (2a + (n-2)b)A - (a-b)(a + (n-1)b)I. \end{aligned}$$

Hence

$$A(A - (2a + (n-2)b)I) = -(a-b)(a + (n-1)b)I,$$

from which we conclude (provided that $a \neq b$ and $a \neq (n-1)b$),

$$A^{-1} = \frac{(2a + (n-2)b)I - A}{(a-b)(a + (n-1)b)}.$$

\square

D Additional claims about optimal algorithms

D.1 All optimal algorithms are shifts of one another

In this section, we characterize all optimal (deterministic) algorithms for the SAC problem in the centralized setting. We show that each of these algorithms can be obtained from \mathcal{W}^* , by shifting all the agents by the same quantity λ_t , though we stress that shifts λ_t are not necessarily the same for all rounds t .

Theorem 9. *A deterministic algorithm is optimal in the centralized setting if and only if for every round t , there exists λ_t such that for every $i \in \{1, \dots, n\}$, $d\theta_i^{(t)} = \rho_\star^{(t)} Y_i^{(t)} + \lambda_t$.*

Proof. We have already established that the (deterministic) weighted-average algorithm \mathcal{W}^* is a Kalman-perfect algorithm. Therefore, by Proposition 1, any other deterministic algorithm is optimal in the centralized setting if and only if it is Kalman-perfect. In other words, it is optimal if and only if it produces a sequence of moves such that for every round t , the Kalman-filter estimator operating on the corresponding process yields

$$\begin{aligned}\hat{\theta}_{t+1} = 0 &\iff \hat{\theta}_t + M_n d\theta^{(t)} = 0 \\ &\iff K_t Y^{(t)} + M_n d\theta^{(t)} = 0 \\ &\iff -\rho_\star^{(t)} M_n Y^{(t)} + M_n d\theta^{(t)} = 0 \\ &\iff M_n \left(-\rho_\star^{(t)} Y^{(t)} + d\theta^{(t)} \right) = 0 \\ &\iff -\rho_\star^{(t)} Y^{(t)} + d\theta^{(t)} \in \ker(M_n).\end{aligned}$$

Writing $\mathbf{1}$ to denote the vector whose coefficients are all equal to 1, we observe that $\mathbf{1} \in \ker(M_n)$. Since $\text{rank}(M_n) = n - 1$, $\dim(\ker(M_n)) = 1$, so for every round t ,

$$-\rho_\star^{(t)} Y^{(t)} + d\theta^{(t)} \in \ker(M_n) \iff \exists \lambda_t \in \mathbb{R}, \quad -\rho_\star^{(t)} Y^{(t)} + d\theta^{(t)} = \lambda_t \cdot \mathbf{1} \iff \exists \lambda_t \in \mathbb{R}, \quad d\theta^{(t)} = \lambda_t \cdot \mathbf{1} + \rho_\star^{(t)} Y^{(t)}.$$

This concludes the proof. \square

D.2 Computing the shifts between \mathcal{W}^* and Algorithm 1

In this section, we consider one execution of the process when \mathcal{W}^* is used, and one execution when Algorithm 1 (meet at the center) is used. The variables involved in the execution of \mathcal{W}^* are denoted with $[\cdot]^{\mathcal{W}^*}$, while the variables involved in the execution of Algorithm 1 are denoted with $[\cdot]^{\text{MatC}}$.

We assume that the randomness is the same for both algorithms, that is, the initialization of agents is the same, and for every round t , and every $i \in I$, we have $[N_{m,i}^{(t)}]^{\mathcal{W}^*} = [N_{m,i}^{(t)}]^{\text{MatC}}$, $[N_{d,i}^{(t)}]^{\mathcal{W}^*} = [N_{d,i}^{(t)}]^{\text{MatC}}$ and $[\bar{\theta}_i^{(0)}]^{\mathcal{W}^*} = [\bar{\theta}_i^{(0)}]^{\text{MatC}}$.

Claim 8. *For every round t , and for every $i \in \{1, \dots, n\}$,*

- $[\bar{\theta}_i^{(t)}]^{\mathcal{W}^*} = [\bar{\theta}_i^{(t)}]^{\text{MatC}}$,
- $[d\theta_i^{(t)}]^{\mathcal{W}^*} - [d\theta_i^{(t)}]^{\text{MatC}} = \frac{1}{n} \rho_\star^{(t)} \sum_{i=1}^n [Y_i^{(t)}]^{\mathcal{W}^*}$.

Proof. The proof proceeds by induction. More precisely, we prove the first item in the claim by induction on t . For any round t , we prove that the second item follows from the first one. Then, in the induction step, when proving that the first item regarding time $t + 1$ holds, we use the second item regarding the previous time t .

The base case for the first item in the claim, i.e., $[\bar{\theta}_i^{(0)}]^{\mathcal{W}^*} = [\bar{\theta}_i^{(0)}]^{\text{MatC}}$ for every $i \in I$, holds by assumption.

Next, let us assume that for some round t , we have for every $i \in I$, $[\bar{\theta}_i^{(t)}]^{\mathcal{W}^*} = [\bar{\theta}_i^{(t)}]^{\text{MatC}}$. Since the measurement noises are equal, then by the induction hypothesis, the measurements are also equal, that is, for every $i \in I$,

$$[Y_i^{(t)}]^{\mathcal{W}^*} = [\bar{\theta}_i^{(t)} + N_{m,i}^{(t)}]^{\mathcal{W}^*} = [\bar{\theta}_i^{(t)} + N_{m,i}^{(t)}]^{\text{MatC}} = [Y_i^{(t)}]^{\text{MatC}} = Y_i^{(t)}.$$

Thus, by definition,

$$\begin{aligned}[d\theta_i^{(t)}]^{\mathcal{W}^*} - [d\theta_i^{(t)}]^{\text{MatC}} &= \rho_\star^{(t)} Y_i^{(t)} - \frac{n-1}{n} \rho_\star^{(t)} \left(Y_i^{(t)} - \frac{1}{n-1} \sum_{j \neq i} Y_j^{(t)} \right) \\ &= \frac{1}{n} \rho_\star^{(t)} Y_i^{(t)} + \frac{1}{n} \rho_\star^{(t)} \sum_{j \neq i} Y_j^{(t)} = \frac{1}{n} \rho_\star^{(t)} \sum_{i=1}^n Y_i^{(t)} := \lambda_t.\end{aligned}$$

Finally, by Eq. (16),

$$\begin{aligned}
\left[\bar{\theta}_i^{(t+1)}\right]^{\mathcal{W}^*} &= \left[\bar{\theta}_i^{(t)} - d\theta_i^{(t)} - N_{d,i}^{(t)} + \frac{1}{n-1} \sum_{j \neq i} \left(d\theta_j^{(t)} + N_{d,j}^{(t)}\right)\right]^{\mathcal{W}^*} \\
&= \left[\bar{\theta}_i^{(t)} - N_{d,i}^{(t)}\right]^{\text{MatC}} - \left[d\theta_i^{(t)}\right]^{\mathcal{W}^*} + \frac{1}{n-1} \sum_{j \neq i} \left[d\theta_j^{(t)}\right]^{\mathcal{W}^*} + \left[N_{d,j}^{(t)}\right]^{\text{MatC}} \\
&= \left[\bar{\theta}_i^{(t)} - (d\theta_i^{(t)} + \lambda_t) - N_{d,i}^{(t)} + \frac{1}{n-1} \sum_{j \neq i} d\theta_j^{(t)} + \lambda_t + N_{d,j}^{(t)}\right]^{\text{MatC}} \\
&= \left[\bar{\theta}_i^{(t)} - d\theta_i^{(t)} - N_{d,i}^{(t)} + \frac{1}{n-1} \sum_{j \neq i} d\theta_j^{(t)} + N_{d,j}^{(t)}\right]^{\text{MatC}} = \left[\bar{\theta}_i^{(t+1)}\right]^{\text{MatC}}.
\end{aligned}$$

This concludes the induction step, and establishes the proof. \square

D.3 Proof of Claim 2

Claim 2 (restated). *No algorithm in the distributed setting can be simultaneously optimal (Definition 2) and drift-optimal (Definition 6).*

Proof. Let A be an optimal algorithm different than Algorithm 1. Again, we denote the variables involved in the execution of A by $[\cdot]^A$. We have shown in Appendix D.1 that all optimal algorithms are shifts of one another, i.e., for all t we can find a random variable λ_t s.t. for all i ,

$$\left[d\theta_i^{(t)}\right]^A = \left[d\theta_i^{(t)}\right]^{\text{MatC}} + \lambda_t.$$

It implies that

$$\frac{1}{n} \sum_{i=1}^n \left[d\theta_i^{(t)}\right]^A = \lambda_t + \frac{1}{n} \sum_{i=1}^n \left[d\theta_i^{(t)}\right]^{\text{MatC}} = \lambda_t,$$

where the last equality follows from the definition of Algorithm 1. Therefore,

$$\left[\Delta_t^{\text{rel}}\right]^A = \frac{1}{n} \sum_{s=0}^t \sum_{i=1}^n \left[d\theta_i^{(s)}\right]^A = \sum_{s=0}^t \lambda_s.$$

Since A is different than Algorithm 1, we can define $t_0 := \min\{t \in \mathbb{N}, \mathbb{E}(\lambda_t^2) > 0\}$, and have

$$\mathbb{E} \left(\left[\Delta_{t_0}^{\text{rel}}\right]^A{}^2 \right) = \mathbb{E} \left(\left(\sum_{s=0}^{t_0} \lambda_s \right)^2 \right) \geq \sum_{s=0}^{t_0} \mathbb{E}(\lambda_s^2) > 0.$$

By Eq. (14), we conclude that, among optimal algorithm, “meet at the center” is the only one minimizing Δ_t for every t . Note that it is not possible for the agents to implement the “meet at the center” algorithm in the distributed setting, because it requires for each agent to know all measurements – and this observation concludes the proof of Claim 2. \square

E Proof of Lemma 1

The goal of this section is to prove Lemma 1. We start by the following general result about normally distributed variables.

Claim 9. *For any $\sigma \geq 0$, there exists normal random variables Z, X_1, \dots, X_n such that $\sum_{i=1}^n X_i = 0$,*

$$(Z + X_1, \dots, Z + X_n) \sim \mathcal{N}(0, \sigma^2 I),$$

Z is independent from (X_1, \dots, X_n) and $Z \sim \mathcal{N}(0, \sigma^2/n)$.

Proof. The first step of the proof is to explain how to construct the variables of the statement. We will apply the following idea recursively: to sample $k + 1$ identically distributed normal variables A_1, \dots, A_{k+1} with variance σ^2 summing to 0, we first sample $A_1 \sim \mathcal{N}(0, \sigma^2)$, then we sample A'_2, \dots, A'_{k+1} with variance σ'^2 summing to 0, and finally, for $i \geq 2$ we take $A_i = -A_1/k + A'_i$. By construction, $\sum_{i=1}^{k+1} A_i = 0$ and for $A_i, i \geq 2$ to have the desired variance, we just need to choose $\sigma'^2 = (1 - 1/k^2)\sigma^2$.

Let $Z \sim \mathcal{N}(0, \sigma^2/n)$. Following the aforementioned construction, let $\sigma_1^2 = (1 - 1/n)\sigma^2$, and for $i \in \{1, \dots, n-1\}$, let

$$\sigma_{i+1}^2 = \left(1 - \frac{1}{(n-i)^2}\right) \sigma_i^2.$$

For $i, j \in \{1, \dots, n\}$, let $W_i \sim \mathcal{N}(0, \sigma_i^2)$ s.t. $(W_i)_{1 \leq i \leq n}$ are independent, and

$$\lambda_{i,j} = \begin{cases} -1/(n-j) & \text{if } i > j, \\ 1 & \text{if } i = j, \\ 0 & \text{if } i < j. \end{cases}$$

Eventually, let $X_i = \sum_{j=1}^n \lambda_{i,j} W_j$ and $Y_i = Z + X_i$.

The second step of the proof is to check that $\sum_{i=1}^n X_i = 0$. Note that, by definition, for any $j \in \{1, \dots, n\}$, we have

$$\sum_{i=1}^n \lambda_{i,j} = \sum_{i=1}^{j-1} \lambda_{i,j} + \lambda_{j,j} + \sum_{i=j+1}^n \lambda_{i,j} = 1 - (n-j) \cdot \frac{1}{n-j} = 0.$$

Therefore,

$$\sum_{i=1}^n X_i = \sum_{i=1}^n \sum_{j=1}^n \lambda_{i,j} W_j = \sum_{j=1}^n W_j \sum_{i=1}^n \lambda_{i,j} = 0.$$

The third step of the proof is to compute the distribution of each Y_i individually. For every $i \in \{1, \dots, n\}$, Y_i is normally distributed with mean 0 (as a sum of independent normal random variables with mean 0). The variance of Y_i is, by definition,

$$\text{Var}(Y_i) = \frac{\sigma^2}{n} + \sum_{j=1}^n \lambda_{i,j}^2 \sigma_j^2. \quad (36)$$

Claim 10. *For every $k \in \{1, \dots, n\}$, and for every $i \geq k$,*

$$\sum_{j=k}^n \lambda_{i,j}^2 \sigma_j^2 = \sigma_k^2. \quad (37)$$

Proof. The proof proceeds by a backwards induction on k . First, let us consider the base case $k = n$. In this case, we only need to consider $i = k = n$. By definition, $\lambda_{n,n} = 1$, and indeed

$$\sum_{j=n}^n \lambda_{i,j}^2 \sigma_j^2 = \lambda_{n,n}^2 \sigma_n^2 = \sigma_n^2.$$

Next, let us fix $k < n$, and assume by induction that the statement holds for $k + 1$. Our goal is to show that it also holds for k . By definition, $\lambda_{k,k} = 1$ and for $j > k$, $\lambda_{k,j} = 0$, so Eq. (37) holds trivially for $i = k$. Let $i > k$. We have

$$\sum_{j=k}^n \lambda_{i,j}^2 \sigma_j^2 = \lambda_{i,k}^2 \sigma_k^2 + \sum_{j=k+1}^n \lambda_{i,j}^2 \sigma_j^2 = \lambda_{i,k}^2 \sigma_k^2 + \sigma_{k+1}^2,$$

where the second equality is by induction hypothesis. By definition, this is equal to (since $k < i$)

$$\frac{1}{(n-k)^2} \cdot \sigma_k^2 + \left(1 - \frac{1}{(n-k)^2}\right) \sigma_k^2 = \sigma_k^2,$$

and so Eq. (37) holds for $i > k$, which concludes the induction and the proof of Claim 10. \square

By Claim 10, Eq. (36) becomes

$$\text{Var}(Y_i) = \frac{\sigma^2}{n} + \sigma_1^2 = \frac{\sigma^2}{n} + \left(1 - \frac{1}{n}\right) \sigma^2 = \sigma^2,$$

and we can conclude that $Y_i \sim \mathcal{N}(0, \sigma^2)$.

The last step of the proof is to show that the $(Y_i)_{1 \leq i \leq n}$ are mutually independent. Since they are normally distributed, it is enough to show that they are pairwise independent. For this purpose, let us fix $i, k \in \{1, \dots, n\}$ s.t. $i \neq k$, and show that for every $t, s \in \mathbb{R}$,

$$M_{Y_i, Y_k}(t, s) = M_{Y_i}(t) \cdot M_{Y_k}(s),$$

where M_X stands for the moment generating function of the random variable X . Recall that, since $Y_i \sim \mathcal{N}(0, \sigma^2)$, we have

$$M_{Y_i}(t) = \exp\left(\frac{1}{2} \sigma^2 t^2\right).$$

For the sake of simplicity, from now on we will denote $W_0 = Z$, and $\lambda_{i,0} = 1$, so that

$$Y_i = Z + \sum_{j=1}^n \lambda_{i,j} W_j = \sum_{j=0}^n \lambda_{i,j} W_j.$$

Moreover, we will note $\sigma_0^2 = \sigma^2/n = \text{Var}(W_0)$, so that Eq. (36) translates nicely to

$$\text{Var}(Y_i) = \sum_{j=0}^n \lambda_{i,j}^2 \sigma_j^2.$$

For every $t, s \in \mathbb{R}$, we have

$$\begin{aligned} M_{Y_i, Y_k}(t, s) &= \mathbb{E} \left(\exp(tY_i + sY_k) \right) \\ &= \mathbb{E} \left(\exp \left(t \sum_{j=0}^n \lambda_{i,j} W_j + s \sum_{j=0}^n \lambda_{k,j} W_j \right) \right) \\ &= \mathbb{E} \left(\exp \left(\sum_{j=0}^n (t\lambda_{i,j} + s\lambda_{k,j}) \cdot W_j \right) \right) \\ &= \mathbb{E} \left(\prod_{j=0}^n \exp \left((t\lambda_{i,j} + s\lambda_{k,j}) \cdot W_j \right) \right) \\ &= \prod_{j=0}^n \mathbb{E} \left(\exp \left((t\lambda_{i,j} + s\lambda_{k,j}) \cdot W_j \right) \right) \\ &= \prod_{j=0}^n M_{W_j} (t\lambda_{i,j} + s\lambda_{k,j}) \\ &= \prod_{j=0}^n \exp \left(\frac{1}{2} \sigma_j^2 (t\lambda_{i,j} + s\lambda_{k,j})^2 \right), \end{aligned}$$

so eventually,

$$M_{Y_i, Y_k}(t, s) = \exp \left(\frac{1}{2} \sum_{j=0}^n \sigma_j^2 (t\lambda_{i,j} + s\lambda_{k,j})^2 \right). \quad (38)$$

To conclude, we need the following technical results.

Claim 11. *For every $1 \leq k < n$,*

$$\sum_{i=1}^k \frac{1}{(n-i)(n-i+1)} = \frac{k}{n(n-k)}.$$

Proof. Let $n \in \mathbb{N}$. We proceed by induction on k . The statement holds trivially for $k = 1$. Assuming the statement holds for some $k < n - 1$, by the induction hypothesis,

$$\sum_{i=1}^{k+1} \frac{1}{(n-i)(n-i+1)} = \frac{k}{n(n-k)} + \frac{1}{(n-k)(n-k-1)} = \frac{k(n-k-1) + n}{n(n-k)(n-k-1)} = \frac{k+1}{n(n-k-1)},$$

which concludes the induction and the proof of Claim 11. \square

Claim 12. For every $i, k \in \{1, \dots, n\}$ s.t. $i \neq k$,

$$\sum_{j=0}^n \lambda_{i,j} \lambda_{k,j} \sigma_j^2 = 0.$$

Proof. Without loss of generality, we consider the case that $k < i$. By definition, we have $\lambda_{i,j} = \lambda_{k,j} = -1/(n-j)$ for $1 \leq j < k$, $\lambda_{k,k} = 1$, $\lambda_{i,k} = -1/(n-k)$, and $\lambda_{k,j} = 0$ for $k < j \leq n$. Hence,

$$\sum_{j=0}^n \lambda_{i,j} \lambda_{k,j} \sigma_j^2 = \sigma_0^2 + \sum_{j=1}^{k-1} \frac{\sigma_j^2}{(n-j)^2} - \frac{\sigma_k^2}{n-k}. \quad (39)$$

Next, we claim that for every $j \in \{1, \dots, n\}$,

$$\frac{\sigma_j^2}{(n-j)^2} = \frac{n}{(n-j)(n-j+1)} \cdot \frac{\sigma_1^2}{n-1}. \quad (40)$$

We prove Eq. (40) by induction on j . It holds trivially for $j = 1$. Assume it holds for some $j < n$. We write

$$\sigma_{j+1}^2 = \left(1 - \frac{1}{(n-j)^2}\right) \sigma_j^2 = \frac{(n-j)^2 - 1}{(n-j)^2} \sigma_j^2 = \frac{(n-j+1)(n-j-1)}{(n-j)^2} \sigma_j^2.$$

Therefore,

$$\frac{\sigma_{j+1}^2}{(n-j-1)^2} = \frac{n-j+1}{n-j-1} \cdot \frac{\sigma_j^2}{(n-j)^2} = \frac{n}{(n-j)(n-j-1)} \cdot \frac{\sigma_1^2}{n-1},$$

where the second equality is by the induction hypothesis. This concludes the induction and the proof of Eq. (40).

By Eq. (40), Eq. (39) becomes

$$\sum_{j=0}^n \lambda_{i,j} \lambda_{k,j} \sigma_j^2 = \sigma_0^2 + \frac{\sigma_1^2}{n-1} \left(\sum_{j=1}^{k-1} \frac{n}{(n-j)(n-j+1)} - (n-k) \frac{n}{(n-k)(n-k+1)} \right).$$

We can rearrange this expression using Claim 11, to obtain

$$\sigma_0^2 + \frac{n\sigma_1^2}{n-1} \left(\frac{k-1}{n(n-k+1)} - \frac{1}{n-k+1} \right) = \sigma_0^2 - \frac{\sigma_1^2}{n-1}.$$

By definition,

$$\sigma_0^2 - \frac{\sigma_1^2}{n-1} = \frac{\sigma^2}{n} - \left(1 - \frac{1}{n}\right) \frac{\sigma^2}{n-1} = \frac{\sigma^2}{n} - \frac{\sigma^2}{n} = 0,$$

which concludes the proof of Claim 12. \square

Eventually, by Claim 12, Eq. (38) becomes

$$\begin{aligned} M_{Y_i, Y_k}(t, s) &= \exp \left(\frac{1}{2} \sum_{j=0}^n \sigma_j^2 (t\lambda_{i,j} + s\lambda_{k,j})^2 \right) \\ &= \exp \left(\frac{t^2}{2} \sum_{j=0}^n \lambda_{i,j}^2 \sigma_j^2 + \frac{s^2}{2} \sum_{j=0}^n \lambda_{k,j}^2 \sigma_j^2 + st \sum_{j=0}^n \lambda_{i,j} \lambda_{k,j} \sigma_j^2 \right) \\ &= \exp \left(\frac{t^2}{2} \text{Var}(Y_i) + \frac{s^2}{2} \text{Var}(Y_k) \right) \\ &= \exp \left(\frac{t^2}{2} \text{Var}(Y_i) \right) \cdot \exp \left(\frac{s^2}{2} \text{Var}(Y_k) \right) \\ &= M_{Y_i}(t) \cdot M_{Y_k}(s), \end{aligned}$$

which concludes the proof of Claim 9. \square

Lemma 1 (restated). *For every protocol and for every round t , Δ_t^{inh} and Δ_t^{rel} are independent.*

Proof. First we apply Claim 9. Specifically, for every $s \in \mathbb{N}$, we can find normal random variables $Z^{(s)}, X_1^{(s)}, \dots, X_n^{(s)}$ such that:

- $\sum_{i=1}^n X_i^{(s)} = 0$,
- $Z^{(s)} \sim \mathcal{N}(0, \sigma_d^2/n)$,
- $Z^{(s)}$ is independent from $(X_1^{(s)}, \dots, X_n^{(s)})$, and
- $(Z^{(s)} + X_i^{(s)}) \sim \mathcal{N}(0, \sigma_d^2 I)$.

In our analysis, for every $s \in \mathbb{N}$, we can replace the noise vector $(N_{d,i}^{(s)})_{i \in I}$ by $(Z^{(s)} + X_i^{(s)})_{i \in I}$, since these two vectors follow the same distribution. The inherent drift then rewrites

$$\Delta_t^{\text{inh}} = \frac{1}{n} \sum_{s=0}^t \sum_{i=1}^n X_i^{(s)} + \frac{1}{n} \sum_{s=0}^t \sum_{i=1}^n Z^{(s)} = \sum_{s=0}^t Z^{(s)}. \quad (41)$$

We have that the drift for Agent i at round t is $Z^{(t)} + X_i^{(t)}$. Moreover, while its stretch $\bar{\theta}_i^{(t+1)}$ may depend on $X_i^{(t)}$, we know that the variables $X_i^{(t)}$ and $Z^{(t)}$ are independent. Since adding the same quantity to the position of each agent does not change the stretches, we have that the stretch $\bar{\theta}_i^{(t+1)}$ is independent from the particular realization of $Z^{(t)}$. Hence, for every $t \in \mathbb{N}$, the stretch vector $(\bar{\theta}_1^{(t)}, \dots, \bar{\theta}_n^{(t)})$ is independent from $(Z^{(0)}, \dots, Z^{(t)})$, and thus independent from Δ_t^{inh} , by Eq. (41). By definition, this implies that the measurement vector $(Y_1^{(t)}, \dots, Y_n^{(t)})$ is also independent from Δ_t^{inh} . Since the agents' moves are based solely on their measurements, we conclude that the vector of moves $(d\theta_1^{(t)}, \dots, d\theta_n^{(t)})$ is independent from Δ_t^{inh} as well. This concludes the proof of Lemma 1. \square