Computational Intelligence

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Contents

1 Introduction **2**

2 What is computational intelligence? **3**

3 Artificial versus computational intelligence **5**

4 Computational intelligence subfields from different perspectives **8**

5 Activities in computational intelligence **10**

6 Concluding remarks **12**

Glossary

Artificial Intelligence (AI) The science of creating a non-human intelligence with machines and/or computers.

Computational Intelligence (CI) Subject of this introduction and a name for the combined fields of Neural Computation, Evolutionary Computation and Fuzzy Computation. Recently the number of fields have been expanded to include DNA Computing and Quantum Computing.

Neural Computation (NC) and Neural Networks (NN) One of the core fields of CI, uses the (human) brain as a model for solving problems. It is known for its ability to deal with noisy and variable information.

Evolutionary Computation (EC) and Genetic Algorithms (GA) Uses Darwinistic methods for generating and evaluating a population of possible solutions to a problem. It is known for its generality and robustness. One of the core fields of CI.

Fuzzy Computation (FC) and Fuzzy Systems (FS) Instead of using Boolean logic, Fuzzy Systems use the notions of almost true or false to solve problems were Boolean logic would fail. Also one of the core fields of CI.

DNA Computing (DNAC) By coding actual DNA sequences on a prepared medium and using specially encoded enzymes to remove the infeasable one, DNA Computing uses the inherent parallelism of nature in the most direct way to solve problems.

Quantum Computing (QC) Using the quantum mechanics of quantisation, interference and entanglement, is a fundamentally new mode of information processing.

1 Introduction

The study of (human) intelligence has a rich history over three millenniums. In the twentieth century the invention of computers provided a facility for building and studying systems that exhibit features or behaviour traditionally attributed to intelligence, but are not natural in the sense that they are human engineered. The emerging science, or engineering discipline, is usually called the field of artificial intelligence (AI). Although the name itself is general enough to cover any approach to human engineered intelligent systems, its meaning – at least its most common interpretation – is restricted by the conventions of the AI research community. Roughly speaking, traditional AI is strongly oriented to symbolic representations and manipulations (reasoning) in a top-down manner. That is, the structure of a given problem (environment, domain context) is analysed beforehand and the construction of an intelligent system is based upon this structure. Think, for instance of expert systems representing the problem domain in formal logical terms and applying formal reasoning procedures to derive conclusions, determine actions, within the given structure.

Recently it has been argued that there is a group of alternative approaches to realize intelligent features or behaviour. These approaches, although different from each other, share the property of being non-symbolic and operating in a bottom-up fashion, where structure emerges from an unordered begin, rather than being imposed from above. These fields, evolutionary computation (EC), fuzzy systems (FS), and neural networks (NN) were grouped under the name computational intelligence (CI). The most influential pioneering publication from Marks and Bezdek date back to the early nineties. The major scientific event often seen as marking the birth of the new field has been the IEEE World Congress on Computational Intelligence in 1994, Orlando, Florida. It featured three simultaneous conferences, the IEEE International Conference on Evolutionary Computation, Fuzzy Systems, and Neural Networks.

2 What is computational intelligence?

Although used fairly widespread, there is no commonly accepted definition of the term computational intelligence. Attempts to define, or at least to circumscribe, CI usually fall in one or more of the following categories:

- Conceptual treatment of key notions and their roles in CI.
- "Relative definition" comparing CI to AI.
- Listing of the (established) areas that belong to it.

In the sequel we summarise various interpretations of the term CI along the lines of development (quasi-chronologically). The first published definition is due to J.C. Bezdek who states that:

> "... (strictly) computational systems depend on numerical data supplied by manufactured sensors and do not rely upon "knowledge"."

Later, in 1994, Bezdek offers that CI is "low-level computation in the style of the mind", whereas AI is "mid-level computation in the style of the mind". The envisioned difference is that mid-level systems include knowledge (tidbits), while low-level systems do not. According to this perception, computational architectures utilise sensor data and the term artificial should be reserved for architectures that have a clearly identifiable non-numerical component or knowledge. His proposal is to call a system computationally intelligent when:

> "It deals only with numerical (low-level) data, has a pattern recognition component, and does not use knowledge in the AI sense; and additionally, when it (begins to) exhibit (i) computational adaptivity; (ii) computational fault tolerance; (iii) speed approaching human-like turnaround, and (iv) error rates that approximate human performance."

A particular aspect of Bezdeks view (discussed in more details in the next section) is the importance of pattern recognition, especially the role of neural networks. Marks' definition – falling into the third category – is listing neural nets as one of the building blocks of CI, the others being genetic algorithms, fuzzy systems, evolutionary programming, and artificial life. Let us remark, that contemporary terminology would place genetic algorithms and evolutionary programming both under the umbrella of evolutionary computing. In their seminal book on CI, Eberhart *et al.* elaborate further on the very notion of CI and relate their vision to that of Bezdek. Their view is summarised as:

> "... Computational intelligence is defined as a methodology involving computing (whether with a computer, wetware, etc.) that exhibits an ability to learn and/or deal with new situations such that the system is perceived to possess one or more attributes of reason, such as generalisation, discovery, association, and abstraction. The output of a computationally intelligent system often includes predictions and/or decisions. Put another way, computational intelligence comprises practical adaptation concepts, paradigms, algorithms, and implementations that enable or facilitate appropriate actions (intelligent behaviour) in complex and changing environments."

One of the main differences between this view and that of Bezdek is the emphasis on adaptation, rather than pattern recognition. This is stated explicitly as:

> "In summary, adaptation is arguably the most appropriate term for what computationally intelligent systems do. In fact, it is not too much of a stretch to say that *computational intelligence and adaptation are synonymous.*" (Italics from Eberhart *et al.*)

This line is carried further by Fogel.

> "These technologies of neural, fuzzy and evolutionary systems were brought together under the rubric of Computational Intelligence, a relatively new field offered to generally describe methods of computation that can be used to adapt solutions to new problems and do not rely on explicit human knowledge."

While the first part of this quote describes CI by listing the fields belonging to it, the second part stresses adaptation as a key notion in computational intelligence. Actually, Fogels view is an amplification of that of Eberhart *et al.* in the sense that he sees *intelligence and adaptation as synonyms*[1] (italics from the authors of this paper) formulating it this way:

[1] Note that Eberhart *et al.* identify **computational** intelligence and adaptation.

> "Any system ... that generates adaptive behaviour to meet goals in a range of environments can be said to be intelligent. In contrast, any system that cannot generate adaptive behaviour and can only perform in a single limited environment demonstrates no intelligence."

It exceeds the scope of this paper to go into investigations of the notion of intelligence. A detailed discussion of this and many related issues from a CI point of view can be found in a later paper by Bezdek (1998). We close this section with an 'outlier', a particular interpretation of computational (and artificial) intelligence after Poole *et al.*, where the authors state:

> "Computational intelligence is the study of the design of intelligent agents. ... An intelligent agent is a system that acts intelligently: What it does is appropriate for its circumstances and its goal, it is flexible to changing environments and changing goals, it learns from experience, and it makes appropriate choices given perceptual limitations and finite computation."

Further reading discloses that the term computational intelligence is offered as an alternative for artificial intelligence. We will further discuss this aspect in the next section.

3 Artificial versus computational intelligence

The relationship between computational intelligence and artificial intelligence has formed a frequently discussed issue during the development of CI. While the last quote from the previous section implies they are synonyms, the huge majority of AI/CI researchers concerned with the subject sees them as different areas, where either

- CI forms an alternative to AI;
- AI subsumes CI;
- CI subsumes AI.

An example of the first option can be found in Marks publication in 1993: "Although seeking similar goals, CI has emerged as a sovereign field whose research community is virtually distinct from AI".

A strongly different view belonging to the second category is due to Bezdek who summarised the relationships among components of intelligent systems with a figure, reproduced here as Figure 1 after Bezdek's elaboration on his first definition in 1994. He describes three levels of system complexity, level A, B, and C. Level A stands for artificial or symbolic, level B for biological or organic, and level C stands for computational or numeric systems.

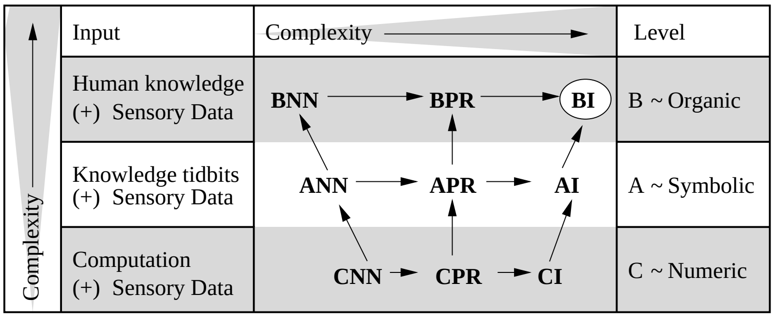

Figure 1: Relationships among components of intelligent systems (after Bezdek 1994)

The letters NN refer to neural networks, PR to pattern recognition, and I to intelligence. The top layer in Figure 1 represents biological intelligence and the two lower layers represent machine intelligence, CI being computational intelligence. In Figure 1, complexity increases from left to right and bottom to top. The distances between the nodes are placed to show the disparities between the terms they represent, e.g., the distinction between computational neural networks (CNNs) and computational pattern recognition (CPR) is less than that between biological neural networks (BNNs) and biological pattern recognition (BPR). Finally, he suggests that a node at the tail of an arrow is a subset of the node at the head of that arrow. CI would therefore be a subset of AI, which in turn is a subset of BI. He rephrased this view in his 1998 publication by saying that methods such as fuzzy, neuro and evolutionary computing are enabling technologies for AI.

A rather different perception is presented in 1995 by Eberhart. Eberhart *et al.* had four objections to the view of Bezdek. The most important two for our discussion here are the dichotomy of functions (nodes) along biological versus computational lines, (that is, distinguishing types of intelligence by the physical carrier they are grounded in) and the characterisation of nodes as subsets of subsequent nodes (i.e., that BI would subsume AI and AI would subsume CI). As for the first objection, recall the quote from the previous section where computational intelligence is defined as a methodology for computers, wetware, etc. Eberhart *et al.* illustrate their global view on relationships among the components of intelligent systems by a scheme, reproduced here in Figure 2. The figure reflects that intelligence is as intelligence does in an environment, depicting the inputs as sensory inputs (like a computer keyboard etc.) and the outputs as communications to, or actions upon, the environment. One arrow in the system goes directly from sensing to intelligent behaviour, reflecting reflex actions while another 'takes the long route', from sensing via algorithms and pattern recognition, to either directly intelligent behaviour or to CI as intermediate step to intelligent

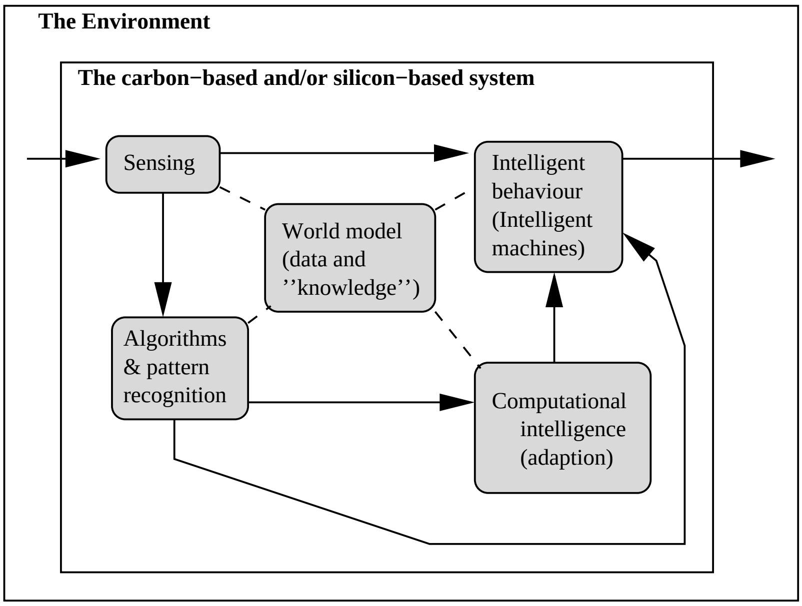

Figure 2: Relationships among components of intelligent systems (after Eberhart 1995)

behaviour. There are two important aspects of Figure 2 to consider here. First, the representation emphasises that, in general, nodes at the tails of arrows are *not* subsets of those at the heads, and that all nodes provide input to the intelligent behaviour node. Second, that computational intelligence is buried deeply within the core of the system (either carbon-based or silicon-based), the furthest from the environment interface. With Figure 2, Eberhart also underlines his view of the difference between AI and CI, stating that traditional AI's place in the figure is at the outer level, or near the interface surface, of the computational intelligence node, where the arrow departs for the intelligent behaviour node. Evolutionary/fuzzy/neural tools (whether or not in combination) reside "at the heart of the computational intelligence node" and they do have access to, and utilise, knowledge elements. Indeed, a very different viewpoint from that of Bezdek.

A rather harsh distinction between artificial intelligence and computational intelligence is offered Fogel in 1995. The basis of this distinction is identifying adaptation as the crucial feature of intelligence (recall the quote in the previous section). Fogel observes that the central focus in traditional AI research has been on emulating human behaviour by extracting rules and knowledge from human experts. Furthermore, the vast majority of AI programs has nothing to do with learning. Traditional symbolic AI systems do not adapt to new problems in new ways, therefore they emphasise "artificial" and not the "intelligence". They may play excellent chess, but in essence they are but complicated calculators. In contrast, CI techniques (i.e., evolutionary, fuzzy, and neurocomputing) model natural processes or end-products associated with intelligent behaviour, either at the level of neuronal activity and function, human behaviour, or evolutionary learning in the terms of adaptive behaviour or adaptive genetics. Pushing it to the extreme, from these premises it may be implied that (traditional) AI systems are not intelligent, while CI systems are.

Rather than formulating a judgement about the above views, let us close this section with a remark on the diminishing borders, that is, examples of 'symbiosis'. On the one hand, topics concerning evolutionary, fuzzy, or neurocomputing are frequently given a broad treatment in AI textbooks. On the other hand, core CI publications, such as the International Journal of Computational Intelligence and Applications, consider symbolic AI as one of the areas integrated in CI.

4 Computational intelligence subfields from different perspectives

The previous sections indicate that a universally accepted definition of computational intelligence is hard to give. Nevertheless, there is a broad consensus about what areas in computer science belong to it: evolutionary computation, fuzzy computation (FC) and neurocomputation (NC) are seen as the core areas of computational intelligence. In this book an extended view is represented adding DNA computing (DNAC) and quantum computing (QC) to the usual three areas. To position these fields – and thereby to draw a roadmap of this extended CI – we will consider them from different perspectives.

One perspective is that of the applied computational medium. This separates the fields of EC, FC, and NC on the one hand and DNAC and QC on the other hand. Namely, the first group of techniques belongs to the traditional silicon medium, where the physical basis of computation is a piece of hardware based on silicon chips. This approach, like any engineering paradigm, has its limitations originating from the underlying physics. These limitations are related to the issues on miniaturisation, energy dissipation, speed of information exchange, etc. DNA computing and quantum computing represent an alternative by relying on a different medium. Quantum computing is an approach to overcome some of the aforementioned limitations by going down to the level of quantum mechanics. At this level different physical laws are at play and exploiting the possibilities of the different settings promises enormous speedups for some computational tasks. The distinguishing feature of DNA computing is the fact that the medium in which computations are realized consists of biomolecules and enzymes. This medium is often called bioware, as opposed to hardware.

Another perspective is offered by considering parallelism. Since the traditional computer hardware is essentially built for sequential computing, most of the algorithms are sequential as well. Nature, however, is intrinsically parallel. One single brain consists of billions of neurons working simultaneously and any given animal population is performing the main adaptation/survival task by trying out many solutions (the individuals of the population) parallelly. NC and EC be viewed as mimicking these natural phenomena, and hence being fundamentally parallel. In this respect, sequential implementations of neural nets and evolutionary algorithms are "unnatural", enforced by the constraints of todays computer infrastructure. DNAC and QC go further in this respect, by their different computational medium they are truly parallel, although the first practical quantum computer is yet to be built. Thus, DNAC, EC, NC, and QC can be seen as building on parallelism to various extents. Fuzzy computing is the outlier from this perspective.

Inspiration from nature forms the third aspect that can be used to classify the disciplines treated in this chapter. The so-called natural computation consists of research fields in computer science that are inspired by natural processes. In this context, natural is often interpreted as biological, bio-chemical. For instance, simulated annealing algorithms, while being based on a natural process of cooling down liquid metals, are usually not seen as part of natural computing. Among the five areas in this chapter, three are clearly also members of the natural computation family. In particular, evolutionary computation is based on ideas from Darwinian evolution, neurocomputation builds on abstract models of brains, and DNA computing is effectively carried out in a biological medium. FC and QC do not belong natural computation.

The last division we make here is based on emphasising the computational, respectively the intelligent aspect within computational intelligence. The computational aspect forms the focus of DNAC and QC. Both disciplines are concerned with redefining the very basics of computation and the computers that carry out computational tasks. This aspect is closely related to the issue of the used medium as discussed above. EC, FC, and NC follow a complementary approach in that they emphasise the "intelligence" within CI. EC and NC form a further sub-group by their shared vision of how to interpret intelligence. According to this view, adaptivity is a core feature of intelligent behaviour and intelligent systems. Evolutionary computation and neurocomputation are often named together under the umbrella of adaptive systems. However, it is important to observe that adaptivity is implemented and realized at different levels in evolutionary, respectively neurocomputation. In EC, or at least in the majority of evolutionary systems, adaptation takes place only at population level. That, is an individual is born, evaluated and its features are possibly propagated by reproduction, but the individual itself is not learning anything – it is not adapting. It is the population that is adapting since the creation of new individuals and the selection of the fittest one for survival are continuously changing the populations composition from random begin towards highly fit individuals. In NC, however, adaptation takes place on a local, individual level. It is one single brain that is being adapted to perform a given task. Adaptation in this context mainly means that the connections between the neurons are changing (sometimes together with their number and network structure), whereby the brain performs the given task better and better – in short, it is learning.

5 Activities in computational intelligence

Activities in computational intelligence have been on the increase since the field started. This can be measured both by the number of scientific papers produced or in the number of products developed, the last measured in the patent activity. This last measure shows that industry has greatly benefited from adopting this technology to address a variety of problems, as can be seen not only by the number of patents but also by the diverse range of products developed. In Figure 3, the number of patents that have been issued from the United States Patent and Trademark Office are mapped to columns of five years. The first set runs from 1790 to 1975 while the last set runs from 2000 to May the 6th of 2001. The search patterns for the search engine are the same as those mentioned in the graph. Although some overlap between the patents is bound to exist (patents containing two or more search patterns), the graphs clearly show an increase in the number of patents issued for almost all fields. From the curves of DNA computing and computational intelligence, one can conclude that, as is likely in patents, the owners of the patents, name the used method in the most explicit way they can. Notice also that not artificial intelligence but neural networks produced the most hits and that, although newer fields, neural networks and evolutionary algorithms have caught up fast with the rest. In Figure 4, the number of publications in the ACM digital Library Search system is mapped to columns of five years. The search system went back to 1960 and was last updated on the 7th of June 2001. Again, the same search patterns as in the patents graph were used, which are the same as mentioned in the graph legend. Again some overlap is unavoidable as we have been unable to check all papers and the search engine did not provide for an exclusion of other search patterns. For an overall indication of the field this should be no problem. In the number of publications, artificial intelligence and fuzzy logic, both have the highest number, with evolutionary algorithms and DNA computing coming last. Interesting feature of the artificial intelligence curve is the explosive growth in the years 1985 to 1990, it's relative stagnation in the succeeding five years and it's continuing growth afterwards. We believe this is the result of a number of factors, most foremost, we believe, the

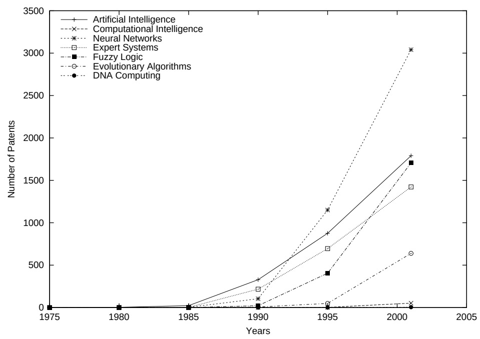

Figure 3: Number of patents for the different regions in computational intelligence

advent of different subgroups of artificial intelligence, and the break-up of the general community into smaller parts. The general picture gained from

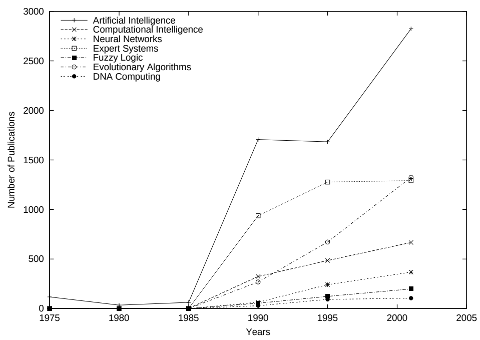

Figure 4: Number of ACM publications for the different regions in computational intelligence

both graphs is that the computational intelligence field, and it's subgroups are prospering, both in research interest, as in the number of applications of the field. Lately, but hard to show, it has been noticed that publications tend to combine the different subgroups more closely than was earlier the case, a further notice of a more mature field. The decrease in growth of the scientific papers seems to collaborate this view while the continued increase of the growth of in the number of patents issued seems to indicate that there are much more applications to come. In the ACM digital library search system, at the 7th of June 2001, there were 2824 papers with the search term 'artificial intelligence', 667 with the term 'computational intelligence', 368 with the term 'neural network', 1292 with the term 'expert system', 199 with the term 'fuzzy logic', 205 with the term 'evolutionary algorithm', and 105 with the search term 'DNA computing'.

6 Concluding remarks

Computational intelligence is a relatively young field, where discussions about the field's identity are still going on. Clearly, introspective definitions necessarily rely on interpretations of the notions of 'computational' and 'intelligence', which are far from having a generally accepted crisp meaning. This explains some of the controversy. Another rather intensively discussed issue is that of the relationship between computational intelligence and artificial intelligence. While we do admit that these discussions can have a clarifying effect and help to position computational intelligence within computer science, we advise caution with too firmly articulated statements. If nothing else, the vagueness of the terms and borders of the fields involved should motivate caveats. Our own view is rather pragmatic and permissive.

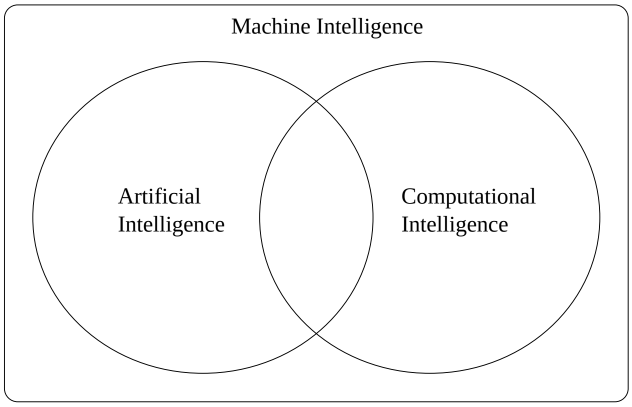

Figure 5: Machine intelligence, artificial intelligence, and computational intelligence

We envision machine intelligence as being the whole discipline of human engineered systems that exhibit facets of intelligence. Artificial intelligence is one 'movement' therein, characterised by the traditions of the AI research community. For instance, it can be argued that being knowledge-based is one of the characteristics covering a large part of AI. Computational intelligence is another stream including technologies that primarily work on non-knowledge-based principles. In this sense we see (traditional) AI and CI as complementers. The other side of the coin is that these non-knowledge-based approaches, such as EC, FC, and NC, are sometimes seen as part of AI. Furthermore, there is an increasing number of hybrid solutions combining, for instance evolutionary methods and explicit knowledge, or having a genetic algorithm evolving rules. Thus, without being too specific, we consider AI and CI as two intersecting areas, both within the field of machine intelligence. This view is depicted in Figure 5

Despite of all uncertainties around its exact identity, it can be observed that the field of CI is rapidly developing. One can expect exciting progress in the coming decade.

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