Modeling Team Interaction and Interactive-Decision Making in Agile Human-Machine Teams

Mustafa Demir, Mustafa Canan and Myke Cohen

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Mustafa Demir
Human Systems Engineering
Arizona State University
Mesa, USA
https://orcid.org/0000-0002-5667-3701

Mustafa Canan
Information Sciences Department
Naval Postgraduate School
Monterey, USA
anthony.canan@nps.edu

Myke C. Cohen
Human Systems Engineering
Arizona State University
Mesa, USA
myke.cohen@asu.edu

***Abstract*—In a complex task environment in which team behavior emerges and evolves, team agility is one of the primary determinants of a team's success. Agility is considered an emergent phenomenon in which lower-level system elements interact to adapt to the dynamic environment. One of the dimensions of team agility is interactive decision-making. In this study, we conceptually model individual team members' interactive decision-making process for their taskwork; we observe how much the choices of one team member depend on antecedent decisions and the behavior of other team members. This also helps us understand how team members synchronize during the decision-making process in agile teams, especially when team members team up with a machine. To improve the understanding of interactive decision-making, we propose two modeling techniques: (1) quantum cognition for the taskwork decision-making processes and (2) nonlinear dynamical systems modeling for teamwork processes.**

Keywords— AI, Human-Machine Teaming, Decision Making, Nonlinear Dynamical Systems, Quantum Cognition, Team agility

I. Introduction

Ever since the Industrial Revolution, advancements in machines have been a driving force in the achievement of scientific milestones, from conventional automation to autonomy. As Isaac Asimov indicated, technological evolution is faster than biological evolution, but it has been slow until this century [1]. With recent advancements in machine learning and artificial intelligence (AI; [2]), highly autonomous machines ("autonomy" hereafter) now function more as a teammate instead of an optimization tool in various dynamic task environments, such as in human-synthetic teams in remotely piloted aircraft systems [3], in human-robot teams in urban search and rescue [4], or in marine operations [5]. *Human-Machine Teams* (HMTs) are concomitantly characterized by human and autonomous members with distinct roles working together for a common goal or task. To be considered part of a team, the machine must participate either by serving as interactive external repositories of information or as executors and mediators between members [6]. But even if autonomy can now be considered a teammate, HMTs may still not be agile enough to adapt to dynamic tasks.

Agility is an emergent phenomenon in which lower-level system elements (e.g., team members) interact to adapt to a dynamic environment [7]. Therefore, understanding complex adaptive team behavior is critical to the design of agile HMTs. For instance, interactions among team members (i.e., communication and coordination) are a dimension of team agility that is crucial for good team performance in a dynamic task environment [8]. The relationship of complex team interactive behaviors with team performance has been studied in different dynamic task environments, including communication [9], coordination [10], and trust [11]. Another dimension of team agility is interactive decision-making, which is defined as "a process where team members consult one another and make their final decision [regarding their task] alone" [12, p. 306]. In other words, this process forces team members to explain their choices and think about those they have not considered before; in turn, they make decisions to maintain teamwork.

This paper conceptually outlines the role of interactive decision-making for HMT agility. We discuss an experiment that used a machine as a team member who communicated and coordinated with human counterparts. Our results identify empirical findings that we believe can advance the design of HMTs and team interactions therein. We follow this with a framework that can aid in identifying what interactive decision-making means in the context of agility in HMTs, and how to empirically study interactive decision-making in agile HMTs.

II. Literature

A. Team Agility: Exploration and Exploitation

In complex task environments in which team behaviors emerge, team agility is one of the primary determinants of a team's success. Based on the findings of a previous study [10], we define *team agility* as a team's capability to remain flexible in facing a task's inherent dynamism by adjusting team behavior continuously and developing new ones (e.g., coordination) to adapt to unpredictable changes in the task environment. This capability is not only a response to a major disruption; it also implies that a team is consistently able to projectively change its course of action to sustain its performance [10]. Team agility has three common themes. Firstly, team agility involves a set of actions taken by a team that operates in an environment characterized by rapid and unpredictable change, i.e., agile teams can successfully adapt to this disruptive environment. Secondly, team agility requires changes that are different from routine changes, i.e., the changes that result from team agility are specified as continuous, systematic variations in a team's perception, comprehension, and projection. The intensity and variety of

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these changes are high; thus, agile teams demonstrate complex adaptive behavior. Finally, rapid information gathering is critical to gleaning the environmental changes that might require agile-adaptive behavior, i.e., team agility requires team-level situation awareness to maintain adaptiveness.

A salient characteristic of team agility is that it comprises exploration and exploitation in a continuum of team cognitive processes. Exploration involves the pursuit of new information, while exploitation involves using resources that are already known [13, p. 105]. Exploration, and in turn agility, is associated with the team's knowledge base. Together, these processes form a loop that departs from established modes of coordination between team members. For example, team members coordinate in established ways (exploitation) and then shift to a new mode of coordination (exploration) to respond to unexpected events promptly. Agile exploration, in other words, involves seeking a solution to a novel situation by increasing the flexibility of established team coordination. Exploratory team interactions have previously been defined as any unique interaction in light of a team's collective history [14]. Therefore, they are characterized by how signals and feedback are explored in a novel situation in an exploitation-exploration process, consistent with a team's tendency to transition from exploitation to exploration, and vice versa, over time.

B. Team Interaction

Team communication occurs between team members regardless of their proximity to one another and can be asynchronous or synchronous and face-to-face [15], but generally rely on linguistic components over nonverbal cues [16]. In contrast, cross-species teams (e.g., human-canine teams), while having been previously identified as an analog to HMTs, normally do not use natural language as a means of communication beyond one-word commands [17]. Cross-species communication is simply "an interchange of meaning"—a transfer of a significant concept, but not "an interchange of language," spoken or written, making it a largely nonlinguistic system of communication [18]. Animals and humans understand each other through social cues and social signals (e.g., eye movements, gestures, body language, tone of voice, and demeanor). But because animals are very limited and task-dependent; if the task is too complex, the challenge is to simplify these cues and signals such that cross-species communication between team members will not impair the dynamic task. Simple changes in a signal or a cue can allude to an entirely different meaning. Hence, human-canine team interaction is indeed an analog to HMT interaction—but it is not sufficient to provide good synchrony between human and machine teammates in a highly dynamic environment. Natural Language Processing systems allow AI to be better suited to more linguistic forms of communication. Therefore, good HMT design should make use of this by incorporating interchanges of meaning and language, in contrast, to solely relying on the exchange of meaning for human-animal teams.

C. Interactive Decision Making and Situation Awareness

Team communication and coordination are dynamic interaction constructs in HMTs and are both factors and manifestations of another cognitive construct: interactive decision making, which is a process of identifying and choosing alternatives in interactive tasks. This activity also involves other cognitive aspects, such as theory of mind, social cognition, and goal-directed behaviors [19]. Team interactions allow team members to develop coherent rationales and opinions from other team members regarding a team task, but because they make their final decisions individually, they can either use or ignore the information they collect during team interaction. In other words, interacting team members make choices that favor their taskwork over teamwork because of their common goal. Related to team agility, interactive decision-making also depends on exploitation and exploration in team coordination. From the definitions of exploration and exploitation, interactive decision-making as a process is thus affected by contextual changes, i.e., cost and benefit in the context of routine and novel conditions. Team members need to choose either established or new forms of coordination with other team members to be agile, and in turn, maintain a desirable level of performance. Thus, team agility is a quality/measure of interactive decision making

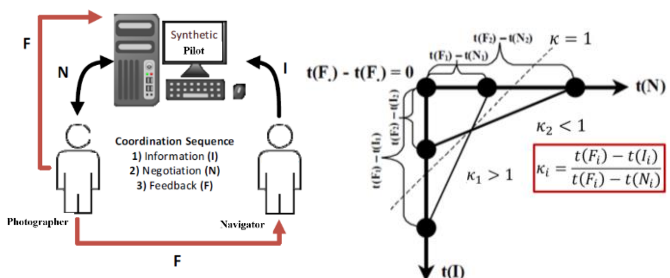
Determining the best combination and sequence of cognitive capabilities towards maintaining team performance can be explained through Endsley's three-level framework for situation awareness [20]. Level 1 situation awareness comprises the *perception* of data elements and cues in the environment. At Level 1, the cognitive systems of machines can be superior to human cognitive systems due to limitations in the latter's processing capacity of individual environmental elements. For this reason, agile HMT behavior should leverage the cognitive systems of machines as a primary information perception system, relegating that of humans to a support role. Level 2 situation awareness is the cognitive systems' *comprehension* of the current situation based on Level 1 elements. This is the level in which the gleaned contextuality is imposed upon Level 1 elements. Since human cognitive systems are better adapted to context-sensitive environments compared to cognitive machine systems, the former should be the primary basis for agile team behavior. Furthermore, the contextual quirks of the situation are gleaned upon by the human mind, and thus Level 2 mental models for team members may be augmented with quantum cognition models so that order and interference effects will not impede agile team behavior. Level 3 situation awareness is defined as the *projection* of the future status of the system. In complex situations, the projection of the future status of the system is still highly context-dependent. Therefore, the evolution of a team's situational awareness of the situation and its associated mental models becomes of paramount importance, projecting the future status of shared mental models [21], both at the team and individual level, for agile team behavior.

In this study, we model team members' interactive decision-making process for taskwork; we observe how much the choices of one member depend on antecedent decisions and the behavior of other team members. This also helps us understand how agile HMT members synchronize during decision-making.

III. Current Study

A. Simulated RPAS Task Environment and Team Interaction

The experiment took place in the Remotely Piloted Aircraft System-Synthetic Task Environment (RPAS-STE) testbed, which emulates the individual and team cognitive activities that occur in an RPAS ground station. The RPAS-STE comprises three heterogeneous and interdependent task roles ([22]). The goal of this task was to take good photos of target waypoints while navigating the RPA along a safe route. Timing and content of communication were important for the teams to succeed. In this study, the pilot role was either an ACT-R based cognitive model or a randomly selected participant, or an "AI" teammate that was simulated by a trained confederate using a "Wizard of Oz" methodology (WoZ) [23]. The AI's capabilities were limited in verbal comprehension, production, and piloting behaviors for this experiment. The confederate followed a script that indicated when and what to communicate throughout the task and described behaviors for controlling the flight of the RPA. Pilot behaviors were generally limited to the script.



$t(I)$ = Information sent time
$t(N)$ = Negotiation sent time
$t(F)$ = Feedback sent time

Fig. 1. (a) Team coordination sequence: (*I*)nformation–(*N*)egotiation–(*F*)eedback; and (b) the intrinsic geometry coordination score, Kappa (κ).

In the RPAS team task, team coordination comprises three key communication events at each target waypoint, which happen in the following optimal coordination sequence (Fig. 1(a) [24]): (1) *information* (I) is given by the navigator to the pilot about the target waypoints of the mission (i.e., altitude, speed restrictions, and effective radius), (2) *negotiation* (N) occurs between the pilot and photographer regarding camera settings, airspeed, and altitude at the target, and (3) *feedback* (F) is given by the photographer to the pilot and navigator about whether the photograph taken at the target is acceptable. As team members interact, the variability in their repeated use of this sequence (specifically, the relationship between the timing of each of the three parts of the sequence) was used to compute a coordination score for each team at each target waypoint. Assuming that *INF* is the principal axes of the procedural model, a geometry-based measure of coordination was created (Fig. 1 (b) [24]). These axes are related by a variable (κ), computed by normalizing the area around feedback at every target to develop a distribution over the intrinsic procedural model geometry. It is unitless because all three constituent parts are measured in seconds, and these units cancel the computation of κ. It also contains two qualitatively different states: uncoordinated ($\kappa < 1$) and coordinated ($\kappa > 1$) with a transition point at $\kappa = 1$ HMT differentiates the two. In uncoordinated teams, either *N* precedes *I*, or *F* precedes either *I*, *N*, both. When *N* occurs before *I*, this indicates that there is a backlog of information. On the other hand, in well-coordinated teams, *I*, *N*, and *F* occur in accordance with the procedural model, with larger values of κ indicating that the *I* component is established well in advance of the target approach [10].

IV. Interactive Decision Making in RPAS Roles

Interactive decision-making across the RPAS roles varies in terms of the level of complexity of the decision-making structure. We divided each role's interactive decision-making process into the three-level situation awareness model [20]. Across all three roles, the teamwork-related indicators (i.e., altitude, airspeed, and current and next waypoint-related information) play an important role in facilitating transparency in team tasks, primarily for the pilot's task role. Controlling the teamwork-related indicators is the pilot's task based on the interaction with the other roles. At the individual level, we model each individual's situation awareness based on their taskwork. Then we discuss how to quantify only the navigator's taskwork ontic uncertainty via a quantum cognition model because of the page limit. In Fig. 2, taskwork and teamwork-related indicators are demonstrated for each task role. Accordingly, each role focuses on their taskwork: the navigator to the waypoint map, the pilot to the route and fuel, and the photographer to the camera settings and photo log. However, all three team members monitor the teamwork-related indicators regarding the current and next waypoint.

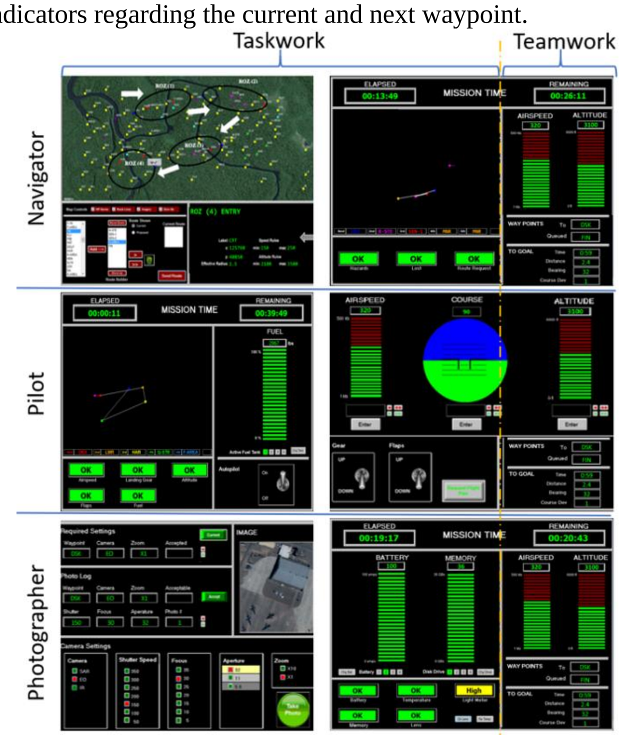


Fig. 2. Teamwork and taskwork indicators across the three roles. Teamwork: altitude, airspeed, and current and next waypoints' information). Taskwork: navigator (map and waypoint list), pilot (course deviation, fuel, air flaps, and gears), and photographer (camera and camera settings).

Fig. 3 categorizes each task role's situation awareness regarding perception, comprehension, and projection. In terms of INF coordination sequence, comprehension plays an important role in relating to the perception and projection stages of the navigator's task because sending *information* about the target waypoint happens during the task comprehension. However, considering the only comprehension and ignoring perception and projection is insufficient in understanding the individual level of the task. Since we argue that agility is the capability of having and developing multiple ways of coordination to adapt to the dynamic task environments while preserving the team performance, the integrity of the team structure must be monitored when a perturbation occurs. These perturbations increase the uncertainty of the system, which necessitates changes in team member situation awareness. Due to the interdependence between team members, any change in situation can engender incongruent shared understanding (i.e., situation awareness). For instance, when the navigator looks at the map and finds the relevant waypoints based on the colors and notices a message expressing disagreement from the pilot; the pilot disagrees with the navigator, the ensuing disagreement at the perception level permeates situation awareness at the comprehension level and gives rise to uncertainty.

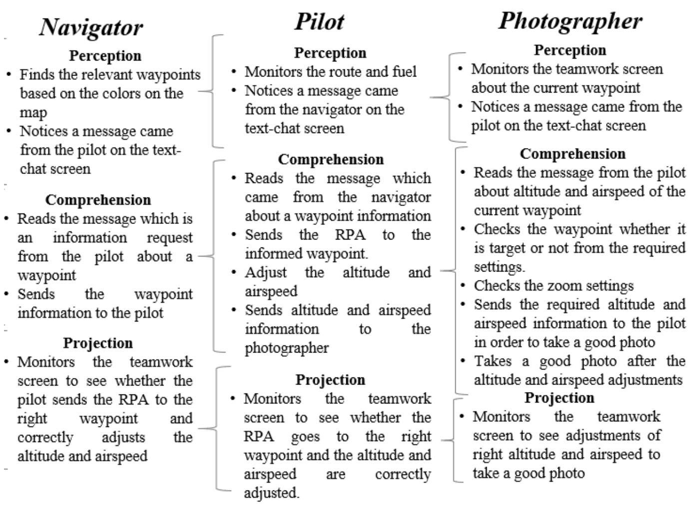


Fig. 3. Situation awareness across three task roles.

V. Modeling Interactive Decision Making in RPAS Task Context

To improve the understanding of interactive decision-making in the experimental context, we propose two modeling techniques: (1) quantum cognition for taskwork decision-making processes to discern the effects of ontic uncertainty for each individual and (2) nonlinear dynamical systems modeling teamwork to capture epistemic uncertainty.

A. Quantum Cognition

Quantum models of cognition can ameliorate the understanding of interactive team cognition [25] when a situation involves interference effects. Consider the mentioned case in which the navigator finds the relevant waypoints based on colors on the map and notices a disagreeing message from the pilot. Suppose that the navigator needs to make a binary decision in this situation: yes (1) or no (0). Fig. 4 shows two different scenarios that can take place for the comprehension and projection levels of situation awareness in this case; the premise in this discussion is that the navigator considers their other teammates' possible decisions to comprehend and project the level-1 SA elements. The process of projection, in this case, can occur in two ways. First, the navigator can consider the pilot's possible decisions–yes (1) or no (0)– and then the photographer's; the second way is that the navigator can think about the photographer's possible decision first, then the pilot's next. During comprehension and projection, to project a yes (1) decision, the navigator can follow four different paths in both scenarios, shown in Fig. 4.

For example, the navigator can comprehend and project a yes (1) decision by considering the condition in which the pilot's possible decision is yes (1), and the photographer's possible decision is no (0); solid lines in Fig. 4a represent this decision path. Due to interference effects, the navigator may have varying probabilistic outcomes in complex situations depending on the followed path, thus experiencing intrinsic (ontic) uncertainty. Interference effects can be observed if the followed path is unknown, i.e., the navigator does not interact with any of the team members. Since interactive team cognition theory [25] implies that decision paths are made known via interactions, it can explain the effects thereof on team efficiency. However, to ameliorate human-centered design, interactive team cognition needs more comprehensive models.

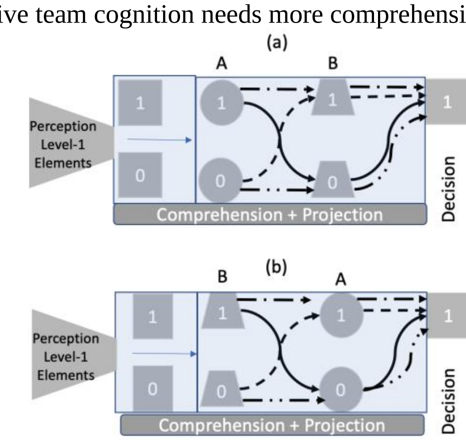


Fig. 4. Level of situation awareness for the navigator. Both figures show the comprehension and projection levels after perception elements occur. Comprehension and projection parts depict possible thought processes while the navigator thinks about A (pilot) and B (photographer) decisions. The difference between (a) and (b) is in the order of thought processes in comprehension and projection. Each scenario consists of four possible paths to decide yes (1).

A Hilbert space representation of the comprehension and projection levels of SA, during which the navigator does not interact, is shown in Fig. 5. Fig. 5 describes one of the decision paths shown in Fig. 4a, in which the navigator first considers the others' perspectives in the following order: pilot (yes) → photographer (no) → navigator (yes). The three perspectives shown in Fig. 5 can become incompatible in complex situations, from which interference effects can arise. Complex situations are the time constraint situations in which the decision-maker can not form a complete understanding of the situation, e.g., can not think about the events simultaneously. One way to increase team agility by reducing interference effects may be through direct communication about perspectives between team members instead of leaving teammates' perspectives to unspoken guesses. Alternatively, this can also be done through another approach: the quantum cognition concept of entanglement. This form of entanglement emerges when team members are trained together, such that a composite team perspective could emerge. Such a perspective cannot be decomposed into individual perspectives (i.e., "simple"). Having entangled states has distinct effects on the uncertainty, entropy, and probabilistic understanding of decision processes. Fig. 5 (b) shows that an entangled team perspective is a distinct "other" perspective.

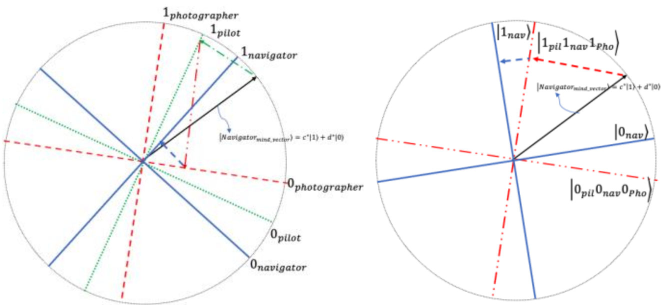


Fig. 5. (a) Hilbert space representation of comprehension and projection levels of situation awareness. There are three perspectives in this representation. The blue solid line perspective is the navigator's perspective; the green dotted (pilot) and red dashed (photographer) perspectives represent the others' perspectives in the navigator's cognitive system; (b) Hilbert space representation of navigator perspective and entangled team perspective.

An implication of having a non-composite entangled team perspective is that during the comprehension and projection levels of SA, in which there is no explicit communication or interaction, interference effects can be accounted for to preserve the integrity of team performance. For example, the complicated possible multiple decision paths in Fig. 4 can be minimized and simplified, as shown in Fig. 6. Another implication of accounting for entangled states is that team situation awareness can more easily be modeled as a function of time [9]; taskwork decision processes can then be modeled probabilistically. This allows for an analysis of team structure concomitant with both quantum cognition and nonlinear dynamical systems modeling techniques.

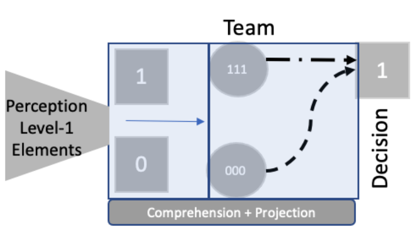


Fig. 6. Comprehension and projection levels of entangled team SA.

B. *Nonlinear Dynamical Systems Modeling*

We visualize the characterization of three teams' coordination dynamics by applying attractor reconstruction on κ score time series at the team level [24], [26]. This is followed by stability analysis (Lyapunov exponents) for each coordination order parameter κ at the team level. In attractor reconstruction visualization, based on Taken's theorem [27], one can recover a system's dynamical structure (i.e., reconstruct the attractor) from a one-dimensional signal (in this study, this signal is the κ time series) and a set of independent, time-delayed versions of itself. The reconstructed attractor exposes the dynamical structure that produced the patterns observed in the original one-dimensional signal. The attractor was reconstructed for each team's κ series by first estimating two embedding parameters: the optimal time delay (τ) and the embedding dimension (m) [26], [28]. τ identifies the lag for which the original signal is maximally different from itself. These lagged versions are then used as the dimensions (m) in the phase space to unfold the signal. Following standard practice, τ was estimated as the first minimum of the Average Mutual Information function [26], [28]. The selection of m followed the False Nearest Neighbors (FNN) method outlined in [28]. This process surveys data points and their neighbors in dimensions ranging within spaces of increasing dimension. The goal is to find "false neighbors," that is, points that separate when examined in a higher dimension. Per convention, m was determined as the lowest dimension where the percentage of false neighbors ≤ 10 [10].

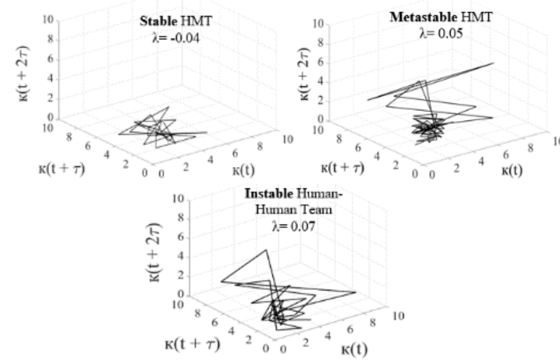


Fig. 7. Example reconstructed attractors from three RPA teams which provide means to show chaotic behavior geometrically in three-dimensional phase space: $\kappa(t)$, $\kappa(t+\tau)$, $\kappa(t+2\tau)$ [10].

We also examined team coordination stability from the reconstructed attractors by estimating the largest Lyapunov exponent (λ). The λ measures the exponential rate of divergence of two nearby trajectories on the attractor [28], [29]: stable ($\lambda_1 < 0$), unstable ($\lambda_1 > 0$), and metastable or parallel trajectories ($\lambda_1 \approx 0$) of team coordination [30]. The magnitude of λ relates to the speed with which a dynamic system reaches an equilibrium point, stable or unstable. A system with large negative λ reaches an equilibrium state quickly and will have difficulty moving away from it (i.e., the system becomes rigid), while a system with large positive λ will quickly become unstable, leading to a breakdown in communication coordination and, perhaps, a jeopardized mission. Systems with λ close to zero will begin to meander, stabilize (if λ is negative), or meander and destabilize (if λ is positive). Systems that exhibit either of these metastable situations can be said to be agile and, thus, are likely to perform well [31]. Reconstructed attractors for the three teams are presented in Fig. 7, showing that differently composed teams based on their interaction may differ in their temporal dynamics; λ estimates provide converging evidence of that observation. The stable HMT's coordination was focused on a small part of phase space with less variability and a rigid appearance ($\lambda_{\text{Stable HMT}}$ = -0.04). On the other hand, the HMT with a timely interaction and human-human team with random interaction demonstrated more variability ($\lambda_{\text{MetastableHMT}}$= 0.05) and instability ($\lambda_{\text{Unstable}}$= 0.07). The metastable HMT performed better within these three teams than the unstable human-human team, which performed better than the stable HMT [10].

VI. Conclusion

Team agility for an HMT subsumes the ability to be stable; it also includes flexibility in order to adapt to a dynamic task environment. In this study, first, we defined team agility in terms of the team interaction process: exploration and exploitation of the team coordination. Then, based on these two important coordination concepts, we conceptually examined and modeled interactive decision-making in an RPAS task environment by applying: (1) quantum cognition for the taskwork decision-making processes (to discern the effects of ontic uncertainty for each individual) and (2) nonlinear dynamical systems modeling for the teamwork (to capture epistemic uncertainty). Considering both the ontic (taskwork level) and epistemic uncertainty (teamwork level) of a team is necessary to understand the whole more than its sum of parts [32]. Thus, team agility is an emergent behavior from all these interactive processes and is developed in response to the task environment (i.e., task-dependent). In the future, we will empirically examine the HMT in the RPAS task context to address the questions: (1) how does team agility evolve in a dynamic task environment? (2) how is it maintained over time, and what are the design requirements for an HMT to be agile?

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