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Layered Dynamics and System Effectiveness of Human-Autonomy Teams under Degraded Conditions

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Layered dynamics is a recent modeling technique in dynamical systems, which is based on information entropy. This considers system reorganization and multilevel layers (communication – interaction between team members, control – interaction with consoles, and vehicle – interaction with the airplane). The current study examined multilevel dynamics of Human-Autonomy Teams (HAT)s during automation and autonomy failures. Two team members were informed that the third team member was a "synthetic" agent, although it was an experimenter mimicking a synthetic agent. This study addresses how members of HATs interact with each other and the technology. Findings indicate that communication and vehicle entropy were positively associated with target processing efficiency, while control entropy was negatively associated. This may reflect that low performing teams anticipated targets poorly because they did not interact with the technology in a timely manner. The effect of control entropy on target processing efficiency was substantially delayed.

INTRODUCTION

Teamwork leads to joint, dynamic team interaction between two or more interdependent members to achieve a shared task goal. In the last decade, many studies have exhibited how team coordination dynamics are associated with team effectiveness in the context of all-human teams (Gorman, 2014; Gorman, Amazeen, & Cooke, 2010; Guastello, 2010; Guastello & Guastello, 1998), and later, in human-autonomy teams (HAT)s (Demir, Likens, Cooke, Amazeen, & McNeese, 2018; Demir, McNeese, & Cooke, 2017, 2018; Gorman, Demir, Cooke, & Grimm, 2018; McNeese, Demir, Cooke, & Amazeen, 2018). For human-autonomy teaming (HAT), autonomous agents must be designed to function as collaborative systems, or, in other words, as team players (Behymer & Flach, 2016). In these recent studies, there are two parallel threads of research on (1) team cognition, and (2) dynamical systems modeling to support HAT.

Generally speaking, systems are entities comprised of interdependent multilevel factors (i.e., human and technology: e.g., tools, computers) that interact with their task environment in order to complete required tasks. Based on the interaction of teammates with their environment and with each other, sociotechnical systems adapt to changes in the dynamic environment to maintain stability (Badham, Clegg, & Wall, 2000). A sociotechnical system is comprised of humans and autonomous team members, whose interaction with each other and also interaction with their task related technological factors determines overall system performance (Walker et al. 2008). Harmonious interaction between these factors is important to ensure successful system performance (Badham et al., 2000). Thus, synergistic relationships among a system's human and technological components are the basis for emergent properties (systems-level outcomes), such as safety and efficiency. However, understanding and characterizing the factors of sociotechnical systems poses an interesting challenge for computational social science (Watts & Strogatz, 1998). One way to address that challenge and design an effective/efficient sociotechnical system is to empirically model the system's multilevel factors: human, technological, and environmental. The objective of this technique is to maximize the fit among all three components (Salvendy, 2012), resulting in better system performance.

Layered dynamics is a recent empirical modelling technique aimed at achieving this objective (Gorman et al., 2018). Layered dynamics takes into account reorganization (defined using entropy; Shannon, 1948) of the sociotechnical system across its components, i.e., communication, control, and vehicle, and also at a systems level. These layers, either individual components or system, were originally studied in a simulated Remotely Piloted Aircraft System (RPAS; Cooke & Shope, 2004) across all-human and HATs which have either a human or an Adaptive Control of Thought - Rational (ACT-R; Anderson, 2007) based fully fledged synthetic agent for a pilot.

In the Gorman et al. (2018) paper, entropy time series were used to measure systems with various configurations of human and agent operators and after experiencing autonomy failures (synthetic agent unexpectedly fails during the task). Correlations between layered dynamics and team effectiveness indicated how the RPAS system had to be coordinated across its components to maintain effectiveness under changing system configurations. Hence, layered dynamics complements existing approaches to understanding sociotechnical complexity in order to enhance system effectiveness. This approach also allows one to understand temporal associations between system components that may be useful in avoiding unintended consequences of a system change.

The current study focuses on the layered dynamics of HATs and their relationship to team effectiveness during automation and autonomy failures. In the current study, the two human team members were informed that the third team member was a "synthetic" agent, even though in reality it was a trained experimenter mimicking a synthetic agent. This study addresses the question of how members of HATs interact with one another and with the technology over time and in response to automation and autonomy failures. Using the layered dynamics approach, entropy at the operator communication, vehicle, vehicle controls, and system overall were used to measure system reorganization and to predict a coordination-based performance score, called target processing efficiency (TPE). Based on these results, we discuss how to build mechanisms to make HAT more effective in the future.

METHODS

Participants

22 teams (44 participants) from a large Southwestern University as well as surrounding areas completed the experiment. Two participants per team filled the roles of photographer and the navigator, and the pilot position was always filled by a non-participant, the well-trained experimenter who mimicked the synthetic agent's communication and coordination behaviors. Participation required normal or corrected-to-normal vision and fluency in English. The age range of participants was from 18 to 36 (M_{age}= 23, SD_{age}= 3.90) with and the gender distribution was 21 males and 23 females. Each team participated in two seven-hour sessions and all participants were compensated $10 per hour.

Experimental Procedure. There were ten separate 40-minute missions in this task. The experiment was split into two separate sessions with a one or two-week interval in between (see Table 1). Prior to the task, each team completed a one-hour, role-related training (30 minutes of PowerPoint slides and 30 minutes of hands-on training). After the training, the experimenters utilized a checklist to ensure that the navigator and the photographer were comfortable and capable with their roles. A separate series of failures or anomalies in the system occurred and were of three types: automation failures, autonomy failures, and malicious attacks. Each failure was applied to pre-selected target waypoints according to a set schedule (see Table 1).

The primary study manipulation is the application of three degraded conditions: (1) automation failure - role level display failures during specific targets, (2) autonomy failure - autonomous agent's abnormal behavior during specific targets (such as misinformation provided to other team members or the demonstration of misaction), and (3) malicious cyber-attacks - the hijaking of the RPAS, which led to the synthetic agent providing false detrimental information to the team (Grimm, Demir, Gorman, & Cooke, 2018). This malicious cyber attack was only applied once during the last failure of the last mission. Failures were introduced at pre-selected target waypoints (Table 1). Teams had a limited amount of time to discover a solution and overcome each failure. Each failure had a time limit, which was positively related to its difficulty. Because they were repeated multiple times, we focus on automation and autonomy failures in this paper.

Apparatus

For this study, we utilized the Cognitive Engineering Research on Team Tasks RPAS Synthetic Task Environment (CERTT-RPAS-STE), an environment composed of three separate task-role consoles and four experimenter consoles. Participants communicated using a text chat system in this task environemnt, and simulated teamwork-related aspects of RPAS operations (Cooke & Shope, 2004). In this mock RPAS task environment, participants were tasked with the objective of taking photographs of strategic targets represented on a color-coded target map. Three different interdependent team member roles were designated for this task: (1) a navigator, who was responsible for the dynamic flight plan and providing the waypoint related information to the pilot, including name, altitude, airspeed, and effective radius; (2) a pilot, who used this information from the navigator to monitor and adjust the altitude, airspeed, effective radius, fuel, gears and flaps. Additionally, the pilot communicated with the photographer to negotiate altitude and airspeed in order to enable proper conditions for a good photograph of the target; and (3) a photographer, who monitored and adjusted the camera to obtain good target photos, and also provided feedback to the team to ensure good photo quality.

This study utilized a Wizard of Oz (WoZ) paradigm (Riek, 2012), in which the navigator and photographer were seated together in one room and were instructed that their pilot teammate was a synthetic agent. In reality, the pilot was actually a highly-trained experimenter located in a separate room. The 'synthetic' pilot, who used restricted vocabulary to a computer's restricted language, communicated in a timely fashion, similar to the ACT-R based synthetic pilot in a previous experiment; see (Demir et al., 2015). To facilitate communication with the 'synthetic' pilot's limited language repertoire, the navigator and photographer were provided cheat sheets to provide assistance towards effectively communicating with the synthetic agent.

Table 1. Experimental Session and Failure schedule

		Target/ Automation	Target/ Autonomy	Target/ Malicious
Session I	Training	No Failure	No Failure	No Failure
	Mission 1	No Failure	No Failure	No Failure
	Mission 2	2nd target	4th target	No Failure
	Mission 3	4th target	2nd target	No Failure
	Mission 4	1st target	3rd target	No Failure
Session II	Mission 5	2nd target	4th target	No Failure
	Mission 6	4th target	2nd target	No Failure
	Mission 7	1st target	3rd target	No Failure
	Mission 8	3rd target	1st target	No Failure
	Mission 9	3rd target	5th target	No Failure
	Mission 10	2nd target	4th target	Last 10 min

Measures

In this study, we used two type of measures for our analysis:

(A) Layered dynamics entropy: First, we defined four layers to symbolically represent RPAS, and calculated entropy measures for each of them (Gorman et al., 2018): (1) *communications layer*: the time (in seconds) during which team members interacted within the chat system, and the variables included: sender identity (by role), time message was sent, and time message was read by the recipient; (2) *vehicle layer:* states of the RPA itself (e.g., airspeed or altitude), including: airspeed/altitude changes, left/right turns, fuel levels, battery levels, remaining film, termperature level; (3) *control layer:* the

interface display between the RPA and the users (team members). Input variables included command type, and which operator sent the command, as well as information from the photo log; and (4) *the system layer:* entropy across all system layers. Based on the current focus of this study, we only consider the sublayers (communication, control and vehicle level).

Then, we obtained information entropy based on the number of possible arrangements that a system (in this case, RPAS) can occupy in a given window of time. Symbols correspond to changes in system parameters, such as airspeed and altitiude changes (vehicle layer), changes in control settings (control layer), or operator communication, where unique symbols represent which team member is communicating with whom. Formula 1 demonstrates this calculation:

$$Entropy = -\sum_{n=1}^{\#Sym} (p_n \, x \, log_2 p_n) \tag{1}$$

where p_n is the relative frequency of a symbol (a system state such a speed increase) over a window of time, and the p log$_2$ p value is summed over the current symbol set.

(B) Target Processing Efficiency (TPE): This is calculated (Formula 2) based on the time spent inside the effective radius of a target to get a good photo (the designation of "good" is based on having correct camera settings) (Cooke et al., 2007).

$$TPE = 1000 - r - (p{*}200) \tag{2}$$

RESULTS

We first applied Multivariate Analysis of Variance (MANOVA) to answer whether sublayer (communication, control, and vehicle) entropy differs over time (i.e. mission); we briefly summarize significant results. Next, Growth Curve Modelling (GCM) (Mirman, 2014) was applied on the dataset to examine whether there was a significant relationship between each level of entropy with TPE, and whether these relationships differ across different levels of entropy. In R, "lmerTest" package version 2.0–32 was used to conduct the GCM analysis (Kuznetsova, Brockhoff, & Christensen, 2016) .

MANOVA. We performed a 2 (failure type: automation vs. autonomy) x 3 (layer: communication, control, and vehicle) x10 (mission) mixed ANOVA on the entropy scores. Table 2 summarizes the results of the ANOVA. Three of the interaction effects were statistically significant: layer by failure type, mission by failure type, and mission by team (within failure type). We summarize only the first two of interaction effects based on the focus of this paper.

Table 2. MANOVA Results for each factors' entropy

Source	*df*	*F*	*p*	η^2
Failure Type	1	11.32	0.002	0.23
Team (within Failure Type)	38	1.35	0.091	0.15
Sublayer by Failure Type (within Mission)	16	4.90	0.000	0.11
Mission	8	4.34	0.000	0.11
Sublayer (within Mission)	16	6.52	0.000	0.14
Sublayer by Failure Type	2	11.91	0.000	0.04
Mission by Failure Type	8	6.82	0.000	0.16
Mission by Team (within Failure Type)	281	1.63	0.000	0.42

As shown in Figure 1 (Layer by Failure Type), entropy during automation and autonomy failures was significantly higher in the vehicle layer than the control layer (p < .05). Similarly, entropy for autonomy failures in the vehicle layer was significantly higher than the communication layer (p < .05). This means that the synthetic agent's abnormal behavior during the autonomy failure resulted in high reorganization at the vehicle layer. For instance, during the autonomy failure, the synthetic agent directed the RPA to the next waypoint without allowing the team to take a good photo of the previous waypoint. The solution to this issue was to send the RPA back to the previous waypoint in order to take a good photo.

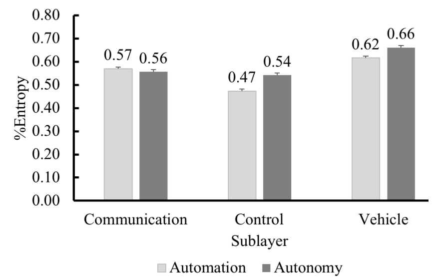

Figure 1. %Entropy across the layers for each type of failure

According to the Mission by Failure Type interaction (see Figure 2), in Session I, while vehicle and communication level entropy increased over time, the control layer decreased. In the beginning of the second session, vehicle and control entropy increased (Missions 5 to 6: p < .05), but communication entropy decreased (Missions 5 to 6: p < .05). In later missions, while communication entropy demonstrated a steady increment (from Missions 6 to 10: p < .05), vehicle and control entropy fluctuated over time. Overall findings indicated that teams gradually learned how to effectively communicate in order to successfully reach each target. However, based on the control layer, teams did not demonstrate stable behavior when they interacted with the interface of their consoles (such as adjusting the camera settings for the photographer). The fluctuation in the vehicle layer was not as strong as the control layer. It is possible that the stable communication of the teams over time had an impact on the vehicle layer (see Figure 2).

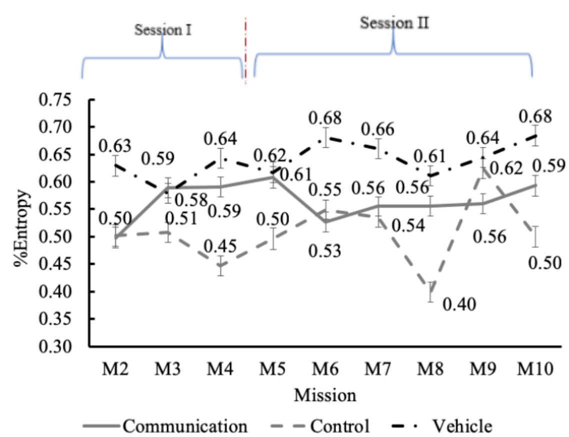

Figure 2. %Entropy for each layer across missions

Growth Curve Modeling for System Layers. Growth Curve Modelling (GCM) (Mirman, 2014) was applied on the dataset to examine whether there was a significant relationship between each level of entropy with TPE, and whether these relationships differ across different levels of entropy.

Overall TPE was modeled using a linear growth model with fixed effects for layer entropy (of communication, control, and vehicle) and a linear time term. Because Model 0 and Model 1 are the same as the previous GCM model building steps, we started building the model from Model 2. In Model 2, the level-1 variable, the effect of layers' entropy, was included to the best fitting model, and it did improve model fit (Model 1 – Model 2 comparisons: $\chi 2$ (3) = 69.8, $p< .001$). After that, we also added the interaction term of layer entropy by linear, but it did not improve model fit based on the previous model ($\chi 2$ (3) = 6.89, $p= .08$). Therefore, we did not include this interaction effect in the model building steps, but we retained the main effects to investigate potential interactions with the level-2 variable. In Model 3, the level-2 variable, type of failure, was added in the model, and it improved model fit compared to Model 2, $\chi 2$ (1) = 6.04, $p< .05$. Similarly, in Model 4, the level-2 variable interaction effect with linear time was added to the model and it improved model fit in comparison to Model 3, $\chi 2$ (1) = 10.1, $p< .05$. Next, the interaction effect of type of failure and layer entropy was added to the model, but it did not improve model fit compared to Model 4, $\chi 2$ (3) = 4.87, $p = .18$. Thus, we excluded the interaction effect of type of failure and sublayer entropy and summarize the test statistics of Model 4 in this study. However, we have still provided fixed effect parameter estimates and their standard errors with p-values estimated using normal approximation for the *t*-values for each model during the step by step model development process in Table 4.

Table 3. Results of Model Tests for Target Processing Efficiency

Model	*No of parameter*	*Log Likelihood*	*Deviance*	χ^2	χ^2 *df*	*p*
M0	3	-171.68	343.36			
M1	4	-167.39	334.78	8.59	1	0.003
M2	7	-132.50	264.99	69.79	3	0.000
M3	8	-129.47	258.95	6.04	1	0.014
M4	9	-124.44	248.89	12.29	1	0.002

In Model 4, initial status was significantly different from zero (γ_{00} = 1.45, *SE* = 0.13, $p < .001$), which may indicate that the teams already displayed reorganization behavior due to the training before starting the task. The rate of change, i.e., slope, for linear time was significantly negative ($\gamma_{10} = -0.40$, *SE* =0.08, $p < .001$). Similar to the previous model, the linear time indicates that TPE decreased over time, likely due to high workload of the last mission. Also, teams demonstrated low TPE performance during the autonomy failure (γ_{01} = -0.099, *SE* = 0.04, $p < .05$).

Although the main effect of communication entropy was non-statistically-significant (γ_{20} = 0.03, *SE* = 0.15, $p = .83$), the main effects of control and vehicle entropy were negative and positive on the initial status of TPE, respectively (γ_{30} = -0.59, *SE* = 0.15, γ_{40} = 1.35, *SE* = 0.16, $p < .001$, respectively). In this case, the negative association of the control level entropy indicates that during the failure, team members' actions on the interface were negatively related with their TPE performance, but when these actions were executed by the vehicle (vehicle entropy), they were positively related with TPE performance. We can explain these opposite effects as the delayed response of the entropy on TPE performance from control to vehicle level. Because TPE is calculated based on how quickly teams take a good photo and get out of the target radius, teams exhibiting high levels of control entropy would be the teams that waited until the last moment to input commands to the vehicle. We would expect such teams to be less efficient than those who planned ahead and input commands at earlier times, i.e., before entering the target radius. On the other hand, high vehicle entropy within the target radius is necessary in order to successfully achieve the task, and we would expect it to be positively related with TPE. The interaction effect of type of failures by linear time was also significant (γ_{50} = 0.38, *SE* = 0.12, $p < .05$). However, the simple slope based on this interaction effect was not statistically significant (γ_{11} = 0.03, *SE* = 0.09, $p = .73$).

Table 4. Results of model tests for predicting TPE by each level of entropy

Fixed effects	*β*	*SE*	*t*	*p*
Initial status (β_0)				
Intercept (γ_{00})	1.45	0.13	11.04	0.000
Communication Entropy (γ_{20})	0.03	0.15	0.22	0.827
Control Entropy (γ_{30})	-0.59	0.15	-3.99	0.000
Vehicle Entropy (γ_{40})	1.35	0.16	8.24	0.000
Autonomy (γ_{01})	-0.09	0.04	-2.48	0.014
Rate of Change (β_1)				
Time (linear) (γ_{10})	-0.41	0.08	-5.11	0.000
Time by Autonomy (γ_{11})	0.03	0.09	0.34	0.733

DISCUSSION AND CONCLUSION

In this study, our main findings were: 1) vehicle and communication entropy were higher than control entropy and were associated with better adaptation to automation and autonomy failures, and 2) control entropy had a negative association with initial status on TPE, while vehicle entropy had a positive association.

Taken together, these findings describe the tendency of low performing teams to poorly anticipate the targets. This poor anticipation was due to a failure to interact with the technology in a timely manner. This lagged effect can be attributed to teams waiting until the last minute to interact with the technology.

Additionally, the finding that entropy was significantly higher in the vehicle layer than both the control (for both automation and autonomy failures) and communication (for autonomy failures) layers, suggests that RPAS coordination involved greater organization at the vehicle rather than controls or communication level. This is interesting because the higher vehicle entropy during the autonomy failure is reflective of the actions (such as turns, altitude, and airspeed changes) needed by the RPA to ensure that a good photo was taken.

One interesting finding was that teams demonstrated more stable communication entropy compared to other layers as the sessions went on. This may indicate that human team members were able to learn the skills necessary to interact more effectively with one another and with the synthetic agent during failures. Consequently, we may infer that effective team interaction and coordination of the vehicle is a requisite team-level skill to overcome dynamic failures. There is evidence to suggest that interactive training may be necessary to interact with one another (dynamic and coordination-based) in order to adapt to dynamic environments and overcome unexpected failures, or that the interaction could be a result of the high performance. It is helpful to emphasize this interactive training, as it may help calibrate participants' expectations of the synthetic teammate's abilities and limitations. Interactive training also can help us understand and how real-time modeling may provide the opportunity to better understand TPE performance during automation and autonomy failures.

We hope that our conclusions have shed light on how the layered dynamics approach can help us identify a team's behaviors in a particular situation. Other future areas that should be investigated include trust, team training, and resilience. Examination of how trust is associated with different layers and failures of the team can inform us about trust patterns with autonomous agents. Additionally, layered dynamics can help to identify sources of resilience during failures. Observing possible interactions across layers and how they relate to resilience would be a potential aide to the training of HATs and the design of interface displays to support real-time feedback regarding system coordination across layers.

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