Trust Repair in Human-Swarm Teams[+]

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***Abstract*— Swarm robots are coordinated via simple control laws to generate emergent behaviors such as flocking, rendezvous, and deployment. Human-swarm teaming has been widely proposed for scenarios, such as human-supervised teams of unmanned aerial vehicles (UAV) for disaster rescue, UAV and ground vehicle cooperation for building security, and soldier-UAV teaming in combat. Effective cooperation requires an appropriate level of trust, between a human and a swarm. When an UAV swarm is deployed in a real-world environment, its performance is subject to real-world factors, such as system reliability and wind disturbances. Degraded performance of a robot can cause undesired swarm behaviors, decreasing human trust. This loss of trust, in turn, can trigger human intervention in UAVs' task executions, decreasing cooperation effectiveness if inappropriate. Therefore, to promote effective cooperation we propose and test a trust-repairing method (*Trust-repair*) restoring performance and human trust in the swarm to an appropriate level by correcting undesired swarm behaviors. Faulty swarms caused by both external and internal factors were simulated to evaluate the performance of the *Trust-repair* algorithm in repairing swarm performance and restoring human trust. Results show that *Trust-repair* is effective in restoring trust to a level intermediate between normal and faulty conditions.**

I. Introduction

Robotic swarms consist of simple, typically homogeneous robots that interact with other robots and the environment. Swarm robots are coordinated via simple control laws to generate emergent behaviors such as flocking, rendezvous, and deployment. Owing to their scalability and natural robustness to individual robot failures, swarms are attractive for large-scale applications such as environmental monitoring [16], exploration [35], search and rescue [21], and agriculture [1].

Human presence is important in swarm applications since humans can recognize and mitigate shortcomings of the swarm, such as limited sensing and communication. Humans can also provide new goals to the swarm as the environment and mission requirements dictate [13]. Intervention, however, carries its own costs. The evolution of swarm behavior has been shown to be highly time-dependent with delay in input leading to better outcomes under some conditions, a phenomena termed Neglect Benevolence [18] and shown to be difficult for humans to manage [17]. In addition, perturbing a swarm leads to transient reductions in consensus and corresponding loss of efficiency. By maintaining correct trust calibration, the operator can balance the costs of complacency (not intervening when needed) with those of intervening when it is unnecessary.

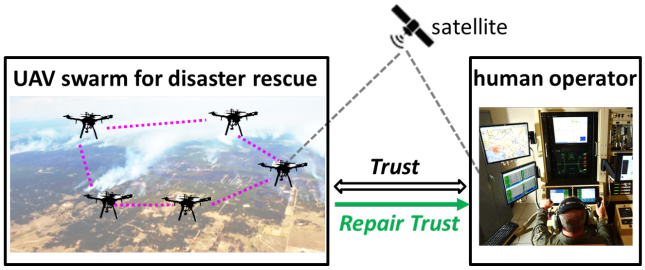

Fig. 1. Illustration of trust repair between swarm and human. When a swarm realizes its faulty behaviors decrease human trust, it will correct these behaviors to regain human trust during swarm-human cooperation.

Human-swarm cooperation can be easily influenced by real-world uncertainty, such as wear to a robot's motor, sensor failures, or wind disturbances. Because swarms are coordinated by consensus the presence of faulty robots can lead to increasing divergence of the swarm from its intended behavior. External factors such as wind can also act to disrupt individual behavior and divert the swarm from its intended goal. These faulty behaviors change both the appearance and performance of a swarm.

Prior literature on human-robot trust, has found that trust is influenced primarily by the perceived performance of the robot [8]. However, task performance of swarms is often not intelligible to the operator [26], [29], since swarms perform tasks through complex interactions among the swarm members themselves, such as consensus that takes time to converge. For example, the swarm may not follow the operator's command in a case where it first needs to maintain connectivity which may not be readily apparent to the operator. Such misperceptions make trust modeling and estimation challenging.

These difficulties might be avoided if the swarm could detect anomalies and act to repair itself. In our previous paper [22], a decentralized trust-aware behavior reflection method was demonstrated to effectively correct swarms' faulty behaviors. In this paper we ask whether observers of a faulty swarm being repaired through this algorithm will retain their trust in the swarm.

Prior studies have reliably modeled human interaction with mobile robots and swarms predicting within trial judgments of trust and interventions from one another and system state [10], [19], [32]. In the present experiment we collect trust judgments for an immediately preceding behavior sequence

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without allowing intervention, relying on the earlier studies to establish that relationship. An earlier study [19] has shown trust judgments to be more influenced by swarm appearance than performance. Therefore, this experiment aims to investigate whether the behavior corrections will lead to trust recovery, given that both faulty and repairing swarms exhibit weakened coherence. If so, a supervising human could be predicted to calibrate trust in the proper direction leading to better human-swarm performance. Otherwise, improvements due to self-repair might be cancelled out by unnecessary human intervention.

II. Related Work

While swarms are largely robust against loss of individual members, failure mode [2], effects analysis finds them far more vulnerable to partial failures where faulty robots continue to contaminate the swarm's consensus. Research in swarm self-healing, however, 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. Zhang et al. [33], for example, 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. Zhe et al. [34] extend this robot replacement strategy by introducing a gradient for selecting repair robots yielding small improvements over random selection used by Zhang [33].

More recently, Saolnier et al. [25] has addressed the problem of partial failures and adversarial robots by protecting the swarm though resilience by restricting robot updates to values 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. Their scenario, however, did not encompass the variety of real-world conditions such as faulty robots which might continue to be influenced by their neighbors or external influences, such as gusts of wind which could disrupt consensus. In this paper we extend their approach through an active *Trust-repair* method that can address these typical robot faults, such as motor degradation or wind disturbance

Current strategies for swarm self-healing passively increase the swarm resilience in order to cancel the negative influence of faulty robots. Passive methods require greater connectivity for the swarm and need to specify fault types and speed/angular ranges, which are difficult to preset in practical environments. Because of the cumulative effect of faulty values on consensus it is necessary to actively correct faulty behaviors when they appear. The proposed *Trust-repair* method corrects faulty robots by updating a robot's motion with reference to its trusted neighbors. *Trust-repair* can correct faulty behaviors that cannot be prevented by other resilience-increasing techniques. Combining both passive and the Trust-repair active methods corrects faulty swarm behaviors more effectively than either alone.

Researches have been done in the field of trust loss in human-robot interaction. As Salem [24] investigated, 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. However, fewer researches investigated the trust recovery. Kohn et al. [12] applied some common strategies in human-human interaction to self-driving vehicles and found they kept effective while some strategies, like apology, may be more effective than others. Because of the lack in the communication between swarm and the operators, we have to differentiate our method from these strategies. In our *Trust-repair* method, we reduce the proportion from the erratic one in updating a single robot's motion and simultaneously repair the faulty robot with the current motion status of those trusted.

III. Human-Swarm Cooperation

We envision a human-swarm system in which a UAV swarm is remotely supervised by a human operator. The swarm performs "distributed biased flocking", a critical tactic in tasks such as UAV rendezvous, area coverage and search. To focus on the *Trust-repair* algorithm's effects on human trust, the experimental environment is obstacle-free.

When a faulty robot appears in a swarm, it becomes unreliable to update other robot's status by referring the faulty robots' motion status [9]. Instead, it is more reliable to constrain information sharing between a faulty robot and its neighbors. In particular, if the trust level is high (faultiness is low) then the strategy "accept high-trust information" is employed. On the other hand, if trust level is medium (fault level is medium) then "reduce middle-trust information" is employed; and if trust level is low (faultiness is high) then "refuse low-trust information". We propose a novel information updating method based on the weighted mean subsequence reduced algorithm (WMSR) [23]. Instead of merely averaging values as in the previous update method, our *Trust-repair* method updates information differently based on the communication quality (Equation 1). Here 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. The velocity of each robot u_i is updated with weighted reference to its neighbors. Swarm modeling and trust-guided behavior corrections are detailed in our previous paper [22].

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

IV. Evaluation

The effectiveness of *Trust-repair* for a human-swarm system depends both on its effectiveness in protecting the swarm from faulty robots and disturbances and its effectiveness in supporting an appropriate level of trust in its human supervisor. In this section we present both swarm performance data and human ratings of trust for fourteen scenarios.

To validate the effectiveness and generalizability of *Trust-repair* in helping the swarm self-heal, swarm behavior

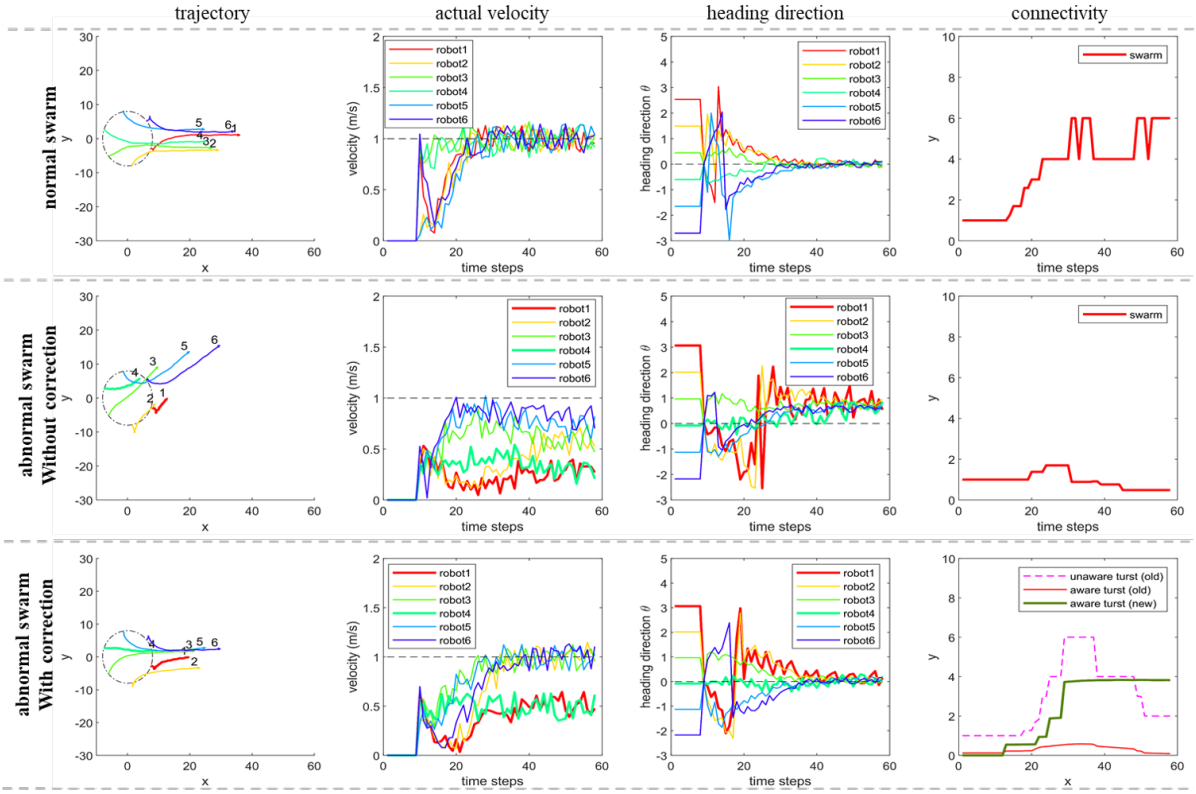

Fig. 2. System responses in three situations, with two faulty robots under motor-wear influence. In a normal situation, the swarm flock to east with a motion consensus on both linear speed and heading direction; while when a robot has a faulty motor, swarm consensus is destroyed; after corrections using Trust-repair, the swarm's faulty behaviors were corrected to reach a motion consensus again.

correction was conducted in two types of faulty scenarios {internal influence - motor issue, external influence - wind disturbance}, with two types of swarm size {6 robots, 12 robots}. Normal, faulty and repair conditions were simulated using MATLAB. The experiment includes 14 simulated scenarios. For each swarm size, there is one normal scenario, four scenarios with degraded motor (faulty or repaired $\times$ one or two faulty robots), and two scenarios with wind disturbance (faulty or repaired). Simulated faults were chosen as representative of faults commonly found in real-world UAV deployments, such as densely distributed forests/buildings and extreme weather conditions, which can affect robot communication, spatial distributions and system reliability [11] [28]. The task for the swarm in all scenarios was distributed biased flocking with human-desired heading-direction "East". The faulty/failed robots for each degraded motor scenario were 1 or 2 robots, which are the minority in the swarm so that the faulty robots could potentially correct themselves by incorporating sufficient values from trusted robots. Under the influence of abnormal robots, neighboring robots can also became faulty/failed. The map size for the flocking was 60m$\times$60m. The velocity for each robot was set as $1.0m/s$. To observe the misleading effect of one faulty robot on its neighbors, robot locations were randomly initialized but still in a circle with radius of $8m$. The heading direction of all the robots pointed to the circle center. To avoid collision, the repulsion radius securing robot safety was set as $2m$. For all conducted experiments $\beta_1 = 10\%$ and $\beta_2 = 50\%$ were used for the faulty behavior detection.

A. The Evaluation of Swarm Behavior Correction

Due to a motor wear, the speed of the faulty robots was lower than the normal robots. Through distributed control, the robot's lower speed will be exchanged with its neighbors lowering their speed as well potentially even affecting other robots' headings. These undesired speed and heading changes decrease a swarm's performance potentially reducing human trust on the swarm's capability.

For a normal swarm (Figure 2 Row 1), after about 27 time steps ($13.5s$), the velocity of all 6 robots achieved the desired consensus of $1.0m/s$ with a $0.1m/s$ deviation; After about 28 time steps ($14s$), the heading of all 6 robots achieved consensus on the "East" direction. The connectivity λ_2 was 6, which means all robots achieved the best communication in this scenario.

Figure 2 shows a scenario in which Robot 1 and 4 had worn motors. As shown, despite faulty robots in the swarm, the velocity consensus was maintained (Figure 2 Row 2). Robot 1 and 4 were disconnected from the swarm with connectivity finally reaching 0. The heading direction of the swarm shifted to $0.8rad$ after 30 time steps ($15s$).

Trust-repair uses trust awareness to help a robot to identify faulty behaviors of itself and its neighbors. In this case, Robot 1, whose speed is 50% lower than the expected speed, was considered as an distrusted and failed robot(Figure 2 Row 3), thereby decreasing swarm performance and po-

tentially human trust. The communication quality between Robot 1 and other normal robots then decreased. With the *Trust-repair* correction, the information exchanged with the robot 1 and 4 was tightly constrained. After 28 time steps ($14s$), robot 1 and 4 were disconnected from the normal robots. The swarm with only trusted robots achieved velocity consensus after 28 time steps ($14s$), and achieved consensus on heading after 38 time steps ($19s$) with only a 0.2 rad deviation from the east direction. This demonstrates that *Trust-repair* was effective in correcting the faulty behaviors of the swarm. After behavior correction, the swarm which constrained the information exchanged with the faulty robots 1 and 4 had connectivity that increased to a high level of 3.8, showing the effectiveness of *Trust-repair* in encouraging connectivity among trusted robots.

Similar effectiveness in behavior corrections are verified for the other scenarios with different error type, swarm size or faulty robot numbers.

B. User Study: Effects of Trust-Repair Algorithm on Human Trust

1) Methods: To measure the effects on human trust of observing the repair algorithm in action we conducted a study on the crowd-sourcing platform Amazon Mechanical Turk [3]. 123 English speaking Volunteers were recruited and paid $3.00 to assess trust levels and answer additional questions about swarm behavior portrayed in brief 15 sec videos. Volunteers are required to have a "master" qualification on the Mturk platform to guarantee the quality of the answers. The average time of an experimental session was approximately 30 minutes. Data for one of the fourteen conditions, large swarm single motor failure, was lost for 24 participants due to logging difficulties.

Videos were made for each of the 14 scenarios described in the previous section. A brief tutorial in which participants viewed sample videos of each type (Normal, Faulty, Repair) and were introduced to the questions and scales, preceded data collection. On experimental trials after initially viewing the video, participants were asked whether they had detected a fault. They were then allowed to view the video again before rating their trust in the swarm. Trust was rated on a five point scale: Completely Distrust; Distrust; Neutral; Trust; Completely Trust. On trials in which participants reported a fault, they were once again allowed to view the video and asked to identify the faulty robots. This was followed by an opportunity to rate their trust in the robots they had identified as faulty and comment on the features leading to their detection of a fault. At the end of the trial they were asked to rate the swarm's performance on a 5 point scale. Every participant will watch all the fourteen videos and answer questions.

2) Results: As the data we have collected are ordinal categorical variables, Mann-Whitney U test is applied in result analysis. Participants were more likely to report faults in faulty conditions (Mdn=no fault) than in normal ones (Mdn=fault) (U=37899, $p < .001$). Participants also expressed higher levels of trust (U=45660, $p < .001$) under

Table I Faulty and Repaired conditions
*Mann Whitney U

Swarm Scenarios	Median Trust Level		
Faulty robot's Number/swarm size	Faulty	Repaired	P*
Motor 1/6	Neutral	Trust	<.001
Motor 2/6	Distrust	Neutral	<.001
Motor 1/12	Trust	Trust+	.069
Motor 2/12	Neutral	Neutral+	n.s.
Wind 6	Distrust	Distrust+	n.s.
Wind 12	Distrust	Neutral	<.001
Motor	Neutral	Trust	<.001
Wind	Distrust	Distrust+	<.001
All	Distrust	Neutral	<.001

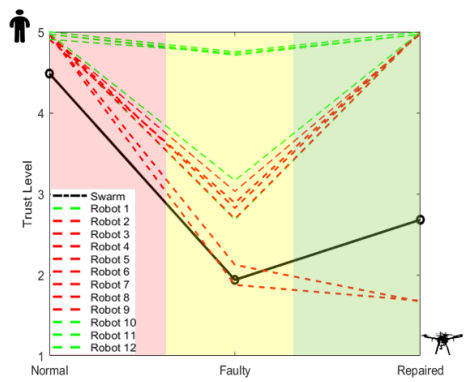

Fig. 3. The trust levels for a swarm and individual robots in different stages normal, faulty, repaired.

normal conditions (Mdn=5, completely trust) than when faults occurred (Mdn=1, completely distrust). Participants, however, were not significantly more likely to report a fault in Faulty conditions than in Repair conditions indicating that the *Trust-repair* algorithm did not mask the occurrence of failures. Participants, however, expressed significantly higher trust (U=132,524, $p < .001$) in repair conditions (Mdn=3, neutral) than in Faulty ones (Mdn=1, completely distrust). Participants in fault conditions experiencing motor failures reported (U=106707, p=.002) slightly more failures (mean=1.13 vs. 1.21) than those in the repair condition who also reported significantly higher trust (U=80850, $p < .001$) (Mdn=4 trust) than those without repair (Mdn=3 neutral). Results are more equivocal for trust in the wind disturbance for which Faulty conditions (mean=2.03) differed only slightly (U=24502, $p < .001$) from repair ones (mean=2.36). Effects of repair for maintaining trust were more evident for the smaller swarm (ϕ=.255, $p < .001$) than the larger swarm where they were only marginally (ϕ=.111, p=.066) significant. Results for trust and number of faulty robots were also small with differences in trust of one (mean=3.03) and two (mean=2.75) faulty robots (U=23612, p=.007) found for unrepaired failures, while a greater difference (U=24574, $p < .001$) was found in the repair condition between one (Mdn=2,distrust) and two (Mdn=3, neutral) faulty robots. Note that a Bonferroni correction for multiple comparisons would require $p < .004$ corresponding to an alpha level of .05. Most values reported as $p < .001$ were reported by the

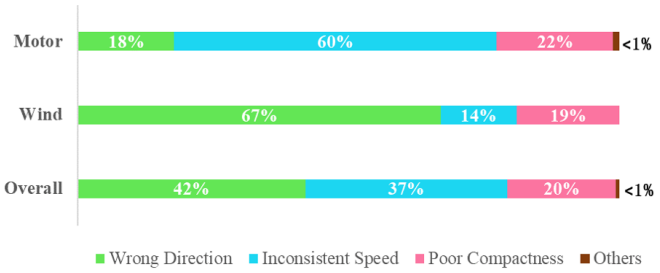

Fig. 4. Performance characteristics influencing a human's trust on a swarm.

software as p= .000, well below the adjusted level.

Table 1 shows median trust levels for scenarios with and without correction.

To examine the effects of *Trust-repair* on human trust more closely, figure 3 shows trust ratings for individual robots in the 12 robot wind disturbance scenario. Six of 8 faulty robots, which were considered faulty by more than 50% subjects in the Faulty condition (ranging from 61% $\sim$ 89% with a mean of 73%), were trusted in the Repair condition. Only the two most influenced robots remained distrusted. This illustrates the effects of the *Trust-repair* algorithm which actively isolates faulty robots in order to reduce their influence on the swarm. While reduction in trust for individual robots was largely avoided through the repair, trust in the swarm itself remained depressed with a median of rating of Neutral.

3) Explanation of Trust Loss

The first 20 participants were asked to describe in a free text comment how they had identified the reported faults. We classified the three most common responses as: a) wrong heading direction, b) inconsistent speed among robots, c) poor compactness of the swarm. The remaining participants were asked to select from among these three causes or provide an alternative in free text.

Figure 4 shows the contributions of these factors to the participants' trust judgments. Direction and speed proved to be the primary determinants of these judgments with inconsistent speed dominating ratings where motor degradation reduced speed of affected robots while 'wrong headings' was the most commonly cited cause for robots blown off course by wind disturbances.

Given the feedback provided by subjects, trust loss was consistent with the heading-direction deviation of the swarm influenced by motor issue (mean=0.33 *rad/s*) and wind disturbance (mean=0.74 *rad/s*), indicating the strong role of performance in the decision to trust. As figure 5 shows, subjective estimates of performance were highly correlated with trust judgments (ρ=.82, p $<$ .001).

V. Conclusion & Future Work

In prior work [22], we developed a method, *Trust-repair*, for protecting a swarm from the influence of faulty members or external disturbances and demonstrated its effectiveness. In the present paper we report an experiment in which human participants observed brief vignettes of swarm behavior under normal, faulty, and repair conditions in which the

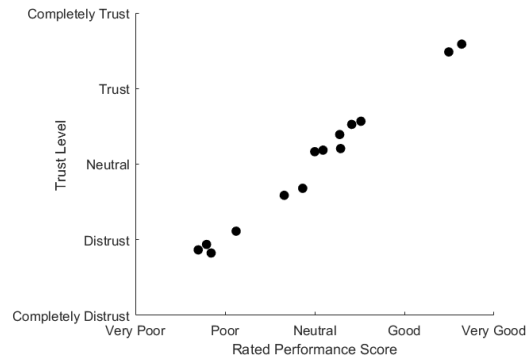

Fig. 5. The linear relation indicates human trust heavily depends on the performance score.

Trust-repair algorithm acted to reduce the effects of faulty behavior. *Trust-repair* effectively corrected faulty swarm behavior by maintaining an original heading direction within an error of $\pm 0.2rad$ and maintaining a desired flocking speed of $1.0m/s$ with a $0.1m/s$ deviation. Participants rated performance more highly and showed significantly greater trust when the Trust-repair algorithm was employed to protect the swarm. However, despite the small deviation in swarm parameters when protected by *Trust-repair*, reductions from completely trust to trust or neutral were observed in comparison to conditions without failures. So, *Trust-repair* did not completely avoid loss of trust. From the present experiment we cannot determine whether the observed loss of trust was due to the brevity (10 sec) of the videos and would have been fully restored had the swarm (less its quarantined members) continued to exhibit correct behavior for an extended time. We also cannot tell how the ranges of trust observed in our experiment would affect decisions to intervene were the swarm under active control. To remedy these problems, we plan an additional study in which participants will actively control a flocking swarm performing a foraging task. Failures and disturbances will be introduced at predetermined points and either repaired or allowed to persist until the participant intervenes. Trust ratings will be collected at regular intervals on an interactive slider [19] and these data used to model the dynamic effects of failure and *Trust-repair* on ratings of trust and the performance of the human-swarm system.

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