Guest Editorial: Special Issue on Human–Machine Symbiosis

MORE than 55 years have passed since Licklider published his seminal paper titled "Man-Machine Symbiosis" [item 1) in the Appendix], and yet, despite that time Licklider's argument still resonates today; a vision that seems to be plausible in the not-so-distant future. In 1960, Licklider noted that "A multidisciplinary study group, examining future research and development problems of the Air Force, estimated that it would be 1980 before developments in artificial intelligence make it possible for machines alone to do much thinking or problem solving of military significance. That would leave, say, five years to develop man-computer symbiosis and 15 years to use it. The 15 may be 10 or 500, but those years should be intellectually the most creative and exciting in the history of mankind." On a conceptual level, Licklider's vision has certainly been extended to include (in a chronological order of their appearance in the literature): Biocybernetics [item 2) in the Appendix], Brain Computer Interfaces [item 3) in the Appendix], Adaptive Aiding [item 4) in the Appendix], Adaptive Automation [item 5) in the Appendix], Human-Machine Teaming, Augmented Cognition [item 6) in the Appendix], Cognitive-Cyber Symbiosis [item 7) and 8) in the Appendix], and Human-Autonomy Teaming [item 9) in the Appendix]. By way of engineering, most of these concepts have actually already been implemented in one form or another. The field of Air Traffic Control has served as "the" testbed for almost all of these concepts. However, more recently, autonomous systems are rapidly becoming a new and most interesting testing environment.

The field of Computational Intelligence (CI) continues to introduce game-changing and disruptive technologies with the potential for large acceleration of the human-machine symbiosis. Deep learning is resulting in machines that are smarter and adaptive. Fuzzy systems offer opportunities to provide more human-like processing and transparency for humans to understand what their machine counterparts are doing. Evolutionary computation can be used to optimize and adapt these systems. Swarm intelligence offers the foundation for effective machine teaming. Behavioral analytics using CI can be used to convert low-level actions by both humans and machines into high-level meaning. Yet, the literature on the use and effect of these tools on human-machine symbiosis is dispersed over scientific areas and researchers. This special issue aims to help foster a synergy of thought in this emerging direction.

The first paper in the special issue focuses on two central principles that enable effective interaction. Patterson and Eggleston first focus on the need to develop common meaning and representation for the objects that surround us. Researchers in artificial intelligence are familiar with the symbolic grounding problem, where the association between symbols, such as "words" and objects in the environment need to be defined clearly. To put it simply, how did we come to decide to call a chair a "chair"? Symbolic grounding could be solved for each agent independently, but given that approach, there is no guarantee that the two agents will refer to the same concept with the same word. A "common meaning" fundamentally refers to the problem of symbolic grounding across agents, but it also extends from the level of symbols to the level of symbol "interpretation." Common meaning is foundational for common understanding and its resulting improved human-machine interaction. Patterson and Eggleston follow the discussion with a second factor: common expertise. There is a level of interdependency between meaning and expertise. Experience allows agents to interpret information. Agents are unlikely to develop common meaning if their expertise is unique and not of interest to other agents.

Having established the two factors of common meaning and expertise as necessary conditions for effective synergism, in the second paper, Demir, McNeese and Cooke explore the impact of human perception of an autonomous system in two settings. In the control group, a team of humans was told that the "synthetic" agent they were working with was a real human. In an experimental group, the human team was told the truth about the synthetic agent-that it was a machine. The results suggest that humans were able to improve their control with this information. Such a finding from this study has important implications for the effectiveness of human-autonomy teaming. While it is believed, and indeed it is important, that the performance of an autonomous system will directly effect the human operator's trust in the system, Demir *et al.* demonstrate that even for the same autonomous system, trust is impacted by the mere perception of a machine being in the loop as a team player.

If we assume that over time, humans may become more comfortable in dealing with machines in beneficial relationships, we need to continually educate and adapt the machine so that its performance continues to match human expectation. The paper by Peng, MacGlashan, Loftin, Littman, Roberts, and Taylor discusses the relationship between the reward an artificial learner receives (through a process such as reinforcement learning), the quality of curricula, and the ability of non-experts to produce curricula in the absence of rewards. The impact of the work rests in the insights generated on how machine learning algorithms accommodate machine and human created curricula.

A new communication between humans and machines can be developed through a direct machine-to-human brain interface.

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Wang, Abdelfattahy, Moustafa, and Hu present a deep learning model that results from hybridizing the embedded information within an autoencoder trained on EEG data as features for the hybrid model to classify the signal. They achieved a high classification accuracy on two EEG tasks, suggesting that it is possible to improve the speed and accuracy of understanding information coming directly from the human brain.

Chavarriaga, Uscumlic, Zhang, Khaliliardali, Aydarkhanov, Saeedi, Gheorghe, and Millán offer a case study that uses EEG data to enhance human driving. EEG data is used as input to an automated driving assistant. Through their experiments, Chavarriaga *et al.* demonstrate that the EEG data offer information on human anticipation, movement preparation, and error processing. This information is key towards augmenting automated driving assistants with contextual information to improve the driving experience.

The five papers in this special issue present a slice from a very rich and diverse literature. They demonstrate that many still unexplored opportunities remain for improved human-machine symbiosis. For example, EEG could be used to understand the mechanisms by which humans derive meaning from sensory information. This understanding could be used by machines that extract and interpret information in similar ways. If both humans and machines extract equivalent meanings, it is plausible that it will lead to an improved shared understanding, which results in effective interaction. The approach by Wang *et al.* could be used to extract this knowledge from EEG data or at least, use the EEG data to detect if particular concept is understood by a human. We acknowledge that current scalp-level EEG data of today may not have sufficient resolution to do this. But looking to the future, it may be possible; in this case, the approach by Peng *et al.* could be extended to design the curriculum for the machine to learn to share this interpretation and meaning with a human partner. We hope that this special issue helps convert an emerging science into eventual fulfilment of Licklider's promise of human-machine symbiosis.

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APPENDIX
RELATED WORK

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4) W. B. Rouse, "Adaptive aiding for human/computer control," *Human Factors: J. Human Factors Ergonom. Soc.*, vol. 30, no. 4, pp. 431–443, 1988.
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Hussein A. Abbass, biography not available at the time of publication.

Gary Fogel, biography not available at the time of publication.

Justin Fidock, biography not available at the time of publication.