Guest Editorial
Special Issue on Systematic Approaches to Human–Machine Interface: Improving Resilience, Robustness, and Stability

I. INTRODUCTION

We are pleased to present the special issue on “Systematic Approaches to Human–Machine Interface: Improving Resilience, Robustness, and Stability.” The motivation for this special issue is the growing increase of remote mission management, unmanned aircraft systems, NextGen operations in the U.S. and its Single European Sky Air Traffic Management Research counterparts in Europe, and other similarly integrated systems of systems that include complex human–machine systems with high levels of autonomy and team dynamics that are difficult to understand and analyze. It is important to develop techniques that facilitate a better characterization of the behaviors and performance of these complex systems, first in the lab and, then, in the field. Techniques including formal verification, cognitive modeling, and task analysis are being explored in several disciplines [1], [2]. These efforts strive to quantify resilience, robustness, stability, and other properties of these complex systems. This special issue presents papers which epitomize interdisciplinary works that cross the various communities studying these important and complex human–machine interactions. The issue explores key research areas that impact the properties of these systems, which rely on varied degrees of human and machine interactions.

The special issue is a result of the continued interest in the formal verification of complex human–machine systems. For example, at the 2011 IEEE International Conference on Systems, Man, and Cybernetics in Anchorage, AK, researchers from Belgium, France, Israel, Italy, and the United States came together to present and to discuss research in a session entitled “Applications of Formal Methods to Human–Automation Interaction.” In May 2012, more researchers met at the Imperial College in London for the Workshop on Formal Methods in Human–Machine Interaction (Formal H). An even larger group presented at the workshop entitled Formal Verification & Modeling in Human–Machine Systems at the AAAI 2014 Spring Symposium. These sessions and workshops brought together experts from many communities to explore key research areas, common solutions, near-term research problems, and advantages in combining the best of different communities such as formal verification, cognitive modeling, and task analysis to study the design and verification of real human–machine systems. Recent papers in each of these communities discuss modeling challenges and the application of basic formal verification in human–machine interaction; however, there is often little communication between researchers in these different areas, and there are many open questions that require cross-disciplinary collaboration. The goal of these sessions and workshops was to bring together experts from many communities in an environment where it is possible to explore key research areas, common solutions, near-term research problems, and advantages in combining the best of the different communities.

II. RELATED WORK

The terms resilience, stability, and robustness all have long histories in everyday language, with their first uses from the 19th, 14th, and 16th centuries, respectively. All of these terms derive from Latin words, resiliere (to jump back), stabulum (to stand), and robustus (oaken). Thus, in everyday language, these three terms focus on an ability to resist external forces and to maintain some form of essential constancy.

As in everyday language, the uses of resilience, stability, and robustness in science and engineering center around the ability to resist external forces. An early comparison of resilience and stability in science came from Holling (1973) who applied these constructs to ecological systems [3]. Holling proposed that resilience is the ability of systems to persist as a function of flexible responses to a perturbation, whereas stability involves a rapid return to an initial state following a perturbation. He further distinguished application of the stability and resilience approaches to resource management, with resilience focused on keeping options open, whereas the stability approach would attempt to maintain a predictable ecosystem with limited fluctuation.

Much like Holling’s concept of resilience and the acceptance of fluctuations in the world as given, Hollnagel et al. proposed that Resilience Engineering attempts to increase the ability of a system to succeed in the face of the fluctuations in the operational conditions [4]. Note that Hollnagel et al.’s more recent approach to resilience engineering changes from their initial writings [5], in which they defined resilience as the ability to return to regain a stable state following a perturbation. The 2006 definition more closely resembles Holling’s concept of stability, whereas the 2011 definition is in line with Holling’s concept of resilience.

In a 2008 review [6] of human error and resilience engineering, Sheridan suggests that resilience is a “family of ideas” (p. 423) and lists different definitions that have been applied to resilience engineering, including one definition that is consistent with the return to initial equilibrium concept of stability from...
Holling [3] and resilience from Hollnagel et al. [5], and another definition “flexibility and adaptability in responding to surprises so as to mitigate any undesirable consequences” (p. 428) that is consistent with the concept of resilience from [3] and [4].

A key insight from the early conceptions of resilience engineering, e.g., [5], especially in its application to human error and system safety, is that the perturbations to which a resilient system has to respond flexibly typically come from the variability in human performance. That insight lead to the realization that this human performance variability is often an underlying cause of both successful human performance and errors.

Robustness engineering derives from the post World War II reconstruction of the Japanese industrial system, particularly the ideas proposed by Taguchi et al. (for a review, see [7]). Taguchi et al. defined robustness as the ability to minimize sensitivity to perturbations that cause variability in an outcome [8]. That is, in accord with its Latin derivation, robustness in this sense involves resistance to outside influences that might affect performance. Thus, these three terms, applied in engineering and science, provide three slightly different approaches to perturbations caused by variations in human performance or fluctuations in an operational environment: 1) the quick return to normal of stability; 2) the flexibility of responding of resilience; and 3) the resistance to the effects of perturbations of robustness.

III. OVERVIEW

The central theme in the contributions selected in this special issue is modeling, and they illustrate the utility of models in system design, analysis, optimization, and verification of human–machine systems. To show the breadth of how models are employed for human–computer systems, the contributions are grouped as follows: model checking (verification), optimization, risk analysis and robustness, and human–machine interface analysis.

In each of the contributions, the model changes to meet the goals of the analysis. The models abstract aspects of the systems that are not fully relevant while retaining characteristics that are critical to the problems being explored. In all instances, the models are used in a formal way. Formal in this context means that the models have a precisely defined semantics, and the meaning of the analysis, including the limits of its results, is equally defined with rigor as well.

A. Model Checking

Model checking is the process of proving a property of a model [9]. Specifications about the system are expressed as temporal logic formulas [10]. Efficient symbolic algorithms are used to traverse the defined formal system model and check if the specification holds. When there is a violation of a specification (the criteria in the specifications do not hold), an execution trace called a counterexample is produced. This counterexample depicts a model state (a valuation of the model’s variables) corresponding to a specification violation along with a list of the incremental model states that led up to the violation (a trace). Such a trace is useful in distinguishing potential unsafe steps or issues with the manual.

Model checking is an important area of interest due to its relevant social impact in improving the reliability of complex systems. A few recent examples include: the application of model checking to aircraft automation to help uncover problematic human–automation interaction [11]; the automatic generation of properties from task models for detecting human–automation surprises [12]; the automatic characterization of human activities in temporal logic that provide properties for the verification of ambient-assisted living applications [13], and an approach to help improve user manuals for medical devices [2]. These represent a small sampling of the social relevance of model checking in human–machine interaction.

There are three contributions in this special issue that each apply model checking to different aspects of human-machine systems. The first contribution from Bolton et al., Using Model Checking to Detect Simultaneous Masking in Medical Alarms, exploits the ability of model checking to find rare events in deep execution traces of complex systems. In this instance, the event is multiple simultaneous audible alarms in a medical device. The paper shows that if such alarms can fire concurrently, the alarms are such that they interfere and mask each other. As a result, an attendant may not be able to detect either alarm. Such a situation, although rare, is potentially dangerous. The contribution represents a classical application of model checking applied to a human–machine interface including its use of temporal logic. Temporal logic has the property of being able to relate events in time and is used here to specify the situation of conflicting auditory alarms.

The second contribution in model checking represents another classical application of the technique, only this time, it is applied to the Brahms multiagent modeling language. Brahms uses a beliefs–desires–intentions paradigm to encode the interactions of human–machine systems. The contribution from Webster et al., Towards Reliable Autonomous Robotic Assistants Through Formal Verification, verifies a Brahms model of the Care-o-bot human assistant robot under several different operating environments, each more complex than the other. The verification, via model checking, proves in the model that the robot never does anything unless it believes it was first directed to do so by the user. In so far as the actual robot implementation is faithful to its Brahms model, and the model captures the operating environment of the robot, the verification indicates that the robot only acts under user command. This contribution also introduces the SPIN model checker [14]. SPIN is the most efficient general-purpose model checker available, and this contribution once again demonstrates its utility in a breadth of problem domains.

The third and final contribution in model checking leverages the ability of model checking to explore very large behavior spaces looking for rare critical events only this time to characterize existing solutions. The contribution from Song et al., Improved EGT-Based Robustness Analysis of Negotiation Strategies in Multi-Agent Systems via Model Checking, looks at negotiation strategies from an automated negotiation competition to understand first the robustness of each strategy and, second, the conditions in which each strategy excels. Model checking is the tool used to characterize these strategies. This
is a less traditional application of model checking, and it illustrates how model checking can be used not just for verification, but as a supporting tool for a more complex analysis. In this application, it is used iteratively to understand different aspects of each automated negotiation algorithm.

B. Optimization

Optimization tries to tune a system along some performance metric. Such a process is iterative and represents, for all intents and purposes, a hyperdimensional search depending on the number of inputs to the system. Such multidimensional searches are complex and expensive. Although the contributions in the special issue are not representative of the research area of multidimensional optimization, they do illustrate the importance of having a model, which can be iteratively analyzed in an optimization process.

The first contribution from Ryan and Cummings, A Systems Analysis of the Introduction of Unmanned Aircraft into Aircraft Carrier Operations, presents a model of aircraft carrier operations that looks particularly at the control architectures of such operations (i.e., how an unmanned aircraft is managed in the complex human–vehicle environment of the aircraft carrier). The contribution not only effectively illustrates the power of agent-based modeling and simulation, it also indicates that it may be the case that current flight deck operations are not sufficient to incorporate effective control architectures for unmanned vehicle operations. The contribution is well positioned for future work, that builds on the existing model, to explore how flight deck operations might change to improve the rate of launches when integrating unmanned systems into normal operations.

The second contribution to optimization from Menzies et al., Learning Mitigations for Pilot Issues When Landing Aircraft (via Multi-Objective Optimization and Multi-Agent Simulations), again illustrates the importance of modeling in exploring the behavior space of complex human–machine systems. In this instance, modeling is applied to continuous-decent-approach techniques enabled by recent advances in aircraft navigation systems. In this application, the model is concerned with pilot interactions with the navigation system, and in particular, it searches the input space of the model to discover situations in which the pilot is unable to complete specific tasks. Once input is discovered that leads to a situation where the pilot fails, that input is further analyzed to identify potential mitigating factors to avoid such input. This contribution further introduces the multiobjective optimization tool GALE, which helps improve the exploration of large multidimensional input spaces [15].

C. Risk Analysis and Robustness

There is risk that arises from many human–machine interfaces, and robustness, most often, is a concern in these systems since many are safety or capital critical. Models again come to the forefront in assessing risk or robustness, as it is much more feasible to explore a model space before a more costly, and sometimes dangerous, test on a fully fielded system. There are three very interesting contributions in the area of risk and robustness analysis in this special issue.

The first contribution from Yanushkevich et al., Biometric-Enabled Authentication Machines: A Survey of Open-Set Real-World Applications, delves into the word of biometrics. Biometrics are fast becoming the new secure method for authentication, but such authentication is not fool-proof. Yanushkevich et al. discuss a new probabilistic model for authentication machines and present a review of the state of the art in authentication machines including a comparison, life-cycle management, training, risk assessment, etc. As society increasingly incorporates biometrics at borders and other areas, it is equally important to understand weaknesses in such authentications systems.

The second contribution from Martinie et al., Task Models Based Systematic Analysis of Both System failures and Human Errors, adapts an existing failure mode analysis to human–machine systems in the space domain. The new analysis, human errors, effects, and criticality, tries to understand the impact of human error and system faults on mission objectives. Most interesting in this contribution is a new formal modeling notation to describe and assess the impact of system faults and human operator errors on the overall system performance.

The third and final contribution to risk analysis and robustness is from Klomp et al. titled, Expertise Level, Control Strategies, and Robustness in Future Air Traffic Control Decision Aiding. Human expertise is a critical factor in the robustness of any control system, and this work explores the impact of expertise on robustness in ecological interfaces. An ecological interface defines the boundaries of safe operations for control decisions [16]–[20]. The contribution evaluates several empirical studies to derive a robustness measure for such interfaces, and it then presents the results from a human-in-the-loop study that correlates the robustness measure with controller expertise. An important result, but not altogether surprising, is that ecological interfaces preserve robustness when used by expert users.

D. Human–Machine Interface Analysis

The formal analysis of human–machine interfaces has a longer record of study. For some time now, researchers have been applying different forms of formal methods, including model checking, to verify aspects of human–machine interfaces. The most common problem is determining if the interface is a sufficient abstraction of the real system to avoid any state confusion for the human operator, where the operator believes the system is in a state, based on the available information on the interface, different from the actual state of the system [21]–[24].

Combéfis et al., Automatic Detection of Potential Automation Surprises for ADEPT Models, Daiki and Toshimitsu, A Bisimulation-Based Design of User Interface With Alerts Avoiding Automation Surprises, and Eskandari et al., An observer/predictor based model of the user for attaining situation awareness, all explore aspects related to the system interface, the belief of the operator, and the actual state of the system, although each using different approaches to explore slightly different aspects of the problem. Combéfis et al. focus on the notion of full control of the actual system. Full control means the interface provides all the needed information about the state
of the system to create a simple mental model that is free of any confusion (i.e., the state of the mental model does not reflect the state of the actual system). This confusion is also referred to as automation surprises where the system behaves in an unexpected way because the operator believes it is in a different state than it actually is based on the user interface. The contribution includes an algorithm to automatically derive minimal full control mental models, where minimal in this setting implies a model that requires the least information about the state of the state of the system. A complete model of the system is required to derive such a mental model, and in the process, users are shown traces that lead to confusion when given insufficient mental models that are not full control.

Daiki and Toshimitsu contribute a technical correspondence at the end of the special issue also focusing on automation surprises or mode confusion. In this contribution, they focus on situational awareness, or the ability to quickly determine the real state of the human–machine system from the displayed user interface. Daiki and Toshimitsu use the classical definition of bisimulation to determine if a user interface is free of any mode confusion. As with the previous approach from Combéfis et al., proving the bisimulation property relies on a formal model of the human–machine system. Using the simulation model from Daiki and Toshimitsu, it is possible to create a user interface that is free from any mode confusion.

Eskandari et al. bring a unique contribution to this special issue by applying the notion of situational awareness to classical control systems; therefore, it bridges the gap between control theory and situational awareness for human operators observing the system. Although the approach is restricted to linear-time-invariant systems and makes the assumption that the derivatives of the input and output are known, it is able to define a test to determine if displayed information is sufficient to achieve and maintain situational awareness and defines a model of the human that explains how the human attains situational awareness. The human model is an extended delayed functional observer/predictor model. The test determines if such a human model is able to attain situational awareness from the displayed user interface values given that the system meets the aforementioned restrictions. This bridge between control theory, which is the cornerstone for most autonomous systems and human–machine interfaces, is an important research area.

Niezen and Eslambolchilar, A Human Operator Model for Medical Device Interaction Using Behaviour-Based Hybrid Automata, explore control theory as a modeling paradigm by building a control-theoretic model of a syringe pump. The goal is to model the human interacting with the syringe pump. As such, the model includes three controllers to provide the environment for the human conceptual model of the interface. This conceptual model is similar to the mental model of Combéfis et al.; only the modeling paradigm is dramatically different: continuous versus discrete. Interesting in Niezen and Eslambolchilar’s contribution is the direct comparison of the model results to those of an actual lab study which shows a strong correlation between the simulated results on the model and those from the study.

The final contribution to human–computer interface analysis from Créissac et al., Formal Verification of a Space System’s User Interface with the IVY workbench, is a direct application of verification to a user interface. In this instance, the IVY workbench is used to model an interface for a space station, focusing particularly on the navigation between screens. The actual users guide for the interface provides the specification of the system to use for the verification. The IVY workbench takes the model and the specification and uses both to determine the correctness and usability of the system. The contribution not only highlights the value of modeling and verification, but also introduces the IVY workbench as a viable tool for user interface verification.

IV. CONCLUSION

We hope the readers enjoy the IEEE TRANSACTIONS ON HUMAN–MACHINE SYSTEMS special issue on “Systematic Approaches to Human–Machine Interface: Improving Resilience, Robustness, and Stability.” We believe that this issue is timely in the sense that there is an increased push toward the design and deployment of systems with complex human–system interactions. Examples include autonomous cars, air traffic management systems, unmanned aerial vehicles, nontraditional use of smart phones, and many others. Each of these systems can only be truly evaluated in the larger context of human operators and other systems that it interacts with. We hope that this issue brings forth the importance of modeling such complex systems in the context of system design, analysis, optimization, and verification of human–machine systems. We thank all the authors for their submissions and making this a successful special issue.

References


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