Editorial
Control Systems and the Quest for Autonomy

THERE has been a great deal of excitement in recent years about autonomy as applied to engineered systems, particularly in the popular media, but also in companies, the military and in research funding agencies. The study of autonomy is being driven by exciting applications in ground, air, and water vehicles, as well as in robotics. Autonomous automobiles, or more accurately autonomous functions in automobiles, have captured the imagination of the public and the expectations are being continuously raised. Announcements of new collaborations of automakers and software companies and predictions of lifestyles where autonomous vehicles are part of everyday life are in abundance. There is lots of excitement about the technological marvels that seem to be around the corner. This euphoria and the optimism for a bright outlook is evident in the huge number of references to autonomy in the Internet. Machine learning and Artificial Intelligence (AI) have taken a center-stage role in these endeavors and have received a lot of credit from the popular media.

Where do Control Systems fit in these pictures of autonomy? Is it reasonable to assume that they play a role, perhaps a central role, in autonomous systems? In the following paragraphs I hope to give you a clear picture of my view, as autonomy is a topic that has been consistently a great interest of mine for many years, since the late 1980s. By doing so, I hope to convince you that research in autonomy is very promising and exciting.

Very briefly, my view is this: *In any autonomous system, the system under consideration always has a set of goals to be achieved autonomously and control mechanisms to achieve them. This implies that every autonomous system is a control system.* Here, I use the term control system in a most general sense, in which control (a decision mechanism typically using sensor measurements and feedback together with ways to implement these decisions via actuators) is used to make the system (a very general collection of processes) attain desirable goals.

Where do traditional control systems described by differential or difference equations fit in this more general view of control systems, of autonomous systems?

First, let us look at autonomy and what it means. The dictionary gives us the etymology of the term, which originates in Ancient Greek: αὐτονομία (*autonomia*), from αὐτόνομος (*autonomos*), which comes from αὐτο (*auto*) "self" and νόμος (*nomos*) "law," hence when combined it is understood to mean one who gives oneself his/her own law. Here is now a useful more precise definition that helps us identify whether a system is autonomous and in what sense.

> Autonomous means having the ability and authority for self-government. A system is autonomous regarding a set of goals, and with respect to a set of measures of intervention (by humans or other systems). (For more details, see, for example [P. J. Antsaklis, "The Quest for Autonomy Revisited," ISIS (Interdisciplinary Studies of Intelligent Systems), University of Notre Dame, Notre Dame, IN, USA, Tech. Rep. ISIS-2011-004, Sep. 2011, and the references therein])

For example, a regular feedback control system can be seen as being autonomous regarding stability goals with respect to (certain level or degree of) model uncertainties. This is because stability is maintained even when there are parameter variations. This robustness is due to the feedback closed-loop mechanism that compensates for uncertainties. On the other hand, an open-loop system with feed-forward control may not possess these robustness properties and no autonomy regarding stability with respect to model uncertainties.

An autonomous system has high- or low degree or level of autonomy regarding a goal. By high degree/level of autonomy it is meant that the degree/level of human intervention (or perhaps intervention by other engineered systems) is low, while by low degree/level of autonomy, a high degree/level of intervention is implied.

More specifically, *there are several degrees or levels of autonomy.* A fully autonomous controller should perhaps have the ability to perform even hardware repair, if one of its components fails. Note that conventional fixed controllers can be considered having a *low degree* of autonomy since they can only tolerate a restricted class of plant parameter variations and disturbances. To achieve a *high degree* of autonomy, the controller must be able to perform a number of functions in addition to the conventional control functions such as tracking and regulation. Some of these additional functions may include the ability to be highly adaptable to change and accommodate drastic system failures, which can be accomplished via capabilities such as failure diagnosis, control reconfiguration, planning and learning.

As it was mentioned above, the word control in autonomous control has a more general meaning than in conventional control; in fact, it is closer to the way the term control is used in everyday language. To illustrate, in a rolling steel mill, while conventional controllers may include the speed (r/min) regulators of the steel rollers, in the autonomous control framework one may include in addition, fault diagnosis and alarm systems; and perhaps the problem of deciding on the set points of the regulators, that are based on the sequence of orders processed, selected based

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on economic decisions, maintenance schedules, availability of machines, etc. All these factors have to be considered as they play a role in controlling the whole production process, which is really the overall goal. Note that in order to increase autonomy, it is typical to implement several layers/levels of automation. Local controllers are often referred to as level 1 automation, set points assignment as level 2, and so on.

Autonomous controllers evolve from existing controllers in a natural way, fueled by actual needs. In autonomous control systems we need to increase significantly the operating range; we must be able to deal effectively with significant uncertainties in models of increasingly complex dynamical systems in addition to increasing the validity range of our control methods. This will involve the use of intelligent decision-making processes to generate control actions so that a performance level is maintained even though there are drastic changes in the operating conditions.

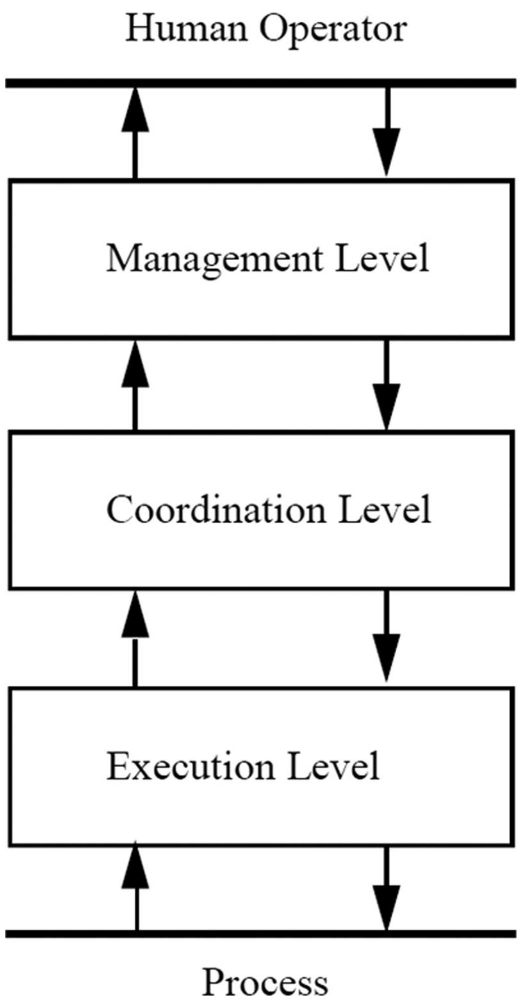
Human in the Loop and Adaptive Autonomy: When one considers humans collaborating with engineered systems, then the overall system that includes humans in the loop may be considered (fully) autonomous with respect to a set of goals. Depending on the role of the humans in the loop and the level of control authority humans exert, the remaining system will have different degrees or levels of autonomy. So, in an automobile, if the goal is, for example, to keep the vehicle inside a lane while travelling at constant speed, the system may consist of the vehicle and the driver where the system attains its goals in the presence of uncertainties/disturbances, such as gust of wind and road incline. The controller may include a human in the loop in which case it may achieve full autonomy, but it may achieve only partial autonomy with or without the human in the loop (meaning that it may need extra help from humans or other systems to attain full autonomy). An example of an automobile as an autonomous system is the system consisting of the human driver and all the control systems in the car with the plant being the vehicle and the goals of the autonomous controller being to provide the right steering and gas pedal commands so the vehicle maintains its course within a lane and at certain constant speed. If one considers in this case just the control systems of the car without the driver, then the system is not autonomous but semi-autonomous, having certain degrees of autonomy.

Below a hierarchical functional architecture for autonomy is described. Humans or other systems may insert themselves at certain levels of the functional hierarchy (that correspond to levels of autonomy), as described later in this Editorial, and take over control functions. For example, humans may insert themselves to take over planning, failure diagnosis and isolation, control reconfiguration, learning functions (see descriptions of functions later in the paper). Or they may insert themselves to take over lower control functions, e.g., a driver may want to take over from the anti-lock breaking system to perform the braking pumping action on his own. Such *adaptive autonomy,* where the authority the human operator exercises may vary, appears to be a very promising direction. Depending on the circumstances, the human operator may give a command to the robots aboard a spacecraft to "repair satellite X;" or may select a robot depending on capabilities and availability and then give detailed commands on how the repair should be performed, or select a level in between. It should be emphasized however that human operators should have ultimate supervisory override control of autonomy functions. Autonomous activities should be highly visible, "transparent," to the operator at the maximum extent possible.

Autonomous Controller Functions: *Autonomous control systems must perform well under significant uncertainties in the plant and the environment for extended periods of time and they must be able to compensate for system failures without external intervention.* An autonomous controller provides high-level *adaptation* to changes in the plant and environment. To achieve autonomy, the methods used for control system design should utilize both 1) algorithmic-numeric methods, based on state-of-the-art conventional control, identification, estimation, and communication theory, and 2) decision-making symbolic methods, such as the ones developed, for example, in computer science and specifically in the fields of AI and machine learning. In addition to supervising and tuning the control algorithms, the autonomous controller must also provide a high degree of tolerance to failures. To ensure system reliability, failures must first be detected, isolated, and identified (and if possible contained), and subsequently a new control law must be designed if it is deemed necessary. The autonomous controller must be capable of planning the necessary sequence of control actions to be taken to accomplish a complicated task. It must be able to interface with other systems as well as with the operator, and it may need learning capabilities to enhance its performance, while in operation. It is for these reasons that advanced planning and learning, among others, must work together with conventional control systems in order to achieve autonomy. The need for quantitative methods to model and analyze the dynamical behavior of such autonomous systems presents significant challenges. The development of autonomous controllers requires significant interdisciplinary research effort as it integrates concepts and methods from areas such as control, identification, estimation, and communication theory, computer science, artificial intelligence, and operations research.

An Autonomous Controller Architecture: A conceptual functional architecture for autonomous controllers is now briefly described. It is a hierarchical architecture and it is one of many possible control architectures for autonomous systems. The choice is dependent on the particular problem addressed. This hierarchical functional architecture makes it easy to describe in a transparent way the kind of functions needed to make a system autonomous. Note that hierarchies make it possible for us to handle complexity better (see, for example, P. Antsaklis, "Defining intelligent control," Report of the CSS Task Force on Intelligent Control, In IEEE Control Syst. Mag., pp. 4–5 & 58–66, Jun. 1994).

These ideas on autonomous control architectures and the material presented in this Editorial were originally developed in a study at NASA's Jet Propulsion Laboratory to develop the vision and identify the functions needed for autonomous spacecrafts. They first appeared in (P. J. Antsaklis, K. M. Passino, and S. J. Wang, "Autonomous control systems: Architecture and fundamental issues," in *Proc. of the 1988 Amer. Control Conf.*,



Atlanta, Georgia, Jun. 15–17, 1988, pp. 602–607. See also, P. J. Antsaklis and K. M. Passino, "Autonomous control systems: Architecture and concepts for future space vehicles," Jet Propulsion Laboratory, Pasadena, CA, USA, Tech. Rep. Contract 957856, Oct. 1987.) Also in (P. J. Antsaklis, K. M. Passino, and S. J. Wang, "Towards intelligent autonomous control systems: Architecture and fundamental issues," *J. Intell. Robot. Syst.*, vol. 1, pp. 315–342, 1989), in (P. J. Antsaklis, K. M. Passino, and S. J. Wang, "An introduction to autonomous control systems," *IEEE Control Systems Magazine*, vol. 11, no. 4, pp. 5–13, Jun. 1991) and later in several other book chapters, encyclopedia articles, journal, and conference publications.

In the figure, the hierarchical controller has three levels, the execution level (lowest level), the coordination level (middle level), and the management level (highest level). It must be stressed that the system may have more or fewer than three levels. Some characteristics of the system, which dictate the number of levels are the extent to which the operator can intervene in the system's operations, the degree of autonomy or the level of intelligence in the various subsystems, the hierarchical characteristics of the plant. Note, however, that the three levels shown here in the figure are applicable to many architectures of autonomous controllers, by grouping together sublevels of the architecture if necessary; the levels are the lower execution level, the higher management level with everything else in between being included in the coordination level. Notice that in the figure, the lowest, execution level involves conventional control algorithms (typically using differential and difference equation models), while the highest, management level involves only higher level decision-making methods (typically using discrete-event system (DES) models involving logics, transition systems, automata, Petri nets). The middle, coordination level, is the level which provides the interface between the actions of the other two levels and it uses a combination of conventional and intelligent decision-making methods (hybrid system models are important here). It includes functions such as failure diagnosis, control reconfiguration, planning, and learning. Software and perhaps hardware are used to implement the execution level. Mainly software is used for both the coordination and management levels.

Areas relevant to autonomous control, in addition to conventional control, include hybrid systems, planning and knowledge-based systems, communication protocols, security, machine learning, search algorithms, fault diagnosis and control reconfiguration, predicate logic, automata, Petri nets, and neural networks. In addition, in order to control complex systems, one has to deal effectively with the computational complexity issue; this has been in the periphery of the interests of the researchers in conventional control, but it is clear that computational complexity is a central issue in autonomous systems that typically are complex.

Functional Operation: Commands are issued by higher levels to lower levels and response data flow from lower levels upward. Parameters of subsystems can be altered by systems one level above them in the hierarchy. There is a delegation and distribution of tasks from higher to lower levels and a layered distribution of decision-making authority. At each level, some preprocessing occurs before information is sent to higher levels. If requested, data can be passed from the lowest subsystem to the highest. All subsystems provide status and health information to higher levels. Human intervention is allowed with the commands however passed down from the upper levels of the hierarchy.

The quantitative, systematic techniques for modeling, analysis, and design of control systems are of central and utmost practical importance in conventional control theory. Similar techniques for autonomous controllers do not exist to a similar degree. This is of course because of their novelty, but for the most part, it is due to the *"hybrid"* structure of the dynamical systems under consideration. Perhaps research should begin by using different models for different components of the autonomous controller. Full hybrid models that can represent large portions or even the whole autonomous system should be examined, but much can be attained by using the best available models for the various components of the architecture and joining them via some appropriate interconnecting structure. For instance, research in the area of systems that are modeled with a logical DES model at the higher levels and a difference equation at the lower level is relevant. Much work needs to be done on hierarchical DES modeling, analysis, and design, let alone the full study of hybrid hierarchical dynamical systems. Abstractions are of course at the center of any such study.

This was a brief summary of the functions needed for high degrees of autonomy and the role of conventional control in autonomous systems.

On a personal note, the above ideas influenced and guided my research for decades, where I pursued research in learning via neural networks, in DES supervisory control via Petri nets, in the control of hybrid dynamical systems, in networked control systems, and more recently in Cyber-Physical Systems.

I am convinced that there are tremendous opportunities for Systems and Control specialists in the area of Autonomous Systems. Of course this is a long held belief of mine as witnessed by my intensive research in the area, and by my earlier attempts to draw your attention to these opportunities. In fact, the closing comments of my first Editorial as the Editor-in-Chief of the IEEE TRANSACTIONS ON AUTOMATIC CONTROL in January 2010 [item 1) in the Appendix] were:

> Throughout my professional career I have been a firm believer first in the Quest for Autonomy as a powerful driving force in engineered systems over the centuries, and in Feedback as the best mechanism to achieve autonomy, witnessed by feedback's ubiquitous presence in all natural and human made systems. I have been including these themes in my talks for many years. In our chosen field of Systems and Control we should go beyond emphasizing exclusively only certain types of models and mathematical techniques. We need to see the bigger picture, to realize that there are many ways to describe the phenomena we want to control, involving for example logic in addition to differential equations, as in hybrid systems, and expanding our horizons and our field. And this will happen if in our theoretical research we are also motivated by application needs and not only by mathematical challenges. We have very much to offer, and we should work towards realizing this potential.

And in my 2013 Editorial [item 2) in the Appendix] I wrote:

> We need to address bigger problems. A system typically is more than a set of ODEs and the specs may not be conveniently described in the frequency domain. While these specs served us well in the past and are still very useful, we need to move on because the problems and their descriptions have become much more sophisticated and much more demanding. We are in the systems area after all, an area that prides itself for considering a wider view of the problem, taking a system's, a bird's eye point of view. In hybrid dynamical systems we combine discrete and continuous dynamics to study the system behavior. Nowadays we have data and lots of it that need to be considered together with our mathematical models. What is the best way to go? This is quite a challenge.

We, in Systems and Control, can be the most important contributors to autonomous systems with our knowledge of feedback (feedback is important throughout, at all levels of autonomous systems; remember that *feedback transcends models*), our mathematical expertise, and with our fundamental understanding of dynamical systems and their interactions. Let's do it! Yes, we can!

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APPENDIX

Related Work:

1) P. J. Antsaklis, "Continuing the tradition of excellence in 2010 and beyond," IEEE Trans. Autom. Control, vol. 55, no. 9, pp. 1–3, Jan. 2010.
2) P. J. Antsaklis, "Continuing the tradition of excellence: Where we have been and where we could go," IEEE Trans. Autom. Control, vol. 58, no. 9, pp. 2157–2159, Sep. 2013. Part of this editorial was published under the title, "Some thoughts about publishing results in our field," IEEE Control Syst. Mag., pp. 22–41, vol. 33, no. 6, Dec. 2013.