Intelligent Control: A Taxonomy*

Callum Wilson, Francesco Marchetti, Marilena Di Carlo, Annalisa Riccardi, and Edmondo Minisci

Intelligent Computational Engineering Laboratory - Department of Mechanical and Aerospace Engineering,
University of Strathclyde,
Glasgow, United Kingdom
Email: callum.j.wilson@strath.ac.uk, francesco.marchetti@strath.ac.uk, marilena.di-carlo@strath.ac.uk,
annalisa.riccardi@strath.ac.uk, edmondo.minisci@strath.ac.uk

***Abstract*— In this paper we highlight the stages of development towards intelligent control and define it based on literature. Furthermore, we propose a novel taxonomy of intelligent control methods which categorises these based on their level of uncertainty in three areas: the environment, the control system, and the goals. These areas are consistent with the key elements of intelligent control present in existing definitions. Using this taxonomy, we present some example intelligent control methods and their classifications to illustrate the applicability of the taxonomy.**

I. INTRODUCTION

Over the past century, more advanced methods have become necessary to handle an increase in the complexity of control problems. We now require control systems which can operate in very challenging environments with limited knowledge. This motivated the use of Artificial Intelligence (AI) techniques in control to incorporate human reasoning. The combination of AI with theories from automatic control and operations research is referred to as "Intelligent Control" [1].

Intelligent Control (IC) has received a great deal of attention in many control applications since the term was first coined by Fu [2]. Due to its wide use, a "terminology war" ensued where there were several competing definitions for different concepts in IC - especially "adaptive" and "learning" control [3]. Following this era, there are now concrete definitions for the various concepts relating to IC. The definition of IC we present here is based on the work of Saridis and Antsaklis which both give clear definitions [1], [4].

The remainder of this paper is organised as follows: Section II shows the development of control techniques towards IC. Section III follows this by defining IC and how it relates to adaptive and learning control. This section then details the three main dimensions of IC where the controller may lack knowledge. Section IV presents a classification framework for IC methods which formalises the level of knowledge in each of the dimensions. In Section V the classification framework presented in Section IV is applied to several applications and we describe some relevant examples to clarify our method. Finally Section VI presents conclusions and future research directions.

*This work was partially supported by the European Space Agency (Contract Number: 4000124916/18/NL/CRS/hh)

II. PATH TO INTELLIGENT CONTROL

Conventional control methods developed significantly over the past century culminating in what is now referred to as IC. As discussed in [5], the path to intelligent control was evolutionary as opposed to revolutionary, meaning control methods improved incrementally over time. At each step the improvements were motivated by the increasingly complex problems being considered. Here we briefly describe this progression.

The fundamental idea of control theory is to make a system behave as desired [1]. Conventionally, the control designer models the system to be controlled and similarly finds a mathematical model of a suitable controller. In situations where the model of the system is precisely known, a controller can take predetermined actions on this system which achieve its goal. This is referred to as *open-loop control* where the controller does not observe the true system state. In reality, a perfect system model is rarely available and even slight variations in the system can cause the controller to be ineffective. Most modern controllers receive feedback from the system indicating its state and use this to decide the control action. This is termed *feedback control*, which is a fundamental concept in control theory that formed the basis of automatic controllers used today.

While feedback controllers successfully handled more challenging systems, this also revealed a need for further improvements to solve more difficult control problems. When the controller's performance can be quantified by some performance criterion, *optimal control* theory solves the problem of optimising this performance. Following this development, the systems being studied began to exhibit stochasticity which meant conventional methods of modelling the system were insufficient. These systems can only be modelled statistically, which requires *stochastic control* methods. At this point, lack of system knowledge became a more significant issue. The control schemes described previously require knowledge of the system dynamics and any uncertainties must be statistically quantifiable. Beyond these systems which can be modelled, there are classes of systems where the dynamics may change over time which degrades the controller's performance. Furthermore, for certain systems the dynamics may be entirely unknown or incompletely known and so the methodologies discussed so far cannot be used. These are referred to as *Self-Organising Control (SOC)* systems, simply defined as any system with features "beyond stochastic control systems" [1].

Adaptive control methods handle changing environments by adjusting the control scheme online. This means the controller maintains a favourable performance even as the environment varies. These methods broadly fall under two categories: direct and indirect. Indirect adaptive control schemes do not alter the controller directly, but instead adapt other components which affect the control scheme, such as a system model. Direct adaptive control schemes adapt the controller parameters themselves instead. These approaches can also be referred to as *Parameter-Adaptive* (indirect) or *Performance-Adaptive* (direct) SOC.

Learning control is the final step towards intelligent control methods. This can be seen as a more specific form of SOC where the controller retains information pertaining to the system's operation and uses this knowledge to alter its control scheme. This is where control systems begin to incorporate planning, where future actions can be selected by the system in advance based on its knowledge. Learning can occur offline such that the control system is trained before operation, or online where knowledge is accumulated during its operation. This distinction is important when it comes to intelligent control systems as will be discussed.

III. DEFINING INTELLIGENT CONTROL

As with many new concepts, the term "Intelligent Control" very quickly became widely used and often abused by many scholars both from the control community and wider fields. This made it difficult to create a suitable definition for IC since it was so commonly used to describe disparate concepts. As a result, in 1993 the IEEE Control Systems Society designated a task force to research and define "Intelligent Control" [4]. In their report they gave the following defining characteristics of IC systems:

> "An intelligent control system is designed so that it can autonomously achieve a high level goal, while its components, control goals, plant models and control laws are not completely defined, either because they were not known at the design time or because they changed unexpectedly."

This importantly shows that IC systems deal not only with system uncertainties, but also cases where the controller does not have specifically defined goals or structures. Saridis gives a more general definition of IC as an interaction between three fields: Artificial Intelligence, Operations Research, and Automatic Control Systems (Figure 1) [1]. This builds on the definition given by Fu, who originally described IC systems as the "intersection of artificial intelligence and automatic control"[2].

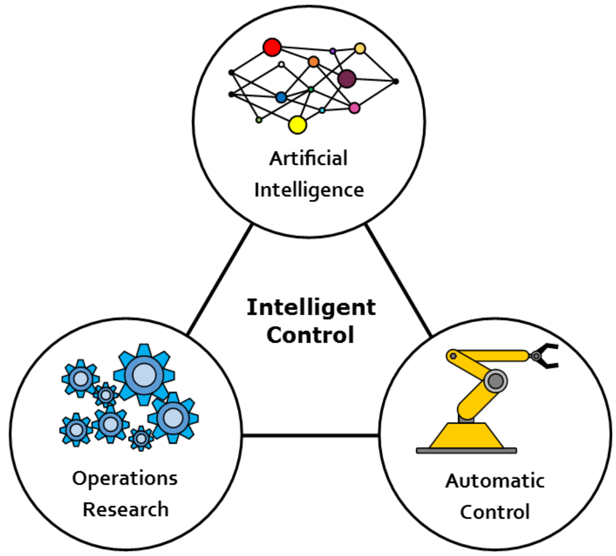

Fig. 1: Intelligent control is the interaction of the fields of artificial intelligence, operations research, and automatic control.

Considering the definitions of conventional control methodologies presented previously, direct or indirect adaptive control systems and learning control systems can be considered intelligent where they incorporate AI techniques. It is important to note, however, that not all adaptive control systems are intelligent since it is possible to derive adaptive systems using analytical formulations, therefore missing the AI component. Similarly, a controller is not necessarily intelligent if it is derived using AI techniques as it must still show adaptivity or learning online to be classed as intelligent. Both these points represent the most common misunderstandings in what is, and is not, classed as IC. For example, a controller may use AI to define its control scheme offline using a system model and then, when in operation, not update its control scheme further. Such a controller is not classed as IC since it does not adjust to substantial environmental uncertainties.

A. Dimensions of Intelligent Control

Since IC deals primarily with substantial uncertainties, it is sensible to define the level of intelligence of a controller in terms of the level of uncertainty in its task. In the task force definition of IC, there are three clear dimensions where uncertainty can be present: the environment (represented by plant models), the control system laws and components, and the control goals. In more abstract terms, this is *what* is being controlled, *how* it is being controlled, and *why* it is being controlled.

1) Environment: We consider knowledge of the environment to be the ability to express a model of the environment mathematically. The design of a control system conventionally requires such a model and the level of knowledge of the model affects the level of intelligence necessary in the controller. Equation 1 shows the general form of a non-linear system being controlled:

$$\dot{x} = f(x,u) \tag{1a}$$
$$y = h(x) \tag{1b}$$

where y is the system output, u is the system input, x is the system's state variables, and the functions f and h are mappings (linear or non-linear) from their inputs to appropriately dimensioned vectors. In the following equations, for simplicity we will only consider expressions for $\dot{x}$. The environment model may also contain some parameters, $A = \{a_1, a_2, \ldots, a_{na}\}$, which vary with time. In this case the deterministic mapping from current state and control action to system output in equation 1 no longer applies and now becomes time dependent. This is shown in equation 2

$$\dot{x} = f(x,u,A(t)) \tag{2}$$

Thus far we have assumed the function f to be known to a precision which allows reasonable tracking accuracy between the model and real environment. This is not possible when the environment's dynamics are poorly understood. We indicate this in equation 3 with the function $\hat{f}$ representing an uncertain mapping.

$$\dot{x} = \hat{f}(x,u,A(t)) \tag{3}$$

2) Control System: Similarly to the environment, a control system can be mathematically modelled with varying levels of knowledge about its components. More intelligent controllers are more flexible and have less precise knowledge of their control laws at design time. A general feedback controller is described as follows:

$$u = g(e) \tag{4}$$

where $e = y_d - y$ is the error between the desired system output, y_d and actual system output. This represents a controller with fixed parameters that are selected at design time. A general adaptive controller has control parameters $K = \{k_1, k_2, \ldots, k_{nk}\}$ which can vary with any number of observations. Such a controller is described in equation 5.

$$u = g(e, K(\cdot)) \tag{5}$$

The error e between desired and true system output can also be subject to significant uncertainties relating to the behaviour of sensors and actuators. Even if the environment itself is stationary and deterministic, there may be errors, for example, in the measurements or unmodelled actuator dynamics. This case is described as shown:

$$u = g(\hat{e}, K(\cdot)) \tag{6}$$

where $\hat{e} = y_d - \hat{y}$ is the measured error given the measured and uncertain state variables $\hat{y}$. The controller must then cope with these uncertain measurements. More sophisticated controllers display more significant variations in their structure than just the control parameters. In this case, there may be several different control laws to select based on observations, or new control laws may be derived online. A general form of such a controller is given here:

$$u = \begin{cases} g_1(\hat{e}, K_1(\cdot)) \\ g_2(\hat{e}, K_2(\cdot)) \\ \vdots \\ g_{ng}(\hat{e}, K_{nk}(\cdot)) \end{cases} \tag{7}$$

3) Goals: Compared to the previous two dimensions, goals are more abstract in general and less rigorously mathematically defined. The level of knowledge of goals can then be thought of as how well it could be expressed mathematically, as well as the level of awareness of goals in the controller. In most cases a controller's goal is defined as fulfilling some stability criterion or maintaining some performance measure across its operating range. In this case, the goal is entirely defined at design time and the controller has no awareness of this goal.

Another approach to defining control goals is to have some cost function which gives the controller an indication of its performance in a task. The controller then seeks to minimise this cost function with its control policy. In doing so the controller now has some awareness of its goals and creates ways to achieve them instead of following prescribed routines to achieve a predetermined level of performance.

Beyond control systems with defined goals or cost functions, the goals become more abstract and defined in high level language rather than mathematically. In some cases, specific short-term goals may change over time as determined by the controller's internal planning. This is done with respect to some global goal which remains constant. In cases where a global goal cannot be defined mathematically and the controller can only be given high level goals, this requires an intelligent system to deduce how to act appropriately and achieve such goals.

IV. TAXONOMY

As discussed in section III, IC methods are used where there is a substantial lack of knowledge at design time. This lack of knowledge comes under three main categories: the environment, the control system, and the goals. Within each of these categories, any controller, including conventional ones, can have a varying degree of knowledge at design time. Here we present a classification scheme for IC methods which is based on the level of knowledge present in the controller at design time. In each case the highest level of uncertainty, level 4, is the hypothetical maximum uncertainty and these do not presently have real examples.

A. Environment Knowledge

0) *Complete and precise environment model:*
   If the environment is precisely known, an open loop controller could be used, thus requiring no degree of intelligence. In reality there are often aspects of the system which are not perfectly modelled or subject to

uncertainties. This then requires a more sophisticated controller.

1) *Complete environment model subject to minor variations:*
In this case a simple feedback controller can be used and potentially incorporated with some adaptation. These controllers are not necessarily intelligent, since they only require low levels of adaptation for dealing with slight uncertainties and do not learn online. There are still some examples of intelligent controllers within this category.
2) *Environment subject to change during operation:*
Now a higher degree of intelligence is required, since substantial changes in the environment cannot always be predicted or may be too complex to model. At this level of uncertainty, some conventional adaptive control methods can still perform sufficiently as well as intelligent ones.
3) *Underlying physics of environment not well defined:*
This is an uncommon scenario for Earth applications, however it is a fundamental problem for many space applications, such as Mars entry vehicles. Here some information about the environment is known, but there are still substantial knowledge gaps requiring an intelligent controller.
4) *No knowledge of environment:*
Where no model exists for the environment and the control designer cannot incorporate any environmental knowledge into the controller, this requires an intelligent control system to safely explore its environment.

B. Control System Knowledge

0) *Stationary, globally stable control system:*
Most feedback controllers have guarantees of stability and maintain a certain level of performance under given assumptions. In simple cases, these assumptions allow the control system to perform well with a fixed set of parameters without any need for adaptation.
1) *Varying controller parameters:*
There are many examples of intelligent and non-intelligent applications which vary some control parameters online. This accounts for a lack of knowledge in the controller parameters, where fixed parameters at design time are insufficient to cover the entire operating range of the system.
2) *Unknown sensor/actuator behaviour:*
This comes under the broad category of fault tolerant control, which itself has many dimensions. Here we consider fault tolerance to represent a level of uncertainty in the control system, where measurements may be erroneous and actions may not create the predicted effect. Some fault tolerant systems use simple thresholds for indicating faults which are specified at design time, but since these are known this does not fall under this category. Here we are instead referring to a control system which must deal with unknown faults.
3) *Varying controller configurations:*
At higher levels of intelligence, a controller can alter its own control structure online. This is commonly done offline using techniques such as evolutionary computation to define the controller structure. An intelligent controller requires online adaptation and therefore an efficient means of adjusting its configuration while operating.
4) *No known controller structure:*
The controller itself designs the control system from scratch using, for example, mathematical operations, control blocks, intelligent architectures, etc. An intelligent controller must be able to do this online, but perhaps with a rudimentary initial control system to give a stable starting point.

C. Goal Knowledge

0) *Goals entirely pre-determined by designer:*
Most control systems, including intelligent ones, have a clearly defined goal which entirely shapes the control system design. In this case the control system is not 'aware' of its goals and is therefore unable to update its goals or improve its performance with respect to the current goals.
1) *Goal specified implicitly, e.g. as a reward function:*
Many optimal control problems come under this category, since the aim of the controller is often to minimise or maximise a defined cost function when the means of optimising this function are not specified. The high level goal of the controller is then to derive a control policy which achieves optimal control with respect to this cost function. This is also the case where the controller is punished for detrimental actions and must find a control policy which avoids such actions. These examples fit well into the framework of reinforcement learning control, where an agent learns by interacting with the environment and observing its state and a reward.
2) *Specific goals subject to change during operation with a globally defined goal:*
In a dynamic environment, the definition of specific goals depends on contingent events and observations. Moreover, if the allocation of goals is performed on ground, such as in a space mission, the robot/spacecraft will have to wait for new instructions every time a new, unforeseen event occurs or a new set of scientific data is available. This requires an intelligent goal planner to elaborate new specific goals based on changes in the environment.
3) *One or several abstract goals with no clear cost function:*
There are cases where the goals cannot be easily defined mathematically and so the controller requires an understanding of high level goals. For example, a controller's goal might be "capture images of scientifically interesting events" or "explore this region and collect data". The controller must be able to decide what events are scientifically interesting or which data

are worth collecting.

4) *No knowledge of goals:*
   The controller has to deduce what actions to take when, to begin with, it has no knowledge or indication of what actions are favourable.

V. CLASSIFICATION OF RELEVANT EXAMPLES

Using the taxonomy presented here, we now give some examples of intelligent controllers and their classification. The specific examples detailed here are used to illustrate the applicability of the taxonomy to a range of methods with varying levels of intelligence. The following notation is used in the classification below:

– E: Environmental Knowledge
– C: Control System Knowledge
– G: Goal Knowledge

Table I shows the classification of IC methods presented in numerous papers with references. For clarity, the classifications with a goal knowledge level of 3 and 4 were omitted since no applications were found with this level of intelligence. Figure 2 presents these classifications in radar plots. As with table I, there are 3 plots each with a certain level of goal knowledge and thicker lines indicate more applications found with that classification. From this figure, it is clear the majority of applications possess lower levels of intelligence and tend to have higher levels in the control system and environment dimensions.

- *E-1, C-1, G-0:*
  Ichikawa and Sawa give an early example of Neural Networks (NNs) being used as direct controllers [20]. In their paper they combine a direct NN controller with genetic model reference adaptive control, which trains the NN based on a model of the ideal plant dynamics. This system is designed to deal with changing environment dynamics and continually updates its network to optimise performance.
- *E-2, C-1, G-0:*
  One of the most popular IC methods is the neuro-fuzzy controller, which combines the adaptability of a NN with the human-like reasoning of fuzzy controllers [28]. In this example, the authors apply a neuro-fuzzy model reference adaptive control scheme to an electric drive system. They show the controller is robust to changes in the environment parameters and adapts quickly to suppress vibrations and improve tracking accuracy.
- *E-3, C-1, G-0:*
  Such an uncertain environment as a Mars entry vehicle benefits from having an intelligent control system [30]. In this paper the authors develop a NN based sliding-mode variable structure controller. This controller has a fast loop, which is a conventional PID controller, and a slow loop, which contains the adaptive NN element. The goal is completely defined by the user through the definition of a nominal entry trajectory.
- *E-1, C-1, G-1:*
  It can be advantageous for IC methods to combine different AI techniques to exploit the their benefits [35]. Handelman et al create an IC system which comprises a knowledge based system for devising learning strategies and a NN controller which learns the desired actions and performs these consistently in real-time. This is designed to mimic human learning which combines rule based initial learning and fine tuning by repetitive learning. The environment and control system considered here have low levels of uncertainty, and the control goals are only implicitly defined.
- *E-2, C-2, G-1:*
  Fault Detection, Isolation, and Recovery (FDIR) is an important class of applications that can be enhanced with IC, as was done in [43]. Here two recurrent NNs are employed to detect and isolate faults - one for sensor faults and another for actuator faults. These NNs also compensate for these faults directly without the need for an additional subsystem for fault isolation.
- *E-1, C-1, G-2:*

TABLE I: Taxonomy of intelligent control applications found in the literature

G0					
	E0	E1	E2	E3	E4
C0					
C1		[6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21]	[22], [23], [24], [25], [26], [27], [28], [29]	[30]	
C2	[31]	[32]	[33]		
C3					
C4					
G1					
	E0	E1	E2	E3	E4
C0	[34]				
C1		[35], [36], [37], [38], [39]	[40], [41], [42]		
C2			[43]		
C3					
C4					
G2					
	E0	E1	E2	E3	E4
C0		[44], [45]			
C1		[46]	[47]		
C2					
C3					
C4					

Key: E = Environmental Knowledge, C = Control System Knowledge, G = Goal Knowledge

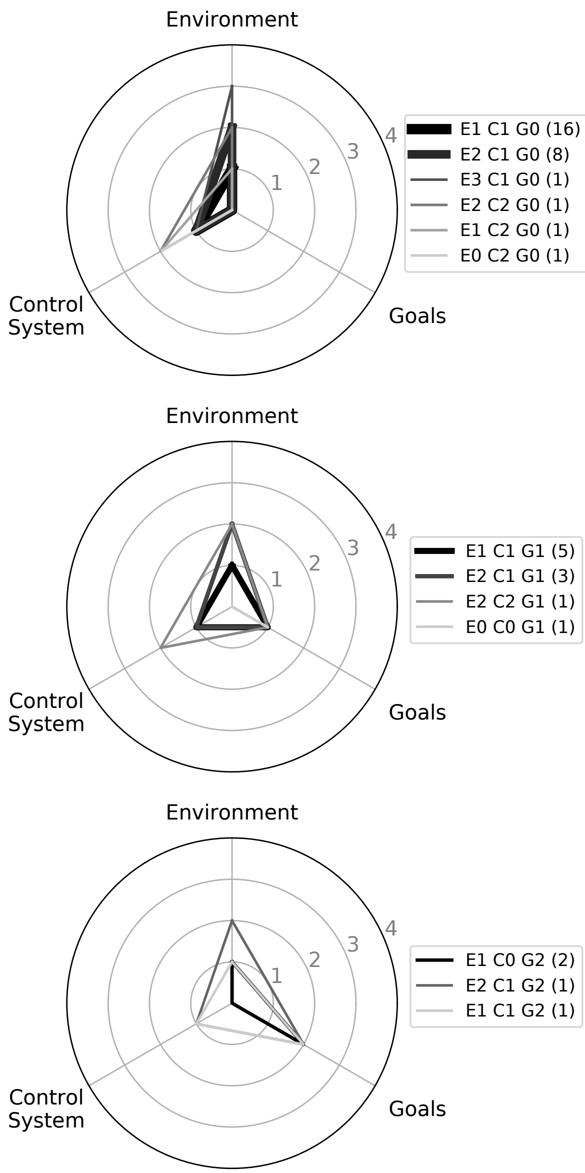

Fig. 2: Radar plots of IC methods and their classifications for each level of goal knowledge - line width indicates number of applications found.

The Autonomous Sciencecraft Experiment onboard NASA's Earth Observing One is one of the most advanced spacecraft IC systems [46]. As with many intelligent control systems, this system has a hierarchical structure. In this case the highest level in the control hierarchy is the CASPER planner, which uses information from the onboard science to plan its activities. This is fed to the spacecraft command language, which then carries out the plan using lower level actions. This level can also adapt to environmental changes and make control adjustments as necessary. Below this level is conventional software which simply carries out control actions as instructed by higher levels. While this system does not operate in a substantially varying environment, it alters its controller parameters online and contains highly autonomous decision making and goal updating.

- *E-2, C-1, G-2:*
  WISDOM is a control system for rovers which is capable of high level planning and adaptive control [47]. Again this control system has a hierarchical structure with three layers. The top layer is responsible for generating plans, which are fed to the adaptive control system at a lower level. This adaptive system deals with immediate changes in the environment and gives instructions to the lowest level in the hierarchy, which is connected directly to the actuators. This system adapts to changing or uncertain environments and has varying parameters. The goals are also evolved over time in the system's planner.

VI. CONCLUSIONS

Here we have discussed the background of IC and presented a taxonomy which indicates the level of intelligence in a controller based on three dimensions: environment knowledge, control system knowledge, and goal knowledge. These dimensions are in line with IC definitions presented previously and provide a framework for classifying IC methods.

IC techniques are the latest step in the progression of control methodologies motivated by the increasingly complex environments being controlled. While the term is often used inappropriately, there are still clear definitions for IC which its pioneers established early in its timeline. As IC has developed so have the fields of Aritificial Intelligence, Operations Research, and Automatic Control which comprise IC. In addition, increased computational power has allowed IC to tackle far more complex control problems than were previously possible. Some IC methods use more basic AI techniques for simple intelligent adaptive controllers which possess a low level of intelligence. There also exist more intelligent controllers which can define their own goals and operate in highly uncertain environments.

It is expected to see more intelligent and autonomous machines developed in the coming years. These will not only be used in newer, more challenging domains such as space exploration but also augment existing control systems. Future research is necessary to create more intelligent adaptive control schemes and to standardise autonomous agents which learn and establish goals online with minimal human input.

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