Biologically-Inspired Human-Swarm Interaction Metrics

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Human-swarm interaction is an emerging field encompassing questions related to biology, robotics, computer science, human-computer interaction, and psychology. Swarms are large groups of individual entities that enact group behaviors; biological examples include fish, birds and insects. Swarms overwhelm humans' abilities to monitor and interact with each entity. Human-robot and human-computer interaction metrics are inappropriate to describe human-swarm interactions alone due to the interaction challenges posed by swarms. It is unknown precisely how humans respond to interacting with swarms. The theory is that biological swarm metrics may be appropriate for analyzing human-swarm interaction. Nine human-swarm interaction metric categories derived from the biological and robotic swarm literature are presented, including example metrics from each category. This paper opens the discussion regarding what types of existing swarm metrics may be applicable and what categories of metrics will be important for human-swarm interaction assessment.

INTRODUCTION

Humans will direct groups of autonomous robot swarms in the near future (Cummings, 2004). Human-swarm interaction (HSI) is an emerging field encompassing research in biology, robotics, computer science, and psychology. A subfield of human-robot interaction, HSI involves understanding and assessment of how humans interact with a swarm. It is important to consider the human's performance when working with the swarm, in order to inform interface design, task assignment strategy, and team performance predictions.

Swarms contain large numbers of individual entities, be they fish, insects or starlings. A swarm in the context of this paper consists of >50 entities, either agents or robots (Hayes & Adams, 2014). The swarm is composed of individual agents with limited capacity for individually accomplishing goals, but, as a group, it performs complex tasks. The micro-level actions (i.e., individual agent behavior) of each swarm member results in the desired macro-level behavior (i.e., swarm behavior).

Common metrics evolve as the essential research questions of a new field are revealed (Steinfeld et al., 2006). A set of human-robot interaction metrics was first presented in the context of assessing the task, the system performance, and the operator performance. These aspects of human-robot interaction are also relevant to HSI. All appropriate HSI metrics will not stem from human-robot interaction metrics, because swarms present new attentional demands and have higher levels of uncertainty (e.g., individuals' navigation, communication reliability (Hayes & Adams, 2014)).

Current HSI research includes investigating different interaction modes. Some interfaces require direct interaction with individuals on the micro-level (e.g., change one robot's heading (Dudenhoeffer, Bruemmer & Davis, 2001), and thus require visualizing the swarm state at the individual agent level (Vasile, Pavel & Buiu, 2011)). These systems assume that there is access to updated information about the state of each swarm member, which is not always possible.

Some researchers postulate that it is beneficial for the human to focus on macro-level control (Lee, 2001; Brown, Kerman & Goodrich, 2014), where interaction may occur with a subset of individual agents (e.g. leaders or stakeholders) (Kerman, Brown & Goodrich, 2012). The stakeholders influence the swarm's actions to create change in the exhibited macro-level behaviors.

Communication reliability is an important HSI consideration, in addition to interaction mode. Low- medium- and high-bandwidth situations were evaluated (Nunnally et al., 2012). Medium-bandwidth communication allowed the participants to complete tasks, indicating that in real-world scenarios without perfect communication, humans have a chance to complete tasks with a swarm. HSI can occur within direct contact and line of sight of the swarm (e.g., Podevijin, O'Grady & Dorigo, 2012), but this paper assumes that interaction with a swarm occurs via computer interface, without direct line of sight.

HSI metrics have not yet been designated. The development of such a set of metrics enables concrete comparisons between alternate algorithms and methods. Additionally, the relationships between specific metrics can be explored (e.g., the interactions between the operator performance, system performance and assessment of the task).

This paper posits that biological swarm metrics may be appropriate for assessing HSI. Additionally, robotic swarm research has adapted some metrics from human-robot interaction (e.g., neglect benevolence (Walker et al., 2012)), and proposed robotic swarm-relevant concepts (e.g., span of control (Goodrich, Kerman & Jung, 2012)). This paper defines nine HSI metric categories and provides examples based on biological swarms. A discussion of the potential use and limitations of the presented HSI metrics is also provided.

THEORY

Human-swarm interaction is a new sub-field of human-robot interaction (e.g., McLurken et al., 2006; Brown et al., 2014; Nunnally et al., 2012). The human-robot interaction literature has investigated the concept and challenges of interacting with multiple robots (e.g., Tews, Mataric & Sukhatme, 2003). Swarms have significantly more entities (i.e., >50); thus, the assumptions for interaction with multiple-robot systems may not apply to HSI. Humans can only maintain individualized knowledge of a limited number of robots (Adams, 2005).

McLurken et al. (2006) identifies handling human input at the macro-scale, without requiring supervision of individual swarm members as a central problem for HSI-capable systems. The human supervising the swarm needs support to maintain awareness of the entire swarm's status, because humans cannot adequately attend to more than a handful of simultaneously moving objects. Psychological science has determined that humans have a severe limitation in tracking multiple moving objects (Alvarez & Franconeri, 2007; Tombu & Seiffert, 2008)). It is also not possible to expect real-world HSI tasks to ensure reliable communication with each swarm entity in most situations, due to environmental and technological limitations (e.g., bandwidth, latency).

A common set of HSI metrics does not exist. HSI metrics cannot necessarily be adapted from other domains (e.g., human-robot interaction) due to the unique characteristics swarms present. Swarms produce macro- and micro-level behavioral differences, have greater uncertainty, potentially visualization overload, and contain >50 entities.

The decades of biological swarm research (e.g., Kilgour & Scott, 1959) describes agent-swarm behaviors that are not covered currently by human-robot interaction. Collective animal behavior demonstrates complex movement, communication, and leadership behavior (Leonard, 2013).

Swarms of agents are often designed to emulate behaviors of biological swarms (e.g., flocking, foraging). Collective animal behavior has been modeled for swarms (e.g., Goodrich, Sujit, Kerman, Pendleton & Pinto, 2011) and implemented on robots (e.g., Garnier, Combe, Jost & Theraulaz, 2013). Swarm controllers have also been devised from animal behavior (Ferrante et al., 2012). Artificial swarm behavior is informed by swarm behavior; thus, descriptive metrics of biological swarm behavior will be relevant to artificial swarm behavior. These metrics will assess humans' ability to track changes in and accomplish tasks with swarms.

The biological research uses metrics to capture the unique swarm attributes. For example, metrics such as mutual diffusion (i.e., how much a swarm member moves relative to its neighbors (Cavagna, Queirós, Giardina, Stefanini & Viale, 2013)) and rule size (i.e., the number of influential neighbors for each agent (Parrish, Viscido & Grünbaum, 2002)) encompass distinct phenomena related to swarms that are currently not defined for human-robot interaction. These metrics were developed for swarms of birds and fish, but can be adapted for use in agent swarms in order to develop metrics that encompass the true challenges of HSI.

HUMAN-SWARM INTERACTION METRICS

A review of the biological and robotic swarm literature resulted in fifty-four metrics applicable to HSI. These metrics were divided into nine categories according to their definitions, use, and relation to HSI. Each of the categories are first defined in the context of HSI, and relevant biological metrics follow. Examples are provided for each category, but, due to space limitations, only one example is defined in detail.

Human Attributes

Human attribute metrics encompass human factors-based responses when humans interact with swarms. The human attributes are affected by swarm behavior and include metrics from human factors, human-computer interaction and human-robot interaction.

Intervention frequency is an example of an objective human attribute measure. It represents the frequency with which the human interacts with the swarm per unit time (Walker et al., 2012). *Trust* in automation plays an important role in HSI. Lee (2001) postulated that too much trust results in over-reliance on the automation's perceived capabilities. *Situation awareness* represents the human's capacity to maintain a mental model of the world's state (Endsley, 1996). Situation awareness is an important HSI metric, because of the inherent complexity in visually tracking a swarm may influence situation awareness throughout the task. Other relevant human attributes include workload and vigilance.

Task Performance

Task performance refers to the human's ability to accomplish the overall task or subtask assignment during the mission. Task performance can encompass the quality with which the goal is achieved, the speed of performance, or the task progression status prior to mission completion. Specific task performance metrics include total coverage (Walker et al., 2012) and mode error (Lee, 2001).

Resource depletion is an objective metric representing the irreversible consumption of a resource by a swarm member (Goodrich et al., 2011). Goodrich et al.'s HSI evaluation modeled the depletion of resource (*j*) with size (*S*) as:

$$S_j(t+1) = S_j(t) - \widehat{N_s}\,, \tag{1}$$

where $s > 0$ represents the amount of the resource to be depleted by each agent and $\widehat{N_s}$ is the number of agents within r_s meters of the resource. Eq. 1 is based on models of collective animal swarm foraging behavior (Sumpter, 2006). Extending the model to represent information foraging (i.e., considering the task to complete as a "resource" placed in the swarm's environment), this metric can be used to assess the human's influence on the swarm's task performance. Higher resource depletion can reflect higher task performance.

Task performance relates to human attributes. Workload overload may result in decreased task performance. Higher intervention frequency may also relate to task performance changes, depending on task type. Other future assessments may evaluate previously established laws from other domains, such as the Yerkes-Dodson law, which relates arousal and performance levels (Yerkes & Dodson, 1908) in HSI scenarios.

Timing

Timing metrics record the global or local occurrences of significant events or the time elapsed between such events. Timing measurements can reflect the human operator's ability to accomplish tasks swiftly, respond promptly to changes, and supervise the swarm in an operationally efficiently manner. Example metrics include settling time (Ferrante et al., 2012) and behavior emergence time (Goodrich et al., 2011).

Mutual delay time is an objective metric defining the time between two swarm members enacting the same behavior (Attanasi et al., 2013). The mutual turning delay times for birds within a flock reflected communication patterns (Attanasi et al., 2013). Mutual delay time is a relevant HSI metric, because it can capture the way information moves across a swarm. For example, the mutual delay time between a leader and all other swarm agents is useful to gauge how fast the entire swarm follows (or does not follow) the leader's action. Mutual delay time is a relevant metric to inform the human of how fast information propagates within the swarm. The human's speed in recognizing and ability to recognize information propagation is dependent upon the mutual delay time. Human attributes, such as intervention frequency and situation awareness, may change depending on swarm timing.

Status

Status metrics refer to the swarm's current condition and include values that change during the mission (e.g., number of stragglers (Parrish et al., 2002)) and static values set before deployment (e.g., rule size). Status can reflect human's ability to maintain the swarm to standards. Examples of status metrics include subgroup size (Spears, W.M., Spears, D.F., Hamann & Heil, 2004), and collision count (Parrish et al., 2002).

The number of *stragglers* represents the number of swarm members that have traveled outside of a minimum distance threshold from the swarm. Parrish et al. (2002) defined stragglers as those fish more than five body lengths away from the rest of the swarm. The number of stragglers is relevant to agent swarms, because large numbers of agents moving together will inevitably leave some members behind that become damaged, lost, or lose communications with the rest of the swarm. The number of stragglers can reflect environmental conditions, obstacles, resources, and also the human's control over the swarm. The relationship between the number of stragglers and the human attributes, such as workload, may reveal an inverse relationship; as the human's workload nears overload, the number of stragglers may increase. Poor commands issued to the swarm or other human errors may increase stragglers. Additionally, monitoring the human's ability to track swarm status information can provide information regarding the human's situation awareness.

Leadership

Leadership metrics track swarm members that possess unique knowledge (i.e., leaders), and the potential transferal of that knowledge from the leaders to the rest of the swarm (Guttal & Couzin, 2011). If leaders are HSI facilitators, then visualization of and interaction with leaders may differ from that of the remaining swarm members. Examples of leadership metrics include proportion of informed individuals (Ferrante et al., 2012) and span of control (Goodrich et al., 2012).

Turning order objectively measured how long it took each bird to respond to the leader's actions (Attanasi et al., 2013). *Action order* is an objective, generalized version of turning order for HSI representing the ranking of each individual in a swarm by the order in which members complete a specific action or enacted a behavior (e.g., set orientation to 30°, reached a goal). This metric requires defining the action or behavior of interest and the global time at which each member performs it. Due to the very large number of agents, it is impossible for a human to track every individual simultaneously, but tracking the action order of the agents may reveal information about the human's situation awareness.

Decisions

Decisions represent how subsequent swarm actions are chosen. The human can determine future swarm tasks, and these metrics can reflect decision quality. Decisions regarding a swarm can be made by a swarm leader, a human, a combination of the two, or the aggregation of swarm's knowledge (Katsikopoulos & King, 2010).

Decision accuracy represents the likelihood that a correct or preferred outcome results from a single instance of the decision process (e.g., a leader choosing the shortest path, or not, to a goal location). Decision accuracy was analyzed in relation to the proportion of informed individuals in a swarm (Torney, Levin & Couzin, 2013). As group size increased, the same level of accuracy was maintained with relatively fewer informed individuals. Accuracy also increased as the number of leaders increased. Decision accuracy is measured on a scale from 0 (random choice) to 1 (always correct) and is influenced by individual behavior, degree of available information, and swarm size. Decision accuracy can reflect how well the decision-making process was handled by the human. The need for the calculation of decision accuracy in swarms is unique due to the ways a swarm can be managed (e.g., choosing leader(s), majority-based decision-making), which differs from human-robot interaction. Decision type may relate to the human's trust levels in the swarm and resultant intervention frequency.

Communications

Metrics in the communications category reflect how information is passed between swarm members or the human and the swarm. Communications metrics assess information quality within the swarm and the strength of the communication network created by the swarm members. An example communications metric is cohesion (Walker et al., 2012).

Network efficiency (Mersch, Crespi & Keller, 2013) is the rate of information flow measuring how fast behavioral changes move across a swarm. Network efficiency requires providing information to carriers and measuring the time to pass information between swarm members to a desired goal location, state, or specific swarm member. The rate of information flow and the maximum rate of information flow were measured in an ant colony (Mersch et al., 2013). Network efficiency compared information transmission speeds in multiple differing swarm communication models (Strandburg-Peshkin et al., 2013). Network efficiency was also measured via a dispersion law to assess information flow rates for starlings (Atanasi et al., 2013). The rate of information flow can determine the effectiveness of swarm communication strategies. Differing communication models can also be compared.

Network efficiency may affect the measured levels of other HSI metrics. Measuring network efficiency provides context during HSI for the human; for example, if known, a lower network efficiency may provide context for longer mutual delay time and prevent the human from increasing his or her intervention frequency. Additionally, network efficiency and other communications metrics are relevant for HSI because of the swarm-specific inherent communication complexity. Network efficiency can impact decision-making and the way that tasks are defined. There is also potential to reflect the human's ability to assess information flow rates as an aspect of maintaining situation awareness.

Micro-level Movements

Micro-level movements measure how swarm members travel on an individual basis and in relation to one another in order to accomplish task goals. Micro-level movements also reflect the human's ability to communicate mission goals to the swarm. Example metrics include mutual diffusion and border survival probability (Cavagna et al., 2013).

Neighbor overlap represents a micro-level movement metric referring to changes over time in a swarm member's neighborhood (Cavagna et al., 2013). Neighborhood overlap is measured for an individual swarm member and is defined as:

$$Q_{M(t)} = \frac{1}{N}\sum\frac{M_i(t)}{M}, \tag{2}$$

where $M_i(t)$ is the number of swarm members among the M nearest neighbors of bird i at both t_0 and $t + t_0$. N is the swarm size. Neighbor overlap indicates the amount of relative position reshuffling and can be relevant during specific situations, such as leadership changes or long duration tasks. Neighborhood overlap encompasses the swarm-specific concept of agent dispersion among the swarm over time. Neighborhood overlap can be tracked for an agent of interest, such as a leader, to assess how many other swarm agents the leader can affect during a specific time period. Tracking the human's knowledge of individual movements (e.g., how a leader repositions itself in the swarm) may reveal situation awareness information. The ability to track micro-level movements may be subject to limitations of vigilance and inversely related to workload.

Macro-level Movements

Macro-level movements refer to the entire swarms' movement patterns. This movement metric characterizes attributes, such as the swarm's physical shape (e.g., elongation (Couzin Krause, Franks & Levin, 2005), direction (e.g., orientation error (Spears et al., 2004), and the center of gravity (e.g., Leca, Gunst, Thierry & Petit, 2003). These measurements reflect the human's ability to monitor and modify swarm activity during a mission.

Elongation characterizes the rectangular shape of the swarm (Couzin et al., 2005) and is defined as the ratio of the length (i.e., along the direction of travel) to the width (i.e., perpendicular to the direction of travel) of a bounding box surrounding the swarm. Robotic swarms may include leadership aspects and degrees of information passed along the members. Elongation is pertinent for HSI because the human supervisor will be unable to monitor the location of each individual swarm member. He or she must have methods of discerning general information regarding the macro-level movement. Swarm movements reflect the human's ability to track the swarm's macro-level changes, which may be affected by the human's intervention frequency. Intervention frequency may overlap with the human's level of trust in the swarm and situation awareness during the mission.

DISCUSSION

Agent and robotic swarms are becoming an inevitable reality. As the HSI field expands, so does the diversity in ideas and opinions regarding the best swarm supervision, control, and interaction techniques, thus motivating the development of appropriate metrics to allow for comparisons. Swarms pose unique challenges that are not captured fully by metrics for other domains, including information overload and uncertainty, macro- vs. micro-level behavior representation and control.

HSI is a field that developed as a branch of human-robot interaction, yet the field's metrics are insufficient for assessing HSI on their own. Human-robot interaction focuses on maintaining awareness of individual robot(s) and their behaviors; however, HSI goals are to maintain awareness and control of the swarm as an entity, as well as the swarm members on an individual level.

The presented metric categories encompass the important HSI challenges, and each category, except for the human attributes category, contains metrics derived from the biological swarms literature. The biological swarms literature provides appropriate metrics in all categories, but biological swarms do not typically reflect human intervention or interaction with the swarm. All of the challenges that swarms bring to HSI cannot be addressed with human-robot interaction metrics alone, but they cannot be addressed solely with biological swarms metrics either.

The human's role is what unites HSI with human-robot interaction and human-computer interaction. HSI must look to those fields for human attribute assessment techniques. It is important to remember that the human attributes metrics category interacts with each of the other metric categories. The set of appropriate HSI metrics need to integrate the biological-inspired swarms metrics with user-centered metrics from other domains.

There are limitations to the presented metrics. Few highly sophisticated HSI systems have been developed at the current time. HSI system attributes will depend highly on many design factors that will vary by individual system, including the physical swarm entity implementations, communication capabilities, and the operator interface. It is crucial to consider that real-world HSI deployments will have a high degree of uncertainty as well as imperfect communications and swarm feedback Future work will include validating metrics using robot and agent swarms, while tracking human performance in relation to the presented and additional HSI metrics.

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