Trust of Humans in Supervisory Control of Swarm Robots with Varied Levels of Autonomy

Changjoo Nam*, Huao Li†, Shen Li‡, Michael Lewis†, Katia Sycara*

*Robotics Institute
Carnegie Mellon University
Pittsburgh, PA, USA
{changjon, katia}@cs.cmu.edu

†School of Information Science
University of Pittsburgh
Pittsburgh, PA, USA
{huao.li, cmlewis}@pitt.edu

‡CSAIL
Massachusetts Institute of Technology
Cambridge, MA, USA
shenli@mit.edu

***Abstract*—In this paper, we study trust-related human factors in supervisory control of swarm robots with varied levels of autonomy (LOA) in a target foraging task. We compare three LOAs: manual, mixed-initiative (MI), and fully autonomous LOA. In the manual LOA, the human operator chooses headings for a flocking swarm, issuing new headings as needed. In the fully autonomous LOA, the swarm is redirected automatically by changing headings using a search algorithm. In the mixed-initiative LOA, if performance declines, control is switched from human to swarm or swarm to human.**

The result of this work extends the current knowledge on human factors in swarm supervisory control. Specifically, the finding that the relationship between trust and performance improved for passively monitoring operators (i.e., improved situation awareness in higher LOAs) is particularly novel in its contradiction of earlier work. We also discover that operators switch the degree of autonomy when their trust in the swarm system is low. Last, our analysis shows that operator's preference for a lower LOA is confirmed for a new domain of swarm control.

I. Introduction

Trust is an important ingredient in everyday human relations, at home, work and public life, and has been hailed as a bedrock of human interactions [1]. In the context of automation, trust has typically been interpreted as a human's willingness to rely on automation to perform a fixed task. Studies about trust in automation have found that because a human may fail to use automation when it would be advantageous (i.e., under-reliance) or fail to override inappropriate actions (i.e., over-reliance) [2], proper levels of reliance are needed for best performance. Studies [3]–[6] have shown that trust towards automation can mediate this reliance.

For supervising autonomous systems in mission based contexts, over-reliance can be reflected in failures to correct significant deviations from an operator's intentions while under-reliance can result in unnecessary interventions eroding efficiency. In such systems, operator trust has been found to vary dynamically, accumulating over periods of successful performance, then declining sharply when failures or poor performance are encountered [6]–[8]. In systems which can operate either automatically or manually, reversion to manual control is commonly considered an indication of lack of trust [4]–[6]. For autonomous supervised systems which cannot be manually controlled, operator's interventions toward the ongoing behavior can be given a similar interpretation.

The research has been funded by AFOSR award FA9550-15-1-0442.

Recently, there has been increased interest in swarm robots that operate using simple local control laws. Global swarm behaviors, such as flocking, deployment, and rendezvous, emerge via local interactions of swarm members. In human-swarm systems where a human operator occasionally intervenes the swarm while the swarm exhibits the emergent behaviors for given missions, neither swarm states nor performance are readily perceivable by the human [9] owing to the nonlinear dynamics of swarm systems [10]. Moreover, the operator must control a swarm indirectly through changes to its members' control laws whereas automation systems are directly controlled by the operator's commands. This unique mechanism, indirection and control through influencing autonomous behaviors, leads to greater uncertainty.

This paper investigates the effects of levels of autonomy (LOA) on human trust and workload in supervisory control of swarm robots. In the supervisory control for a target foraging task, a flocking swarm [11] searches a region until targets grow sparse. It then needs to be redirected to a new region richer in targets. We compare three LOAs: manual, mixed-initiative (MI), and fully autonomous LOA. In the manual LOA, the human chooses headings for flocking, issuing new headings as needed. In the fully autonomous LOA, the swarm is redirected automatically by changing headings using a search algorithm. In the MI LOA, when the target search rate declines, control is switched from human to swarm or swarm to human. Based on this setting, our hypotheses are that (a) a high LOA affects trust negatively because operators often do not have control of the swarm and (b) workload is negatively correlated with LOA as increased autonomy reduces human intervention.

The variations in the relation between trust and performance over differing LOAs is a new finding that illustrates the importance of examining old issues in the context of swarms where the system state and performance may be more difficult for operators to perceive and influence. Specifically, we find that the relationship between trust and swarm task performance is improved if the swarm is fully autonomous. We also discover that operators switch the degree of autonomy when their trust in the swarm system is low. Last, it is encouraging that operator's preference for a lower LOA [12], [13] is confirmed for a new domain of swarm control. The result of this work is essential to building trustworthy swarm systems where the swarm can help reduce workload of the operator with its autonomous capability without disturbing the supervisory relationship.

II. Related Work

The effects of automation on trust and resultant use depend jointly on what aspects of a task are automated and how they are automated. These distinctions have commonly been organized as levels, stages, or degrees of automation (see [14] for an exhaustive review of taxonomies). The oldest of these taxonomies, Levels of Automation [15] focuses on locus of control and proceeds from aspects of the task involving information (low) to those dealing with actions (high). For a high LOA, the operator may lack the ability to perform the task independently and thus be less able to predict or evaluate the system's performance. This tradeoff between lowering operator workload through automation and avoiding loss of situation awareness at higher levels of automation has frequently led to recommendations for choosing medium levels of automation [16].

There have been a limited number of work addressing LOA in supervisory control of swarms. Coppin and Legras [17] proposed a modification of the levels of automation scale for human-swarm systems, which offers different modes at each control task that the user can choose from. Their human experiment with patrolling and pursuit scenarios showed that the humans perceived the system positively as they can change the LOA. In [18], the human operator can switch the control mode of the swarm between high and low autonomy. In the high autonomy mode, the swarm can cover an environment by itself by spreading its members to the open space. In the low autonomy mode, the human operator selects the areas that the members should go. The task performance was the best when the operators used the two modes together, rather than using only one of them.

Several studies have measured the effects of LOA on trust. Rovira et al. [19] found ratings of trust higher in a condition prioritizing a list of possible engagements than in either an unprioritized list or higher levels of automation where smaller numbers of alternatives were presented. Amato et al. [13] as well found a lower level of automation preferred for aiding an air traffic control task. Ruff et al. [12] similarly reported higher ratings of trust for management by consent than for management by exception for multiple UAVs. In a recent comprehensive review of human-swarm interaction (HSI) [20], it is pointed out that more investigation is needed for LOA in HSI to discover how humans react to different, changing levels of autonomy. Since swarm behaviors are often unintelligible, switching between varied LOAs may be different from existing work in single- or multi-robot (which is not swarm) supervisory control. Yet, there has been no prior work investigating human factors, especially human trust and workload, jointly with varied LOAs in supervisory control of swarms.

In [21], we developed computational models of trust in swarm control for a target search mission. In that work, the participants' in-process ratings of trust were most strongly associated with the swarm appearance (i.e., the heading alignment of the robots, the sparseness of the swarm distribution), rather than the task performance. This result suggested that the swarm performance was not readily perceivable to the operators. The swarm in that work was with a low LOA since the heading direction was determined by the operator manually whereas we are now interested in how human behaviors are different if the operator supervises a swarm with higher LOAs such as a mix of manual and full autonomy. Our prior research is complemented by this work investigating conditions under which operators choose to relinquish or assume control providing a basis for achieving adaptive autonomy for human swarm interaction.

III. Problem Description

We consider a target search mission where a swarm of robots explore an unknown environment using a flocking behavior with static obstacles. Each robot is assumed to be equipped with sensors with a known (and short) field of view. The swarm has leader robots who communicate heading directions towards which the swarm should flock to swarm members via peer to peer communication, so the heading directions could be used in the consensus formation process of the swarm.

We have three different LOAs of the swarm: (i) the manual LOA, (ii) the autonomous LOA, and (iii) the mixed-initiative (MI) LOA. In the manual LOA, the swarm receives the heading directions from a human operator (i.e., *manual search mode*). In the autonomous LOA, the swarm finds the heading directions by itself using a search algorithm [22] while the operator is completely out of the decision-making loop (i.e., *autonomous search mode*), which is guaranteed to search the entire space of an unknown area if the given time is sufficient. In the MI LOA, the system (not the swarm but a separate computational process) recommends when to switch between the manual and the autonomous search mode based on the current task performance. The operator may or may not follow the recommendation. The system may force a switch of the search mode if the low performance continues and the operator does not follow the recommendation. The human may switch the mode at any time even if there is no recommendation. Notice that we use *search mode* and *LOA* differently. In the manual and the autonomous LOA, we have only the manual search mode and autonomous search mode, respectively. In the MI LOA, we have a mix of the manual and autonomous search mode determined by the interaction between the swarm and the operator. Within this setting, we study the following:

- an analysis of human trust and workload in supervisory control of swarms with different LOAs and
- an analysis of switching between the search modes in the MI LOA.

IV. User Study of Human Behaviors

We conducted a user study to understand how humans behave and perceive the swarm performing the search mission with different LOAs. 20 paid participants, with no prior experience in swarm control, were recruited from the Univ.

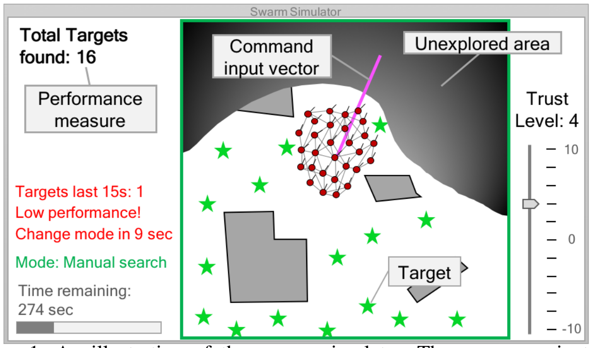


Figure 1: An illustration of the swarm simulator. The swarm navigates in the unknown area to find targets. The participants adjust the trust slider on the right panel using the mouse wheel to give *trust feedback* as their trust changes. The left panel shows task related information.

of Pittsburgh and Carnegie Mellon Univ. communities with average age 24.1 ($\sigma = 2.89$).

A. Methods

We used a simulator [23] for testing human-swarm interaction (illustrated in Fig. 1). The swarm consisted of 32 homogeneous robots, which began at random poses at the center of the $200\,\mathrm{m} \times 200\,\mathrm{m}$ environment. Each trial had different random configurations of robot poses, obstacles, and targets. The swarm received the heading for flocking [11] from the operator, the autonomous search algorithm, or both depending on the LOA.

The main task involved moving the swarm through the environment to discover 100 initially hidden random targets (stars in Fig. 1). Targets were found if at least one robot senses them for a fixed time. The performance metric is the number of targets found displayed on the interface. The interface has a slider on the right panel that the participants can adjust using the mouse wheel to indicate their current subjective trust ratings. The participants were queried for their in-process ratings of trust (i.e., *trust feedback*) at 30-sec intervals, on the scale from -10 (strongly distrust) to $+10$ (strongly trust) and were allowed to adjust this value at any other time if they feel trust changes. The information from command inputs (the angle and length of command vectors, the purple line shown in Fig. 1), swarm parameters (the mean and variance of heading angles of the robots shown in Fig. 2a, convex hull area defined by the robots shown in Fig. 2b, connectivity), and the number of targets found were recorded for each time step (60 Hz).

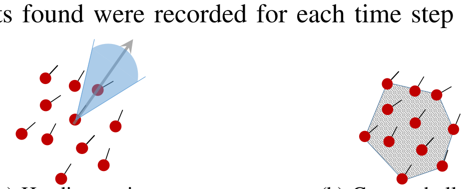

(a) Heading variance (b) Convex hull area

Figure 2: Some swarm parameters. (a) The variance of the heading angles of all swarm members. (b) The convex hull area that the swarm makes.

B. Levels of autonomy

In the manual search mode, the operator could give the heading direction to the swarm by dragging a line on the screen using the mouse. The swarm is able to avoid obstacles but not capable of changing its own heading by itself so it, for example, cannot escape from a dead-end.

In the MI LOA, the simulator starts with the autonomous search mode in which the participants could switch to the manual search mode by giving a heading direction or pressing a toggle key. In the manual search mode, the participants could use the toggle key to switch to the autonomous search mode. The current search mode is always shown on the interface in text whose color matches to the color of the bounding box of the map to increase the visibility (e.g., the green text in the left panel and the green bounding box in Fig. 1). In any mode, the interface showed the current task performance (i.e., # targets found) which is measured during the last 15 seconds (the red text on the left panel in Fig. 1). If the current performance did not exceed a predefined constant (we used 3 which is determined using data from a pilot study), the interface prompted an alert (in red) for the low performance on the left panel. If the low performance continued for 10 seconds, the system recommends the participants to switch the mode in another 10 seconds (a countdown appeared on the left panel). If the countdown completed without a user-initiated mode switch, the system switched the mode. However, the participants could reverse the forced switch by pressing the toggle key or giving a heading direction.

C. Study procedure

The experiment employed a 3-level within-subject design, in which each participant ran a 2-min training session and three 5-min identical trials in each of three different LOAs. The sequence of LOAs was counterbalanced between subjects[1]. The participants were asked to finish a survey in the beginning of the experiment in order to measure general trust towards autonomy (*trust pre-test*). The questionnaire asked about three trust components (performance, process, and purpose) in 5-Likert scale proposed in [24]. In the main session followed by a 5-min training session, the participants were asked to finish three identical 5-min trials. After finishing each trial, the participants were asked to fill out a survey to collect their trust towards the swarm that they just supervised (*trust post-test*) and a NASA-TLX survey [25] for their workload measurements. Note that the participants were asked to consider the swarm (e.g., individual robots and the search algorithm) and the system (e.g., the interface and the alert/recommendation) as a whole when they rate trust. The experimental procedure lasted for 75 minutes.

V. Analysis of User Study and Discussions

We analyzed the experiment data to discover how the participants reacted to different LOAs. Especially, we had a close look at the MI LOA since it involved user- and system-initiated switches between search modes.

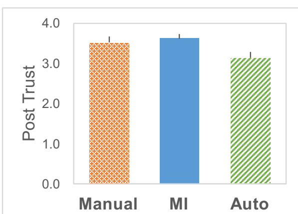
A. Survey results

One-way repeated measures ANOVA showed that there was a significant difference in the post trust report between LOAs ($F(1.37, 19.20) = 7.80$, $p = 0.007$, see Fig. 3a). Pairwise

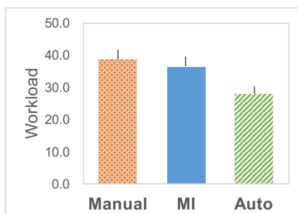
[1]There was no significant learning effects found in terms of task performance (one-way ANOVA, all $ps > .10$).

comparison showed that the participants had a significantly lower trust towards the autonomous LOA than the MI LOA ($p = 0.001$). There is also a significant difference in workload between LOAs ($F(1.38, 19.37) = 13.52$, $p = 0.001$, see Fig. 3b), in which the workload of the autonomous LOA is much less than the other two LOAs ($p = 0.023, p = 0.001$). This result is consistent with our hypotheses and confirms previous findings on trust [12], [13] and workload [16] with varied LOAs in a new domain of swarm supervisory control.

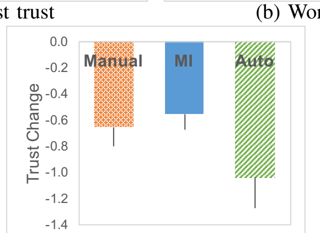
Also, we compared the difference between the pre- and post-trust survey (*trust change*) to take participants' preexisted trust levels towards the autonomy into consideration (Fig. 3c). In all LOAs, trust decreased after the participants experienced swarm control because of the low controllablility and intelligibility of swarm behaviors. Among all LOAs, the MI LOA had the smallest negative trust change. The survey results of trust and workload show that the mode switching and recommendation in the MI LOA neither damaged trust towards the swarms nor increased operator's workload.



(a) Post trust



(b) Workload



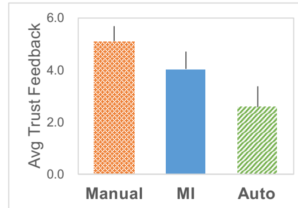
(c) Trust change

Figure 3: Results from surveys. Error bars are 1 Standard Error from means (SEM). (a) The participants had a significantly low trust towards the autonomous LOA than the MI LOA. (b) The workload of the autonomous LOA is much less than the other two LOAs. (c) The participants had the smallest negative trust change in the MI LOA.

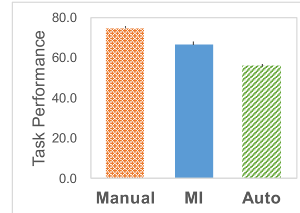
B. Trust-related factors

The average trust feedback values (i.e., the mean of the in-process ratings of trust) had a significant difference in the three LOAs (one-way ANOVA, $F(2, 57) = 3.35$, $p = 0.0423$, see Fig. 4a). The participants had a significantly lower trust feedback values in the autonomous LOA whose mean was 2.571 while the manual LOA had the highest trust feedback (the mean was 5.086). The MI LOA's mean trust feedback was 4.014. A likely explanation for the low trust in the auto LOA is that the participants did not like being excluded from the decision-making loop because they cannot control the swarm.

In the autonomous LOA, participants' trust feedback reflected the current task performance better than in human involved supervision. The correlation coefficients between the trust feedback and the current task performance have a significant difference between the three LOAs (one-way ANOVA with Fisher transformation of the coefficient since



(a) Average trust feedback



(b) Task performance

Figure 4: Results from in-process measurements (error bars are SEM). (a) The participants had a significantly lower average trust feedback values in the autonomous LOA while the manual LOA had the highest trust feedback. (b) The task performance of the manual LOA was significantly higher than the autonomous LOA.

the normality assumption does not hold for correlation coefficients). The means of the coefficients were -0.0768, -0.0140, 0.1353 in the manual, MI, autonomous LOA, respectively ($F(2, 57) = 3.3$, $p = 0.0439$). We hypothesize that the decreased workload in the autonomous LOA would enable the participants to perceive task performance correctly (i.e., if the swarm performance is higher then the participants trust the swarm more). However, the correlation in the autonomous LOA is still weak ($R = 0.1353$) as swarm behaviors are not clearly intelligible. A similar result is found within the MI LOA. For the manual search mode, there was no statistically significant correlation between the performance and trust feedback ($R = 0.1230$, $p = 0.3620$). However, for the autonomous search mode, a correlation ($R = 0.2715$, $p = 0.041$) indicates that MI LOA participants were able to align their in-process trust feedback to task performance when not actively engaged in controlling the swarm. This positive relationship between the degree of autonomy and the human perception of swarm task performance is novel since earlier work in automation [26], [27] showed that a higher LOA reduces operators' awareness about surroundings.

The average task performance in different LOAs have a significant difference ($F(2, 57) = 55.18$, $p \ll 0.01$). The means of the targets found in the three LOAs are 74.3 (manual), 66.4 (MI), and 55.6 (autonomous), respectively (Fig. 4b). The result indicates that the autonomous search algorithm did not outperform humans in the given environment, perhaps owing to the presence of obstacles.

C. User intervention commands

In [21], it was shown that the *intervention* commands of humans correcting the heading direction of the swarm occur owing to low trust. In that work, intervention commands and the rest, *non-intervention* commands, were distinguished by a linear classifier learned from the experimental data, which uses the length of the vector drawn by the participants to give a command input. Shorter lines were associated with interventions indicating dissatisfaction with swarm behavior while longer lines used to redirect the swarm to more productive search regions indicated dissatisfaction with the current region but not the swarm itself. In the present work, we used the same classifier to divide the data from the three trials into intervention and non-intervention groups[2]. The latter group

[2]Note that the experimental setup of the present work is identical to that of [21] except the presence of LOA.

includes the data when the operator did not issue any command so is the complement of the first group in the entire data (i.e., intervention vs. others).

In both the manual and the MI LOA (the autonomous LOA is not applicable as it does have no command input), the two groups showed a statistically significant difference in the trust feedback (manual: 2-tailed $t = 25.98$, $p \ll 0.001$, $df = 1080058$, MI: 2-tailed $t = 32.76$, $p \ll 0.001$, $df = 1074381$) with participants tending to give low trust feedback when they issued interventions.[3] The average trust feedback values of the intervention and non-intervention groups were 4.789 and 5.114 in the manual LOA (3.445 and 4.040 for the MI LOA), respectively. It indicates that the participants issued intervention commands when their trust was lower.

We compared swarm physical parameters for the two groups. In the manual LOA, the heading variance (Fig. 2a) of the swarm when interventions were issued was larger than the heading variance when interventions were not issued (2-tailed $t = -22.26$, $p \ll 0.001$, $df = 1080058$ with means of $13.64\,\mathrm{rad}$ and $12.91\,\mathrm{rad}$). The convex hull area (Fig. 2b) was smaller when interventions were issued (2-tailed $t = 7.141$, $p \ll 0.001$, with means of $2160\,\mathrm{m}^2$ and $2229\,\mathrm{m}^2$). We hypothesize that the participants preferred a swarm that is more dispersed since such a swarm can search a larger area so discover more targets. Task performance showed a significant difference between the intervention and non-intervention groups (2-tailed $t = 25.98$, $p \ll 0.001$), but the difference did not have a meaningful magnitude (means were 40.46 and 39.78 targets, respectively).

Observable swarm parameters affected intervention decisions in distinctly different ways in the MI LOA for both heading variance and convex hull area. The heading variance of the swarm when interventions were issued was smaller (2-tailed $t = 50.80$, $p \ll 0.001$, $df = 1074381$ with means of $14.20\,\mathrm{rad}$ and $16.79\,\mathrm{rad}$). The convex hull area of the swarm was larger when interventions were issued (2-tailed $t = -22.10$, $p \ll 0.001$, with means of $3078\,\mathrm{m}^2$ and $2738\,\mathrm{m}^2$). Task performance was better when interventions were issued (2-tailed $t = 32.76$, $p \ll 0.001$, with means of 38.94 targets and 35.24 targets). A potential explanation could be an example of human intervention that corrects the heading of the swarm more frequently to control the swarm more dexterously when the swarm is in a rich region of targets.

The above result shows that the participants intervened in the swarm operation differently between the manual and the MI LOA. In the manual LOA, the participants tended to intervene the swarm when the headings of the robots were less aligned and the size of the swarm is small. In the MI LOA, the participants issued interventions when the robots were relatively aligned and the size of the swarm is large. This result can be explained by the fact that the autonomous search algorithm tended to increase the heading variance and reduce the convex hull area: compared to the manual search mode, the search algorithm made the swarm less aligned (2-tailed $t = -9.380$, $df = 118$, $p \ll 0.001$) where the means of the autonomous mode and the manual mode were $21.17\,\mathrm{rad}$ and $13.99\,\mathrm{rad}$, respectively. The search algorithm made the swarm more compact (but with no statistical significance, $p = 0.1481$ with means of $2439\,\mathrm{m}^2$ and $3026\,\mathrm{m}^2$). We hypothesize that the participants perceived that the autonomous search is less efficient than their manual manipulation so tried to control the swarm in contrast to the way the search algorithm. Thus, they would try to make the swarm aligned and dispersed.

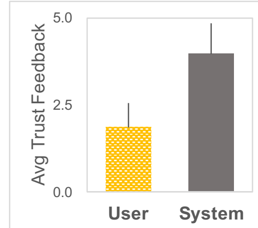


Figure 5: The average trust feedback when the mode switches occurred (user-initiated vs. system-initiated switches). Error bars are SEM.

In the MI LOA, the difference of swarm parameters and performance between two groups of commands were generally larger than those in the manual LOA, which means that the participants could issue interventions more discernibly based on swarms' current state and performance. That would prove a hypothetical argument that a higher LOA could reduce the workload of users and enable them to observe the swarm behaviors and performance closely.

D. Mode switch in the MI LOA

In the MI LOA, the average numbers of user-initiated and system-initiated switches were 6.500 ($\sigma = 3.138$) and 5.050 ($\sigma = 3.916$), respectively. Trust feedback values when users or the system initiated the mode switch were significantly different (2-tailed $t = -8.988$, $df = 1045$, $p \ll 0.001$). The means of trust feedback were 1.858 and 3.954 (Fig. 5), suggesting that the participants had significantly lower trust when they switched the search mode themselves. However, the occurrence of user-initiated switches and trust (both in the post-test survey and average of trust feedback) were uncorrelated. Also, there were almost no user-initiated switches in the absence of a recommendation to switch. When the system recommended a switch in the MI LOA, the participants changed the mode by following the recommendation 99.18%. On average, the participants used the autonomous search mode 38% of the entire running time. There was a tendency for participants who used the manual mode longer to give higher average trust feedback (correlation coefficient = -0.2275) but not statistically significant ($p = 0.08$).

In addition, there was no statistically significant difference in trust feedback between the manual search mode and the autonomous search mode in the MI LOA (2-tailed $t = 0.6135$, $df = 118$, $p = 0.5407$, with the means of 4.062 and 3.706). Although the manual and autonomous LOA had a significant difference in the trust feedback (5.086 and 2.571,

[3] In a single trial, there are 18,001 time steps where each time step records the swarm parameters, human input, and the trust feedback. We included every record in each time step in the tests. The intraclass correlation coefficients of data were less than 0.02 in almost all cases, which indicates that intraclass correlation is not significant.

respectively), the two modes in the MI LOA did not show such a difference. The trust of participants would be more influenced by whether they have control of the system. Since the MI participants still can direct the swarm, their trust was not sensitive to the search mode.

E. Remarks

As in prior work [12], [13], [19], we found that the participants had higher trust when they have control of the swarm (the manual and MI LOAs). The task performance was the highest in the manual LOA. However, the workload in the manual LOA is also much higher than the autonomous LOA, so there was a tradeoff between trust/performance and workload. If we always keep the operator in the decision-making loop to secure the trust level and performance, it has to increase the workload at a cost. By giving operators the choice to switch between the two search modes, the MI LOA could balance trust and workload while not reducing task performance significantly. On the other hand, the reduced workload in the autonomous LOA helped the participants perceive task performance correctly. Similarly, the participants in the MI LOA could have more chances to perceive the state of the swarm better when the autonomous search algorithm is used so would issued more discriminating interventions. This finding that the relationship between trust and performance improved for passively monitoring operators, which indicates that the situation awareness of operators is improved if the swarm is with a higher degree of autonomy, is particularly novel in its contradiction of earlier work [26], [27].

VI. Conclusion

In this paper, we studied human factors related to trust in supervisory control of swarm robots where the level of autonomy varies. We developed three LOAs, which are the manual, mixed-initiative, and full autonomous LOAs. We conducted a user study to know how human trust changes along the different LOAs and how humans behave in the MI LOA in which they can switch the degree of autonomy while the system displays information relevant to swarm appearance, state and performance as well as the alert regarding task performance. We provided results about the relation between trust, workload, and task performance in different LOAs. We plan to develop an adaptive system where the swarm adjusts the degree of autonomy according to the level of human trust. The result of the present work is fundamental to developing trustworthy swarm systems where the workload of operators can be reduced by adjusting autonomy adaptively without disturbing the supervisory relationship. For the development, we have done a preliminary experiment of estimating human trust in swarm with varied LOAs. Our future work includes human experiments with the adaptive system to see how autonomous switch of LOA affects human trust and performance.

References

[1] R. Mayer, J. Davis, and D. Schoorman, "An integrative model of organizational trust," *Academy of Management Review*, 1995.

[2] J. Lyons and C. Stokes, "Human-human reliance in the context of automation," *Human Factors*, 2012.

[3] S. Lewandowsky, M. Mudy, and G. Tan, "The dynamics of trust: Comparing humans to automation," *J. of Experimental Psychology: Applied*, 2000.

[4] J. Lee and N. Moray, "Trust, control strategies and allocation of function in human-machine systems," *Ergonomics*, 1992.

[5] B. Muir and N. Moray, "Trust in automation: 2. experimental studies of trust and human intervention in a process control simulation," *Ergonomics*, 2013.

[6] J. Lee and N. Moray, "Trust, self confidence and operator's adaptation to automation," *Int. J. of Human-Computer Studies*, 1994.

[7] J. Gao and J. Lee, "Extending the decision field theory to model operators' reliance on automation in supervisory control situations," *IEEE Trans. on System, Man, and Cyb.: Part A*, 2006.

[8] A. Xu and G. Dudek, "OPTIMo: Online probabilistic trust inference model for asymmetric human-robot collaborations," in *Proc. of ACM/IEEE Int. Conf. on Human-Robot Interaction*, 2015.

[9] P. Walker, M. Lewis, and K. Sycara, "Characterizing human perception of emergent swarm behaviors," in *Proc. of IEEE Int. Conf. on Systems, Man, and Cyb.*, 2016.

[10] F. Bullo, J. Cortés, and S. Martinez, *Distributed control of robotic networks: a mathematical approach to motion coordination algorithms*. Princeton University Press, 2009.

[11] C. Reynolds, "Flocks, herds and schools: A distributed behavioral model," in *Proc. of ACM SIGGRAPH Computer Graphics*, 1987.

[12] H. A. Ruff, S. Narayanan, and M. H. Draper, "Human interaction with levels of automation and decision-aid fidelity in the supervisory control of multiple simulated unmanned air vehicles," *Presence: Teleoperators and Virtual Environments*, 2002.

[13] F. Amato, M. Felici, P. Lanzi, G. Lotti, L. Save, and A. Tedeschi, "Trust observations in validation exercises," in *Proc. of Int. Conf. on Secure SW Integration and Reliability Improvement*, 2011.

[14] M. Vagia, A. A. Transeth, and S. A. Fjerdingen, "A literature review on the levels of automation during the years. what are the different taxonomies that have been proposed?" *Applied Ergonomics*, 2016.

[15] T. B. Sheridan and W. L. Verplank, "Human and computer control of undersea teleoperators," MIT Man-Machine Systems Lab, Tech. Rep., 1978.

[16] M. Endsley and E. Kiris, "The out-of-the-loop performance problem and level of control in automation," *Human Factors*, 1995.

[17] G. Coppin and F. Legras, "Autonomy spectrum and performance perception issues in swarm supervisory control," *Proc. of the IEEE*, 2012.

[18] P. Walker, S. Nunnally, M. Lewis, N. Chakraborty, and K. Sycara, "Levels of automation for human influence of robot swarms," in *Proc. of the Human Factors and Ergonomics Society Annual Meeting*, 2013.

[19] E. Rovira, K. McGarry, and R. Parasuraman, "Effects of imperfect automation on decision making in a simulated command and control task," *Human Factors*, 2007.

[20] A. Kolling, P. Walker, N. Chakraborty, K. Sycara, and M. Lewis, "Human interaction with robot swarms: A survey," *IEEE Trans. on Human-Machine Systems*, 2016.

[21] C. Nam, P. Walker, M. Lewis, and K. Sycara, "Predicting trust in human control of swarms via inverse reinforcement learning," in *Proc. of IEEE Int. Symp. on Robot and Human Interactive Communication*, 2017.

[22] Z. J. Butler, A. A. Rizzi, and R. L. Hollis, "Contact sensor-based coverage of rectilinear environments," in *Proc. of IEEE Int. Symp. on Intelligent Control/Intelligent Systems and Semiotics*, 1999.

[23] P. Walker, "CUDA swarm simulator," https://github.com/pmwalk/cuSwarm, 2015–2017.

[24] S.-Y. Chien, M. Lewis, Z. Semnani-Azad, and K. Sycara, "An empirical model of cultural factors on trust in automation," in *Proc. of the Human Factors and Ergonomics Society Annual Meeting*, 2014.

[25] S. Hart and L. Staveland, "Development of a multi-dimensional workload rating scale: Results of empirical and theoretical research," *Human Mental Workload*, 1988.

[26] R. Parasuraman, T. B. Sheridan, and C. D. Wickens, "A model for types and levels of human interaction with automation," *IEEE Trans. on Systems, Man, and Cyb.-Part A: Systems and Humans*, 2000.

[27] C. D. Wickens, "Situation awareness and workload in aviation," *Current directions in psychological science*, vol. 11, no. 4, pp. 128–133, 2002.