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Types of Mimetics for the Design of Intelligent Technologies

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Abstract. Mimetic design means using a source in the natural or artificial worlds as an inspiration for technological solutions. It is based around the abstraction of the relevant operating principles in a source domain. This means that one must be able to identify the correct level of analysis and extract the relevant patterns. How this should be done is based on the type of source. From a mimetic perspective, if the design goal is intelligent technology, an obvious source of inspiration is human information processing, which we have called cognitive mimetics. This article offers some conceptual clarification on the nature of cognitive mimetics by contrasting it with biomimetics in the context of intelligent technology. We offer a two-part ontology for cognitive mimetics, suggest an approach and discuss possible implications for AI in general.

Keywords: Intelligent technology · Design methods · Design mimetics · AI

1 Introduction

A critical point in any design process is to get ideas for solutions. Often this is based on analogical thinking [1]. Mimetic design means using a source in the natural or artificial worlds as an inspiration for technological solutions. Designers may imitate existing solutions. In biomimetics they may imitate the biological structures found in nature. However, in creating intelligent technologies designers can use existing organizational and individual information processes as the source of ideas. Designing intelligent systems by utilizing existing human information processes as the source of solutions we have termed 'cognitive mimetics' [2],[3],[4]. Cognitive mimetics differs from typical and established biomimetics as it has different source of mimicking: human shared and individual cognitive processes, as well as the mental contents, representations, and constraints that establish the boundaries and forms it takes. It analyses how people carry out intelligent tasks today and uses this information in designing novel technological solutions.

The rationale for cognitive mimetics is clear. From a mimetic perspective, if the design goal is an intelligent artefact, then a natural source of inspiration is that which it is seeking to replace or support, and we can turn to human thinking for inspiration. However, it is not yet clear what this entails more exactly or how cognitive mimetics should methodologically speaking proceed. To take steps towards articulating these issues, the purpose here is to explore the principles of mimetic design in general and to position cognitive mimetics in that conceptual space.

2 Mimetic Design

To solve the problems and to make life easier, people have for thousands of years developed new artefacts and new ways of working with them. It is perhaps no exaggeration to say that the world we inhabit is more man-made than it is natural [5]. Especially in modern engineering design, information systems and social system design have grown in importance [6],[7],[8]. Thanks to the intensity of modern innovative processes, reflection of design thinking has become central [5]. An important problem is formed by the origin of ideas. Design thinking begins with a problem which one cannot trivially solve. Thus, one must develop the solution with one's mind [9],[10]. Often the crucial hint is given by some cue or analogical formation [11],[12],[10]. When the origin of the cue is outside the actual design target domain, the designer is mimicking its source. The source may be a simple cue or a hint or it may be closer to the source [13]. Typically, there is an explicit mapping between the source and target domains. This is rarely an exact mapping, but of the aspects of the source which make it an effective solution. Thus, it is crucial that the mimesis occurs at the correct level to capture the working principles which enable the function [14].

The logical structure of mimetic design has certain necessary elements. To be an instance of mimetic design, there must be a **source domain**. The logical corollary to the source is the **target domain**. Furthermore, there is a process of interpretation or translation [15] between the source and target domain, which we can call **mimetic transfer**. Implicit here is the **designer** who can extract and implement design-goal - relevant information from a source. Important to note is that the process of interpretation is observer-relative given that designers with different backgrounds and knowledge observe different aspects in the source [16]. Thus, specifically identifying the source domain type and level enables the relevant analytical and empirical tools to identify the principles which make a solution work in the source. Here, we shall focus on the kinds of sources people can use for the design of intelligent technologies.

3 Types of Mimetics for Intelligent Technology

There should be no a priori limitations on what can act as a source of inspiration. However, given that technical artefacts are designed to achieve some function an obvious source the natural biological world. The field of biomimetics is well established. The number of patents granted for biomimetic solutions has exploded [17] and an analysis by Lepora and colleagues [18] encompassed approximately 18,000 publications in biomimetic research between 1995 and 2011 on an increasing growth track.

Intelligent technology is a major subfield in biomimetics as shown by the prominence of robotics and autonomous technology and their concern with control methods [18]. Other subfields include animal-based robot hardware; biomimetic actuators; biomaterials science; and structural bioengineering [18]. Bio-inspired computing is another field with direct applications to intelligent technology. Kar [19] reviewed bio-inspired algorithms including neural networks, genetic or evolutionary algorithms, and ant colony optimization among others. Biological neural networks were the early inspiration for artificial neural networks [20]. Deep Learning in neural networks took inspiration from Hubel and Wiesel's [21] analysis of the visual cortex [22]. Earlier advances were made by Hebb [23],[22], whose concern was to "present a theory of behavior that is based as far as possible on the physiology of the nervous system". Advances in intelligent technology have been made based on mimicking the *physiological basis* of information-processing or *human/animal behavior*. The examples share a common characteristic: they have not used the information contents and thinking *itself* as a source.

A major line of research and inspiration for intelligent systems has been the information processing in humans which we call cognitive mimetics [2],[3],[4]. Early AI was a collaborative effort between neuroscience, computer science and psychology [24] united under the topic of cognitive science. Mathematicians thinking was the inspiration behind the Turing machine [25]. Tree search, mimicking the way human searches for information [26], [9], has been used from the 1950s in AI solutions. Whereas Newell and Simon [27] focused on general cognitive abilities, a more domain-specific approach was taken by expert systems, which combine a knowledge base with an inference engine [28]. A recent article [29] argued for moving beyond both classical symbolic and neural networks methods by calling for machines that could learn and think like people by building in abilities such as causal modeling and intuitive physics and psychology, among others.

What is clear is that both bio- and cognitive mimetics have made significant contributions to the development of intelligent technology. Based on these examples alone, it is also clear that there is significant variation within them. Thus, from a mimetic perspective, we need more precise concepts to capture what is being mimicked in the source domain. A recent article identified seven analogy categories for biomimetic design: form; architecture; surface; material; function; process; and system [30]. However, the processing of information and its' contents are left implicit in the schema. Thus, for cognitive mimetics as a design method no similar schema is available. Clearly, there is a need for conceptual clarification on the sources for cognitive mimetics.

4 Cognition as a source of mimicking

Recall that the point of mimetic design is capture what makes the source an effective solution. When using human thinking as the source, the picture becomes complex. On the one hand, human behavior is structured by content-specific information processes and representations which organize work. In intelligent behavior, we think about specific things and represent them *as* something. On the other, those are based on various general cognitive abilities. It is obvious that all human behavior is predicated on some general abilities, articulations of which include cognitive architectures [31] and cognitive ontologies [32]. There the concern is on either task-specific cognitive modules or more general aspects of mind, like attention. However, it is clear that human expertise is in fact domain-specific: expertise in chess does not carry over to expertise in ship handling though both are on some level served by the same general abilities. Domainspecificity means that human thinking can be called content-specific [10],[33]. This is the first conceptual clarification for the sources of cognitive mimetics. The two levels of cognitive mimetics are complimentary, but stressing their difference makes the issues clearer.

Circling back to the question of effective solutions, are there reasons to favor one level over the other as a source? Given they are connected and design goals differ, no decisive answer should be given. However, if we use expert performance in a specific domain as a benchmark, it is clear going by the discussion before that the reasons are on the information level. Furthermore, technical solutions are usually domain-specific and starting with expert understanding makes it clearer what the technical system should do. Connections to general abilities can and should be drawn, but the disconnect between technical systems and humans causes the downward integration of information levels towards physical implementation to diverge regardless. For example, if a chess master or a ship captain makes a move or maneuver, our primary concern should be in an articulation of things like goals and reasons for the chosen action. Through empirical inquiry we may draw a rich description of the domain-specific information environment in which the action is embedded. Note that this inquiry is not trivial, because much of the information is tacit and unconscious [4]. The entry-point for cognitive mimetics are the representations which organize and structure information processes. Experts have a rich multi-leveled and domain-specific representation that accounts for their expertise. It is multi-leveled as much of the information-processing and contents are subconscious. It is domain-specific because it is populated by domain-specific mental contents. Capturing and articulating these is the first goal of cognitive mimetics as we see it. It is reasonable to approach the design of intelligent technology this way, because it allows flexibility on the implementation level. We may then connect the dots to logically necessary abilities and consider how those can be done by technical systems. Note that this approach may also afford a better integration of humans and technical systems.

Taking a wider perspective, the foundational ability on the information level is the capacity to take the shape of the demands of the environment, as shown by expertise [34]. This leads cognitive mimetics to slightly different problem formulations in terms of general goals for AI. For example, a super computer solves the problems stemming from the computational analysis of complex systems by increasing computational power, thus adding more energy and processing units to the system. In contrast, people solve problems by *lessening* the need for energy by having informational representations that organize work and mitigate the combinatorial explosion that has troubled AI systems in even moderately complex environments [35]. For cognitive mimetics, the formulation should be 'how is the system using information to narrow an information-processing task to minimize the size of the search space, energy use and time' and not 'how can we increase computational power so as to be able to solve this information-processing task within a specified time frame'. The optimization of programs over hardware is part and parcel of computer science and AI but illustrates the difference in perspective. Interestingly, this realization has also been recently articulated by Stuart Russell [35] who is the co-author of a very influential textbook on AI [36]. They argue for the rational approach in AI, which explicitly does not take direct inspiration from human intelligence. However, in the article, Russell [35] expresses doubts whether the standard method of "building calculatively rational agents and then speeding them up" will "enable the AI community to discover all of the design features needed for general intelligence". In the background is the insight that pressure towards optimality within finite resources leads to complexity on the "program level" [35]. In our terms, on the information level or more specifically its representations and contents.

5 Conclusion

The purpose of this article was to examine different types of mimetics for the design of intelligent technology. Mimetics can be classified into types based on the sources they use. From a mimetic perspective, if the design goal is intelligent technology, a viable source of inspiration is human information processing, which we have called cognitive mimetics. The basic idea has two parts. One is that mimetic design is based around the abstraction of the relevant operating principles in a source domain. This means that one must be able to identify the correct level of analysis and extract the relevant patterns. Since in our view major operating principles behind human intelligence are informational kinds, it follows that to use them in mimetic design, a viewpoint and a classification that can articulate those is needed. The categories available in biomimetic theory are not suitable because they have only tacitly implied information processes. We identified two major categories for cognitive mimetics: general abilities and domain-specific contents. Finally, we argued that there are practical and theoretical reasons for starting with the latter.

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