Trust Aware Emergency Response for A Resilient Human-Swarm Cooperative System

Yijiang Pang
Cognitive Robotics and AI Lab
College of Aeronautics and Engineering
Kent State University
Kent, OH 44240, USA
ypang2@kent.edu

Rui Liu
Cognitive Robotics and AI Lab
College of Aeronautics and Engineering
Kent State University
Kent, OH 44240, USA
rliu11@kent.edu

Abstract—A human-swarm cooperative system, which mixes multiple robots and a human supervisor to form a heterogeneous team, is widely used for emergent scenarios such as criminal tracking in social security and victim assistance in a natural disaster. These emergent scenarios require a cooperative team to quickly terminate the current task and transit the system to a new task, bringing difficulty in motion planning. Moreover, due to the immediate task transitions, uncertainty from both physical systems and prior tasks is accumulated to decrease swarm performance, causing robot failures and influencing the cooperation effectiveness between the human and the robot swarm. Therefore, given the quick-transition requirements and the introduced uncertainty, it is challenging for a human-swarm system to respond to emergent tasks, compared with executing normal tasks where a gradual transition between tasks is allowed. Human trust reveals the behavior expectations of others and is used to adjust unsatisfactory behaviors for better cooperation. Inspired by human trust, in this paper, a trust-aware reflective control (Trust-R) is developed to dynamically calibrate human-swarm cooperation. Trust-R, based on a weighted mean subsequence reduced algorithm (WMSR) and human trust modeling, helps a swarm to self-reflect its performance from the perspective of human trust; then proactively correct its faulty behaviors in an early stage before a human intervenes. One typical task scenario (emergency response) was designed in the real-gravity simulation environment, and a human user study with 145 volunteers was conducted. Trust-R’s effectiveness in correcting faulty behaviors in emergency response was validated by the improved swarm performance and increased trust scores.

Index Terms—Trust, Emergency Response, Human-UAV Cooperation

I. INTRODUCTION

A human-swarm cooperative system mixes multiple robots and a human supervisor to form a heterogeneous team. Given the advantages of integrating a robot team’s large-scale and large-range task execution capability and a human’s comprehensive understanding of the environment, a human-swarm system has been widely used for scenarios, such as unmanned aerial vehicle (UAV) swarm cooperated navigation in an unknown environment [3], [4], UAV team assisted precision agriculture [5], [6], and mixed ground-aerial robot team for environmental monitoring in large areas [7], [8]. Due to real-world complexity and task variety, many tasks mentioned above require a human-swarm system to respond to emergent tasks, such as switching tracking vehicle in social security and multiple-victim searching in natural disaster rescue. The mixed team needs to execute emergent tasks without re-calibrating its motion status after each task.

Although the emergency response improves the performance of a human-swarm system, these emergent scenarios require a cooperative team to quickly terminate the current task and transit the system to a new task, bringing difficulty in motion planning. First, due to the immediate task transitions, uncertainty from both physical systems and prior tasks is accumulated to decrease swarm performance, causing robot failures and influencing the cooperation effectiveness between a human and a robot swarm. It is challenging for a human-swarm system to respond to emergent tasks, compared with executing normal tasks where a gradual transition between tasks is allowed. Second, real-world factors, such as motor degradation, sensor failure, and wind disturbances, bring uncertainty in swarm task performance. It is challenging for a robot swarm to maintain a high-quality performance with timely behavior adjustments since faulty robots cause unexpected degradation for swarm performance. Third, in a decentralized
team, a robot may decrease speed to maintain connectivity; even though the robot reacts slowly to task requests, it is still in normal status. Without an intelligent control method that adjusts robots based on a customized status estimation, it is challenging to effectively calibrate the swarm behaviors for effective collaboration with a human during emergency response.

Trust in human-swarm collaboration is the human belief of a robot team’s sufficient capability and reliability in performing a task. A higher level of trust will bring an increased human willingness of task allocations and plan sharing, and a lower frequency of swarm behavior corrections. On the contrary, a lower level of trust will trigger human interventions in both behavior correction and communication [9]. Given that trust influences interaction, trust modeling has the potential to facilitate cooperation between a human and a swarm.

Attracted by these benefits, this research developed a trust-aware reflective control Trust-R method to calibrate swarm behaviors during human-supervisory emergency response. The rationale is that Trust-R designs robot understanding of human trusted behaviors and then support robots to proactively reflect and correct its faulty behaviors, shown in Figure 1. Supported by a trust estimation, a weighted update algorithm helps a robot to share information with its trusted robot neighbors selectively and to reduce information sharing with distrusted neighbors, constraining negative influence from abnormal robots to the whole swarm. In this way, faulty behaviors of robots are repaired, and cooperation between a human and a swarm is calibrated, mitigating error accumulation during the emergency response. In this paper, there are mainly three contributions.

- A trust-based control algorithm, Trust-R, is developed based on control algorithm and trust modeling to plan swarm motions based on its understanding of human expectations, facilitating the cooperation between a human and a swarm for emergency response.
- Second, a reflection mechanism is developed for cooperation calibration between a swarm and a human. Based on trust estimation, Trust-R enables a swarm to self-diagnose its faulty behaviors and proactively mitigate the fault influence by either correcting or abandoning a robot.
- A novel framework of “behavior-repair to trust-repair” is developed to maintain trust between a human and a robot swarm during the cooperation. A robot swarm repairs its undesired behaviors, to prevent the trust loss between the human supervisor and the robot team.

II. RELATED WORK

Trust repair mechanisms were investigated previously. [10], [11] evaluated methods of repairing trust in human-robot cooperation through robot apology of its mistakes or promise of improved performance. [12] investigated the explanation mechanism’s impact on trust repair to help a robot to restore human trust by explaining the decision-making processes. However, due to the experiment settings of assessing trust after tasks, the study did not explore the in-process changes of the trust, making it difficult to capture critical factors influencing cooperation quality during robot task executions. This paper focuses on the cognitive framework of repairing human trust by repairing faulty robot behaviors. By developing robots an understanding of human expectations in the form of trust modeling, the Trust-R helps a swarm to self-correct its faulty behaviors by self-reflecting its abnormal behaviors in a timely manner.

Prior research investigated fault detection in robot swarms [13], [14]. Inspired by synchronized flashing behavior observed in the fireflies, [15] developed a general abnormality detection approach to detect non-operational robots in a robot swarm by identifying different flashing frequency of each robot’s onboard light-emitting diodes. However, the method requires faulty robots to proactively detect and report its fault status to the swarm for correction. Otherwise, the swarm will ignore unrepaired issues and suffer continually negative influence from faulty robots. [16], [17] developed behavior-based approaches to distinguish normal robots from abnormal robots in a swarm where the behaviors in the swarm that were persistent and abundant were to be treated as normal while rare behaviors were to be classified as abnormal. However, it is challenging for robots to find out higher-level faulty issues through self-diagnosis without a holistic view, such as an ant mill. This paper investigates a fault detection method for the robot swarm by developing a robot understanding of human trust. With the self-reflection of robot behaviors according to its estimation of human trust, Trust-R helps a robot swarm to correct its faulty behaviors proactively.

In our previous work [18], [19], a decentralized trust-aware behavior reflection method was demonstrated to correct faulty behaviors of a swarm effectively, and the Trust-R that restored performance and human trust in the swarm to an appropriate level by correcting undesirable swarm behaviors was also investigated. This paper further investigates the effectiveness of Trust-R in emergency response, where emergent task assignments cause uncertainty accumulation to undermine swarm performance.

III. DISTRUSTED FLOCKING IN EMERGENCY RESPONSE

A. Illustrative Scenario for Swarm Correction

Consider a robot swarm of n holonomic robots with positions \( X_i \in \mathbb{R}^3 \), where \( X_i = (x_{i,1}, x_{i,2}, \theta_i) \). Each robot is assigned a unique identifier (UID) \( i \in \{1, 2, ..., n\} \). The communication graph is given by \( G = (\mathcal{V}, \mathcal{E}) \). Every node \( v \in \mathcal{V} \) represents a robot. Every robot \( i \) only communicates with its direct neighbors \( j \in N_i \), where \( N_i \) is the set of all neighbors of \( i \) within the communication radius, \( R \). If robot \( j \) is a neighbor of \( i \), then edge \( (v_i, v_j) \in \mathcal{E} \). The connectivity graph is connected and undirected (i.e., \( (v_i, v_j) \in \mathcal{E} \Rightarrow (v_j, v_i) \in \mathcal{E} \)). The dynamic model for each robot is defined as follows. A robot \( i \) is controlled by the linear velocity \( u_{x}^i \) and angular velocity \( u_{\theta}^i \) generated by motors. \( x_i, \theta_i \) denotes horizontal and vertical positions and orientation state, respectively.
The speed $u_i$ of the robot $i$ is updated using Equation 1. At each time step $t$, a robot $i$ updates its motion status by averaging its neighbors’ motion status.

$$u_i[t + 1] = \frac{1}{N_i + 1}(u_i[t] + \sum_{j \in N_i} u_j[t])$$  \hfill (1)$$

As seen from the distributed update method above, faulty robots will relay unreliable motion information to their neighbors, which in turn will mislead their neighbors’ motions.

**B. Emergency Response with Accumulated Uncertainty**

In order to ensure the robot swarm move towards the dynamic task destinations, the robots in the swarm are divided into two types: leader robots and follower robots. With a typical setting in a hierarchical swarm control [20], only leader robots can receive control information from the base station, such as dynamic destination coordinates and cruising speed.

Meanwhile, faulty robots accumulate motion uncertainty, such as location shifting, heading direction deviation, and extra speed, mapping into the swarm because of the update of consensus policy. In this paper, given the speed and heading direction requirement in the flocking, the accumulated uncertainty is described by the accumulated speed $\delta u$ and accumulated location shifting $\delta x$ of the swarm compared with the expected swarm status of receiving the new-task assignment. Given that assumption, the velocity $u_i$ of the leader robots is updated using equation 2.

$$u_i[t + 1] = \frac{1}{N_i + 1}(u_i[t] + \sum_{j \in N_i} u_j[t]) + u_i^\gamma[t]$$  \hfill (2)$$

Where $u_i^\gamma$ is the navigational feedback and accumulated uncertainty and is given by

$$u_i^\gamma[t] := f_i^\gamma(x_i[t], x_\gamma, \delta x, u_i[t], u_\gamma, \delta u)$$

$$= -c_1^\gamma(x_i[t] - x_\gamma + \delta x) - c_2^\gamma(u_i[t] - u_\gamma + \delta u)$$

and the $\gamma$ - robot $(x_\gamma, u_\gamma)$ is the virtual leader that leads the swarm to follow its trajectory [21], [22]. The parameters $x_\gamma$ and $u_\gamma$ are the destination and cruising speed that the leader robots get from the base station. $c^\gamma$ denotes the gain of the components. During a normal task execution, $|x_i[t] - x_\gamma| \to 0$, $|u_i[t] - u_\gamma| \to 0$, as $t \to \infty$. When the swarm responds to an emergent task, the expected swarm status of receiving the new-task assignment will be influenced by $\delta x$, $\delta u$. As seen from the dynamic task update method above, faulty robots will be able to introduce uncertainty to the swarm and worsen the swarm task performance. In order to mitigate the uncertainty for swarm performance assurance, our method will target on suppressing negative influence $\delta x$, $\delta u$ in real time, to finally correct swarm behaviors.

**IV. TRUST-AWARE REFLECTIVE CONTROL FOR EMERGENCY RESPONSE**

The architecture of the Trust-R is shown in Figure 2. With Trust-R, an understanding of human-expected behaviors is developed to determine the robot’s communication quality with its neighbors, maximally reducing the negative influence of a faulty robot on the whole swarm.

**A. Human Supervision**

In human-swarm cooperation, the human serves as the operator to monitor and guide the executions of the robot swarm. As the operator of the swarm, the human monitors the real-time status of all robots in the map and knows the requirements for swarm behavior, such as minimal velocity, heading direction, and reasonable formation. The operator distinguishes between current performance and expected performance, and scores the current performance for individual robots and the whole swarm.

**B. Trust-Aware Connectivity**

In general, each robot in the swarm calculates its speed by averaging all its neighbors’ speed to reach consensus.
However, when faulty robots appear in a swarm, the faulty robots have a negative influence on the performance of the swarm bringing the risk of failure to assigned tasks. This paper used a weighted connection method, based on the weighted mean subsequence reduced algorithm [24], to enhance connectivity and communication between trustworthy robots, and decrease information-sharing by faulty robots. Every robot only communicates with its direct neighbors \( j \in N_i \). The velocity of each robot \( u_i \) is updated with weighted reference to its neighbors.

\[
u_i[t + 1] = w_i[u_i[t] + \sum_{j \in N_i} w_j[u_j[t]]] \tag{3}
\]

### C. Trust-Aware Communication Quality Assessment

The overall communication graph for robot \( i \) is \( \mathcal{E} = \{(i, j) \mid j \in N_i\} \). Based on the estimated trust levels of the two robots \( \{i, j\} \), communication quality, \( f_{ij} \in [0, 1] \), is used to measure the reliability of exchanged information. The trust-aware communication quality is dynamically updated to reflect the changing communication graph using Equation 4. The best communication distance between two robots \( i \) and \( j \) is \( \rho \). Communication within \( \rho \) is considered as communication with the best quality.

The parameter, \( \eta \), is used as a weighting factor to discourage the impact of faulty robots on their neighbors.

\[
f_{ij} = \begin{cases} 0 & \left| ||x_i - x_j|| \geq R \right| \\ \frac{g_i + g_j}{2} ^ \eta \exp \left( - \frac{\gamma (||x_i - x_j|| - \rho)}{R - \rho} \right) & \left| ||x_i - x_j|| \leq \rho \right| \end{cases} \tag{4}
\]

Where \( g_i \) is the trust level of robot \( i \). The above communication quality evaluation method implies that within the communication range, the communication reliability is the average of the two robots’ trust values.

The rationale for designing the trust-aware communication quality is to encourage information-sharing with trusted robots by using higher upper limits on their communication quality while discouraging information sharing with untrusted robots by using lower upper limits on the communication quality. Meanwhile, to encourage a compact swarm with closer distances among robots, the communication quality is decreased as the robot distance increases.

### D. Trust-Aware Behavior Correction

A swarm proactively corrects its faulty behaviors using a two-step process. First, it corrects for faulty robots by restraining the sharing of unreliable information from faulty robots and referring to trusted robots for behavior correction. The failed robots are isolated from other trusted robots, preventing the sharing of unreliable motion information. In doing so, a robot adjusts its behavior – heading direction and speed – using a larger amount of trusted motion information.

\[
w_k[t] = \frac{\hat{f}_k[t]}{\hat{f}_i[t] + \sum_{j \in N_i} \hat{f}_j[t]}, k \in [i, N_i] \tag{5}
\]

Weights for updating each robot’s status are calculated by Equations 3 and 5. The result of the weighted update mechanism is shown on the right side of Figure 2, and by Equation 6.

\[
u_i[t + 1] = \frac{\hat{f}_i[t]}{\hat{f}_i[t] + \sum_{j \in N_i} \hat{f}_j[t]} (u_i[t] + \sum_{j \in N_i} u_j[t]) \tag{6}
\]

### V. EXPERIMENT

In order to validate the effectiveness of Trust-R in helping swarm self-diagnose its faulty behaviors and proactively mitigate the fault influence from abnormal robots, one task scenario was designed to compare the accumulated error and human ratings of trust on swarm before and after applying the Trust-R.

#### A. Environment Design

A simulation environment was designed based on a CRAImr framework, which was developed based on simulation software gazebo, task-related swarm control laws, and trust models [25], [26], shown in Figure 3.

There are six robots in the experiment, including one failed robot with motor issues. The velocity for each robot is set to 5.0m/s. In order to avoid collision, the repulsion radius is set as 2m. For all robots, the communication radius is 7.5m. In the communication quality evaluation method, Equation 4, \( g \) and \( \eta \) are used to set upper limits on the communication quality. \( \gamma \) defines the sensitivity of quality to mutual distance. As explored in our previous work [18], to optimally distinguish various status, the \( g \) values are set at (1, 0.5, 0) for trusted robots, faulty robots and failed robots, respectively. \( \eta \) values are \( (1, 1, 0.4, 0.3, 0.2, 0.2) \) and \( \gamma \) values are \( (0.1, 0.5, 1, 3, 5, 7) \) for communications between trusted-trusted robots, trusted-faulty robots, trusted-failed robots, faulty-faulty robots, faulty-failed robots, failed-failed robots.

#### B. Task Scenario Design

One typical task covering basic elements of the emergency response scenario was designed. Scenario: emergency response. In the scenario, the UAV swarm is designed to monitor a target so the swarm will flock from "target 1" to "target 2".

![Fig. 3. The simulation environment. In each task, the robot swarm will flock to an assigned target area marked in green on the map.](image-url)
Fig. 4. Experiment result for the Case Study: emergency response. In faulty condition, the UAV swarm performs the task in the presence of a faulty robot; while applying the **Trust-R**, the UAV swarm will restrict the influence of the faulty robot that improves the performance of the UAV swarm.

However, in the middle of the flight, the leader UAV will get an order that changes the target from "target 2" to "target 3". The whole UAV swarm is expected to shift from the normal target to the emergent target; and the state of the UAV swarm will change from cruising-response to emergent-response direction and velocity.

The scenario consists of four simulated conditions: two different levels of influential factors conditions and for each condition corresponding cases of before and after applying the **Trust-R** to the swarm. The two different levels of influential factors, motor issues, have a restricted maximum speed of 40% and 70%, respectively, to test the effectiveness of the **Trust-R** with different faulty levels.

### C. Human User Study

A human user study with 145 volunteers is conducted (The full questionnaire can be found in this link [1], on the crowdsourcing platform Amazon Mechanical Turk [27].

The user study has two main parts, a tutorial and an actual survey. The tutorial includes video examples of one task and responses to questions. The actual survey has four parts - the designed task scenario with four simulated conditions. In each part of the study, the participants are required to monitor one task progress and motion behaviors of the swarm, such as flocking speed, heading direction, and robot spatial relations (connectivity and formation).

### VI. RESULT

The data we have collected are ordinal categorical variables. The Mann-Whitney U test is applied to analyze the effect of the following factors on human trust in the swarm. A mapping relationship is defined between human trust levels and numbers for convenience. **Completely Distrust**:1, **Distrust**:2, **Neutral**:3, **Trust**:4, **Completely Trust**:5.

**Case Study : emergency response** Figure 4 shows the results of the experiment under the designed scenario. The chance of participants reporting faults in the faulty conditions and repaired conditions had a significant difference in the scenario. The participants were more likely to report faults in the faulty conditions than in the repaired conditions ($U = 850, \rho = 0.09$). The mean trust level for the faulty conditions and the repaired conditions are 2 and 4.22, respectively, and also, the participants were more likely to report a higher trust level to the repaired conditions than the faulty conditions ($U = 480, \rho = 0.05$).

In the scenario, for different levels of faulty issues, the chance of participants reporting faults in the faulty conditions is close ($U = 1050, \rho = 0.42$). The participants showed no clear difference to report faults with different faulty levels in the scenario. In the faulty conditions, participants showed similar trust levels in different faulty levels ($U = 1060, \rho = 0.42$). In the repaired conditions, participants showed similar trust levels in different faulty levels ($U = 1071, \rho = 0.43$).

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Overall, the result of testing the effects of **Trust-R** on restoring human trust shows a great difference between faulty conditions and repaired conditions. Table I presents the human

| Swarm Status | Median Trust Level |
|--------------|--------------------|
| Faulty       | 2                  |
| Repaired     | 4.22               |

### TABLE I

**EMERGENT SCENARIO CONDITIONS**

| Scenario     | Median Trust Level |
|--------------|--------------------|
| Distrust/2   | Trust/4.22         |

### TABLE II

**VALUES OF FLOCKING HEADING-DIRECTION AND FINAL DISTANCE TO TARGET**

| Scenario | Value 1 | Value 2 |
|----------|---------|---------|
|          | Designed | Faulty | Repaired | Designed | Faulty | Repaired |
|          | 0       | -19     | -4       | 0.0      | 9.8    | 3.2      |

Value 1: heading-direction / °.  
Value 2: distance to target / m.
trust levels of the faulty and repaired conditions for UAV swarm under the scenario. Table II summarizes the final values of flocking heading direction and distance to destination.

VII. CONCLUSION

This paper reported the methodology of facilitating human-swarm cooperation and the result of an experiment where Trust-R acted to reduce the influence of faulty UAV to the swarm. In the scenario, the participants could easily distinguish the faulty conditions from the repaired conditions ($\rho = 0.09$), and after implementing the Trust-R, the participants showed greater trust in the repaired conditions than the faulty conditions. The Trust-R could largely reduce the negative influence from faulty UAV to the swarm.

VIII. DISCUSSION & FUTURE WORK

This paper has explored the potential application of Trust-R. The typical application scenario is a robot swarm supervised by a human operator, where information sharing by neighbors will be involved in the control loop of the current agent. The weighted connection mechanism can map human trust into the information sharing process, which restricts the sharing of untrustworthy information to improve the performance of the whole team. The application of a trust mechanism has been shown to strengthen UAV performance and enhance human-swarm cooperation.

In the future, more fault factors caused by unstable systems and environmental disturbances will be considered so that an accurate trust-based method can be designed to improve the performance of a UAV swarm for emergent tasks. Meanwhile, environment with obstacles or a swarm composed of large numbers of UAV brings challenges to practical human-swarm cooperation because of limitations of human cognition capability on shifting attention on multiple robots, so that future research is needed to adapt robots to the human limitations.

REFERENCES

[1] Reynolds, Craig W. "Flocks, herds and schools: A distributed behavioral model." Proceedings of the 14th annual conference on Computer graphics and interactive techniques. 1987.
[2] Jadbabaie, Ali, Jie Lin, and A. Stephen Morse. "Coordination of groups of mobile autonomous agents using nearest neighbor rules." IEEE Transactions on automatic control 48.6 (2003): 988-1001.
[3] McGuire, K. N., et al. "Minimal navigation solution for a swarm of tiny flying robots to explore an unknown environment." Science Robotics 4.35 (2019): eaaw9710.
[4] Soares, Patrick Prieto, et al. "Group of Robots Inspired by Swarm Robotics Exploring Unknown Environments." 2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE). IEEE, 2018.
[5] Albani, Dario, et al. "Monitoring and mapping with robot swarms for agricultural applications." 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS). IEEE, 2017.
[6] Albani, Dario, Daniele Nardi, and Vito Trianni. "Field coverage and weed mapping by UAV swarms." 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). Ieee, 2017.
[7] Carpentierio, Marco, et al. "A swarm of wheeled and aerial robots for environmental monitoring." 2017 IEEE 14th International Conference on Networking, Sensing and Control (ICNSC). IEEE, 2017.
[8] Duarte, Miguel, et al. "Application of swarm robotics systems to marine environmental monitoring." OCEANS 2016-Shanghai. IEEE, 2016.
[9] Lee, John, and Neville Moray. "Trust, control strategies and allocation of function in human-machine systems." Ergonomics 35.10 (1992): 1243-1270.
[10] Robinette, Paul, Ayanna M. Howard, and Alan R. Wagner. "Timing is key for robot trust repair." International Conference on Social Robotics. Springer, Cham, 2015.
[11] Schweitzer, Maurice E., John C. Hershey, and Eric T. Bradlow. "Promises and lies: Restoring violated trust." Organizational behavior and human decision processes 101.1 (2006): 1-19.
[12] Wang, Ning, David V. Pynadath, and Susan G. Hill. "Trust calibration within a human-robot team: Comparing automatically generated explanations." 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 2016.
[13] Visinsky, Monica L., Joseph R. Cavallaro, and Ian D. Walker. "Robot fault detection and fault tolerance: a survey." Reliability Engineering and System Safety 46.2 (1994): 139-158.
[14] Khaldi, Belkacem, et al. "Monitoring a robot swarm using a data-driven fault detection approach." Robotics and Autonomous Systems 97 (2017): 193-203.
[15] Christensen, Anders Lyhne, Rehan OGrady, and Marco Dorigo. "From fireflies to fault-tolerant swarms of robots." IEEE Transactions on Evolutionary Computation 13.4 (2009): 754-766.
[16] Tarapore, Danesh, Anders Lyhne Christensen, and Jon Timmis. "Generic, scalable and decentralized fault detection for robot swarms." Plos one 12.8 (2017).
[17] Tarapore, Danesh, Jon Timmis, and Anders Lyhne Christensen. "Fault detection in a swarm of physical robots based on behavioral outlier detection." IEEE Transactions on Robotics 35.6 (2019): 1516-1522.
[18] Liu, Rui, et al. "Trust-Aware Behavior Reflection for Robot Swarm Self-Healing." Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems. International Foundation for Autonomous Agents and Multiagent Systems, 2019.
[19] Liu, Rui, et al. "Trust Repair in Human-Swarm Teams+." 2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN). IEEE, 2019.
[20] Gupta, Lav, Raj Jain, and Gabor Vaszkun. "Survey of important issues in UAV communication networks." IEEE Communications Surveys & Tutorials 18.2 (2015): 1123-1152.
[21] Olafati-Saber, Reza. "Flocking for multi-agent dynamic systems: Algorithms and theory." IEEE Transactions on automatic control 51.3 (2006): 401-420.
[22] La, Hung Manh, and Weihua Sheng. "Adaptive flocking control for dynamic target tracking in mobile sensor networks." 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems. IEEE, 2009.
[23] Ren, Wei. "Multi-vehicle consensus with a time-varying reference state." Systems & Control Letters 56.7-8 (2007): 474-483.
[24] Saldana, David, et al. "Resilient consensus for time-varying networks of dynamic agents." 2017 American control conference (ACC). IEEE, 2017.
[25] Quigley, Morgan, et al. "ROS: an open-source Robot Operating System." ICRA workshop on open source software. Vol. 3. No. 3.2. 2009.
[26] Koenig, Nathan, and Andrew Howard. "Design and use paradigms for gazebo, an open-source multi-robot simulator." 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)(IEEE Cat. No. 04CH37566). Vol. 3. IEEE, 2004.
[27] Flatrum, Michael, Tracy Kwang, and Samuel D. Gosling. "Amazon’s Mechanical Turk: A new source of inexpensive, yet high-quality data?." (2016).