Trust Repairing for Human-Swarm Cooperation in Dynamic Task Response
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Abstract—Emergency happens in human-UAV cooperation, such as criminal activity tracking and urgent needs for ground assistance. Emergency response usually has high requirements on the motion control of the multi-UAV system, by maintaining both the team performance and team behaviors. However, when a UAV swarm execute tasks in a real-world environment, because of real-world factors, such as system reliability and environmental disturbances, some robots in the swarm will behave abnormally, such as slow flocking speed, wrong heading direction, or poor spatial relations. In the meanwhile, incorrect trust between human and UAV swarm could map the abnormal behavior of faulty robot to the whole swarm and request an time consuming intervention from human supervisor, damage the UAV swarm response for dynamic task, even evolve to a failure of task because of accumulated error. To correct reflect the trust between human and UAV swarm and rebuild the trust to improve the performance caused by incorrect trust. We propose a dynamic trust repair model. The dynamic trust model focus on human-supervisory UAV system which can help UAV swarm to reduce the negative influence from faulty UAV on the performance of the UAV swarm, get a flexible reaction and stable human-supervisory UAV task performance. Results show that trust model could improve the performance of the swarm for dynamic task response and regain human trust.

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

I. INTRODUCTION

Robot swarm are coordinated via simple control laws to achieve some desired behaviors such as flocking, cruise, and deployment while maintaining connectivity and avoiding collision. Combining these kinds of basic behaviors with human intelligence, an human-supervisory UAV swarm may only need a few human operators to be able to control a very large number of UAVs to execute a variety of tasks. In the meanwhile, human operators could remotely adjust the UAV swarm to adapt the unstable environment and dynamic tasks. Through this way that could save lots of human resources and bring extra stability to the swarm. So research on human-swarm cooperation has draw lots of attention.

Human trust in the swarm is critical in human-swarm cooperation which is a quantitative method to estimate the performance of the swarm and individual robot and is also a precondition to dynamic adjust their performance [1]. In general, Human trust plays an important role in the human-supervisory system which combining human intelligence with robot swarm that could bring a better performance of the swarm in real world environment and expand the ability of swarm. Normally a trustworthy swarm means human operators are more willing to rely on automation to execute tasks, thereby reducing unnecessary interventions. A low trust level correspond to potential issues which means necessary interventions must be taken [2].

However, real-world faults, such as motor degradation, sensor failure or environmental disturbances, make maintaining trust between humans and swarms challenging. When a swarm need to respond dynamic tasks, such as a sequential tasks and emergent task, which require the swarm to have a consistent performance and a timely adjustment to current state. Because the swarm intend to reach consensus behavior, faulty robots can cause a unexpected and uncontrolled performance to the whole swarm. Unlike a centralized system, there exists motion uncertainty for individual robot in a decentralized system. For example, under a dynamic environment, it is hard to distinguish if a robot has normal performance or abnormal performance based on simple laws. A normal robot may decrease speed to maintain connectivity with its faulty neighbor, while react slowly to a collective task response. Without human supervision and correct method reducing negative influence to the swarm, the swarm is easy to be influence by faulty robots and can’t adjust and repair its undesired behavior that makes the performance of the swarm unstable.

To solve these challenges, in our previous paper [3], we propose a decentralized trust-aware behavior reflection method that was demonstrated to effectively correct faulty behaviors of swarm. In anther paper [4], we test that the trust-repairing method restoring performance and human trust in the swarm to an appropriate level by correcting undesired swarm behaviors.

In this paper, we envision a mission-driven human-supervisory UAV swarm system that a UAV swarm is as-
signed to execute dynamic tasks that requires a high flexible movement and timely response but a minority of robots in the swarm have irreparable issues. While faulty robots appear in an original trustworthy swarm, the swarm suffering continuing negative influence from faulty robots were far more vulnerable comparing with loss of individual members. So the remaining robots could finish assigned tasks only if the faulty robots have no negative influence on the normal robots. We model human trust for dynamic task and use trust-repairing method to avoid a accumulated fault in the first stage in case evolving to serious fault. In the experiment we collect trust judgments from human to different mission-driven scenarios, then estimate whether trust rebuild between human and UAV swarm after applying our method. The result shows our trust repair framework could rebuild trust in a mission-driven human-supervisory UAV swarm system. We mainly have three contributions:

1. A complete trust repairing framework applying to human supervised multi-agents system has been developed to correct undesired swarm behaviors, and repair human trust in swarm.

2. Generalizing the trust repairing method into dynamic situation, proving its effectiveness in restraining accumulated error in dynamic task situation.

3. A simulation platform is designed to help with building different kinds of scenarios of human-swarm cooperation and estimation the human-swarm cooperation through directly observing the performance of UAV swarm.

II. RELATED WORK

Swarm self-healing is investigated to improve the collective performance of robots. In [10],[11], a fault-tolerant rendezvous of multi-robot systems is proposed which exploited concepts from combinatorial geometry to help faulty-free robots achieved goal without the influence of the faulty robots. However, their result didn’t have dynamic cooperation between human operator and swarm lacking adaptability to real-world dynamics. Some research in swarm self-healing has focused largely on replacing lost robots within formations, which ignores the greater danger of partial failures likely to be encountered in real-world deployments. For example, [12] develop methods for mobile robot networks to maintain logical and physical topology of the network when robots fail and must be replaced within a formation. They further demonstrate the stability of motion synchronization under their topological repair mechanism.

Moreover, a number of work focus on dealing with failure caused by faulty robots in the swarm with trust. In [6], human and a single robot collaborated to execute a mission, trust in Human-Robot Collaboration was measured in simulation environment. In [7], a multiple UAV control simulation was utilized, to test the effect of a system-wide trust in multi autonomous agents in a supervisory control setting. In [8], a trust model was used to dynamically adjust strategy of the multi-robot patrolling task. Similar to our work, [2] considered protecting the swarm though resilience by restricting robot updates to data information of neighbors near their own. Their results for swarms meeting connectivity requirements and based on communication of constant or time varying values by faulty robots showed convergence of the swarm to correct headings. However, their scenarios didn’t deal with dynamic task such as UAVs executed some sequential tasks suffering accumulated error. In this paper we designed different scenarios to explore effectiveness of our self-healing method in dynamic tasks with suffering corresponding accumulated error.

Trust-Aware human-robots collaboration was critical in a human-robots system, especially the system was in the presence of faulty robots. However, fewer researches investigated the scenarios that rebuilding trust between human and swarm for dynamic tasks. In our paper, combining the trust-aware connectivity between team members with self-healing method brought adaptation to swarm for dynamic task in the presence of faulty robots.

Researches have been done in the field of trust loss in human-robot interaction. [13] has the result that the robot performance and attributes were the largest contributors to the development of trust in HRI. In [14], the result shows the error and the trust loss were not strictly correlated. Besides the task performance, Users’ personality, task type and the effect caused by the errors also cause trust decrease. In this paper, we extend the approach that investigating the influence of accumulated error and modeling the trust rebuilding.

III. DYNAMIC TASK RESPONSE WITH HUMAN-SWARM COOPERATION

The scenarios for the UAV swarm is selected as executing popping up patrol tasks. In these scenarios, the UAV swarm is flocking to human-assigned locations in the meanwhile maintaining expected motion behaviors, such as similar flocking speed and heading direction, and robot spatial relations(connectivity and formation).
A. Swarm Control

Consider a group of agents described by $(p_i, u_i)$, $i=1,...,N$, where $p_i = (x_i, y_i)^T$ is the position of agent $i$, $u_i = (V_x, V_y)^T$ is its velocity. To make sure the swarm flock with safety, we define $r_{comm}$ and $r_{collision}$. $r_{collision}$ denote the collision range between two robots. $r_{comm}$ is the communication range between two robots, and beyond this distance there is no interaction. And we can also define a set of neighbors of agent $i$.

$$N_i = \{ j \in \nu : ||p_i - p_j|| \leq r_{comm}, \nu = \{1,2,\ldots,N\}, j \neq i \}$$  \hspace{1cm} (1)

The distance and the unit direction vector between robot $i$ and its neighbor $j$ are described as follows:

$$d = ||p_i - p_j||, d_{ij} = \frac{p_i - p_j}{||p_i - p_j||}, j \in N_i \hspace{1cm} (2)$$

The flocking control law consists of three components as follow[13]:

$$u_i = u_i^\alpha + u_i^\beta + u_i^\gamma \hspace{1cm} (3)$$

The first component $u_i^\alpha$ regulates the velocity vector of agent $i$ to reach consensus with its neighbors.

$$u_i^\alpha[t + 1] = \frac{1}{N_i + 1} \left( v_i[t] + \sum_{j \in N_i} v_j[t] \right) \hspace{1cm} (4)$$

The Second component $u_i^\beta$ is used to avoid collision with the agents in the group.

$$u_i^\beta = c_1^\beta \sum_{j \in N_i} \frac{\theta_{j,i}^\beta(d)}{||p_j - p_i||} (p_j - p_i) + c_2^\beta \sum_{j \in N_i} b_{j,i}^\beta(d) (u_j - u_i) \hspace{1cm} (5)$$

The relative position and velocity of the obstacle are both influence factor to avoid collision, parameters $\theta_{j,i}^\beta(d)$ and $b_{j,i}^\beta(d)$ are adjustable gain of position and velocity respectively, which are both related to (2) of $d$. They can be define as

$$\theta_{j,i}^\beta(d) = \rho^\beta ||r_{collision} - d||$$

$$b_{j,i}^\beta(d) = \rho^\beta ||r_{collision} - d|| \hspace{1cm} (6)$$

The last component $u_i^\gamma$ is used for navigation which ensures that the robots moves towards an assigned position.

$$u_i^\gamma = -c_1^\gamma (p_i - p_r) - c_2^\gamma (u_i - u_r) \hspace{1cm} (7)$$

where the $\gamma$ - agent $(p_r, u_r)$ is the virtual leader that leads the swarm flocking to follow its trajectory. The following section DynamicTaskAllocation will have detail illustration on $u_i^\gamma$. $c^\alpha, c^\beta$ and $c^\gamma$ denote the gain of each component of (3).

B. Dynamic Task Allocation

In our experiment, we have an assumption that communication networks in UAVs is Software Defined Networking (SDN) based routing [5]. Only the leader robot could receive control information from base station which could consider as the team leader, and other UAVs could only share sensor information with team members in the communication range. The human as the operator could supervise the UAV swarm, monitor the task progress and behavior of the swarm. For instance, the swarm is flocking to assigned location with designed speed and formation. As the operator of the swarm, the human could get the real-time position of all UAVs in the map and know the swarm behavior requirement, such as minimal velocity, heading direction, and reasonable formation. So the operator can distinguish the current performance from expected performance, and then score the current performance for individual robot and the whole swarm. So the performance of the UAV swarm has a trust level assessed by human operator. If the trust between human and UAV swarm is low which means the human operator find faulty behavior of individual UAV or the whole swarm, then the human will consider the swarm is unreliable to execute tasks. In our paper, the trust score assigned by human operator for each robot is the fundamental parameter to adjust the performance of the UAV swarm.

IV. Trust Aware Human-Swarm Cooperation

We apply the human trust into the coordinated behavior of the swarm, making individual robot in the swarm has a trust-aware connectivity ability, then investigate that whether a UAV swarm suffering negative influence from faulty robots could regain human trust for dynamic task response after being repaired.

A. Human Supervision

In scenarios such as search and rescue, robots are often required to execute tasks under dynamic environment, in the mean while demanding a quickly, safely and reliable response. Unfortunately, in current technical situation it is insufficient for robot to complete tasks in these scenarios without the aid of a human. Compared with the advantage of a robot system, such as stability in repeatable tasks, accuracy with non-physical interference, and adaptation to harsh natural conditions, humans have the capabilities of situation assessment and quick decision-making which could improve the adaptability of a robot system. To combine these two advantages for enhancing the performance of system, a human can be introduced into the robot system.

In this paper, a human-swarm cooperation system is built. The UAV swarm is the task executor, one or minor UAV could receive information from base station which could consider as the team leader, and other UAVs could only share sensor information with team members in the communication range. The human as the operator could supervise the UAV swarm, monitor the task progress and behavior of the swarm. The human could get the real-time position of all UAVs in the map and know the swarm behavior requirement, such as minimal velocity, heading direction, and reasonable formation. So the operator can distinguish the current performance from expected performance, and then score the current performance for individual robot and the whole swarm. So the performance of the UAV swarm has a trust level assessed by human operator. If the trust between human and UAV swarm is low which means the human operator find faulty behavior of individual UAV or the whole swarm, then the human will consider the swarm is unreliable to execute tasks. In our paper, the trust score assigned by human operator for each robot is the fundamental parameter to adjust the performance of the UAV swarm.
B. Trust-aware connectivity

In general, each robot in the swarm calculated its speed by averaging all its neighbors speed to reach consensus. But when faulty robots appear in a swarm, the faulty robots have negative influence on the performance of the swarm which may lead to a failure to assigned tasks. For instance, one robot in the swarm has unexpected linear velocity and angular velocity due to a motor issue. Because the swarm try to reach consensus, robots will exchange state information with their neighbors. The performance of the swarm will be influenced by faulty robots. In this paper, we use a weighted connection method to enhance the connection and communication between trustworthy robots and decrease the information sharing from faulty robots.

\[ u_i^n[t+1] = w_i v_i[t] + \sum_{j \in N_i} w_j[t] v_j[t] \]  

(8)

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 ?? . The best communication distance between two robots \( i \) and \( j \) is \( \rho \). Communication within \( \rho \) is considered as the communication with the best quality. The parameter, \( \eta \), is used as a weighting factor to discourage the impact of faulty robots on their neighbors.

\[ f_{ij} = \begin{cases} 0 & \frac{1}{n} (g_i + g_j) \eta \exp \left( -\frac{r_{ij}}{r_{comm}} \right) \geq r_{comm} \\ \frac{1}{n} (g_i + g_j) \eta \exp \left( -\frac{r_{ij}}{r_{comm}} \right) \leq \rho & \text{otherwise} \end{cases} \]

(9)

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. If both robots are trusted, their communication is the most reliable; if one robot is faulty, the most reliable communication under that connection is the communication from the trusted robot.

The rationale of 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 if the robot distance increases.

The recommended settings is that the \( g \) values are \((1, 0.5, 0)\) 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 (trust-trust), trusted-faulty robots (trust-faulty), trusted-failed robots (trust-failed), faulty-faulty robots (faulty-faulty), faulty-failed robots (faulty-failed), failed-failed robots (failed-failed), \( g \) and \( \eta \) are used to set upper limits on the communication quality. \( \gamma \) defines the sensitivity of quality to mutual distance.

The adjacency matrix, \( A \), that describes the communication graph is given by:

\[ [A]_{ij} = \begin{cases} 0 & i \neq j \\ f_{ij} & i = j \end{cases} \]

(10)

The degree matrix, \( D \), is:

\[ [D]_{ij} = \begin{cases} 0 & i \neq j \\ \sum_j f_{ij} & i = j \end{cases} \]

(11)

The novel trust-weighted Laplacian matrix, \( [L]_{ij} \), calculated as \( [L]_{ij} = [D]_{ij} - [A]_{ij} \) can then be defined as:

\[ [L]_{ij} = \begin{cases} -f_{ij} & i \neq j \\ \sum_j f_{ij} & i = j \end{cases} \]

(12)

The eigenvalues \( \{\lambda_i \mid i = 1, 2, ..., n\} \) of \( L \) are real and they satisfy \( 0 = \lambda_1 \leq \lambda_2 \leq ... \leq \lambda_n \). The connectivity measure \( \lambda_2 \) is estimated by the equation \( Le_2 = \lambda_2 e_2 \) and the eigenvector \( e_2 \).

D. Trust-aware Behavior Correction

A robot swarm corrects the faulty behaviors by restraining the negative influence from faulty robots. The connectivity control in above Section Trust-aware connectivity is used to reduce the interplay between faulty robots and their normal neighbors. In doing so, a robot adjusts its swarm behavior - consensus velocity and connectivity using a larger amount of information from trusted robots.

\[ w_k = \frac{f_k}{f_i + \sum_{j \in N_i} f_j} \]

(13)

For updating a robot \( i \), weights \( w_k \) are calculated by normalizing all the communication quality values in a communication range, shown in equation 13. When \( k = i, f_k = g_i \) (i.e., the trust level of itself). If \( k = j \in N_i \) then \( f_k = f_{ij} \) (i.e., the communication quality between robots \( i \) and \( j \)). \( f_i = g_i \) for all values of \( k \).

Over all, weights for updating component \( \beta_i \) are calculated by Equations 8 and 13.

\[ u_i^n[t+1] = \frac{f_k}{f_i + \sum_{j \in N_i} f_j} (v_i[t] + \sum_{j \in N_i} v_j[t]) \]

(14)

For a robot, it might correct its faulty behaviors based on the types of the faulty issues. If a robot is required with its maximum speed in a mission, the behavior of the robot can’t be repaired when the robot has motor failure. But a robot flying with cruising speed, which has a wearing motor with decreasing power output, can be soft-repaired with lager control input.

With the trust-weighted update, the component \( u_i^n \) are changed to \( u_i^n_{t,\text{trust}} \). The gain \( k_v \) is parameters for adjusting the motor output.

\[ u_{i,\text{trust}} = (K_v + K_{v,\text{trust}})(u_i^n + qN_i) \]

(15)

\( qN_i \) denotes the average velocity of a robot and its trusted neighbors within \( r_{\text{comm}} \). Let \( u_i^n[t+1] \) denote the speed of
consensus component of a robot with abnormal behaviors at the moment \( t + 1 \), then the expected speed calculated by referring to its neighbors is denoted by \( u^c_{i,\text{trust}}[t+1] \). The extra trust-gain \( K_{v,\text{trust}} \) can be used to adjust the control output of motor. The gain is updated based on the difference between the actual and human-trusted robots speed.

\[
K_{v,\text{trust}}[t+1] = \frac{u^c_{i,\text{trust}}[t] - u^c_i[t]}{u^c_i[t]} \tag{16}
\]

V. Evaluation

To validate the effectiveness of Trust-repair for human-swarm system for dynamic task response, we built a simulation environment using ROS, CRAImultirobots. We presented the effectiveness of the method by human ratings of trust.

A. Experiment Settings

CRAImultirobots is a modeling, control and simulation of robots system that will measure and assess the performance of UAV swarm in dynamic task. The environment consists of several components:

1. A set of models and control interface which could simulated manned and unmanned vehicle executing tasks in real world scenarios.

2. A Performance Assessment System which could record quantitative data, including location coordinates, velocity, etc., to measure the performance. It also provides the function that generating expert data for learning algorithm.

![Fig. 5. simulation environment](image)

In this paper, we built a 3D world based from real map. The map size is 50*50 square meters. There are three green area in the simulated world, Fig 5, which represent destination of three different tasks. The "H" pattern in the map is the initial point for the UAV executing tasks. We also built a quadrotor UAV model in the simulation world. The UAV can be controlled through velocity components in three axis directions and the status of UAV, such as velocity, angular velocity, altitude, and absolute coordinate in the simulation world, can be got by the provided API.

Robots Task Scenarios There were 6 robots in total in the experiment and the faulty robots for motor issues were 1 or 2 robots. The velocity for each robot was set as 5.0m/s. To avoid collision and maintain connectivity, the repulsion radius and maintenance radius was set as 2m and 6.5m respectively. For all robots, the communication radius is 7.5m.

The experiment includes 12 simulated scenarios: three types of task scenarios, two different levels of real-world faults - motor issue, and before and after Trust-repair conditions.

a. Three types of task scenarios consists of three sequential tasks: two regular tasks and one emergency task, all requires the swarm flocking to human assigned locations. Refer to Fig. 5, for task one, the swarm will flock and fly from "base station" to "Destination 1", and the swarm will fly from “Destination 1” to “Destination 2” in task two. In the last task, the swarm will fly from “Destination 1” to “Destination 2”, in the middle of the flight, the leader UAV will get order that changing destination to “Destination 3”, then it will lead the swarm dynamic adjust velocity flying to “Destination 3”. In each task scenarios, there are four kinds of situation corresponding two different faulty level and before and after trust-repair conditions.

b. In our scenarios, the motor issue is irreparable. We set a restricted maximum speed to the faulty robot: 40% and 70% compared with normal robots and a fixed vector component of velocity disturbing the heading direction. Under the influence of faulty robots, the performance of neighboring robots can also become abnormal. So the two different levels of real-world faults will test the intuitive judgement of human to the performance of the swarm.

c. Because all the 12 simulated scenarios have a faulty issue, the before and after trust-repair scenarios will give the result that whether the swarm regain human trust after being repaired for dynamic task response.

Human User Study The efficient interaction between human and supervised swarm is important to our current human-Swarm Cooperation system. The very first precondition is that the human supervisor could distinguish if the swarm is suffering negative influence from faulty robots in the swarm, which robot or robots in the swarm behave abnormally, and which robots are normal. And also after applying the trust-repaired method for UAV swarm executing dynamic tasks, if the repaired UAV swarm regain trust of human supervisor is anther key point. To validate the effectiveness of trust-repaired method for dynamic tasks, we conducted a human user study on the crowd-sourcing platform Amazon Mechanical Turk. English-speaking volunteers were recruited with 1 dollar payment for each. They were required to read tutorials, watch survey videos then assess trust level for different scenarios.

In the prior study, we figured out the time to finish the experimental session was approximately 30 minutes. So to guarantee the data quality, volunteers were required to be Amazon Turk Masters and had answer Approval Rate greater than 80%.

In the user study, the task of the participant is to monitor the task progress and motion behaviors of the swarm, such as flocking speed, heading direction, and robot spatial relation (connectivity and formation). Then the participant will be asked to observe videos where UAV swarm is flocking to different destination and decide whether a fault may have occurred during the flocking, and identify of robots implicated in the fault. The trust level from human to the swarm and specific UAV will be recorded too.
Fig. 4. In three task scenarios, Swarm suffered negative influence from faulty robots

The user study has two main parts, a tutorial with three kinds of examples and an actual survey. The tutorial includes details, such as video example and answered questions, about (1) Normal performances of UAV swarm. (2) Faulty performance of the UAV swarm. (3) Repaired performance of the UAV swarm. The actual survey has twelve parts, including three kinds of task scenarios and corresponding two different faulty level and before and after trust-repair conditions. The three kinds of task scenarios is sequential, but in each task scenario, the four conditions are randomly presented to participants in case of priori knowledge. In each part, the participant will be asked to observe a video of UAV swarm executing task, then decide if a fault occurs in the video. After that, a series of questions about judgement from participants to the swarm and specific UAV will be presented.

B. Results

As the data we have collected are ordinal categorical variables, Mann-Whitney U test is applied to analyze the effect of the following factors to the human trust to the swarm.

1. Faulty condition to repaired condition

The participants were likely to report faults in faulty conditions than in repaired conditions ($U = 3960, \rho = 0.23$). Result for testing the trust-repair method on human trust showed a great difference between faulty condition and repaired condition. We define that \textit{CompletelyDistrust} : 1, \textit{Distrust} : 2, \textit{Neutral} : 3, \textit{Trust} : 4, \textit{CompletelyTrust} : 5. The mean trust level for faulty condition and repaired condition are 2.4 and 4 respectively. The participants are more likely to report a higher trust level to repaired condition than faulty condition ($U = 3641, \rho = 0.21$)

2. Dynamic scenarios

Compared with scenarios two and three with scenario one, the chance of participants reporting faults in faulty scenario and repaired conditions have significant difference ($\rho_1 = 0.45, \rho_2 = 0.09, \rho_3 = 0.09$). In the meanwhile, Table I shows the effect of accumulated error evolve to expanded distrust to the swarm. In scenario one, participants were not expressed significantly higher trust in faulty conditions than in repair conditions. However, in scenario two and three, participants were more like give their trust to repaired conditions than faulty conditions.

| Swarm Scenarios | Median trust level |
|-----------------|--------------------|
|                 | faulty             | repaired          | $\rho$ |
| scenario 1      | Neutral/3.3        | Trust/3.6         | 0.45   |
| scenario 2      | Distrust/1.8        | Trust/4.1         | 0.1    |
| scenario 3      | Distrust/2.1        | Trust/4.2         | 0.09   |
error to the swarm formation and flocking direction is not obvious, the participants can’t distinguish if there was faulty in swarm. But for the dynamic tasks response, the results shows Trust-repair method help UAV swarm reduce negative influence from faulty UAV and human participants shows greater trust to scenarios after repaired.

In the future, more faulty factors leaded by system unstable and natural environment will be considered. A more accurate trust-based methods will be designed to improve the performance of UAV swarm for dynamic tasks. Moreover, trust-level estimated by human operators and corresponding threshold will be measured to illustrate the relationship between the faulty factors and human judgement. As for the final goal, we try to build a learning algorithm which could replace the position of human supervisor to estimate the performance of individual robots and the whole UAV swarm in cluttered workspace.

VI. Conclusion & Future Work

In prior work, we developed Trust-repair method for protecting a swarm from the influence of faulty robots or external environment disturbances, and designed experiment to test the effectiveness of the method of regaining human trust by reducing the effects of faulty behavior. In the present paper, to get a more universal framework for gaining trust between human and UAV swarm, we built a simulation environment, envisioned that the swarm responded for dynamic tasks while suffering negative influence from faulty robots. We report a experiment that human participants observed brief videos of swarm behaviors under faulty, and repair conditions in which Trust-repair method acted to reduce the effects of faulty behavior. In the early stage, because the effects of accumulated influence to the whole swarm, even the faulty robot was removed from the team, the experiment shows that the swarm with the rest of the normal robot having normal behavior could regain the human trust.

3. faulty level

In different level of faulty issues, the chance of participants reporting faults in faulty scenario and repaired conditions are very close($\rho_1 = 0.45, \rho_2 = 0.49$). In faulty condition, participants shows similar distrust level in different faulty level($U = 1991, \rho = 0.46$). In repaired condition, participants shows similar trust level in different faulty level ($U = 2166, \rho = 0.50$). Overall, different faulty level had little influence on the trust of human to the same conditions.

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