Efficiency Metrics for Flocking with Implicit Leadership

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***Abstract*—The purpose of this work is to present a novel efficiency metric for flocking with implicit leadership. Five sets of simulated experiments were conducted to compare proposed metric with metrics existing in literature. Experiments were executed in perfect and imperfect conditions, as well as in presence of malicious agents. Proposed metric shows dependencies similar to those of other metrics in perfect conditions with average correlation coefficient of 0.77. Results in imperfect conditions show that proposed metric can be used to detect group fragmentation. Proposed metric can be used to detect both kinds of studied malicious agents, as opposed to all other studied metrics.**

I. Introduction

Flocking is a widely observed in nature coordinated motion of animals. Studies in biology showed large groups of animals can move coherently as if they were a single organism [1], as well as move in a specific goal direction even if only a minority of the group is aware of this direction [2]. Studies also showed that information in the group can be transferred explicitly [3], [4], or implicitly without any signaling mechanisms [2], [5].

In one of the first studies regarding flocking outside of biology [6], flocking was defined as composition of three simple concurrent behaviors: separation (avoiding collisions), cohesion (staying close to neighbors), and alignment (heading in the same direction as neighbors). Later works expanded this concept by adding goal-seeking behavior [7], [8], and limiting it to the minority of informed agents through algorithms of implicit leadership [2], [9]. In [10] flocking with implicit leadership is defined as composition of three behaviors:

- proximal control behavior (avoiding collisions and staying close to neighbors);
- alignment behavior (heading in the same direction as neighbors);
- goal-following behavior for informed agents.

Efficiency metrics are required to evaluate and compare different flocking algorithms. These metrics should evaluate system's performance not only in perfect conditions, when system is expected to perform well, but also in imperfect conditions, as well as in case of malicious agents' presence. There are works [11-14] describing how flocking should be done to avoid collapses in imperfect conditions, what threats exist to systems, and how systems should be protected, but ways to quantify efficiency of flocking are still needed.

II. Related work

Researchers and developers of flocking algorithms often introduce their own efficiency metrics. Authors of one of the first works in the field introduced concept of group accuracy [2]. Group accuracy was quantified as normalized angular deviation of group direction around the preferred direction of informed agents. While being relatively simple to calculate and able to reflect efficiency of flocking in perfect conditions, the metric had some major flaws outlined by experimental results provided by authors of the original work: higher values of the group accuracy were correlated to higher probability of group fragmentation, and the metric often did not reflect malicious agents' impact on the group at all. Group accuracy also had little use for algorithm comparison, because it did not represent speed.

In order to fix these flaws, more sophisticated metrics were introduced in more recent works [9], [10], [15]. While fixing some problems associated with group accuracy, these metrics had their own flaws. Specifically, some of the most recent works introduced metrics, which require information about heading of every agent in the group, and cannot provide information about group performance over time [9], [15].

Thus, the goal of this work was to develop a metric, which does not have aforementioned flaws. Such metric had to satisfy following criteria:

- can be used for algorithm comparison,
- provides information about group performance over time,
- does not require information about every agent in the group,
- reflects the impact malicious agents have on the group performance

III. Algorithms and metrics

Algorithms and metrics from three different works [2], [9], [15] were analyzed in this paper together with one new metric. In order to differentiate between these three algorithms, they were given names corresponding to how these algorithms treat proximal control behavior: prioritized proximal control algorithm (PPCA) from [2], weighted proximal control algorithm (WPCA) from [9], and no proximal control algorithm (NPCA) from [15]. Some of the equations used to define these algorithms in original works were slightly transformed in order to keep the notation constant throughout the paper.

These algorithms were studied for number of reasons:

- these are algorithms for flocking with implicit leadership;
- these algorithms were already evaluated with the metrics, used in this work;
- these algorithms utilize three different approaches to proximal control behavior;
- these algorithms are also concerned with situation when there are two or more conflicting goal directions, with WPCA and NPCA having modified versions to account for such situations.

Having two or more conflicting goal directions is considered normal for these algorithms, so malicious agents acting as informed agents with wrong goal direction can be harder to detect. Because of that, it is important for efficiency metric to reflect their impact on the system.

A. Prioritized proximal control algorithm

This algorithm's key feature is prioritizing collision avoidance above all else. Desired travel direction $\boldsymbol{d_i}(t)$ of ith agent at any given moment of time t is computed as following:

$$d_i(t) = \frac{p_i(t) + h_i(t) + \omega g_i}{\|p_i(t) + h_i(t) + \omega g_i\|}$$

where $\boldsymbol{p}$, $\boldsymbol{h}$ and $\boldsymbol{g}$ are vectors represent proximal control, alignment control and goal direction respectively. Weighting term ω is used to express agent's desire to follow goal direction and will be referred to as "confidence degree". The value of $\boldsymbol{p}$ is based on relative positions of other agents in communication range ρ, while $\boldsymbol{h}$ is computed as average heading direction of these agents.

If there are agents in collision-avoidance range α, proximal control takes priority:

$$d_i(t) = p_i(t)$$

B. Weighted proximal control algorithm

WPCA utilizes artificial physics described in [16, 17] to achieve flocking behavior. Every control step force vector is computed as

$$f = \alpha p + \beta h + (\alpha + \beta)\omega g$$

Values $\alpha = 1$ and $\beta = 5$ were used in original work [9]. Computed force vector is then used to determine desired travel direction according to the Newton's second law of motion.

C. No proximal control algorithm

Last algorithm does not utilize proximal control behavior at all [15]. At each time step desired travel direction is computed as following:

$$d = \frac{1}{1+\omega}h + \frac{\omega}{1+\omega}g$$

D. Metrics

1) Group travel accuracy: Introduced in [2], group travel accuracy is quantified as normalized angular deviation of group direction around the preferred direction of informed agents. Group centroid coordinates are measured at 50^{th} and last step of simulation, difference between measurements is then used as displacement vector. The angle between displacement vector and goal direction serves as angular deviation of group direction. Values are then normalized so that no deviation corresponds to the value of 1, while deviation met in groups moving chaotically corresponds to 0.

2) Order and instantaneous group accuracy: Two metrics were used in [9]: order and accuracy. The order metric is used to measure the angular order of the robots, groups with all agents heading in common direction have higher order values. The order is computed as:

$$\psi = \frac{\|\bar{a}\|}{N}$$

where N is the total number of robots and $\bar{a}$ is the vectorial sum of robots' headings.

Accuracy is used to measure how accurately close to goal direction robots are moving. Since it represents group accuracy at one specific point of time, rather than performance over time, it is referred to as "Instantaneous group accuracy" later in the paper. The instantaneous group accuracy is computed as:

$$\delta = 1 - \frac{\sqrt{2(1 - \psi\cos(\angle\bar{a} - \angle g))}}{2}$$

3) Average heading accuracy: Average heading accuracy is normalized version of metric used in [15]. First, average error in heading direction within the group is computed. It is then normalized in the same way as group travel accuracy.

4) Group kinetic efficiency: Designed to show how efficiently group moves compared to a single informed agent moving in the same direction. It is defined as inner product of displacement vector and goal direction divided by the distance traversed by a single informed agent within the same amount of time:

$$e = \frac{s \cdot g}{ut}$$

where u is maximum speed of an agent, t is time passed since the start of algorithm execution and $\boldsymbol{s}$ is computed as difference between initial and final group centroid coordinates.

5) Group Elongation: Introduced in [2], elongation is not a metric designed to evaluate group performance, and is not studied as one in this work. It is referred in the work to explain impact certain conditions have on the group. Group with higher elongation has fewer agents getting information directly from informed agents. Elongation was measured in the original work by "creating a bounding box around the group aligned with the direction of travel and calculating the ratio of the length of the axis aligned with the group direction, to that perpendicular to group direction. This value is 1 when both axes are identical, > 1 as the group becomes more elongated in the direction of travel, and < 1 as it becomes elongated perpendicular to the direction of travel."

IV. Simulation Methodology

All experimental data in this research was gathered in a simulated environment. All experiments were executed using Octave v4 with different approaches depending on the algorithm in use. These approaches were identical to the ones described in original works [2], [9], [15]. In case of simpler PPCA and NPCA, every agent was represented by a point in 2D-space with certain properties, changing according to algorithm within the limitations described in [2], [15]. In case of WPCA, more sophisticated approach of artificial physics described in [16], [17] was used.

Each agent is modeled with following properties:

- position $\boldsymbol{c}$,
- velocity $\boldsymbol{v}$,
- maximum speed u,
- goal direction $\boldsymbol{g}$,
- confidence degree ω,
- communication range ρ,
- collision-avoidance range α

Every experiment starts with N agents being randomly distributed within a circle of radius R. Some number of agents N_I has information of goal direction $\boldsymbol{g}$ and predefined confidence degree ω, which does not change throughout the course of simulation. Agents then execute one of three flocking algorithms for t time steps, and efficiency values are recorded after that.

V. Experimental setup

To evaluate efficiency metrics described in section III, five sets of experiments were conducted. First set is conducted in perfect case scenario, when system is known to perform well. Second and third sets were carried out to gauge the effect varying time t and radius R has on the efficiency. Last two sets are concerned with malicious agents' impact on the system in different attack scenarios. In all experiments amount of agents, maximum speed, communication range and collision-avoidance range were constant and set to:

- $N = 50$,
- $N_I = 10$,
- $u = 1$,
- $\rho = 30$,
- $\alpha = 5$.

A. Perfect case scenario

In perfect case scenario agents are distributed within a circle $R = 10$ and then execute flocking algorithm for 500 simulation steps. In this set, impact of the confidence degree ω on the efficiency was studied. For each value of $\omega = 0.05, 0.1, 0.15, .., 2$ there were 300 replicates (100 for each algorithm).

Perfect-case scenario is studied for two reasons. First, these experiments provide results which can be directly compared to already existing results obtained in original works [2], [9], [15], in order to evaluate simulated environment. Secondly, impact of varying confidence degree ω on these algorithms' performance is already thoroughly studied. Because of that, proposed metric should show similar dependencies, to be considered applicable. To evaluate the similarities between existing metrics, and kinetic efficiency, correlation coefficients were calculated.

B. Imperfect conditions

In second and third sets higher simulation durations and distribution radiuses were studied. In both sets informed agents had a confidence degree of 2.00, and other parameters were identical to perfect case scenario. In second set different simulation durations from 500 to 2500 with 500 increments were studied with 300 replicates for each value. In third set distribution radius R varied from 10 to 50 with increments of 10 and 300 replicates for each value.

B. Malicious agents

Last two sets of experiments are performed once again in perfect conditions with confidence degree of informed agents being $\omega = 0.5$. However, in these experiments some agents are malicious and act as informed agents with different goal direction. In 4th set there are 10 malicious agents with goal direction orthogonal to that of informed agents and confidence degree of 0.5. These malicious agents also change their confidence degree t^* steps before the end of execution. Values (0, 10, 50, 100, 200) of t^* were studied in this set of experiments with 300 replicates for each value.

In 5th set, malicious agents try to slow the group down by moving at the speed 4 times lower than regular speed. In this set, amount of malicious agents is varied from 0 to 25 with increments of 5.

VI. Results

Results in perfect conditions are shown in Fig.1. Metrics can be divided into two different categories. First category, later referred to as "metrics of overall performance", is represented by group travel accuracy and kinetic efficiency. These metrics reflect group performance over the entire time of algorithm execution. Metrics of instantaneous performance in the second category, instantaneous group accuracy and average heading accuracy, only provide data about group state at one particular moment of time.

In case of algorithms with proximal control, group becomes more spread out with the course of time, and informed agents can reach fewer agents with messages. Because of that, uninformed agents are not perfectly aligned at the end of algorithm execution, and metrics of instantaneous performance rate these algorithms lower.

No proximal control algorithm's efficiency is close to 1, according to all studied metrics except for kinetic efficiency. Kinetic efficiency reflects that not all agents are perfectly aligned at the start of simulation.

Kinetic efficiency shows dependencies similar to those of other metrics, with average correlation coefficient of 0.77277, according to Table I. The only exception is WPCA where metrics of overall performance differ from metrics of instantaneous performance. Average correlation coefficient between kinetic efficiency and group travel accuracy is 0.96401.

If agents execute the flocking algorithm for longer periods of time, probability of group fragmentation increases [2]. In case of PPCA, uninformed agents just stop moving if they get left behind, while WPCA agents wander off in random direction. Because of that, group travel accuracy cannot be used for fragmentation detection in groups running PPCA (Fig. 2a).

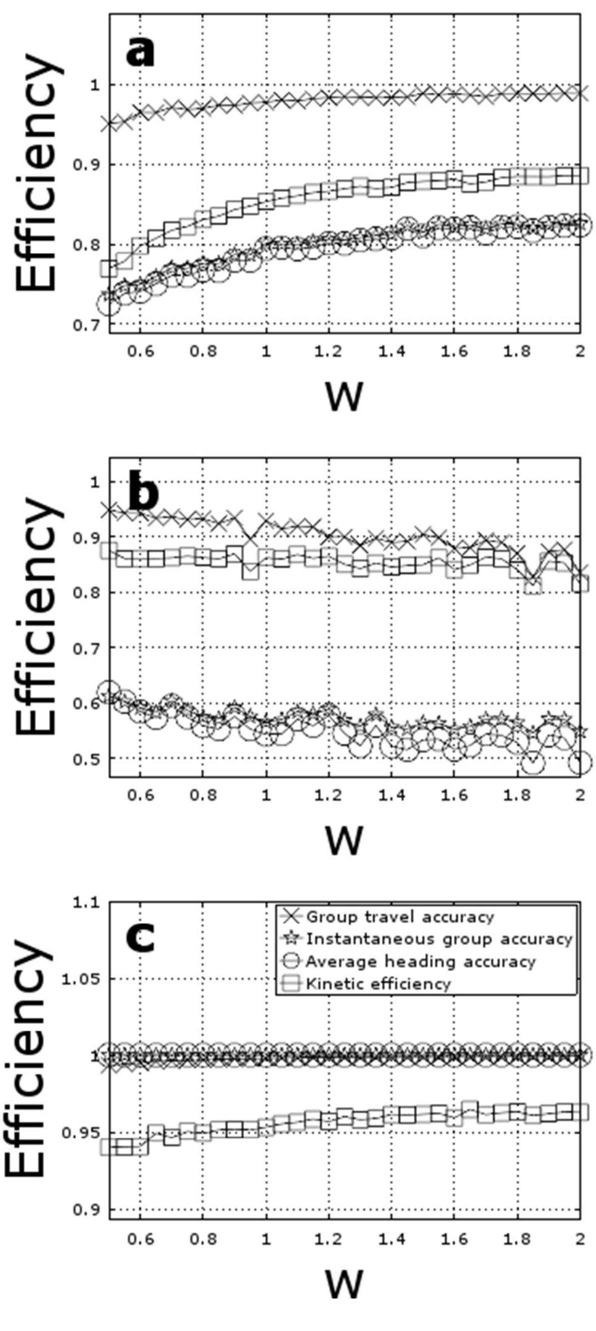

Fig. 1. Effect of varying confidence degree for different algorithms: (a) prioritized proximal control; (b) weighted proximal control; (c) no proximal control

TABLE I. CORRELATION COEFFICIENTS BETWEEN KINETIC EFFICIENCY AND OTHER METRICS FOR DIFFERENT ALGORITHMS

Name	Instantaneous group accuracy	Average heading accuracy	Group travel accuracy
Prioritized proximal control	0.99798	0.99533	0.95701
Weighted proximal control	-0.028711	0.407299	0.954568
No proximal control	0.84552	0.84552	0.98044

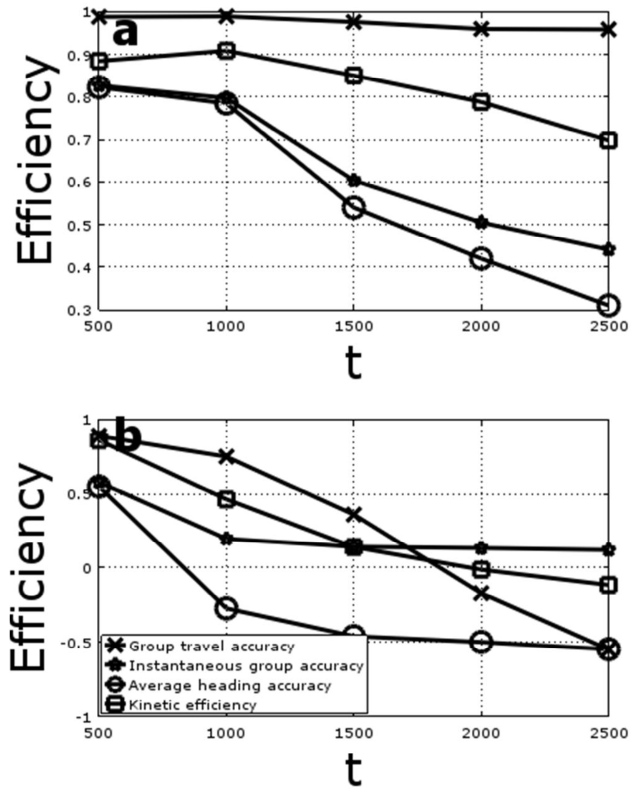

Fig. 2. Effect of varying execution time for different algorithms: (a) prioritized proximal control; (b) weighted proximal control

In the case of WPCA, uninformed agents continue moving after getting separated from the main group. After separation, these agents try to align themselves with other separated agents in the neighborhood. After this initial alignment phase, agents don’t change their travel direction and just continue to move away from the group. Because of that, metrics of overall performance decrease if the group was fragmented for longer periods of time, while metrics of instantaneous performance only decrease as fragmentation probability increases.

The same problem can be observed, if the group executing WPCA is initially more spread out (Fig. 3). As the distribution range increases, group elongation also increases, which results in more agents not getting messages directly from informed agents. Because of that, these agents tend to deviate from goal direction more than the ones closer to informed agents, and move slower in a goal direction overall That causes other agents to deviate too, due to proximal control behavior. Group travel accuracy does not decrease for more spread out groups, while other metrics indicate that agents are less aligned with respect to the goal direction and move slower in this direction.

Malicious agents can hide their impact on the group, if certain efficiency metrics are being used. Malicious agents can act as informed agents with wrong goal direction, but switch to acting uninformed some time prior to efficiency evaluation. In that case, results vary between metrics of overall performance and metrics of instantaneous performance (Fig. 4).

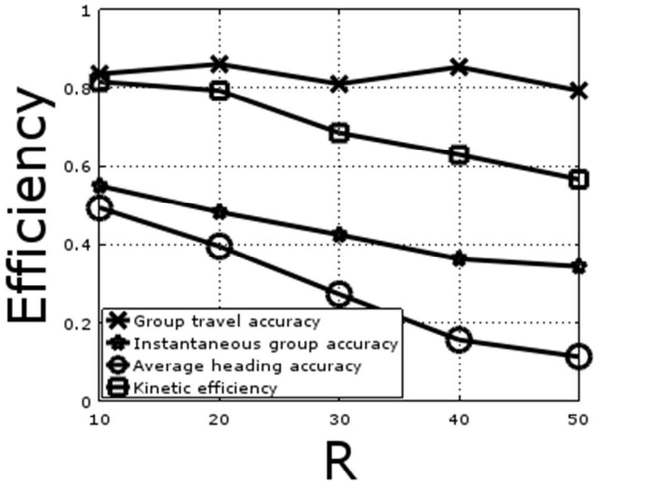

Fig. 3. Effect of varying distribution range for weighted proximal control algorithm

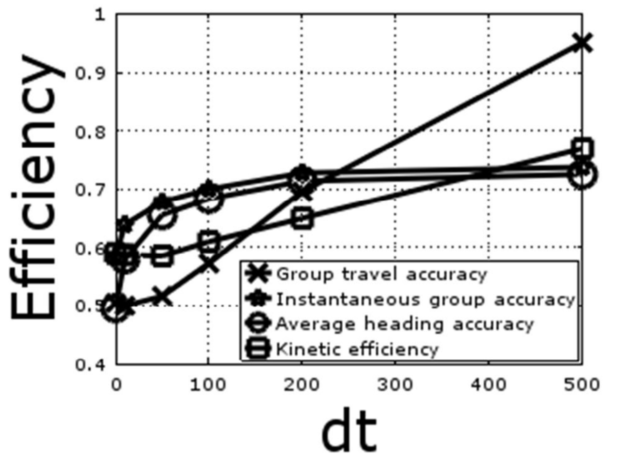

Fig. 4. Effect of varying amount of simulation steps between switching to uninformed mode and end of execution for prioritized proximal control algorithm

If malicious agents do not try to hide their presence in the group (dt = 0), all efficiency metrics have significantly lower values (Table II) compared to perfect case scenario (dt = 500). As the timeframe between malicious agents' switching to acting uninformed and efficiency evaluation increases, metrics of instantaneous performance quickly rise to their perfect-case values, while metrics of overall performance show almost linear dependencies. If malicious agents switch to uninformed state 200 time steps before efficiency is evaluated, relative difference (as compared to perfect case scenario) is 0.0133 for instantaneous group accuracy and 0.016222 for average heading accuracy. These results show that malicious agents can affect the group for 60% of algorithm execution time and have very little impact on metrics of instantaneous performance. Metrics of overall performance can be used to show the impact of malicious agents: relative change is -0.268 in group travel accuracy and -0.156 in kinetic efficiency.

TABLE II. RELATIVE CHANGE IN EFFICIENCY CAUSED BY MALICIOUS AGENTS TRYING TO CHANGE GROUP TRAVEL DIRECTION

dt	Instantaneous group accuracy	Average heading accuracy	Group travel accuracy	Kinetic efficiency
200	-0.013	-0.016	-0.268	-0.156
100	-0.051	-0.058	-0.397	-0.207
50	-0.081	-0.096	-0.457	-0.239
10	-0.133	-0.2	-0.474	-0.237
0	-0.207	-0.316	-0.469	-0.233

Relative difference in this case exceeds 0.01 only after amount of malicious agents becomes greater than amount of informed agents (Table III). Results show, that decreasing the speed of uninformed agents has greater impact on the system performance than decreasing the speed of all agents. If 25 agents (half of all agents, and 0.625 of uninformed agents) are malicious, the group covers 8 times shorter distance, compared to perfect-case scenario. Results provided in Table II and Table III show that kinetic efficiency is the only studied metric that gets significantly impacted by both kinds of malicious agents, as opposed to other studied metrics.

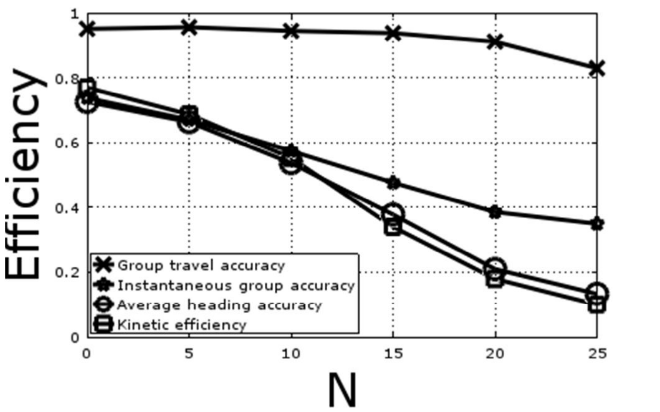

Fig. 5. Effect of varying amount of malicious agents for prioritized proximal control algorithm

TABLE III. RELATIVE CHANGE IN EFFICIENCY CAUSED BY MALICIOUS AGENTS TRYING TO SLOW THE GROUP DOWN

N	Instantaneous group accuracy	Average heading accuracy	Group travel accuracy	Kinetic efficiency
5	-0.092	-0.085	0.005	-0.108
10	-0.222	-0.26	-0.007	-0.282
15	-0.354	-0.479	-0.014	-0.558
20	-0.477	-0.711	-0.042	-0.767
25	-0.526	-0.817	-0.128	-0.87

VII. Conclusion

In this paper, new flocking efficiency metric, called kinetic efficiency, was proposed. Proposed metric is used to evaluate group performance over time, and requires only group centroid coordinates to be computed, as opposed to more sophisticated metrics requiring heading directions of each agent.

Five sets of experiments were conducted to compare proposed metric with other metrics used in literature. First set was executed in perfect conditions, and it proved that kinetic efficiency reflects group performance over time. Kinetic efficiency also shows dependencies on the confidence degree similar to other metrics'. Second and third set were executed in imperfect conditions, where probability of group fragmentation is higher and overall performance should be lower. According to the results, kinetic efficiency can be used to detect group fragmentation and decreases in imperfect conditions. Last two sets of experiments were executed in presence of malicious agents. In the 4th set, malicious agents tried to change group travel direction by acting as informed agents with different goal direction. In the 5th set, malicious agents tried to slow the group down by simply moving slower. Results show that kinetic efficiency is the only metric out of four studied metrics that can be used to detect both kinds of malicious agents.

Experimental results show that proposed metric can be used to evaluate system efficiency in both perfect and imperfect conditions, as well as to detect presence of various kinds of malicious agents. However, it should be noted that algorithms which score higher with existing efficiency metrics often reduce importance of proximal control and collision avoidance, which may result in reduced stability due to robots colliding into each other, and proposed metric does not reflect probability of collision in any way either.

The presented work can be extended in many ways. First, collision probability can be studied to determine whether existing metrics can reflect collisions' impact on the system. Secondly, more complete experimental scenarios may include more algorithms studied, including algorithms without implicit leadership and self-adaptive algorithms; other kinds of malicious agents and imperfect conditions. Experimental setup might also include real robots instead of simulation. In this case, simplicity of a metric becomes a key factor: some metrics might become difficult or impossible to evaluate in a realistic scenario.

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