Special Issue

Teaching Machines to Recognize Neurodynamic Correlates of Team and Team Member Uncertainty

Ronald H. Stevens, University of California, Los Angeles School of Medicine, USA; The Learning Chameleon, Inc., USA and **Trysha L. Galloway**, The Learning Chameleon, Inc., USA

We describe efforts to make humans more transparent to machines by focusing on uncertainty, a concept with roots in neuronal populations that scales through social interactions. To be effective team partners, machines will need to learn why uncertainty happens, how it happens, how long it will last, and possible mitigations the machine can supply. Electroencephalography-derived measures of team neurodynamic organization were used to identify times of uncertainty in military, health care, and high school problem-solving teams. A set of neurodynamic sequences was assembled that differed in the magnitudes and durations of uncertainty with the goal of training machines to detect the onset of prolonged periods of high level uncertainty, that is, when a team might require support. Variations in uncertainty onset were identified by classifying the first 70 s of the exemplars using self-organizing maps (SOM), a machine architecture that develops a topology during training that separates closely related from desperate data. Clusters developed during training that distinguished patterns of no uncertainty, low-level and quickly resolved uncertainty, and prolonged high-level uncertainty, creating opportunities for neurodynamic-based systems that can interpret the ebbs and flows in team uncertainty and provide recommendations to the trainer or team in near real time when needed.

Keywords: cognitive modeling, EEG, information theory, human computer interaction, human robot interaction, team neurodynamics, team processes

Address correspondence to Ron Stevens, The Learning Chameleon, Inc., 5601 W. Slauson Ave, Suite 184, Culver City, CA 90230, immexr@gmail.com.

Journal of Cognitive Engineering and Decision Making
2019, Volume 13, Number 4, December 2019, pp. 310–327
DOI: 10.1177/1555343419874569
Article reuse guidelines: sagepub.com/journals-permissions

INTRODUCTION

Machines use complex search and evaluative functions to efficiently perform tasks that humans can describe like image processing, facial recognition, credit card verification, vehicle navigation, beating chess champions, and most recently, teaching themselves to master board games through self-play (Hsu, 2002; Silver et al., 2018). These advances continue to be achieved by extensive exemplar training and distributing the learning and knowledge across connected layers of artificial neural nodes, that is, Deep Learning (Goodfellow, Bengio, & Courville, 2016; Rumelhart, Hinton, & Williams, 1986).

Machines have been less successful in performing tasks that are easy for people to perform but hard for people to describe such as understanding or predicting the intent of complex systems like teams. One problem is that it is difficult for machines to “make sense” of the changing human states over teaming-relevant time scales, that is, seconds to minutes. Although most often this is attributed to limitations of the machine, it is also possible that machines are working with an impoverished view of the state of human actions and intentions which, for the most part, lack transparency except for other humans. The goal of this paper is to describe a neurodynamic approach for making humans more transparent to machines by focusing on a fundamental property of living systems, uncertainty.

Much of our understandings about others has been learned from observation. Observational analyses have been foundational in developing our understanding of individual and team behaviors by detailing what a person is doing, how they are doing it, and what they are saying

(Cooke, Gorman, & Kiekel, 2008; Entin & Serfaty, 1999; Salas, Stagl, & Burke, 2004). We are still a long way from incorporating these capabilities into machine partners.

A paradigm shift is underway for understanding how teams evolve and mature over time. It is being driven by the generation of dynamic biometric data streams with seconds' resolutions. Such data and tools will support empirical quantitative comparisons across teams, tasks, and experience and help uncover the cognitive interactions between team members during the evolving task. This will enable cognitively informed task designs and accelerate the rates of team and team-member learning by focusing on the cognitively relevant properties of performance. They will likely shape the evolution of existing theories of teamwork and the creation of new performance measures and teaching practices; these data will also increase the transparency of human states enabling effective machine–human collaborations (Stevens, Galloway, Willemsen-Dunlap, Gorman, & Halpin, 2018).

In this paper, we describe efforts to make human uncertainty more transparent to machines. Human uncertainty has its roots in the mismatch between the generative models that each person holds about the environment and the arriving sensory inputs. Through a process initially involving thousands of neurons, these ambiguities become resolved by collective neural decision making as the uncertainty is propagated toward consciousness (Daniels, Flack, & Krakauer, 2017) and resolved further by collective strategic interactions in the social realm (Flack & Krakauer, 2011). The way that nature uses uncertainty to tune itself across neural to behavioral scales makes it a construct that we feel any machine-based team member will need to understand.

Uncertainty is ubiquitous and complex with its origins in the collective decision making of groups of neurons, and yet when it becomes chronic it is recognized as the disease entity anxiety (Grupe & Nitschke, 2013), that is, uncertainty spans the full range of human behaviors, and is something that humans can recognize, but find hard to explain. Uncertainty has been described at the brain level as being sensory, state, rule, or outcome based (Bach & Dolan, 2012), and although the orbital prefrontal cortex seems a locus for uncertainty-related activity, especially for outcome and sensory uncertainty (Kepecs, Uchida, Zariwala, & Mainen, 2008; O'Neil & Schultz, 2010), other active areas exist across the brain. At the physiologic level, uncertainty has been described as being expected or unexpected with the respective involvement of acetylcholine (cholinergic) and norepinephrine (noradrenergic) pathways (Yu & Dayan, 2005). Uncertainty monitoring shows parallels with metacognition and may or may not require mental workload depending on the experience of the subjects (Coutinho et al., 2015).

Despite this multiperspective research base, few ways exist for dynamically tracking our moment-by-moment uncertainties. Being able to do so, even for a subset of the potential varieties of uncertainty, could provide the foundation for incorporating machines as an interdependent member of the team.

We have proposed measures and models which are quantitative and indicative of human uncertainty over time frames that can be linked to characteristic behaviors recognized as belonging to teamwork (Stevens & Galloway, 2017; Stevens, Galloway, Halpin, & Willemsen-Dunlap, 2016). The emphasis on uncertainty arises from the unifying role that uncertainty plays in perception, motor control, and adaptive inference (Friston, 2010; Friston, Kilner & Harrison, 2006; Sengupta, Stemmler, & Friston, 2013). The emphasis also arises from the dynamic nature of the tasks and environment which influences the task complexity and uncertainty as perceived by the team (Hong, 2010; Stroulia & Goel, 1994).

Background principles guiding our work are that individuals (and teams or human-machine teams)

- Need to avoid or resolve surprise/uncertainty;
- Need to keep the environment in a low entropy (i.e., highly predictable) state;
- Need to keep team entropy high to avoid the unnecessary energy/time expenditures of excessive organization, while maintaining optimum variability for adaptation (Schuldberg, 2015).

We view these principles through the lenses of information dynamics (Shannon, 1948; 1951) and nonlinear dynamical systems (Guastello, 2017), starting with ideas about how individuals and teams avoid surprise by taking action to adjust their sensory inputs and their internal mental models of the causes of those inputs (the free energy principle). Next, the factors affecting the flexibility and adaptation of the team in response to the changing information in the environment (Ashby, 1956; Guastello, 2015; Hong, 2010) are described and how information in the environment can be identified that is causally relevant or meaningful to a team and team members, that is, semantic information (Kolchinsky & Wolpert, 2018). These ideas are then integrated with human neurodynamic organizations, that is, the tendency of humans to enter into persistent (10 s–3 min+) neurodynamic states providing the background for machine learning approaches for recognizing when humans are experiencing uncertainty/difficulty and might require support.

The goal is to develop a transparent understanding of a team's and team members' current state (i.e., where they are), their past state (how they got there), and perhaps their future state (where are they going). To be able to learn, and be transparent to humans, the machine should also understand its own past and current states, as well as those of the humans, and be able to create projections of its own, and the humans, future states with reasonable probability. Finally, both humans and machines should understand and learn from the evolving changes in the task environment.

The minimum requirements for the measures / systems we are contemplating would be that they are

- Dynamic with high temporal resolution;
- Quantitative where changes mean something to the team;
- Scalable so measures of individual and team uncertainty can be aggregated or deconstructed to span system scales; and
- Capable of linking changes in the team's cognition with measurable changes in the environment.

Information Theory and Uncertainty

Information theory was originally conceived as a way of describing the fundamental limits on signal processing and communication (Shannon, 1951). A unit of information is the bit which is the amount of information that allows the choice between two equally probable alternatives. Bits can be extracted from many sources by different means, but a common feature is that they measure the amount of uncertainty that can be removed in a variable or process. One measure is Shannon entropy which is the average surprise of outcomes sampled from a probability distribution or density. A distribution with low entropy means that the data have organization and are relatively predictable, whereas a system with higher entropy indicates there is less organization and the system is less predictable.

Information is a common exchange currency that living systems use to support homeostasis and survival. Information can be acquired or created, processed, shared, stored, and destroyed. Forms of information have a past, a present, or a future (James, Ellison, & Crutchfield, 2011), whereas other information may have causal necessity for the system to maintain its own existence over time (Kolchinsky & Wolpert, 2018).

In biological systems, the nested organizational structures found across space and time are thought to encode information hierarchies that reduce uncertainty, facilitate extraction of energy, and foster adaptive behaviors (Flack, 2017). In this way, the information at behavioral scales can be thought of as the summed outputs or aggregated components of the information from components below. Information however can flow both ways on this information hierarchy. Information from regularities (i.e., patterns) in the environment and from other team members during prolonged periods of uncertainty, decision making, and learning are also fed back down to lower levels influencing lower level activities to promote adaptation. The hierarchical predicative coding model of cortical organization separates top down predictions (expectations) from bottom up sensory information, and representations are then based on the mismatches between the two (Marton, Fukushima. Camalier, Schultz, & Averback, 2019). In this context, uncertainty can be thought of as an intermediate representation of the information hierarchy, accepting neural signals about the need for changes and then passing top-down information about the possible actions available.

Although acquiring more information to reduce uncertainty might seem beneficial for an individual or team, there are costs. Reducing uncertainty is synonymous with acquiring and manipulating information which requires pattern formation and energy (Garner, Thompson, Vedral, & Gu, 2017), with the minimum amount of energy required to determine one bit of information being kT ln (2) Joules/bit (Szilard, 1929), a quantity Landauer (1961) generalized to any way of manipulating or processing information such as measuring, encoding, displaying a yes/no decision, and so forth.

Free Energy Principle and Uncertainty

Biological systems exist in continual perception/action cycles where sensory inputs are compared with probabilistic models of the likelihood of incoming information given these models (Knill & Pouget, 2004). The models or sensory inputs are adjusted accordingly and then the environment is resampled or changed. The goal of these cycles is to optimize the values and costs of future actions to minimize surprise. At the intersection of value and costs is the uncertainty that becomes resolved by this process.

Much of this decision-making activity is orchestrated by implicit brain process and occurs rapidly (Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005); it has been proposed that human mental processes have evolved to minimize perception-model errors across systems and avoid the costs of surprise (Barlow, 1961; Friston, Kilner & Harrison, 2006; Friston, 2010).

These ideas have been encapsulated by Friston (2010) into a model, the free energy principle that develops a unified account of perception, action, and learning. One of the tenants of the free energy principle is that of the large number of physiological and sensory states that exist, there is a high probability that an individual's current state exists within a much smaller state space roughly defined by homeostatic requirements; that is, living systems resist entropy and the system is optimized and predictable for the most part. Occasionally, however, prediction errors arise between incoming information and internal probabilistic representations and these errors trigger parts of these systems to drift from homeostatic boundaries and the system becomes less predictable as a result of this surprise. From information theory, this change in predictability can be described as an increase in the uncertainty, or entropy of the system.

The system must then adjust their mental models or their sensory inputs to bring the models closer together. At times, this may mean changing the environment which raises the question about what information individuals and teams are sensing that raise their uncertainty. Thus, according to the entropy conservation framework (Hong, 2010), there is the need to consider the task, the environment, and the team as inseparable, complementary aspects of what we observe as overt human action

Human Adaptations to Environmental Uncertainties

The tasks that teams are assembled to manage, like most physical and living systems, drift toward increasing randomness (i.e., entropy). To optimize performance, individuals and teams need to continually maintain or reduce the degrees of freedom of the environment and keep the environmental entropy to a low (i.e., predicable) state. The quality of this dynamic team-task interplay is enhanced through training where the minimum entropy principle holds that paths of least effort will be discovered by a team and they become capable of reducing the variability in their responses to predictable and unforeseen events (Hong, 2010). At the same time, such training increases the repertoire of responses possible in alignment with Ashby's (1956) law of requisite variety where a model system or controller can only model or control something to the extent that it has sufficient internal variety to recognize it. Adaptation is required when the internal variety is not sufficient for a perturbation. This is when uncertainty would be expected, and the team would need to develop new strategies and configurations to cope with it. As noted above, better trained teams will be able to minimize the frequency, magnitude, and duration of these perturbations/adaptations.

A machine acting as a partner trained to detect neurodynamic correlates of uncertainty should be able to identify the onset and be able to predict the magnitude and duration of these times. In doing so, machines would provide an extra set of "eyes" on the health of the team serving as a resource of extra variability to help control the environment. To capture these ideas to enhance the training and performance of teams requires the identification of consequential task information (or a proxy thereof).

Semantic information is something that is meaningful to a system, or as defined by Kolchinsky and Wolpert (2018), something that is necessary for the system, in this case individuals or teams, to maintain its own existence over time. There is no direct way to measure the information that is being acquired from/about the environment, as for some team members a piece of information might be very "meaningful," whereas for others it will be unimportant, or not even perceived; for example "the 'true' environment is a reflection of what the organism perceives" (Hong, 2010). Although the problem of measuring the entropy of the task environment has not yet been solved, it does suggest the importance of measuring both the uncertainty of the team, and the dynamic contributions each team member makes to that uncertainty.

Team Neurodynamics and Uncertainty

The changing environment and a persons' prior knowledge about it might at times be insufficient to correctly interpret the changing sensory inputs. This can lead to surprising consequences requiring teams/team members to reorganize their thinking, roles, or configuration into corrective structures to resolve the uncertainty. Neurodynamic Organization (*NO*) is the tendency of individuals and teams to enter into persistent neurodynamic states lasting seconds to minutes in response to this need. For individuals, these periods might be seen as a pause like when searching for the right word to say, or more importantly when a surgery team wonders why there is an incorrect sponge count and what to do about it (Grant-Orser, Davies, & Singh, 2012). For a team *NO* might also occur during periods of silence (Gardezi et al., 2009). Neurodynamically *NO* appear as the restricted use of the available state space (Stevens, Gorman, Amazeen, Likens, & Galloway, 2013).

Neurodynamic organizations are detected and modeled by symbolically transforming the physical units of each team member's electroencephalography (EEG) power into bits of information (Stevens & Galloway, 2014, 2017; Stevens & Galloway, 2015). The measures of Neurodynamic Organization are

- *Neurodynamic Entropy (NE)* which is the degree of organization determined by measuring the Shannon entropy over a moving windows (60 s) of the state symbol stream that is updated each second.
- *Neurodynamic Information* (*NI)* which is obtained when *NE* values are subtracted from the maximum entropy of the system. This simplifies the relationship between entropy and organization by making higher organization a positive information value.

Team neurodynamics inherits the idea of surprise/uncertainty from the free energy principle and the ideas of identifying causally meaningful information from the environment. The unique contribution of team neurodynamics is that neural responses of humans confronting uncertain situations can be deconstructed into hundreds of variables that can be differentially quantitated each second, and either independently or jointly modeled across a team or its individuals (Stevens, Galloway, & Willemsen-Dunlap, 2018). The resulting models, despite their apparent complexity, provide detailed, yet explainable cognitive perspectives of team dynamics opening opportunities for designing tools for machine–human teams.

The key to understanding this form of uncertainty, and by extension how a team arrived at a particular situation and what their future might be, lies in the patterns resulting from the neurodynamic reorganizations as teams reconfigure themselves. The resolution of these patterns will depend on the bandwidth of available data and its temporal resolution. For this reason, we chose to model team neurodynamics using EEG (Stevens & Galloway, 2017).

EEG is the recording of electrical activity of the brain at different regions along the scalp. Coordinated firing of synapses give rise to brainwave rhythms that can be amplified and appear as signals on the scalp's surface (Buzaki, 2006).

The organizations that emerge are functional patterns tied to the responsibilities and responses of the team to environmental demands.

The functional patterns furthermore relate not only to the scalp position being recorded from, but also from the frequencies of signals detected. The sensor positions on the scalp are guided by the international 10–20 system and the frequency range generally monitored for cognitive activity "in the wild" ranges from 1 to 60 Hz, as below this range other physiologic signals generated by respiration, heartbeats, electrode pops, and so forth, may confuse the patterns, and above this, electromyographic signals become a serious confounder.

For machine–human teaming, a 1-s temporal resolution might be reasonable as this is in the range (250–500 ms) of functional brain connectivity associated with speech or playing guitar in duets (Dumas, Nadel, Soussignan, Martiniere, & Garnero, 2010; Sänger, Müller & Lindenberger, 2012; Stephens, Silbert, & Hasson, 2010), and nonverbal recognitions (Caetano, Jousmaki, & Hari, 2007), or approximately a half a second for a two-person action-response round trip. In reality individuals in teams probably speed this up by predicting ahead, although at a cost of increased uncertainty (Hsu et al., 2005). Below we describe the modeling of neurodynamic organizations and provide evidence for their links to team and team member uncertainty.

METHOD

Tasks

Although we have modeled *NO* in military, health care, and high school teams (Stevens & Galloway, 2014, 2017; Stevens & Galloway, 2015; Stevens et al., 2016), for training neural networks we have focused on the HCRC Map Task (MT) because of its ability to induce uncertainty in the participants (Doherty-Sneddon et al., 1997). In this task, two individuals sit facing each other, one termed the Giver (G), has a computer screen map with 18 to 20 landmarks like trees, rocks, and buildings, and a dotted line path through these landmarks. The second person, the Follower (F), attempts to use a computer mouse to draw the same path through a similar but not identical set of landmarks on a map on her screen by conversing with (G).

In digital games, uncertainty is a feeling players can recognize and express. Power, Denisova, Papaioannou, and Cairns (2017) reported four factors that contributed to that feeling including Exploration, or knowing the goal of the game but being unable to link actions with it; Disorientation, or losing track of what they need to accomplish; Randomness, or the presence of events out of their control; and Prospect, or not knowing what was required. Examples of uncertainty for the Map Task included the following:

- The mirror image maps on the two computer screens were disorienting for some teams and they needed to formally establish common navigation rules (Disorientation).
- Some landmarks on one person's map might be absent or duplicated on the other persons map (Prospect).
- Occasionally the drawing cursor of (F) "froze" at random intervals due to the software application's lack of connectivity with the mouse (Randomness).
- Several teams spent so much time describing landmarks that they forgot the specifics of what to do (Exploration).

Neurodynamic data streams from eight MT performances, containing 42 segments of uncertainty were used in this paper. Examples from two other tasks were included to increase the variety in the set of exemplar, and to test the generalizability of the trained network on unrelated problem performances. The health care simulations were part of a larger study comparing the neurodynamics of simulated or live patients (Stevens, Galloway, Willemsen-Dunlap, 2019; Stevens et al., 2016) during anesthesia induction. The simulations highlighted focused on the preoperative ventilation of simulated patients by an experienced, and a medical student teams. There were six uncertainty exemplars from a medical student team, and four uncertainty exemplars and three exemplars of no verbalized uncertainty from an expert anesthesiology team.

The submarine navigation task was a required simulated navigation exercise performed by an experienced U.S. Navy navigation team

(Stevens & Galloway, 2014, 2017; Stevens & Galloway, 2015; Stevens et al., 2013). One uncertainty exemplar was used for the dynamic testing described in Figure 7.

Ethics Statement

Informed consent protocols were approved by the Biomedical IRB, San Diego, CA (Protocol EEG01); the Placentia, Yorba Linda School District Institutional Review Board for the Map Task studies; the Order of Saint Francis Healthcare Institutional Review Board for the health care studies; and the U.S. Navy Medical Review Board for the collection of EEG from the submarine navigation team. All participating subjects consented to participate with written approval, and to allow their images and speech available for additional analysis. To maintain confidentially, each subject was assigned a unique number known only to the investigators of the study, and subject identities were not shared. This design complies with Department of Health and Human Services (DHHS): protected human subject 45 CFR 46; Food and Drug Administration (FDA): informed consent 21 CFR 50.

EEG

EEG data were collected using two EEG systems; for the MT there were eight sensors at scalp positions F3, F4, C3, C4, Fz, Cz, P3, and P0, whereas for the health care example the sensor positions were at positions Fp1, Fp2, F7, F8, F3, Fz, F4, C3, Cz C4, P3, P4, P7, P8, P0, T3, T4, O1, and O2 according to the international 10–20 system of electrode placement.

The data acquisition began shortly after the EEG sensors were adjusted for good contact ($<10\ \Omega$) and synchronized with electronic markers inserted into the EEG data streams as well as the events observed in videos. The recorded EEG data were processed using Matlab®-based FieldTrip® toolbox (Oostenveld, Fries, Maris, & Schoffelen, 2011), as detailed previously (Stevens & Galloway, 2017; Stevens et al., 2016).

Team and Individual Neurodynamic Modeling

The starting point for neurodynamic modeling was the creation of symbolic representations of EEG power levels for each person each second, at each EEG sensor, and across forty 1 Hz frequency bins (1–40 Hz). In Figure 1a, the EEG power was separated into high, average, and low values and assigned the symbols 3, 1, and –1, the values chosen to aid visualization. In the symbol in Figure 1a, (G) had high EEG levels and (F) had average levels.

Next, the state of each individual as a part of a team was represented as two histograms within a single Neurodynamic Symbol (*NS*), so Figure 1a also represents a possible 1 s state of the team. The combinations of three energy levels and two persons result in a collection of nine *NS*, and this collection is termed a Neurodynamic State Space (*NSS*). An entire performance performed by dyads, whether 1,000- or 10,000-s long will be represented by a sequence of these nine symbols. The maximum entropy of such a symbol stream is 3.17 bits, whereas the maximum entropy for each team member's data stream with three symbols (i.e., –1, 1, and 3) is 1.585 bits.

In this study, we report *NI*, which is derived by subtracting entropy values from the maximum entropy of the system. This simplifies the relationship between entropy and organization by making higher information a positive value.

Self-Organizing Artificial Neural Network Classification of Uncertainty

Self-organizing maps (SOM) are often the first step of deep learning models. Self-organizing neural networks have an unsupervised competition architecture where during training the association of similar vectors is promoted while more dissimilar vectors are repulsed. This results in a topology of similarity being established across the nodal space. The SOM architecture is useful for identifying a limited, but discriminating, set of features in data. One of the advantages of SOM for preliminary studies is that they require relatively few exemplars compared with tasks like teaching robots to walk. Our plan when using the SOM architecture was to develop a classifier based on temporal neurodynamics that would predict at the onset of uncertainty in either individuals or teams, whether the episode would be of high magnitude and prolonged duration.

When contemplating training machines for recognizing dynamics that are characteristic of a

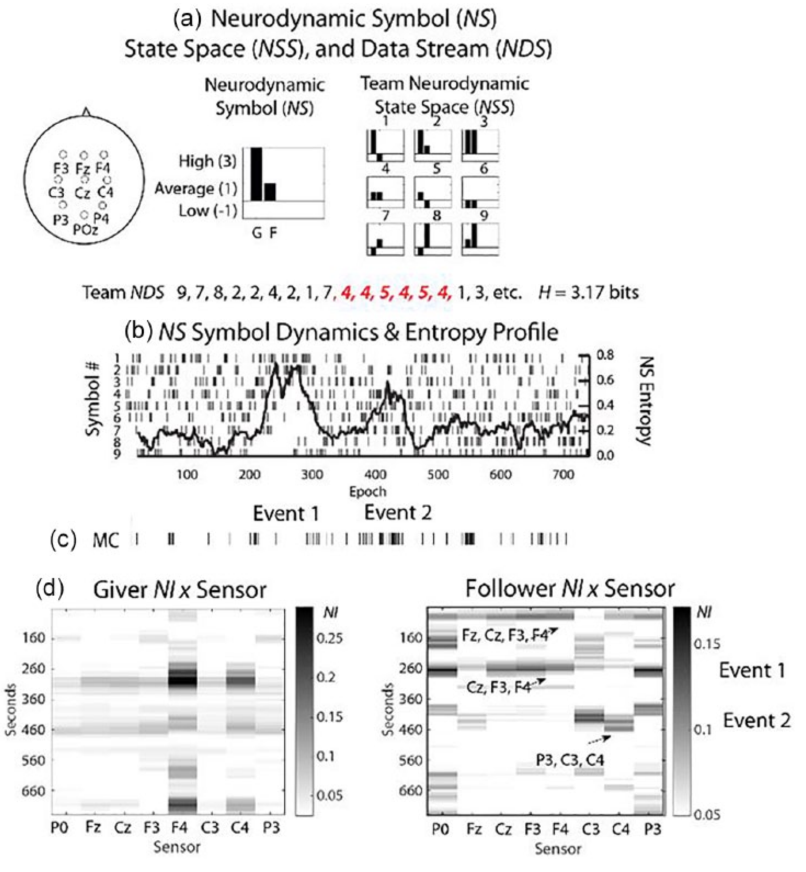

Figure 1. Team and individual neurodynamic modeling of a Map Task performance.

Note. (a) A sample *NS* showing a 1 s period where the EEG power was high for (*G*), and average for (*F*); and, the nine-symbol *NSS* for two persons with three EEG power levels. (b) The *NS* in the data stream (*y*-axis) were plotted sequentially each second for the performance (*x*-axis). The symbols are overlaid with the profile of *NI* calculated over a 60 s moving time window that was updated each second. (c) The Follower's mouse clicks are plotted over time. (d) The performance plots of the *NI* at each EEG sensor position for (G) and (F). NS = neurodynamic symbol; NSS = neurodynamic state space; NDS = neurodynamic data stream; EEG = electroencephalography; NI = neurodynamic information.

team entering a period of uncertainty, we decided on a time frame of 1 to 2 min. This would be sufficient time to accumulate evidence about the possible uncertainty associated with an event, and also long enough to make predictions and deliver supports to the team if needed. We have previously reported that neurodynamic information has a multifractal structure with fluctuations ranging from a few seconds to 10 min or more (Likens, Amazeen, Stevens, Galloway, Gorman, 2014). The timeframe chosen was therefore selected for practical uses.

Fifty-five segments of *NI* were selected for machine classification from eight MT performances and an experienced and a novice health care team. The segments ranged from 71 to 125 s in length (mean/*SD* = 96.1 ± 17.2 s) and the area under the curves ranged from 2.8 to 40.6 bits

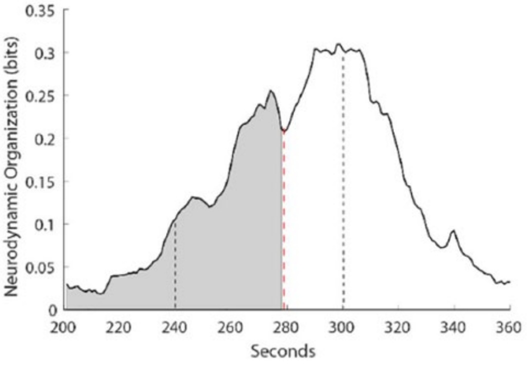

Figure 2. An expanded *NI* profile for Event 1.
Note. The shaded area indicates the period before the team realized they were lost and needed to restart. NI = neurodynamic information.

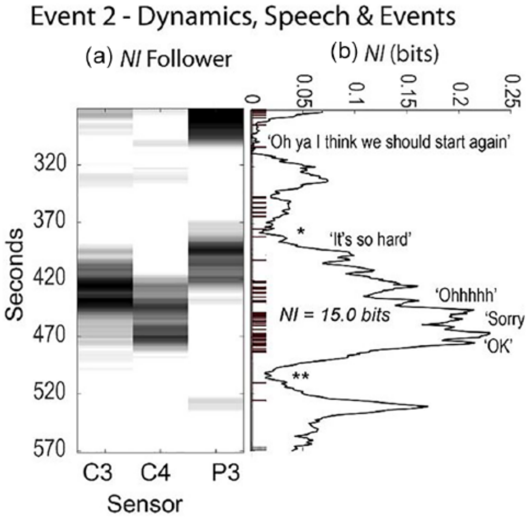

Figure 3. This figure shows (a) an expanded view of the (F)'s *NI* at the C3, C4, and P3 sensors for Event 2 and (b) a profile of (F)'s *NI* along with mouse clicks.
Note. The area under the curve between the single and double asterisks was 15.0 bits. The area under the curve was calculated by the Matlab® trapezoidal integration function. NI = neurodynamic information.

(mean/*SD* = 11.78 ± 10 bits). There were 42 MT exemplars, 7 of which were no verbalized uncertainty examples and 10 health care exemplars, 3 of which were no verbalized uncertainty examples. This sample included 10 examples of Randomness, 11 examples of Prospect, 15 examples of Exploration, and 6 examples of Disorientation.

The SOM described in this study had 16 nodes arranged in a hexagonal topology and was trained for 5,000 epochs. Although the average length of the uncertainty segments was 96 s, we only used the first 70 s of each for clustering as our goal was to develop models of the onset of uncertainty. Projections forward from this period would provide estimates of the magnitude and duration of uncertainty which would be useful for providing feedback to teams.

RESULTS

Team and Individual Uncertainty during a Map Task Performance

The MT performance in Figure 1 illustrates the team's elevated neurodynamic information in response to two forms of uncertainty: the uncertainty generated internally by the team members' disorientation (Event 1), and the uncertainty derived externally from equipment/software failure (Event 2). The neurodynamics and speech associated with these events are described in detail in Figures 2 and 3.

This performance had 739 *NS*, which were plotted over time (Figure 1b). Major discontinuities in *NS* expressions were seen from 200 to 300 s (Event 1) and, 325 to 475 s (Event 2). The predominant symbols during Event 1 were *NS* 1 & 2 indicating (G) had high EEG power and (F) had low to average power. During Event 2, the predominant symbols expressed were *NS* 4-7, indicating times when both team members had average to low EEG power. A neurodynamic information profile overlays the symbol expressions providing quantitative estimates of the information during each event window.

Note that the *NI* increase was greater for Event 1 than Event 2 reflecting a greater team organization (i.e., fewer types of *NS* expressed). This illustrates how quantitative differences are determined between different events (or teams). Having meaningful and dynamic quantitative measures of *NI* is an important feature when teaching machines to recognize differences in the degree of human uncertainty. Also shown are the mouse clicks (MC) associated with (F)'s drawing of the map. The density of MC between

420 and 480 s coincided with Event 2 which was caused by (F) losing control of the cursor due to the software application's lack of connectivity with the mouse.

The *NI* levels that developed during the task often differed in frequency, magnitude, and duration at each sensor. Figure 1c and 1d map the brain origins of these patterns for (G) and (F) by creating *NI* models at each sensor location. Most of the elevated *NI* was associated with Events 1 & 2. The *NI* were greatest for (G) at the F4 and C4 sensors during Event 1. The neurodynamics of (F) were more spatially distributed with elevated *NI* at all sensors except C3 and C4 during Event 1, and mainly at C3, C4, and P3 during Event 2. The finding of high *NI* for (F) over the C3 and C4 sensors during Event 2 was expected as these sensors are located over the sensorimotor brain regions involved in planning and executing movements like drawing.

The links between the elevated *NI* in Figure 1 and uncertainty were made from what team members said during Events 1 (Figure 2) and 2 (Figure 3).

The Giver was providing diffuse drawing instructions until 282 s when F asked about going to a specific landmark (Table 1). At this point, the team was "surprised" by the realization that they were lost and had to start over. Noteworthy is that the team's *NI* had been increasing ~90 s before this realization. This suggests that the team members sensed problems and were experiencing uncertainty for over a minute before this was verbalized, indicating a temporal advantage of using EEG dynamics for detecting elements of uncertainty instead of relying on key terms in a communication stream. This lead time could provide opportunities for possible machine interventions.

During Event 2, (F) temporarily lost the ability to draw with the cursor and repeatedly clicked the mouse at ~450 s exasperating the loss of cursor functionality (Figure 3). During the 120 s, it took for (F) to recover mouse control, the *NI* was elevated, and the speech was minimal, but indicated frustration. Much of the increases in *NI* were at sensors C3, C4, and P3 indicative of sensorimotor brain activity.

The key points illustrated by Figures 2 and 3 are that the individuals in a team respond to uncertainty with increases in their neurodynamic organization. The figures also indicate that interpersonal responses to uncertainty can be traced to neural dynamics in different brain regions providing a glimpse of the cognition behind a person's response. In the future, these features could be expanded by deeper layers of machine learning tools to trigger specific prompts or supports for a team in difficulty.

Team and Individual Uncertainty During a Health care Simulation

The above examples showed that the function of a team was delayed by minutes through uncertainty that was either generated internally to the team by an inability to communicate directions, or by a software failure that prevented a team member from completing her or his task. To increase the ability of the trained SOM network to generalize to more complex tasks, the set of exemplars was expanded to include two health care teams where the task was ventilating a mannequin. The first team had three experienced operating room team members, whereas the second was a team of fourth-year medical students.

During the experienced team's simulation, the mannequin exhibited an adverse response to a relative overdose of aerosolized lidocaine that caused swelling of the larynx which was perceived by the anesthesiologist (AN) as a blockage during an initial and unsuccessful intubation (INT-1) attempt. This was followed by a transient patient seizure evoking a crash cart request and when the seizure subsided, a second, and successful intubation (INT-2). The simulation events with *NI* levels greater than the third quartile were during the first intubation, when seizures occurred and a crash cart was called, and during the second intubation, and these four segments were included in the exemplar set. The total scenario time was 801 s.

During the simulation that the medical students participated in the precipitating event which was an allergic response to a tetanus injection. The subsequent difficulties were similar to those of the experienced team where the allergic response was induced by lidocaine. The medical student *NI* when plotted on the same *y*-axis as those of the experienced team indicated the nearly twofold greater and consistent *NI* dynamics.

TABLE 1: Giver and Follower Dialog for Event 1

Time (s)	Team Member	Dialogue
242	G	. . . and then you sort of . . . it is a straight line and it is sort of slanted down to the left. A tiny bit slanted downward for like 6 . . . like 6 dashes.
251	F	Uhm Uhm
254	G	. . . and then it's probably like uhm . . .
264	G	Ok, this is really weird but ah, do you know like X/Y graph? A graph? On a graph?
266	F	Ya
267	G	If you plotted the line Y= –X. It's like that. So, it's just this way, like this. Actually for you it is like this . . .
282	F	I see an Old Pine. Do I go to the Old Pine?
283	G	**Oh my Gosh, that was like . . . ok wait. Old Pine was back on the . . . ok. You know how we did the dip? I am sorry, I am not using the landmarks. Ya know how we did the dip?**
292	F	ah huh
293	G	. . . that lined, that lined up with the start?
297	F	**oh ya, I think we should start again.**
299	G	**We should start over? How do we start over?**
303	F	Oh, let me erase the line.

Note. The dialogue in bold highlights periods of uncertainty.

The team neurodynamics were separated into those of each team member (Stevens & Galloway, 2017; Stevens, Galloway, & Willemsen-Dunlap, 2018) which provided profiles of each persons' neurodynamics. From Figure 4a, the AN and circulating nurse (CN) who had previously worked closely together were also well coordinated during the simulation with overlapping *NI* profiles during the ITB-1, Crash Cart, and ITB-2 segments. These coordinated *NI* profiles are in contrast to those of the scrub nurse (SN) (Figure 4b) who stood away from the patient to assist during the surgery to follow. The SN observing in isolation showed no clear peaks of elevated *NI*.

The only event where none of the team members showed elevated *NI* was the Handoff of the patient to a second anesthesiologist at the start of the simulation, suggesting this event might not be as meaningful for the team. The remaining events were all causes for concern in the context of the need to establish a patient airway prior to surgery.

For each of the events, there were comments by the AN indicating uncertainty, such as

- *ITB-1*. "There is pus or something in the trachea or an obstruction, I can't tell which; I think I am going to have to go through it, do it with the trachea tube . . . It looks like he is seizing."
- *Seizure/ITB-2*. "I am not sure what my other options are. Because he has a history of seizures I think we are out of drugs."
- *ITB-2*. "There is something in the trachea. . . . I am not sure if I can see if it is a foreign body or . . ."

The above results suggest that the types of events likely to increase the *NI*-related uncertainty of teams in complex settings like health care are also those that raise *NI*. In other words, *NI* may be a barometer of the semantic information for the team in the environment, and by extension, each member of the team. In doing so, they refine what meaningful information might be. Although the SN was watching the task being performed, and likely knew the details of what was proceeding, without actual involvement, her uncertainty associated with individual tasks seemed to be missing as there

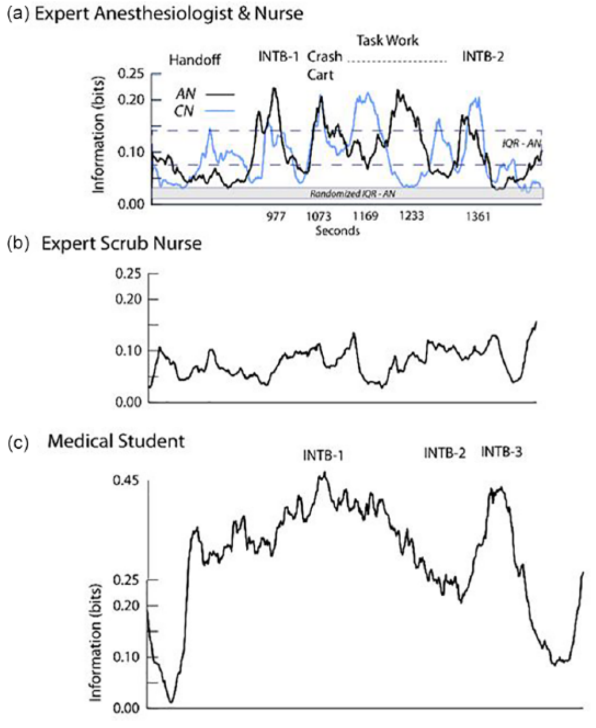

Figure 4. Team member neurodynamics during health care simulations.
Note. (a) The *NI* traces of the AN (dark) and circulating nurse (CN) (light) during the simulation with selected events labeled. (b). The *NI* trace of the scrub nurse (SN). (c) The *NI* trace for a medical student during a similar simulation. The dotted lines indicate the IQR and the gray line indicates the IQR for the randomized data. The neurodynamics of the three individuals are all plotted on the same *y*-axis scale. The simulation the medical student participated in was ~10% longer than that of the expert team (891 s vs. 801 s). NI = neurodynamic information; AN = anesthesiologist; CN = circulating nurse; SN = scrub nurse; IQR = interquartile range.

was no clear association between *NI* rhythms and the task events.

Training Machines to Recognize the Dynamics of Uncertainty

A 16-node SOM was constructed with the topology shown in Figure 5, and the 55 *NI* exemplars were classified as described in the Methods. The nodes in the upper right corner of the SOM (15 & 16) were populated with 8/10 of the segments identified as ‘no verbalized uncertainty’; the other two examples of “no verbalized uncertainty” were in the topologically nearby Node 14. From the exemplar map in Figure 6, these segments were characterized as having low *NI* levels (< 0.02 bits). The nodes furthest away on the topology map, Nodes 1 & 2, were populated with 4/5 of the medical student segments with the remaining segment in the closely located Node 5. The exemplar map in Figure 6 shows these segments as having high levels of *NI* (>0.3 bits) with few indications of

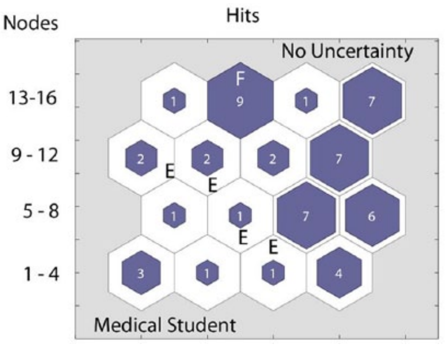

Figure 5. Topology of the Self Organizing Map.
Note. The self-organizing map was batch trained for 5,000 epochs with 55 exemplars, and the number of hits at each node are indicated by the numbers. The Medical Student label identifies Nodes 1 & 2 where 4/5 medical student segments were located and the label No Uncertainty indicates where 8/10 of the segments designated as having little verbalized uncertainty were clustered. The nodes marked with "E" indicate where expert health care segments were located.

there being peaks. This is consistent with novice health care teams having higher levels of *NI* than experienced teams (Stevens, Galloway, Gorman, Willemsen-Dunlap, 2016). The expert health care team performance segments (labeled "E") were located in the sparsely populated central region of the topology map at Nodes 3, 6, 9, and 10 and showed moderate levels of *NI* (> 0.15 bits) with an upslope, rather than a peak tendency. The diverse clustering suggests that health care uncertainty profiles might be more heterogeneous than those from the simpler Map Task. Another node of interest on the SOM was Node 14 where 7/9 clustered segments were from a MT Follower, with no Giver segments. The segments at this node were relatively low level (~ .05 bits) and were characterized by short comments like "(F) Do you have a crashed spaceship? (G) No."

Descriptive characterizations of the most common nodes are shown in Table 2. When appropriate, each of the nodes are characterized as representing Low, Cautionary, Warning, and Severe regarding the likelihood of a prolonged and high-level uncertainty event.

Interpreting Uncertainty Ebbs and Flows During a Submarine Navigation Performance

One possible application of the SOM classifications would be to provide near real-time monitoring of team member uncertainty. In

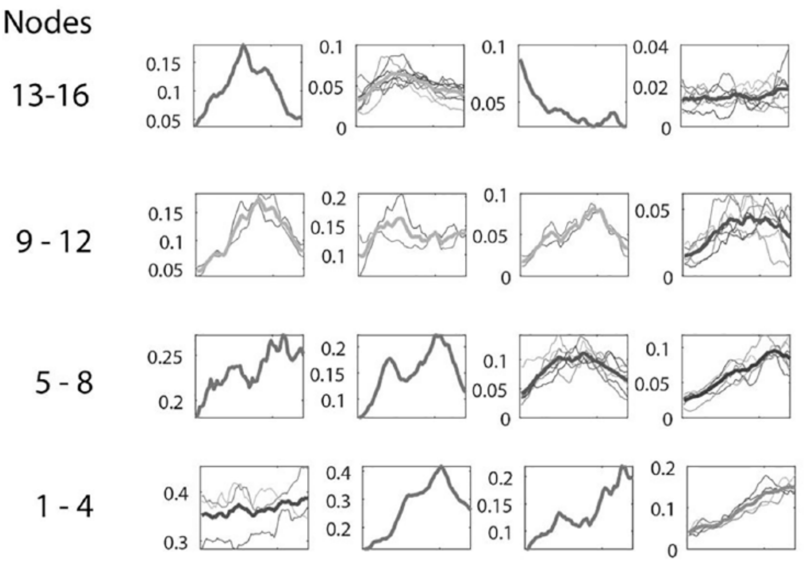

Figure 6. NI Dynamic Profiles at Each Node.
Note. This figure plots the first 70 s of the NI exemplars. The wider line indicates the node average. NI = neurodynamic information.

TABLE 2: Descriptive Characteristics of SOM Nodes

SOM Node	Flags	Description
1	Severe	All the segments classified at this node were from the medical student team. The *NI* levels were high and generally devoid of identifiable peaks, indicating an overwhelmed team.
4	Warning	There was a steady increase in *NI* in these segments with no suggestion of peaking. The high and increasing *NI* levels indicate that this period of uncertainty will be prolonged.
7	Low	The *NI* was beginning to decline after 70 s indicating decreasing uncertainty. The suggestion of a "double top" could indicate a mixture of peaks at different EEG sensors and or frequencies
8	Cautionary	The *NI* profiles at Node 8 indicate a steadily increasing trajectory.
9	Cautionary	These segments show a symmetrical profile and rapid resolution, but the *NI* levels are moderately elevated.
12 & 14	Low	The low *NI* levels with a slow increase and slow decline indicate a minor perturbation.
16	Low	Low *NI* levels with little fluctuation; most of the segments with no verbalized uncertainty were grouped here.

Note. SOM = self-organizing maps; NI = neurodynamic information; EEG = electroencephalography.

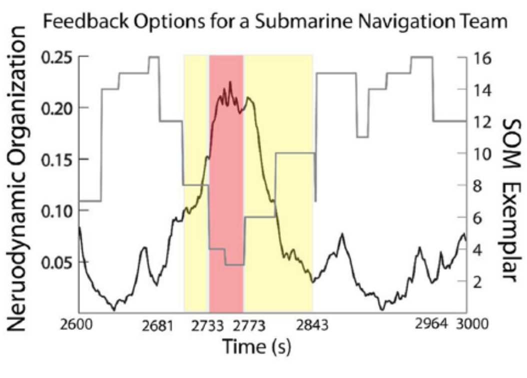

Figure 7. SOM nodal expressions of a submarine navigation contact manager while negotiating passage with another ship.
Note. The solid trace indicates the levels of *NI*, whereas the gray lines indicate the second-by-second expression of the SOM nodes shown in Figure 6. The lightly shaded areas indicate cautionary dynamics, whereas the darker area indicates prolonged difficulty. SOM = self-organizing maps; NI = neurodynamic information.

an exploratory study, the second-by-second expression of SOM nodal classifications were made for a 400 s segment of the *NI* from the contact manager from a submarine navigation team while he was negotiating safe passage into a harbor with another ship (Figure 7).

The Cautionary dynamics appeared shortly after the apparent resolution of minor uncertainty (Node 12) and were associated with a rapidly increasing *NI* (Node 8). The increasing *NI* continued and plateaued until ~2,773 and were represented by Nodes 4 & 3. As the passage plan was finalized with the other ship, the flags dropped to cautionary and eventually low levels.

The sequence dynamics of SOM node expression (12 -> 8-> 4-> 3-> 6) closely followed the *NI* trace indicating that the SOM net trained mostly with MT segments was capable of providing a detailed map of the uncertainty of a crew member performing a task that the net was not trained on.

DISCUSSION

The ability of a machine to rapidly understand when an individual or team experienced uncertainty, and the frequency, magnitude, and duration of these periods would provide pathways forward that leverage increased sensor and analytic capabilities. Such tools could support empirical quantitative comparisons across teams, tasks and experience and help uncover the cognitive interactions between team members with the evolving context. This will enable cognitively informed task designs and accelerate the rates of team and team-member learning by focusing on the cognitively relevant properties of performance.

In this paper, we have presented examples of the type of uncertainty or "surprise" represented by neurodynamic organizations. Earlier studies have shown correlations between the frequency, magnitude, and duration of *NI* fluctuations and team performance. These team performance measures were obtained by two instructors at the U.S. Navy Submarine School using the Submarine Team Behaviors Toolkit, a metric approved by the U.S. Navy Submarine Force (Stevens, Galloway, Lamb, Steed, & Lamb, 2017). These results initially suggested that *NI* fluctuations might be an indicator of team stress/uncertainty, a result that is supported by this study. The result also suggested that large changes in *NI* could target indicators for potential feedback, especially with the suggestion that they may represent periods of uncertainty. The studies in this paper refine these ideas by showing that categories of uncertainty might exist that relate to dynamics seen across teams when challenged.

Across these larger military and health care datasets, we have seen few examples where elevated *NI* occurred in the absence of events important for determining the outcome of the task indicating that *NI* primarily increases around times and events where task events are exceeding the capability of the team members to immediately control. Conversely, events less meaningful for overall task outcomes (like the Handoff in Figure 5), or periods of team member agreement like those clustered around Node 16, or events potentially meaningful, but not recognized as such (Stevens & Galloway, 2015) show little neurodynamic organization.

Machines as Passive Providers of Dynamic Information

How can the dynamics of *NI*-related uncertainty be used to improve teamwork? First, the machine could function as a passive provider of post hoc dynamic information. Training simulations are labor and time intensive, especially the after action reviews where much of the learning is thought to occur (Fanning & Gaba, 2007). The simple provision of *NI* maps (like those in Figures 1 and 4) to the instructor ahead of debriefing could target areas for focused discussion. Or, as data from larger numbers of performances are generated, machines could compare periods of uncertainty with those of other teams to determine their commonality with other teams comprised of similar experience or where there are unique situations for a team.

Machines as Providers of Enhanced Information

In health care, most mannequins do not yet dynamically report changes in physiologic variables in real time. When possible, the details of the evolving tasks could be merged with *NI* models to provide enhanced maps of team performance. These will provide a unique perspective of how uncertainty developed at the individual and team level, and with adequate performance numbers these enhanced and dynamic post hoc models may contain and provide instructional guidance to trainees about how to best handle specific situations.

It will be at this level of machine–human teaming that machines can supply a richer cognitive focus to the feedback by extracting and reporting uncertainty based on a more detailed combination of sensor and frequency information.

Machines as Active Modelers and Dynamic Shapers of Human Behavior

The changing neurodynamic organizations can be used by the machine to determine that an individual is experiencing a difficult situation. Real-time monitoring of individual and team neurodyamics will endow machines with an ability to understand the immediate changing state of human uncertainty. At this level, the machines will transit from being post hoc information providers to dynamic predictors of impending team reorganization based on neurodynamic indicators, that is, predictive models similar to Figure 3, but in real time. These will no longer be for training-based simulations but real-world situations like live patient operations that we have initiated (Stevens et al., 2019). At this level, a machine will need to make its own judgments and possible alternatives transparent to humans to enhance trust.

Although the current studies suggest that SOM classification of different forms of *NI*-related uncertainty can be detected, more detailed brain mappings like those in Figure 1 and 4 indicate there is spatial heterogeneity across the scalp. For instance, in Event 2 the large peak of *NI* between 200 and 300 s (Figure 1b) originated in the P3 scalp region, then switched to the C3 region and switched once again to the C4 region (Figure 1d).

The *NI* levels of the segments used in this paper for training the SOM were across scalp and frequency averages where the *NI* from nine or 19 sensors, each with data points from forty 1 Hz bins, were collapsed into a global measure. It is likely that each of the 55 segments will show scalp region and frequency heterogeneity like those described above, and what appears to be a single type of uncertainty will be resolved into sequences of uncertainty when measured at these finer resolutions. This heterogeneity would be consistent with functional magnetic resonance imaging data showing uncertainty responses distributed across brain regions (Bach & Dolan, 2012), and this redefining of the type of uncertainty may provide links to the underlying cognition. This additional information will better inform the types of scaffolding supplied during real-time monitoring of teams.

These advances will lead to adaptive coaching to maintain uncertainty within limits. The advantages of adaptive tutors are they enable the tailoring of training to specific learning needs, the assessment of learning and performance in minutes versus hours, and the construction of real-time scaffolding rather than post-scenario feedback. Over time, they can also be implemented iteratively to mitigate skill decay.

The important question is how to use this information? In the domain of adaptive automation, assessments made in real time have been referred to as *triggering mechanisms* and form the basis of the assessment-intervention loops (Feigh, Dorneich, & Hayes, 2012). If a machine decides to intervene in the learning process, it will need triggers to identify when to engage an intervention, how long an intervention should persist, and when to disengage the intervention as well as examples for currently lacking constructs, like human uncertainty. The machine will also need to know how to deliver the intervention, perhaps through pedagogical agents (Beal & Stevens, 2011; Stevens, Beal, & Sprang, 2013).

Nearly every human decision, whether conscious or not, has its origins in uncertainty (Tononi, Boly, Massimini, & Koch, 2016). Uncertainty in turn has its origins in what is meaningful for the system, in terms of either short- or long-term survival. We have presented evidence for a candidate measure of uncertainty that applies equally well to individuals, teams, or even groups of teams that is quantitative, dynamic, has high resolution, and is understandable to external observers as well as those experiencing uncertainty. These are all characteristics that would be needed to teach a machine to recognize uncertainty, and to become a transparent and useful partner for humans. The classification of different dynamic trajectories of uncertainty is a beginning step toward these goals.

AUTHORS' NOTE

Preliminary data from these studies were presented at the Human Factors and Ergonomics 63rd International Annual Meeting, Seattle, Washington.

ACKNOWLEDGMENT

The authors wish to thank Dr. Marcia Sprang and the students from Esperanza High School, Orange County, CA; Dr. Ann Willemsen-Dunlap at JUMP Simulation and Education Center, Peoria, IL; and the sailors and staff at the Submarine Learning Center, Groton, CT, for their willingness to participate in these studies.

REFERENCES

Ashby, W. R. (1956). *An introduction to cybernetics*. New York, NY: John Wiley & Sons.

Bach, D. R., & Dolan, R. J. (2012). Knowing how much you don't know: A neural organization of uncertainty estimates. *Nature Reviews Neuroscience*, *13*, 572–586.

Barlow, H. B. (1961). Possible principles underlying the transformations of sensory messages. In W. Rosenblith (Ed.), *Sensory communication* (pp. 217–234). Cambridge, MA: MIT Press.

Beal, C. R., & Stevens, R. (2011). Improving students' problem solving in a web-based chemistry simulation through embedded metacognitive messages. *Technology Instruction Cognition and Learning*, *8*, 255–271.

Buzaki, G. (2006). *Rhythms of the brain*. New York, NY: Oxford University Press.

Caetano, G., Jousmaki, V., & Hari, R. (2007). Actor's and observer's primary motor cortices stabilize similarly after seen or heard motor actions. *Proceedings of the National Academy of Sciences of the United States of America*, *104*, 9058–9062.

Cooke, N. J., Gorman, J. C., & Kiekel, P. (2008). Communication as team-level cognitive processing. In M. P. Letsky, N. W. Warner, S. M. Fiore, & C. A. P. Smith (Eds.), *Macrocognition in teams*. Burlington, VT: Ashgate.

Coutinho, M. V. C., Redford, J. S., Church, B. A., Zakrewski, A. C., Couchman, J. J., & Smith, J. D. (2015). The interplay between uncertainty monitoring and working memory: Can metacognition become automatic? *Memory & Cognition*, *43*, 990–1006.

Daniels, B. C., Flack, J. C., & Krakauer, D. C. (2017). Dual coding theory explains biphasic collective computation in neural decision-making. *Frontiers in Neuroscience*, *11*, 313. doi:10.3389/fnins.2017.00313

Doherty-Sneddon, G., Anderson, A., O'Malley, C., Langton, S., Garrod, S., & Bruce, V. (1997). Face-to-face and video-mediated communication: A comparison of dialogue structure and task performance. *Journal of Experimental Psychology: Applied*, *3*, 105–125. doi:10.1037/1076-898X.3.2.105

Dumas, G., Nadel, J., Soussignan, R., Martinerie, J., & Garnero, L. (2010). Inter-brain synchronization during social interaction. *PloS One*, *5*, e12166. doi:10.1371/journal.pone.0012166.

Entin, E. E., & Serfaty, D. (1999). Adaptive team coordination. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *41*, 312–325.

Fanning, R., & Gaba, D. (2007). The role of debriefing in simulation-based learning. *Simulation in Healthcare*, *2*, 115–125.

Feigh, K. M., Dorneich, M. C., & Hayes, C. C. (2012). Toward a characterization of adaptive systems: A framework for researchers and system designers. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *54*, 1008–1024.

Flack, J. (2017). Life's information hierarchy. In S. I. Walker, P. C. W. Davies, & G. F. R. Ellis (Eds.), *From matter to life: Information and causality* (pp. 283–302). Cambridge: Cambridge University Press.

Flack, J. C., & Krakauer, D. C. (2011). Challenges for complexity measures: A perspective from social dynamics and collective social computation. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *21*, 037108.

Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, *11*, 127–138. doi:10.1038/nrn2787

Friston, K., Kilner, J., & Harrison, L. (2006). A free energy principle for the brain. *The Journal of Physiology*, *100*, 70–87.

Gardezi, F., Lingard, L., Espin, S. L., Whyte, S., Orser, B., & Baker, G. R. (2009). Silence, power and communication in the operating room. *Journal of Advanced Nursing*, *65*, 1390–1399.

Garner, A. J. P., Thompson, J., Vedral, V., & Gu, M. (2017). Thermodynamics of complexity and pattern manipulation. arXiv:1510.00010v3 [quant-ph]. Retrieved from https://arxiv.org/abs/1510.00010

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. Cambridge, MA: MIT Press.

Grant-Orser, A., Davies, P., & Singh, S. S. (2012). The lost sponge: Patient safety in the operating room. *Canadian Medical Association Journal*, *184*, 1275–1278.

Grupe, D. W., & Nitschke, J. B. (2013). Uncertainty and anticipation in anxiety: An integrated neurobiological and psychological perspective. *Nature Reviews Neuroscience*, *147*, 488–501.

Guastello, S. (2015). The complexity of the psychological self and the principle of optimum variability. *Nonlinear Dynamics, Psychology, and Life Sciences*, *19*, 511–528.

Guastello, S. (2017). Nonlinear dynamical systems for theory and research in ergonomics. *Ergonomics*, *60*, 167–193.

Hong, S. L. (2010). The entropy conservation principle: Application in ergonomics and human factors. *Nonlinear Dynamics, Psychology, and Life Sciences*, *14*, 291–313.

Hsu, F. H. (2002). *Behind deep blue: Building the computer that defeated the world chess champion*. Princeton, NJ: Princeton University Press.

Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., & Camerer, C. F. (2005). Neural systems responding to degrees of uncertainty in human decision making. *Science*, *310*, 1680–1683.

James, R. G., Ellison, C. J., & Crutchfield, J. P. (2011). Anatomy of a bit: Information in a time series observation (Santa Fe Institute Working Paper 11-05-019). arXiv:1105.2988v1. Retrieved from http://csc.ucdavis.edu/~cmg/papers/anatomy.pdf

Kepecs, A., Uchida, N., Zariwala, H. A., & Mainen, Z. F. (2008). Neural correlates, computation and behavioral impact of decision confidence. *Nature*, *455*, 227–231.

Knill, D. C., & Pouget, A. (2004). The Bayesian brain: The role of uncertainty in neural coding and computation. *Trends in Neurosciences*, *27*, 712–719.

Kolchinsky, A., & Wolpert, D. H. (2018). Semantic information, autonomous agency and non-equilibrium statistical physics. *Interface Focus*, *8*, 20180041.

Landauer, R. (1961). Irreversibility and heat generation in the computing process. *IBM Journal of Research and Development*, *5*, 183–191. doi:10.1147/rd.53.0183

Likens, A., Amazeem, P., Stevens, R., Galloway, T., & Gorman, J. (2014). Neural signatures of team coordination are revealed by multifractal analysis. *Social Neuroscience*, *9*, 219–234.

Marton, C. D., Fukushima, M., Camalier, C. R., Schultz, S. R., & Averbeck, B. (2019). Signature patterns for top-down and bottom-up information processing via cross-frequency coupling in macaque auditory cortex. *eNeuro*, 6(2), ENEURO.0467-18.2019, doi:10.1523/ENEURO.0467-18.2019

O'Neil, M., & Schultz, W. (2010). Coding of reward risk by orbitofrontal neurons is mostly distinct from coding of reward value. *Neuron*, *68*, 789–800.

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, M. (2011). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence and Neuroscience*, *2011*, 156869. doi:10.1155/2011/156869

Power, C., Denisova, A., Papaioannou, T., & Cairns, P. (2017). Measuring uncertainty in games: Design and preliminary validation. In *CHI EA '17 proceedings of the 2017 CHI conference extended abstracts on human factors in computing systems* (pp. 2839–2845). New York, NY: Association for Computer Machinery.

Rumelhart, D., Hinton, G., & Williams, R. (1986). Learning representations by back-propagating errors. *Nature*, *323*, 533–536.

Salas, E., Stagl, K. C., & Burke, C. S. (2004). 25 Years of team effectiveness in organizations: Research themes and emerging needs. In C. L. Cooper & I. T. Robertson (Eds.), *International review of industrial and organizational psychology* (pp. 56–101). New York, NY: John Wiley & Sons.

Sänger, J., Müller, V., & Lindenberger, U. (2012). Intra- and interbrain synchronization, and network properties when playing guitar in duets. *Frontiers in Human Neuroscience*, *6*, 312.

Schuldberg, D. (2015). What is optimum variability? *Nonlinear Dynamics, Psychology, and Life Sciences*, *19*, 553–568.

Sengupta, B., Stemmler, M. B., & Friston, K. J. (2013). Information and efficiency in the nervous system—A synthesis. *PLoS Computational Biology*, *9*, e1003157.

Shannon, C. E. (1948). The mathematical theory of communication. *The Bell Systems Technical Journal*, *27*, 379–423.

Shannon, C. E. (1951). Prediction and entropy of printed English. *The Bell Systems Technical Journal*, *30*, 50–64.

Silver, E., Hubert, T., Schrittwieser, J., Antonoglou, I., Lai, M., Guez, A., . . . Hassabis, D. (2018). A general reinforcement learning algorithm that masters chess, shogi, and go through self-play. *Science*, *362*, 1140–1144.

Stephens, G., Silbert, L., & Hasson, U. (2010). Speaker-listener neural coupling underlies successful communication. *Proceedings of the National Academy of Sciences of the United States of America*, *107*, 14425–14430. doi:10.1073/pnas.1008662107

Stevens, R., & Galloway, T. (2014). Teams reorganize neurodynamically when they sense loss of control. In D. D. Schmorrow & C. M. Fidopiastis (Eds.), *Foundations of augmented cognition: Advancing human performance and decision-making through adaptive systems. AC 2014—Lecture notes in computer science* (Vol. 8534, pp. 157–166). Cambridge: Springer.

Stevens, R., & Galloway, T. (2017). Are neurodynamic organizations a fundamental property of teamwork? *Frontiers in Psychology*, *8*, 644. doi:10.3389/fpsyg.2017.00644

Stevens, R., Galloway, T., Gorman, J., & Willemsen-Dunlap, A. (2016). Neurodynamic and communication analysis of healthcare teams during simulation debriefings. *Proceedings of the International Symposium on Human Factors and Ergonomics in Healthcare*, *7*, 167–172.

Stevens, R., Galloway, T., Lamb, J., Steed, R., & Lamb, C. (2017). Linking team neurodynamic organizations with observational ratings of team performance. In A. A. Von Davier, P. C. Kyllonen, & M. Zhu (Eds.), *Innovative assessment of collaboration* (pp. 315–330). Cham, Switzerland: Springer.

Stevens, R., Beal, C. R., & Sprang, M. (2013). Assessing students' problem solving ability and cognitive regulation with learning trajectories. In R. Azavedo & V. Aleven (Eds.), *International handbook of metacognition and learning technologies* (pp. 409–423). New York, NY: Springer. doi:10.1007/978-1-4419-5546-3_27

Stevens, R., & Galloway, T. (2014). Toward a quantitative description of the neurodynamic organizations of teams. *Social Neuroscience*, *9*, 160–173.

Stevens, R., & Galloway, T. (2015). Modeling the neurodynamic organizations and interactions of teams. *Social Neuroscience*, *11*, 123–139. doi:10.1080/17470919.2015.1056883

Stevens, R., Galloway, T., Gorman, J., Willemsen-Dunlap, A., & Halpin, D. (2018, October 28). *Making sense of team information*. Paper presented at 2018 Human Factors & Ergonomics National Meeting, Philadelphia, PA.

Stevens, R., Galloway, T., Halpin, D., & Willemsen-Dunlap, A. (2016). Healthcare teams neurodynamically reorganize when resolving uncertainty. *Entropy*, *18*, 427. doi:10.3390/e18120427

Stevens, R., Galloway, T., & Willemsen-Dunlap, A. (2018). Neuroergonomics: Quantitative modeling of individual, shared and team neurodynamic information. *Human Factors*, *60*, 1022–1034.

Stevens, R., Galloway, T. L., & Willemsen-Dunlap, A. (2019). Advancing our understandings of healthcare team dynamics from the simulation room to the operating room: A neurodynamic perspective. *Frontiers in Psychology*, *10*, 1660. doi:10.3389/fpsyg.2019.01660

Stevens, R., Gorman, J. C., Amazeen, P., Likens, A., & Galloway, T. (2013). The organizational neurodynamics of teams. *Nonlinear Dynamics, Psychology, and Life Sciences*, *17*, 67–86.

Stroulia, E., & Goel, A. K. (1994). *Task structures: What to learn?* (Association for the Advancement of Artificial Intelligence Technical Report DD94-02). Retrieved from https://pdfs.semanticscholar.org/1827/0d756809089c99c2a38442017d6fb07b67de.pdf

Szilard, L. (1929). On the decrease of entropy in a thermodynamic system by the intervention of intelligent beings. *Physik Journal*, *65*, 840–866.

Tononi, G., Boly, M., Massimini, M., & Koch, C. (2016). Integrated information theory: From consciousness to its physical substrate. *Nature Reviews Neuroscience*, *17*, 450–461.

Yu, A. J., & Dayan, P. (2005). Uncertainty, neuromodulation and attention. *Neuron*, *46*, 681–692.

Ronald H. Stevens received his PhD in molecular genetics from Harvard University and is professor (emeritus), UCLA School of Medicine and a member of the UCLA Brain Research Institute. His recent research has focused on using electroencephalography-derived measures to investigate team neurodynamics in complex, real-world training settings. These studies are leading to quantitative teamwork models showing how teams dynamically reorganize in response to changing environments.

Trysha L. Galloway is the director of cognitive electrophysiology research for The Learning Chameleon laboratory. Her research interest blends the population-based advantages of probabilistic performance modeling with the detection of neurophysiologic signals to help personalize the individual and team learning processes.