

Computational Intelligence in Control

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Abstract: This milestone report addresses first the position of the areas of computers, computational intelligence and communications within IFAC. Subsequently, it addresses the role of computational intelligence in control. It focuses on four topics within the Computational intelligence area: neural network control, fuzzy control, reinforcement learning and brain machine interfaces. Within these topics the challenges and the relevant theoretical contributions are highlighted, as well as expected future directions are pointed out.

Keywords: Computers for Control, Computational Intelligence, Neural Networks, Fuzzy Systems, Reinforcement Learning, Brain Machine Interfaces

1. THE COORDINATING COMMITTEE FOR COMPUTERS, COGNITION AND COMMUNICATIONS

This paper intends to present the state of the art and the outlook of some important domains of computational intelligence in control, falling under the domain of IFAC Tc 3.2. It will start, however, with a more general view of computers, computational intelligence and telecommunications in control, and their global role of in the world's present and future.

The Coordinating Committee for Computers, Cognition and Communications (CC3) belongs to the group of IFAC's application CCs. It consists of three Technical Committees for Computers for Control (TC3.1), Computational Intelligence in Control (TC3.2), and Telematics: Control via Communication Networks (TC3.3). This introduction will give a more general view of CC 3 methodologies in control and their global role in the world's presence and future.

Although computers for control, computational intelligence and communications do not present the main focus of interest in International Federation for Automatic Control (IFAC), they have traditionally played an important role, providing enabling technologies: they can hardly be avoided in the implementation of control methodologies, techniques, and applications.

In the vision of European ARTEMIS platform and its collaboration with ITEA, there is an excellent description of

the importance of embedded computers and related fields within the contemporary world society:

“Embedded Systems will be part of all future products and services providing intelligence on the spot and capabilities to cleverly connect to the abundance of systems in the environment; either physical or at the cyber space level, in real time or in distributed and heterogeneous systems, in open networks of embedded systems applications from multiple domains or in the Internet: everything can, in principle, be connected to everything else. Networked intelligent embedded systems are, in effect, becoming the Neural System of Society. (ARTEMIS-ITEA, 2012)

It is hard to imagine any technical field where computers would not be employed as a cost-effective, relatively easy to implement, and flexible means for control. Often, they exhibit intelligence, and, except in trivial cases, they are distributed and connected through communication networks.

In the same document (ARTEMIS-ITEA, 2012) (Pétrissans, et al., 2012) (Pétrissans, et al., 2012) (Pétrissans, et al., 2012) (Pétrissans, et al., 2012), the seven most important challenges to the future world society are identified: globalization and demographic change, management of scarce resources, climate change, urbanization, mobility, healthcare and nutrition, and digital society. There may only be a few

exceptions where computers and control would not play a major role.

Looking into the world economy, not many people realize how important to the world market are embedded control systems. Today, from 100 processing devices, 98 will be employed in embedded systems. Over 40 billion devices are expected worldwide by 2020. Embedded systems accounted for almost €852 billion of value in 2010, and €1.100 billion in 2012 are expected worldwide by 2020 (ARTEMIS SRA, 2011). The overall industry is growing at a compound annual growth rate (CAGR) of 12% throughout the forecast period and should reach €1.5 trillion in revenue by 2015 (Pétrissans, et al., 2012).

It is also important to note that the value added by embedded systems exceeds the price of components by orders of magnitude, thus, presenting an excellent opportunity to sell the built-in knowledge. In automotive industry, for example, 80% of product innovation includes Embedded systems (Pétrissans, et al., 2012).

There are many fields in the cross-section of embedded computer, computer intelligence, communications and control domains that experience enormous growth of interest. Because of the growing complexity, there is, e.g., a need to widen the understanding of systems-of-systems, intelligent systems consisting of communicating embedded HW (e.g., in traffic, smart grid, etc.). Cloud computing can provide support for much more powerful ubiquitous solutions. Through the internet of things, even small devices become a part of global systems; already in 2010, of 7 billion devices connected to the internet, 5 billion were not computers (Pétrissans, et al., 2012).

On the more technical field, because of the novel challenges, new methods and tools are needed for faster and cheaper development of much more complex applications, as well as their validation, (rigorous or formal) verification and certification. State-of-the-art hardware components still do not ensure full temporal predictability even on the lowest layers. Through the ubiquity and penetration into extremely safety critical applications, more effort must be stressed on their security and safety issues. The cyber-physical approach, well known for a decade, is gaining interest. Holistic understanding, modeling and implementation of the ever increasing complex controlled and control systems promise more competent solutions.

Without doubt, there is a very strong motivation for research and development in the area of computers, intelligence and communications in control. As mentioned before, these areas are not the main focus of IFAC, which is primarily concerned with automatic control. Besides, there are other professional associations which cover the basic research in these areas. Many members of the Technical committees are also members of those Institutions, attending also their technical events and publishing in their journals, as well. It is our opinion that, within IFAC, the synergies between the basic domains of control and automation, and computing, cognition and communications should be strengthened. During the last year, this has been taking place, as demonstrated by the increasing number of IFAC co-sponsored conferences by the three TCs within CC3, with TCs belonging to other CCs. There is, however, a large room to improve these synergies,

whether by creating common Working Groups among TCs, and by proposing common special sessions in IFAC events, particularly in the World Congress.

It is interesting that the following opinion from the milestone reports from 2002 and 2005 IFAC World congresses is still more or less true: "People are developing most sophisticated control algorithms but are less interested in the transfer of these algorithms to a well-defined real-time control system. Moreover, the application of control algorithms is in practice many times confined to the use of existing hard- and software solutions, which are in many cases application dependent or supplier dependent and sometimes developed for other purposes." (Halang, Sanz, Babuska, & Roth, 2006; Verbruggen, Park, Halang, Irwin, & JZalewski, 2002).

1.1 The future

We strongly believe that it would be of mutual benefit to establish a better collaboration among all domains in IFAC, and in particular within the areas of CC 3. Automation and control scientists and professionals could much better utilize the expertise of the members of the CC3, and the latter would get challenging case studies to solve within their areas of interest.

CC3 hosts several technical events. Currently, the only event in the master-plan is the Telecommunications Applications (TA) Symposium. Another successful conference is the Intelligent Control and Automation Science (ICONS), which is being proposed to the TB to also become a master-plan event.

In 2012, a new conference has been established, and had its first successful issue in Würzburg, Germany. The triennial Conference for Embedded Systems, Computer intelligence and Telematics (CESCIT) is supposed to unite all events of the CC3 in one place every year after the IFAC World Congress, thus fostering the communication and synergy among the fields. Also, tracks for applications, industrial case studies, education and other related areas are organized, providing an opportunity for scientists and professionals from other fields to make bonds with the computer community. It is to be noted that the first issue of CESCIT featured very strong industrial emphasis, with excellent industrial keynote speakers and an interesting industrial round table.

2. COMPUTATIONAL INTELLIGENCE IN CONTROL

The IFAC Technical Committee on Computational Intelligence (CI) in Control (TC 3.2) focuses on all aspects of data fusion and data mining, knowledge-based, fuzzy, neuro-fuzzy, neural (both artificial and biologically plausible) systems, evolutionary algorithms and swarm intelligence, relevant to control and automation, both theoretically and application driven. The techniques used have strong links to other fields, in particularly machine-learning algorithms (Cortes & Vapnik, 1995; Scholkopf, Smola, Williamson, & Bartlett, 2000).

CI methodologies are currently applied to all areas of control. Recent works of TC members cover a spectrum of application areas such as: transport (Fischer, Tibken, Fischer,

& Ieee, 2010; Statheros, Howells, & McDonald-Maier, 2008), medical and biomedical (Azar, El-Said, Balas, & Olariu, 2013; S. L. Chen, Luo, & Lin, 2013; Cismondi, et al., 2012; Goodband, Haas, & Mills, 2008; D. R. Liu, Pang, & Lloyd, 2008; Nomm, et al., 2009; Wojtowicz & Wajs, 2012), biology (B. Chen, et al., 2007; Gormley, Li, & Irwin, 2007; Paik, Lee, Park, Kim, & Lee, 2011; Teixeira, Ruano, Ruano, & Pereira, 2008), aerospace (Chwa, Choi, & Anavatti, 2006; Yang, Chen, & Li, 2012), instrumentation (Benoit & Foulloy, 2013; Cerman & Husek, 2012; Ferreira, Gomes, Martins, & Ruano, 2012; Omatu, Araki, Fujinaka, Yoshioka, & Nakazumi, 2012), biotechnology (Adamy & Schwung, 2010; Heikkinen, Latvala, Juuso, & Hiltunen, 2008; Koprinkova-Hristova & Palm, 2010), mechatronics (Garcia, Rolle, Gomez, & Catoira, 2013; Riccardi, Naso, Janocha, & Turchiano, 2012), automation and manufacturing (Boukef, Benrejeb, & Borne, 2008; Dumitrache, Caramihai, & Ieee, 2008; Guillaume, Grabot, & Thierry, 2013; R. E. Precup & H. Hellendoorn, 2011; Tavakolpour, Darus, Tokhi, & Mailah, 2010; Wong, Tikk, Gedeon, & Koczy, 2005; Zribi, Kacem, El Kamel, & Borne, 2007), process control (Govindhasamy, McLoone, & Irwin, 2005; Karer, Music, Skrjanc, & Zupancic, 2007; Korosi & Kozak, 2013), power systems (Essounbouli, Manamanni, Hamzaoui, & Zaytoon, 2006), energy and smart grid (Ferreira, Ruano, Silva, & Conceicao, 2012; Malatji, Zhang, & Xia, 2013), agriculture (Ferreira & Ruano, 2008), environmental systems (Petelin, Grancharova, & Kocijan, 2013; Vousdoukas, et al., 2011), robotics and autonomous systems (F. Chen, Sekiyama, Fukuda, & Ieee, 2012; Guelton, Delprat, & Guerra, 2008; Marcos, Machado, & Azevedo-Perdicoulis, 2009; Sakaguchi, Horio, & Yamakawa, 2011; Sanz, Hernandez, Hernando, Gomez, & Bermejo, 2009; Schuitema, Busoniu, Babuska, Jonker, & Ieee, 2010; Shakev, Topalov, Kaynak, & Shiev, 2012; van de Ven, Johansen, Sorensen, Flanagan, & Toal, 2007), economics and business systems (Caloba, Caloba, & Contador, 2001; Nagesh, Lendek, Khalate, Babuska, & Ieee, 2012) and telematics (Pulkkinen, Laurikkala, Ropponen, & Koivisto, 2008).

This milestone paper, by lack of space, cannot cover all CI methodologies relevant to control. It will instead, be focused on only four areas: neural network control, fuzzy control, reinforcement learning and brain machine interfaces, trying to highlight, in these areas, challenges, relevant theoretical contributions, as well as point out expected future directions.

3. NEURAL NETWORK CONTROL

The basic idea of neural network is to study the computational abilities of networks composed of simple models of neurons (McCulloch & Pitts, 1943). It has been successfully applied to system control with its universal approximation and adaptation capabilities. The back-propagation method (BP) proposed in (Rumelhart, Hinton, & Williams, 1986) boosts the development of neural network control in a vast number of applications. Besides practical implementations, there is parallel research effort in rigorous analysis of neural network control system on stability and robustness (Ge, Hang, & Zhang, 2001).

In early works of neural network control theory, much research effort has been made on designing stable adaptive neural network control for single-input-single-output (SISO) continuous-time systems in affine forms (Ge, et al., 2001). Due to the fact that most systems in practice are of nonlinear and multi-variable characteristics, many recent studies have been conducted on control design for systems of multi-input-multi-output (MIMO) nature or/and in non-affine forms. The extension of control designs for affine systems to non-affine systems is generally non-trivial, because of the lack of corresponding mathematical tools, e.g., the counterpart of the feedback linearization technique for non-affine systems. Due to couplings among inputs, outputs, and states, the extension of control designs for SISO systems to MIMO systems is also found to be difficult. Since most of control algorithms are realized in digital, neural network control design for discrete-time systems has also attracted a lot of research interest (Ge, Yang, & Lee, 2008).

On the application side, neural network control has been successfully implemented in many practical systems (Ge, Lee, & Harris, 1998), such as robots, helicopters, hard disks, etc. Many kinds of nonlinearities in practical systems such as hysteresis, time-delay, deadzone, have been taken into account in the control design, because it has been demonstrated that neural network control is particularly suitable for controlling highly uncertain nonlinear complex systems.

3.1 Challenges and Future Research Directions

A broadly applicable methodology to develop a workable control strategy for general systems is not yet available. Most of works mentioned in the previous section only focus on addressing a single issue. For example, the discrete-time Nussbaum gain is introduced to cope with the problem of unknown control direction (Ge, et al., 2008). For another example, the implicit function theorem is used to handle the non-affine issue (Ge, et al., 2001). While it is reasonable to incrementally generalize the problem formulation by accumulating different issues into a single system, it is also essential to consider the control design in the sense of a systemic framework.

Most of early works on neural network control focus on a single objective of stabilization, regulation, and tracking. In many cases, control design of a system can be described as a multi-objective control problem. For example, obstacle avoidance, target reaching, and control effort minimization are all essential in the application of robotic exploration. In this sense, a control system which takes all the requirements into consideration is expected. In recent years, optimization once again becomes popular in the control field, and adaptive dynamic programming (ADP) is a timely response which aims at a guaranteed optimized performance subject to unknown environments (Lewis, 2009; Werbos, 2009). Many open problems such as ADP design for time-varying and non-affine continuous systems need to be addressed.

Although neural network control has been well recognized by academic researchers, it has yet been embraced by engineers who are very careful about the feasibility of an algorithm.

One main concern to implement neural network control in practical systems is the computation burden. To cope with this problem, much research effort has been made on developing real-time computational algorithms, in which less neurons and simpler networks are expected. This research direction is believed to be still worthy of further investigation.

The study on the structure and adaptation/learning scheme of neural network itself also attracts a large number of research interests. More efficient and accurate approximation can be anticipated with better network structures and adaptation/learning schemes. As a result, fundamental problems like local minimum may be addressed to some extent and better control performance can be achieved. Recent works in this direction include deep learning (Hinton & Salakhutdinov, 2006) and extreme learning (Huang, Zhu, & Siew, 2006), of which comparatively few results have been applied to the control field.

4. FUZZY CONTROL

We can reuse the question of (Zadeh, 2008) “Is there a need for fuzzy logic?” and go for “Is there a need for fuzzy control?”.

Speaking today about fuzzy control / observation / diagnosis is very often related to the so-called Takagi-Sugeno models (TS) (Takagi & Sugeno, 1985). The view of these models is to interconnect families of models via nonlinear functions having the nice convex sum property. When the conclusion are linear models – most of the cases – then from a point of view of automatic control they rely to families of model said Linear Parameter Variant (LPV) and quasi-LPV when the parameters depend on the state of the system (Tanaka & Wang, 2001). Let us just say that there are three main components in finding results for this area: the way the nonlinear functions are taken into account (including the so-called relaxations on co-positivity problems, see (Sala & Arino, 2007) for an asymptotic solution via Polyá’s stuff, the Lyapunov functions used and at last the solvers and way of solving the problems, generally Linear Matrix Inequalities (LMI) or Sum-of-Squares (SOS) constraints impose to get formulations that are in the pre-described form LMI and/or SOS. Each of these three steps introduces conservatism in the results.



Fig. 1. Whole set of problems

Representing figure 1 the whole set – unknown of course – of problem with a solution, the goal is twofold. One is to exclude points that are unfeasible (cross mark out of the set figure 1 left) and corresponds to necessary conditions, the other to enlarge the set where a solution can be found using a fuzzy representation of a nonlinear system (figure 1 right). For the first point very few results are available, (Johansson, Rantzer, & Arzen, 1999; Alexandre Kruszewski, Sala, Guerra, & Arino, 2009). Most of the results try to solve the second problem. Where are we today? State feedback and quadratic Lyapunov function under various possibilities – performances, H2, Hinfinity, robustness with delays – have got solutions (see (Ding, Sun, & Yang, 2006; Feng, 2006)).

Output feedback has still to keep some works in progress (Chadli & Guerra, 2012). As for quasi-LPV and nonlinear systems it is harder to derive strict conditions that guarantee performances (Input-to-Stability, following trajectories...), these points must also be addressed in the future. A lot of attraction has also been devoted to non quadratic Lyapunov functions with real successes in the discrete case (Ding, et al., 2006; A. Kruszewski, Wang, & Guerra, 2008) and more relative ones in the continuous case (Mozelli, Palhares, Souza, & Mendes, 2009; Pan, Guerra, Fei, & Jaadari, 2012; Rhee & Won, 2006).

Another important part of activities in control is related to adaptive control where the property of universal approximation of fuzzy systems is used in order to approximate an ideal control law. When there no identification of the nonlinear system, the control is called direct, otherwise it is called indirect. Even if pioneering works (L. X. Wang, 1993) are rather “old” it seems that these methods still suffer from technical limitations that apparently are hard to solve. Among them, the necessity of particular Brunowski form for the nonlinear model and the drawback is the fact that the states, i.e. generally the derivatives of the output(s), are supposed known. Several works try to solve these problems, see (Boukroune, Tadjine, M'Saad, & Farza, 2008; Y.-J. Liu, Tong, & Li, 2011; Tong & Li, 2009).

Some new trends coming from the so-called type-2 Fuzzy Sets are entering the general area of control, TS and adaptive frameworks. The works claim that it is an efficient way to cope with vagueness and imprecision and therefore they are more suitable than classical type-1 fuzzy sets (Mendel & John, 2002). A paper reviews industrial applications related to type-2 FS (Dereli, Baykasoglu, Altun, Durmusoglu, & Turksen, 2011) trying to exhibit which problems do require such a modeling. Nevertheless, even if some results claim superiority over type-1 or conventional linear controllers (see

for example (Atacak & Bay, 2012; Oh, Jang, & Pedrycz, 2011)), these results have to be enforced with theoretical arguments. As far as these arguments are not given – to the best of our knowledge, they are not – type-2 FS in control and observation does not really bring some new interesting gap.

The reader interested in applications related to the area of fuzzy control can find an interesting overview in (R.-E. Precup & H. Hellendoorn, 2011). At last, several questions arise: how can we come back to the fundamentals of fuzzy logics? Is there is still space for a linguistic way of doing? Or are we in a sense loosing the “essence” of what fuzziness was created to? Of course, fuzzy control should also go to the areas where automatic control is moving to, among them, large scale systems, interconnected (networks) large systems, hybrid systems...

It seems that, for theoretical aspects, we are at a crossroads where some new interesting “step” has to emerge to go further than just some adjustments in various known techniques in order to say “yes there is a need for fuzzy control”.

5. REINFORCEMENT LEARNING IN FEEDBACK CONTROL SYSTEMS

Adaptive control (Astrom & Wittenmark, 1995; Ioannou & Fidan, 2006) and optimal control (Lewis, Vrabie, & Syrmos, 2012) represent different philosophies for designing feedback controllers. Optimal controllers are normally designed offline by solving Hamilton-Jacobi-Bellman (HJB) equations, for example, the Riccati equation, using complete knowledge of the system dynamics. Determining optimal control policies for nonlinear systems requires the offline solution of nonlinear HJB equations, which are often difficult or impossible to solve. By contrast, adaptive controllers learn online to control unknown systems using data measured in real time along the system trajectories. Adaptive controllers are not usually designed to be optimal in the sense of minimizing user-prescribed performance functions. Indirect adaptive controllers use system identification techniques to first identify the system parameters, then use the obtained model to solve optimal design equations (Astrom & Wittenmark, 1995). Adaptive controllers may satisfy certain inverse optimality conditions.

The computational intelligence technique known as reinforcement learning allows for the design of a class of adaptive controllers with actor-critic structure that learn optimal control solutions by solving HJB design equations online, forward in time, and without knowing the full system dynamics. In the linear quadratic case, these methods determine the solution to the algebraic Riccati equation online, without specifically solving the Riccati equation and without knowing the system state matrix A . As such, these controllers can be considered as being optimal adaptive controllers. Chapter 11 of (Lewis, et al., 2012) places these controllers in the context of optimal control systems.

Reinforcement learning is a type of machine learning developed in the Computational Intelligence Community in

computer science engineering. It has close connections to both optimal control and adaptive control. More specifically, reinforcement learning refers to a class of methods that enable the design of adaptive controllers that learn online, in real time, the solutions to user-prescribed optimal control problems. Reinforcement learning methods were used by Ivan Pavlov in the 1860s to train his dogs. In machine learning, reinforcement learning (Lewis, Lendaris, & Liu, 2008; Powell, 2007; Sutton & Barto, 1998; Werbos, 1991) is a method for solving optimization problems that involves an actor or agent that interacts with its environment and modifies its actions, or control policies, based on stimuli received in response to its actions. Reinforcement learning is inspired by natural learning mechanisms, where animals adjust their actions based on reward and punishment stimuli received from the environment (Busoniu, Babuska, De Schutter, & Ernst, 2009; Mendel & MacLaren, 1970). Other reinforcement learning mechanisms operate in the human brain, where the dopamine neurotransmitter in the basal ganglia acts as a reinforcement informational signal that favors learning at the level of the neuron (Doya, Kimura, & Kawato, 2001; Schultz, 2004; Draguna Vrabie & Lewis, 2009; Werbos, 1992).

Reinforcement learning implies a cause-and-effect relationship between actions and reward or punishment. It implies goal-directed behaviour, at least insofar as the agent has an understanding of reward versus lack of reward or punishment. The reinforcement learning algorithms are constructed on the idea that effective control decisions must be remembered, by means of a reinforcement signal, such that they become more likely to be used a second time. Reinforcement learning is based on real-time evaluative information from the environment and could be called action-based learning. Reinforcement learning is connected from a theoretical point of view with both adaptive control and optimal control methods.

One type of reinforcement learning algorithms employs the actor-critic structure (Barto, 1984). This structure produces forward-in-time algorithms that are implemented in real time wherein an actor component applies an action, or control policy, to the environment, and a critic component assesses the value of that action. The learning mechanism supported by the actor-critic structure has two steps, namely, policy evaluation, executed by the critic, followed by policy improvement, performed by the actor. The policy evaluation step is performed by observing from the environment the results of applying current actions. These results are evaluated using a performance index, or value function (Bellman, 1957; Bertsekas & Tsitsiklis, 1996; Busoniu, et al., 2009; Powell, 2007; Sutton & Barto, 1998) that quantifies how close the current action is to optimal. Performance or value can be defined in terms of optimality objectives such as minimum fuel, minimum energy, minimum risk, or maximum reward. Based on the assessment of the performance, one of several schemes can then be used to modify or improve the control policy in the sense that the new policy yields a value that is improved relative to the previous value. In this scheme, reinforcement learning is a means of learning optimal behaviors by observing the real-

time responses from the environment to nonoptimal control policies.

Werbos (Werbos, 1989, 1991, 1992) developed actor-critic techniques for feedback control of discrete-time dynamical systems that learn optimal policies online in real time using data measured along the system trajectories. These methods, known as approximate dynamic programming (ADP) or adaptive dynamic programming, comprise a family of four basic learning methods. The ADP controllers are actor-critic structures with one learning network for the control action and one learning network for the critic. Many surveys of ADP are available (Balakrishnan, Ding, & Lewis, 2008; Lewis, 2009; Prokhorov & Wunsch, 1997; Si, Barto, Powell, & Wunsch, 2004; F. Y. Wang, Zhang, & Liu, 2009). Bertsekas and Tsitsiklis developed reinforcement learning methods for the control of discrete-time dynamical systems (Bertsekas & Tsitsiklis, 1996). This approach, known as neurodynamic programming, used offline solution methods. ADP has been extensively used in feedback control applications. Applications have been reported for missile control, automotive control, aircraft control over a flight envelope, aircraft landing control (Prokhorov & Wunsch, 1997), helicopter reconfiguration after rotor failure, power system control, and vehicle steering and speed control. Convergence analyses of ADP are provided in (Al-Tamimi, Lewis, & Abu-Khalaf, 2008; X. Liu & Balakrishnan, 2000).

A key object in applying reinforcement learning to the design of feedback control systems is the Bellman equation. The Bellman equation results on setting the system Hamiltonian function equal to zero, and it captures the optimality properties with respect to a given performance index of the system dynamics evolving through time. The temporal difference method (Sutton & Barto, 1998) for solving Bellman equations leads to a family of optimal adaptive controllers, that is, adaptive controllers that learn online the solutions to optimal control problems without knowing the full system dynamics. Temporal difference learning is true online reinforcement learning, wherein control actions are improved in real time based on estimating their value functions by observing data measured along the system trajectories. The basic families of algorithms provided by RL are Policy Iteration, Value Iteration, and Q learning.

Most research over the years in reinforcement learning for feedback control has been conducted for systems that operate in discrete time (Si, et al., 2004; Sutton & Barto, 1998; Werbos, 1992). This is because the Bellman equation for discrete-time systems does not involve the system dynamics, and has two occurrences of the value at different times. This special form immediately lends itself to both Policy Iteration and Value Iteration solution methods that do not require complete knowledge of the system dynamics.

Reinforcement learning is considerably more difficult for continuous-time systems than for discrete-time systems, and fewer results are available. This is due to the fact that, unfortunately, for continuous-time dynamical systems, the Bellman Equation has an inconvenient form that does involve the system dynamics. This hindered the development of RL for continuous-time systems for many years. The

development of an offline policy iteration method for continuous-time systems is described in (Abu-Khalaf, Lewis, & Huang, 2006). The method known as integral reinforcement learning (IRL) developed in (Draguna Vrabie & Lewis, 2009; D. Vrabie, Pastravanu, Abu-Khalaf, & Lewis, 2009) allows the application of reinforcement learning to formulate online optimal adaptive control methods for continuous-time systems. These methods find solutions to optimal HJ design equations and Riccati equations online in real time without knowing the system drift dynamics, or in the LQR case, without knowing the A matrix. Extensions to IRL have been made to solve optimal control problems online for systems with completely unknown dynamics in (Jiang & Jiang, 2012; Lee, Park, & Choi, 2012). A method of RL on time scales (Seiffert, Sanyal, & Wunsch, 2008) allows the treatment of discrete-time and continuous-time systems in the same framework.

5.1 The Future

Reinforcement Learning has been applied in the Computational Intelligence Community to solve complex decision problems with very general performance indices and using various learning techniques including episodic Montecarlo Methods. Problems solved include finding optimal solutions to games such as Backgammon, and solution of multiple-degrees-of-freedom systems such as the truck back-up problem. Applications of RL to feedback control have generally used performance indices that are summations or integrals over time of basic utility functions. Such performance indices may not be suitable for optimal decision and control problems such as adaptive human-robot interfaces, discrete event scheduling and decision problems, and task learning skills for autonomous systems. More general performance indices could capture the essence of such decision problems. More general learning schemes can be developed rather than the standard temporal difference learning that relies on information taken at every time instance. It is not known how episodic learning can be used in feedback control, though it seems to be related to iterative learning control.

Due to the vast amounts of data available in networked control systems, cooperative control, and internet systems, and real-time response scenarios, new methods are needed for fast simplified decision based on emotional cues in uncertain nonstationary environments. Such methods are used in the human brain in the interplay between structures such as the amygdala, orbitofrontal cortex, and hippocampus (Levine, 2012). Decision topologies based on these neurocognitive interplays may have more levels and more complex interconnections than the two-level structure of the actor-critic paradigm. The challenge will be developing such new decision and control schema and providing rigorous guarantees of stability, robustness, and performance for human engineered systems.

6. BRAIN MACHINE INTERFACES

Throughout our evolution as a species, brains have used bodies to interact with the external world. However, the

combination of many emerging technologies is poised to change this status quo and create direct ways of linking the external world directly with the brain, through what has been called brain machine interfaces (BMIs). BMI research may become both a launch pad for technology revolution in medical disciplines, as well as a paradigm shift for research and development in the centuries to come because it represents a new level of integration between biologic and “man made” systems. The general concept of a BMI is to either:

- (1) Create artificial sensory systems (retina, cochlea) by delivering the external world stimuli to the appropriate cortices,
- (2) Allow the motor cortex to command directly external robotic devices,
- (3) Repair brain subsystems, and regain cognitive function (e.g. memory),
- (4) Link remotely brains in social networks.

In view of the amazing plasticity of the brain these external devices may, with appropriate sensory feedback, be assimilated and become a part of the user’s cognitive space, on par with our body. Potentially, BMIs can improve human’s natural reaction time and force through engineered devices that are much faster and more powerful than biologic tissue. In particular BMIs may enable a higher communication bandwidth between the human brain and the digital computer, which has conditioned the present metaphor and research direction for the use of computers in our society.

Work in BMIs is imminently multidisciplinary. In one side we find neuroscientists and the disciplines of systems, computational, and cognitive neurosciences, while the engineering side is shored up in advanced signal processing, control theory, ultra low power VLSI, electrode design, optics, materials, computers, and communications. None of the disciplines can alone solve the challenge of interfacing brains to machines, so this is truly a symbiotic collaboration.

A productive taxonomy is to divide BMIs in invasive and non-invasive, which means that the latter collects brain activity by fitting electrodes or other apparatus externally to the brain and body. Normally these systems are called brain computer interfaces (BCIs) and their current development has focused on communication and control applications using menus in computer screens. The brain is a multiscale spatio-temporal system, so when we decide on a sensing methodology, we only measure some aspects of brain function. For instance when cup electrodes are placed over the scalp, the measurement is the electroencephalogram (EEG). In an analogy, the EEG quantifies the single neuron activity as a microphone mounted on a helicopter hovering over a football stadium quantifies the voice of a spectator watching a game. Only major neural events are quantified with the EEG, but surprisingly the EEG is still today the best indicator of brain activity to diagnose epilepsy, quantify depth of anaesthesia and sleep staging. On the other extreme of the spatial resolution, the invasive microelectrode inserted in the cortical tissue can quantify exactly the firing of a neuron in the vicinity of the electrode. However, its tell

nothing about the other 1011 neurons in the brain. Normally, electrode arrays with 100 microelectrodes or more are inserted in specific brain areas to provide a grossly sub sampled quantification of the neural system under analysis. These are the extremes of available sensing methods in BMIs.

6.1 Example of BMIs

BMIs can be divided in two basic types depending upon the application: sensory or motor. Sensory BMIs stimulate sensory cortex areas with artificially generated signals that translate physical quantities. The most common type of sensory BMI, with over 200,000 implants, are cochlear implants that use tiny microphones and signal processing to translate wave pressure near the ear into spike firings applied to the auditory nerve, allowing deaf people to listen (see, for instance, (McDonnell, Burkitt, Grayden, Meffin, & Grant, 2010)). The same basic concept is being developed for retina prosthesis, which can deliver to the visual cortex the appropriate stimulation that indicates the outline of objects (Abramian, et al., 2014). Motor BMIs on the other hand seek to translate brain electrical activity into useful commands to external devices, mimicking the natural motor control of muscles. There are two basic types of motor BMIs: command BCIs, and trajectory BMIs. Research in command BCIs started in the late 80’s by collecting brain electrical activity over the scalp (EEG) with a set of electrodes. The EEG technology is noninvasive and requires only signal amplification and conditioning. By practicing, subjects learn to control their regional brain activity in a predetermined fashion that can be robustly classified by a pattern recognition algorithm, and converted into a set of discrete commands. The paradigm for communication is mostly based on selection of cursor actions (up/down, left/right) on a computer display. The computer presents to the users a set of possibilities and they choose one of them through the cursor movement, until an action is completed. BCIs require subject training through biofeedback and they display a low bandwidth for effective communication (15-25 bits per minute) (Wolpaw & Wolpaw, 2012), which hinders the speed at which tasks can be accomplished. However, due to their non-invasiveness, BCIs have already been tested with success in paraplegics and locked-in patients. Several groups all over the world have demonstrated working versions of BCIs (Wolpaw & Wolpaw, 2012), and a system’s software standard has been proposed. There is a biannual BCI meeting with a BCI competition and a BCI journal is about to be launched to evaluate the progress of algorithms in this area.

Trajectory BMIs use brain activity to control directly the path of an external actuator in 3D space, mimicking the role of the motor system when it controls, for instance, the trajectory of a hand movement. Alternatively, the commands can be sent to peripheral nerves that have been rerouted to activate the required muscles. The technical problem here cannot be solved by classifying brain signals as in BCIs, but requires the BMI to generate a trajectory directly from brain activity. It has been difficult so far to extract from the EEG the motor command signatures with sufficient spatio-temporal resolution. Therefore, invasive techniques utilizing

directly neuronal firings or local field potentials have been utilized. In the last decade, the introduction of new methods for recording and analyzing large-scale brain activity and emerging developments in microchip design, signal processing algorithms, sensors and robotics are coalescing into a new technology devoted to creating BMIs for controls. Trajectory control BMIs offer the possibility to overcome the bandwidth limitation of BCIs and have been demonstrated with very encouraging results. The first demonstration involved rats that used their brain signals to press a lever and obtain a water reward (K., Moxon, Markowitz, & Nicolelis, 1999). Later, similar BMIs were demonstrated in monkeys in food reaching tasks (Wessberg, et al., 2000), and more recently in humans to control cursor movement in a computer screen (Chadwick, et al., 2011).

6.2 The Future

These are exciting times in BMI research. Although the problems faced are exceedingly difficult there is a sense of optimism and a road map of intermediate solutions that will some day deliver general purpose and efficient BMI. For this audience the challenges in system science are many and I synthesize some below.

I- System identification and control

BMIs include two complex systems (the user and the computer agent) in close loop feedback through a nonstationary environment. This interaction is online and because the brain is plastic and the environment nonstationary, adaptive online system identification and adaptive optimal control are needed for good performance, which includes guaranteed stability. These issues are only now starting to be addressed, because the work to date has addressed proof of concept in subsystems. For instance, the traditional way of designing a trajectory BMI is to identify the system from the collected brain activity to the kinematics, which requires off line training, but system parameters cannot be easily updated during operation, which requires daily retraining (Sanchez & Principe, 2007). Work using reinforcement learning is emerging (DiGiovanna, Mahmoudi, Fortes, Principe, & Sanchez, 2009) but still requires a lot of further work to make training fast, accurate and reliable.

II- Augmented optimal control

Another potential application area of system science is how to integrate optimally spiking models of neural tissue of particular brain areas with the data collected on line by electrodes of disabled users to help them compensate for their disability and solve tasks in the real world. A simplified solution that has been tested is to control an electrical stimulator applied to one part of the brain to generate a desired spike train in another part of the brain. An inverse adaptive control framework was implemented (Li & Principe, 2013), but other approaches are possible and potentially better for this application. One of the lingering difficulties in all these applications is that neurons communicate through discrete events in time called spikes, where the information is contained solely in the time of the event. Therefore all the signal analysis methods described should accept point processes as their inputs and produce also spikes as outputs.

The first steps to accomplish this are underway (Park, Seth, Paiva, Li, & Principe, 2013).

CONCLUDING REMARKS

This milestone paper addressed only four domains within CI methodologies: neural networks control, fuzzy control, reinforcement learning and brain machine interfaces. Additional topics, such as knowledge-based systems, evolutionary algorithms and swarm intelligence systems will be covered in subsequent milestone papers.

CI methodologies are currently applied to all areas of control. It is our view that the Technical Committee on Computational Intelligence in Control should strengthen the collaboration among other IFAC TCs and in particular with the other TCs within CC3, TC 3.1 and TC3.3. The latter can be achieved by promoting the triennial Conference for Embedded Systems, Computer intelligence and Telematics (CESCIT), while the former can be achieved by maintaining, or increasing the number of co-sponsored conferences with other TCs, by creating multi-TCs working groups and by proposing joint special sessions.

IFAC and in particular TC 3.2 has everything to gain in promoting collaboration with external Institutions, such as IEEE and IFSA. This has happened in previous editions of our TC 3.2 ICONS Conference (co-sponsored by these Institutions), and should be also maintained in the future.

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