Preface

Hybrid group autonomy, organizations and teams composed of humans, machines and robots, are important to AI. Unlike the war in Iraq in 2002, the war in Afghanistan has hundreds of mobile robots aloft, on land, or under the sea. But when it comes to solving problems as part of a team, these agents are socially passive. Were the problem of aggregation and the autonomy of hybrids to be solved, robot teams could accompany humans to address and solve problems together on Mars, under the sea, or in dangerous locations on earth (such as, fire-fighting, reactor meltdowns, and future wars). "Robot autonomy is required because one soldier cannot control several robots … [and] because no computational system can discriminate between combatants and innocents in a close-contact encounter." (Sharkey, 2008)

Yet, today, one of the fundamental unsolved problems in the social sciences is the aggregation of individual data (such as preferences) into group (team) data (Giles, 2011) The original motivation behind game theory was to study the effect that multiple agents have on each other (Von Neumann and Morgenstern, 1953), known as interdependence or mutual dependence. Essentially, the challenge addresses the question: why is a group different from the collection of individuals who comprise the group? That the problem remains unsolved almost 70 years later is a remarkable comment on the state of the social sciences today, including game theory and economics. But solving this challenge is essential for the science and engineering of multiagent, multirobot and hybrid environments (that is, humans, machines and robots working together).

Bonito and colleagues (2010) explain why aggregating individual information for human groups is unsolved: "What remains to be clearly elucidated, is how communication among members provides opportunities to make decisions that are not possible by examining only individual competencies, abilities, and motivations." We suspect that if aggregation cannot be solved for human groups, it will be more difficult to solve with AI for hybrid groups.

Aggregating data from teams is not direct: unlike an object in physical reality, each agent sees events in social reality while embedded in different locations; agents are differentially collecting, sending or receiving information with other agents; and uncertainty is a factor in these different information flows.

For teams, we suspect that social uncertainty operates on two tracks. One is based on measurement, the other on probability distributions over allowed states. The first reflects physical characteristic of interdependence (bi-stability and multi-stability, for example, two or more sides exist to every story), while the second reflects an incomplete knowledge about a system as its degrees of freedom increase.

Hybrid agent teams must be able to report on their situation. Reports by humans are often reduced to ordinal data (such as with Likert scales, say, from 1 to 6). But "[t]he notion that modern economic theory can be founded on ordinal utility theory is an error." (Barzilai, 2010, p. 2) The problem was illustrated well for human agents when no correlation was found between the productivity of organizations and the assessments by managers (Bloom et al., 2007). Whether computational hybrid systems will be afflicted by the same problem is an open question.

This AAAI Symposium has in mind an approach to the solution of the following, nonexhaustive list of questions for hybrid teams:

(1) What makes a group autonomous? (2) Is individual autonomy possible for a single hybrid agent (Sharkey, 2008)? If so, can an autonomous individual agent be a social member of a team? What else might be different? (3) Related to question 2, why are hybrid agent reports of behavior not the same as observed behavior? (4) Why are groups, unlike individuals (Wickens, 1992), able to multitask effectively (Ambrose, 2001) and, from an information theory perspective, more efficiently (Conant & Ashby, 1970)? (5) Human systems perform differently depending upon whether they are organized and controlled centrally or locally (see Ahiedh, 2009; Hayek, 1994). This question addresses the theoretical perspective of information flow; for example, is information about a hybrid organization's defenses transmitted with natural language better than the information obtained from observing the same organization's performance under a social perturbation (such as organizational volatility as a consequence of a cyber-attack)? (6) As an alternative to question 4, is the rational construction of reality derived competitively at the individual level different from the dynamic information derived cooperatively at the organizational level? (7) Why isn't the production of hybrid social autonomy a simple problem? (8) What would a mathematical model of aggregation look like (Lawless et al., 2010)? Would such a mathematical model account for social autonomy; the inability of an agent's reports to capture its behavior; and the differences observed between the results obtained with the applications of game theory to the toy problems favored by researchers (viz., normative solutions) versus the real solutions found in the field made by autonomous organizations of humans (such as Apple, Google)?

General Comments

This symposium will bring together researchers interested in how aggregation for humans, machines and robots can be applied directly to solve problems with AI more efficiently or to address previously unsolved problems in other fields with AI. We provide three aspects of the same problem.

First, in the hybrid social model, as opposed to the statistics of frequencies in traditional analyses, measurements collapse the interaction between say two hybrid agents into two single-agent meaning states. That these two meaning states can be reported separately necessarily loses the dynamic actor-observer information being exchanged during an interaction.

Second, one of the unsolved problems in social science is the social interaction (Allport, 1962), long considered unsolvable with traditional psychology (Jones, 1990). Scientists know that measuring human participants in an interaction changes their thoughts and behavior (Carley, 2003). One speculation is that a computational model which tracks bi-stable changes actually tracks non-commutative interdependencies in human action and observation as believed by Bohr (1955) and Heisenberg (1958). This means that researchers must find a way to instantiate "mutual awareness" among interacting agents that then "collapses" into individual agent facts when "measured", but consequently, losing social information (Wendt, 2005).

Third, organizational theory today is in a poor state (Pfeffer and Fong, 2005). Solving the fundamental interaction problem in AI may be key to engineering computational

multi-agent systems, multiple human-robot systems, and robot-robot or hybrid systems. It is possible that the interaction will be solved computationally with brute force, but, we suspect, not efficiently.

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