Keep calm and vote on: Swarm resiliency in collective decision making

Francesco Canciani, Mohamed S. Talamali, James A. R. Marshall, Andreagiovanni Reina

The design of large groups of simple robots that coordinates through local interactions has attracted great interest in engineering research and defined the field of swarm robotics [1]. For most operations, a fundamental ability is collective decision making, that is, the ability of the swarm to reach an agreement among all robots [2]. Several studies proposed alternative solutions, under complementary assumptions, to the collective decision making problem [1], [2], [3]. Most problems analysed the decision performance in terms of speed-accuracy, and took into consideration how problem paramaters, such as decision difficulty, number of options, or spatial correlation, had an impact on the system dynamics. Recently, some attention has been devoted to studying the resiliency of the swarm to disturbances which could be either intrinsic properties, such as robots failures [4], [5], or extrinsic factors, such as malicious attacks [6], [7], [8], [9], [10], [11]; however, only a few work considered decision making tasks [12], [13].

In this study we investigate the swarm resiliency in collective decision making, that is, its ability to reach correct decisions under attacks carried out by malicious robots. We analysed and quantified the ability of existing methods to remain operational in the face of attacks. Note that existing methods do not include strategies to identify and counteract disturbances and therefore we only measured the resiliency of each strategy. As resiliency to attacks in collective decision making has not been extensively investigated, a categorisation of attacks and relative dysfunctions is missing. We made a first endeavour to define and formalise possible dysfunctions and we proposed three representative attacks for collective decision making.

This study focused on the *best-of-n* problem which consists of reaching an agreement in favour of the best quality option among n alternatives. We identified in the literature four methods that matched our assumptions on the problem and the robot's capabilities (see Sec. I). We computationally tested the resilience of these methods to three types of attacks that have been designed to implement three types of dysfunctions, i.e. denial of service, slowdown, and wrong addressing. Denial of service refers to incapability to make a decision, i.e. the swarm remains hung at indecision with split robots' opinions. Slowdown prolongs the decision time requiring longer to reach an agreement; extreme slowdown leads to a denial of service. Finally, wrong addressing consists in leading the swarm to decide for an inferior-quality option.

To identify what made a method more resilient of another, we inspected the robots' behaviour of each method. We described all the investigated behaviours through a common structure which consists in a sequence of phases repeated by every robot each control loop. All behaviours are composed by the same phases with different implementations. A specific implementation of a phase is what we call module. Making use of the modularity of the behaviours, we were able to investigate which module makes behaviours more resilient to malicious attacks.

We conducted our resiliency tests via computational analysis using DeMaMAS—a multiagent simulator for comparison of decentralised decision making strategies. DeMaMAS has been implemented for this study, however, we designed it to be as generic as possible and allow systematic comparisons of decentralised decision making strategies. In DeMaMAS, robots' behaviours are specified through the sequencing of reusable unitary modules. Once we identified the most resilient modules through systematic comparison, we exploited the flexibility and modularity of DeMaMAS to quickly compose a novel behaviour comprising those most resilient modules. The generated behaviour demonstrated the best performance in most of the investigated cases.

Finally, we validated our findings implementing some of the investigated methods on physical devices. In particular, we conducted a set of experiments on a swarm of 50 Kilobot robots [14] under a slow down attack. These tests are preliminary results as they only investigated a limited set of conditions. Notwithstanding, they are promising indication that simulations results can generalise to physical devices systems.

I. Decision problem

We investigate the best-of-n decision problem. We assume there are n options characterised by a quality q_i and a location p_i in a 2D environment, with $i \in \{1, \ldots, n\}$. The robot swarm task is to discover the available n options and select the option with the highest quality. The swarm is composed of S simple robots; they have no prior knowledge, minimal memory, and limited sensing and communication capabilities. In fact, robots start without knowing the number of options, their qualities, and their locations. A robot can only store the information (position and quality) about a

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F.C. is with the Department of Electronics, Information, and Bioengineering, Politecnico di Milano, Milan, Italy (email: francesco.canciani@mail.polimi.it). All authors are with the Department of Computer Science, University of Sheffield, S1 4DP, UK (email: mstalamali1@sheffield.ac.uk; james.marshall@sheffield.ac.uk; a.reina@sheffield.ac.uk).

single option to which it is committed to, we refer to it as the robot's opinion $\omega_a = \{p_a, q_a\}$ with $a \in \{1,\ldots,S\}$. Robots can locate an option and estimate its quality only when it is in its immediate surrounding (range r_d). Robots make noisy individual estimates $\hat{q}_i$ of the nominal option's quality q_i; we assume estimates to be normally distributed around the correct value, *i.e.* $\hat{q}_i = \mathcal{N}(q_i, \sigma)$. Finally robots can communicate with neighbours within a local range r_c and only exchange the location of the preferred option p_a (if any) without additional information such as estimated quality q_a, commitment confidence, or ad-hoc weighted aggregates. We assume that a decision is taken when a quorum of $Q = 0.8\,S$ robots are committed to the same option.

II. Decision behaviours

As robots start without prior knowledge about environment nor options, *i.e.* $\omega_a = \{\emptyset, \emptyset\}$, they explore the environment to locate and estimate the quality of the available options. Then, through communication, each robot spreads its opinion ω_a in order to reach an agreement with the rest of the swarm. A few models addressed the best-of-n problem of Sec. I. To the best of our knowledge, we identified four representative types of behaviours. We analysed the characteristics of these behaviours and decomposed them in a sequence of phases common to all the models. The four selected behaviours were

- Direct Modulation of Voter-based Decisions (DMVD) [15]. This behaviour combines the component of random neighbour selection from the classical voter model [16], [17] with modulation of communication proportional to the quality. Each control loop, the robot selects the opinion of only one randomly selected neighbour. This strategy allows robots to select an option with probability equal to the proportion of neighbours with that opinion. Each selected option becomes the agent opinion, this mechanism is known as *direct switch*.
- Direct Modulation of Majority-based Decisions (DMMD) [18], [19]. This behaviour differentiates from DMVD by selecting the neighbours' opinion through the majority-rule [20], [21], [17], [22], [23], *i.e.* the agent selects the more frequent option among the received messages (tie-breaking with random choice).
- Collective Decision through Cross-Inhibition (CDCI) [24], [25] is a behaviour inspired by the honeybee house-hunting process [26]. It is similar to the DMVD and differentiates by letting a robot lose its opinions if the randomly selected option is different from the robot's opinion. Therefore, robots with already their opinion, *i.e.* $\omega_a \neq \{\emptyset, \emptyset\}$ do not take new options as their opinion, rather, only robots without an opinion $\omega_a = \{\emptyset, \emptyset\}$ adopt a received option.
- The k-unanimity [27] behaviour differentiates from DMVD in the way it selects the option from neighbours. In this behaviour, a robot randomly picks k messages and selects the option of these k messages if it is the same among all, otherwise it ignores the social information. In this study, we considered the case of $k = 3$, therefore we refer to this method as 3-unanimity.

From the simulation results, we were able to identify the most resilient component of the tested behaviours. This allowed us to design a novel behaviour, Collective Decision through Majority-based Cross-Inhibition (CDMCI), by combining these most resilient component. The CDMCI behaviour combined the DMMD with the CDCI. The robot selects the neighbours' opinion through the majority-rule and updates its opinion through the cross-inhibition mechanism.

A. Three types of malicious robots

We implemented three types of malicious robots to perform three types of dysfunctions:

- The *contrarians* are malicious robots that always oppose to the majority of the group [28], [29]. Therefore, the behaviour of a contrarian differentiates from the DMMD by applying a 'minority-rule' [17] by which a robot selects the less popular option among the received messages. The contrarian robots lead to a slow down of the decision process (*e.g.* see Fig. 1).
- The *wishy-washy* are malicious robots that keep changing their opinion every control loop. These robots ignore any information from the environment and the neighbours and just introduce a sort of noise into the swarm communications. The wishy-washy robots lead to a denial of service which corresponds to a decision deadlock in which the swarm is unable to reach the quorum Q. Increasing the number of options n, the impact of small proportions of wishy-washy also considerably increases.
- The *sect* is an organised group of *zealots* which are malicious robots that ignore any information from the environment and the neighbours and keep communicating a constant opinion for a (possibly) inferior option. Zealots organised in sects all share the same opinion and lead to a wrong addressing, *i.e.* the swarm selects an inferior quality option (*e.g.* see Fig. 2).

All attackers do not modulate the probability of communication proportionally to the option's quality but send a message with their (malicious) opinion every timestep.

In opinion dynamics studies, several studies have already investigated the effect of zealots [30], [31], [32], [33], [34], [35], [36] and contrarians [28], [29], [37] on decentralised collective decision. However, these studies investigated decision models in which all options had no quality and the goal was to select any available option (*e.g.* the naming game [38]). On these models, some studies observed that zealots could speed up the consensus dynamics [39], [40], or having multiple sects voting for various options caused decision-deadlocks (*i.e.* denial of service) [41].

III. Experiments

We conducted a large set of simulation experiments for various experimental conditions through the multiagent simulator DeMaMAS. We considered the best-of-n case of a superior option with quality q_H and $n-1$ distractors with inferior equal quality $q_L \leq q_H$. We varied the number of options $n \in \{2,4,6\}$, the decision difficulty $\kappa = q_L/q_H \in [0.4, 1]$, and the proportion of malicious robots $m \in [0, 0.2]$ in

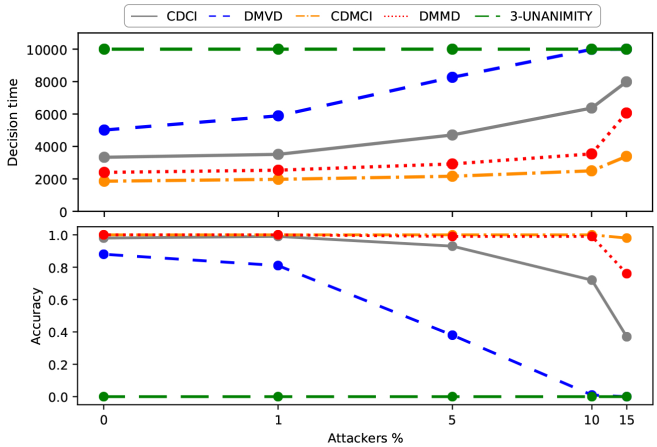

Fig. 1. Effect of contrarians on the decision dynamics of a swarm of $S = 100$ simulated robots with $n = 6$ options and decision difficulty $\kappa = q_L/q_H = 0.8$. The points show the average of 100 multiagent simulations. The top panel shows the slow down effect of contrarians that increase the decision time. High decision time hinders the accuracy of the swarm (bottom panel). The most resilient method is the CDMCI (orange dash-dotted line). Comparing CDCI (gray full line) and DMVD (blue short-dashed line), we can appreciate a resiliency increase for the method that relies on the cross-inhibition model rather than the direct switch model. Comparing DMVD (blue short-dashed line) and DMMD (red dotted line), we can appreciate a resiliency increase for the method that relies on the majority-rule rather than the random selection (voter model).

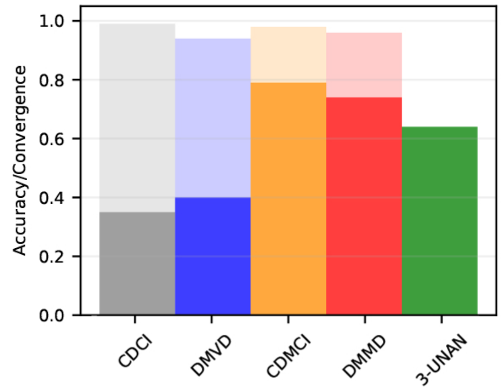

Fig. 2. Sect attacks cause wrong addressing. Results from 100 simulations of a swarm of $S = 100$ robots that includes 5 malicious robots (zealots) delivering a sect attack. Through the coordinated attack, all 5 zealots favour the same inferior option. The scenario is for $n = 4$ options and difficulty $\kappa = 0.4$. The dimer colours bars indicate the swarm proportion of converged runs to a decision. The brighter colour bars indicate the proportion of runs that selected the superior quality option. A sect of 5 coordinated zealots is sufficient to let most behaviour select an much inferior quality option. The behaviours relying on majority rule (CDMCI and DMMD) are the most resilient.

Fig. 3. We tested the most resilient methods on a swarm of 50 Kilobots with 5 contrarians.

a swarm of $S = 100$ robots for a maximum time of 10'000 timesteps.

The results showed in most cases the same trend. The majority-rule performed consistently better than the simple voter method (random neighbour selection). For instance, compare the DMVD with the DMMD, or equivalently the CDCI with the CDMCI, in Fig. 1 and 2. This results can be justified by a larger use of information of the majority-rule compared with the minimalistic voter method. Interestingly, the results also showed the cross-inhibition method more resilient than the direct-switch method. For instance, compare the CDCI with the DMVD, or equivalently the CDMCI with the DMMD, in Fig. 1. Both methods use the same information quantity and computational resources, however a slight change in the opinion update rule led to a more resilient behaviour. Further investigations in this direction may help in understanding the adaptive benefits of this mechanism that evolved in various natural systems [26], [42], [43]. Finally, the 3-unanimity behaviour performed poorly in most cases, except in easy scenarios. As soon the number of options n or the decision difficulty κ increased, the 3-unanimity behaviour could not reach the quorum even in absence of any attack (see Fig. 1). This limitation is due to the high selectivity of the k-unanimity method which has been initially designed for binary decision making problems.

We conducted a set of 20 preliminary experiments with a swarm of 50 Kilobots in binary decision problems (see Fig. 3). The Kilobot were able to perceive localised options through the Augmented Reality for Kilobots system [44]. We tested the performances of the swarm with the CDCI and CDMCI behaviours under no attack and an attack of 5 contrarians ($m = 10\%$ of S). The results were in agreement with the simulations.

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