Smart Knowledge Engineering for Cognitive Systems: A Brief Overview

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Abstract: Cognition in computer sciences refers to the ability of a system to learn at scale, reason with purpose, and naturally interact with humans and other smart systems, much like humans do. To enhance intelligence, as well as to introduce cognitive functions into machines, recent studies have brought humans into the loop, turning the system into a human–AI hybrid. To effectively integrate and manipulate hybrid knowledge, suitable technologies and guidelines are required to sustain the human–AI interface so that communication can occur. However, traditional Knowledge Management (KM) and Knowledge Engineering (KE) approaches encounter new problems when dealing with cutting-edge technologies, imposing impediments for the use of traditional methods in cognitive systems (CS). This paper presents a brief overview of the Smart Knowledge Engineering for Cognitive Systems (SKECS), which is based on methods, technologies, and procedures that bring innovations to the fields of KE, KM, and CS. The goal is to bridge the gap in the hybrid cognitive interface by the use of emerging technologies such as deep learning, experience-based knowledge representation, context-aware indexing/retrieval, active learning with a human-in-the-loop, and stream reasoning. In this work Set of Experience Knowledge Structure (SOEKS) and Decision DNA (DDNA) is extended to the visual domain and utilized for knowledge capture, representation, reuse, and evolution. These technologies are examined throughout the layers of SKECS for applications in knowledge acquisition, formalization, storage/retrieval, learning, and reasoning, with the final goal of achieving knowledge augmentation (wisdom) in CS. Features of the SKECS and their implementation in practice is discussed through a case study – the Cognitive Vision Platform for Hazard Control (CVP-HC) – suggesting that methods, techniques and procedures comprising the SKECS are suitable for advancing systems towards augmented cognition.

Keywords: Cognitive Systems, Human–AI Hybrid, Knowledge Engineering, Knowledge Representation, SOEKS, DDNA, Knowledge Augmentation

Introduction and Background

Knowledge is a valuable asset for individuals, organizations, and society (Mancilla-Amaya et al., 2010). For this reason, humankind has always attempted to make it part of their assets. Knowledge is a complex term to define precisely, and there are many definitions in the literature. Lin at al. (2002) describes knowledge as "An organized mixture of data, integrated with rules, operations, and procedures, and it can be only learnt through experience and practice" (Lin et al., 2002). Knowledge emerges from interpretation, analyses, and judgement of information (processed and useful organized data). Intelligence is the ability to apply knowledge to inform or to help drive decision making (Taylor, 1986). Knowledge learned from training, investigation, observation, or experience directs intelligence towards wisdom (Figure 1). It is important to point out that knowledge has little or no value unless it can be accessed and put into practice.

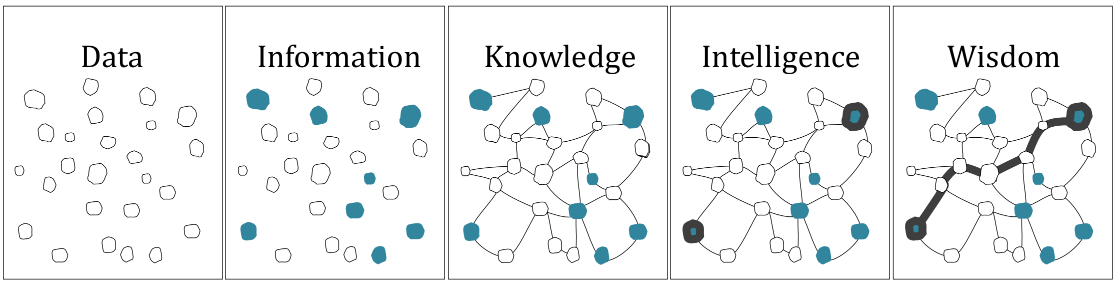

Figure 1. Visual representation of data, information, knowledge intelligence, and wisdom.

In the field of Knowledge Management (KM) and Knowledge Engineering (KE), knowledge is usually categorised into two groups: formal knowledge and informal knowledge (Quintas et al., 1997). Formal knowledge is easily articulated and can be embedded into written rules and procedures in information systems. Systems are also capable of generating it – often called artificial knowledge. Informal or tacit knowledge is individual, subjective, context-specific, and experience-based intuition. It is hard to formalize and communicate. Despite these challenges, tacit knowledge is a valuable component in intelligent systems, such as those based on cognitive computing, since it aims to simulate human thought processes (Shafiq, 2016). The lack of focus on tacit knowledge directly results in a systems reduced capability for smartness, innovation, and cognition.

Cognition in computer sciences refers to the ability of a system to learn at scale, reason with purpose, and interact with humans and other smart systems naturally, such as humans do. Indeed, cognitive systems have emerged as an attempt to mimic in some way human intelligence, and many recent studies have been treated as a human–AI hybrid combination (Zheng et al., 2017). Rather than being systematically programmed for all possible scenarios and situations, these systems should learn and reason from their interactions with their surroundings, through collaboration, and from experience (Demirkan et al., 2017). In these hybrid systems, the interface must be sustained in a way that agents can communicate/exchange knowledge effectively. This will direct the coupling towards purposeful behaviour, at the same time as it ensures adaptability, explainability, extendability, and trustworthiness – key features of cognitive systems. Such requirements and challenges involve several fields of Knowledge Engineering (KE) for implementation.

However, traditional KE approaches are triggered by new problems when dealing with cutting-edge technologies, imposing impediments for the use of traditional methods in cognitive applications (Fensel et al., 2002). Therefore, old-style knowledge engineering techniques must be extended by applying breakthroughs in emerging technology, such as the new trends in machine learning algorithms, Knowledge Representation (KR), learning methodologies, information retrieval, reasoning, etc. – which are grouped and called here Smart Knowledge Engineering for Cognitive Systems (SKECS).

The objective of this paper is to provide an overview on motivations and technologies involved in the proposal of the SKECS as well as brief description of the layers that composes it. This paper is organised as follows: firstly, some background about fundamental concepts and technologies are briefly described. In the subsequent section, the concept of cognitive technologies is presented, as well as how knowledge engineering strategies can be used to bridge the human-AI gap for further advance cognitive systems. Finally, SKECS is introduced as a solution that applies breakthroughs in emerging technology to the field of KE to promote advances in cognitive technologies by endowing the gathering, representing, sharing, learning, and growth of artificial and human experiential knowledge. A short discussion on the practical implementation of suggested technologies is also provided.

Fundamental Concepts

This section presents a brief review of the different technologies that underlie this research. That includes (i) Knowledge Management (KM), (ii) Knowledge Engineering (KE), and (iii) Set Of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA).

Knowledge Management (KM)

Knowledge Management (KM) has become a critical element for organizations (Mancilla-Amaya et al., 2010). In short, KM is a discipline that integrates multiple approaches to identify, capture, evaluate, develop, share, and use knowledge as a valuable asset to achieve organisational objectives (Nonaka, 2008). Due to its interdisciplinary nature, KM is a field that is still far from being consolidated (Maier, 2002); but is commonly considered to have three aspects: Capitalization, sharing and creation of knowledge (Ermine, 2000).

Efforts to promote use of knowledge engineering (KE) methods and practices has contributed to the field of KM. Research to understand what knowledge is needed to make what decision, and enable action, has brought the need to straighten connections within the KE field. Although KM projects can proceed without KE efforts (for instance in people-based KM systems), ideally every KM project should embrace some attempt at KE expertise in order to provide the value-added services that are often needed in knowledge processing (Tsui at al., 2000).

Applications in the field of KM have taken many different direction, and often overlap on a high degree among different sub-fields; for example, KR, KD, knowledge acquisition, knowledge refinement, and knowledge sharing are all topics of different technologies, which may complement each other in a common problem domain (Hansen et al., 1999; Argote et al., 2003; Sanín, 2007; Nowacki & Bachnik, 2016; Choi, Ahn et al., 2020). Furthermore, recent advances in AI, cognitive science, and other research areas have broadened platforms to implement technologies for KM development (Liao, 2003).

Knowledge Engineering (KE)

Knowledge engineering is traditionally concerned with the development of information systems in which knowledge and reasoning play central roles (Preece et al., 2001). It is distinct from but closely related to software engineering (Schreiber et al., 2000; Motta, 1999). Among its distinct aspects are a range of techniques for knowledge elicitation and modelling, a collection of formalisms for representing knowledge, and a toolkit of mechanisms for implementing automated reasoning (Preece et al., 2001).

The disciplines of Knowledge Management (KM) and Knowledge Engineering (KE) have strong ties (Newman, 1996). KE can be understood these days as a discipline that aims to offer solutions to complex problems by means of integrating and manipulating knowledge in computer systems so as to generate value, i.e. to develop the means to accomplish KM. In other words, techniques developed in KE are analogous to "micro" knowledge strategies, whereas approaches to KM are generally considered as "macro" knowledge strategies for an organization (Figure 2). KE involves the use and application of several computer science domains such as artificial intelligence, knowledge representation, databases, and decision support systems, among others, so as to solve complex problems normally requiring a high level of human expertise (Shafiq, 2016).

By definition, Knowledge Engineering techniques could certainly be applied to cognitive technologies since they are extendable to a hybrid AI–human system. In this context, KE relies on instructional methodologies and computer science and tries to mimic knowledge and behaviours that are intrinsically human into a certain domain and into the scope of an artificial system. This broad definition reveals not only the need for specific and advanced technologies, but also the need to overcome related implementation issues, especially when dealing with current cutting-edge technologies (Shafiq, 2016).

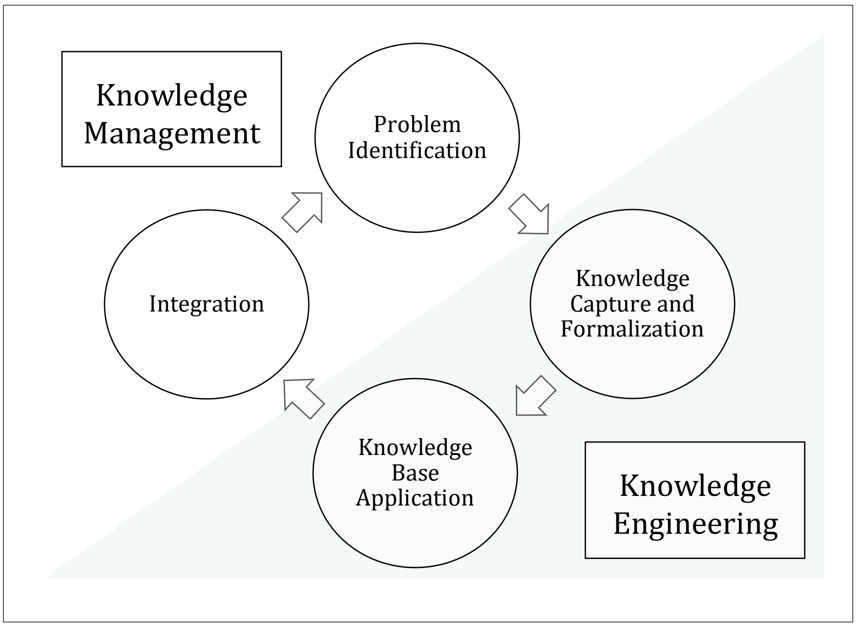

Figure 2: Relationship between Knowledge Management (KM) and Knowledge Engineering (KE).

Set of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA)

A common way for humans to obtain knowledge is through living or experiencing, i.e. raw experience. Crucially, survival of the species is due to our ability to evaluate situations based on experience, that is, experience-based decision-making (Noble, 1998). Hence, it is very common among researchers to study nature in order to develop bio-inspired models. Artificial intelligence techniques based on experience is not the exception; in fact, smart artificial systems try to implement techniques that unify, enhance, reuse, communicate, and distribute knowledge (Shadbolt et al., 2006) as a way to support decision-making.

In nature, DNA contains "the genetic instructions used in the development and functioning of all known living organisms" (Popovici, 2010). The main role of DNA molecules is the long-term storage of information. DNA is often compared to a set of blueprints and the DNA segments that carry this genetic information are called genes (Sinden, 1994). The Decisional DNA (DDNA) technique is a simile of what human DNA does. In this technology, experienced knowledge is primarily captured in SOEKS and then incorporated into Decisional Chromosomes (DC), which in groups create DDNA that can hold this knowledge for future decision-making events (Figure 3).

Set of Experience Knowledge Structure (SOEKS)

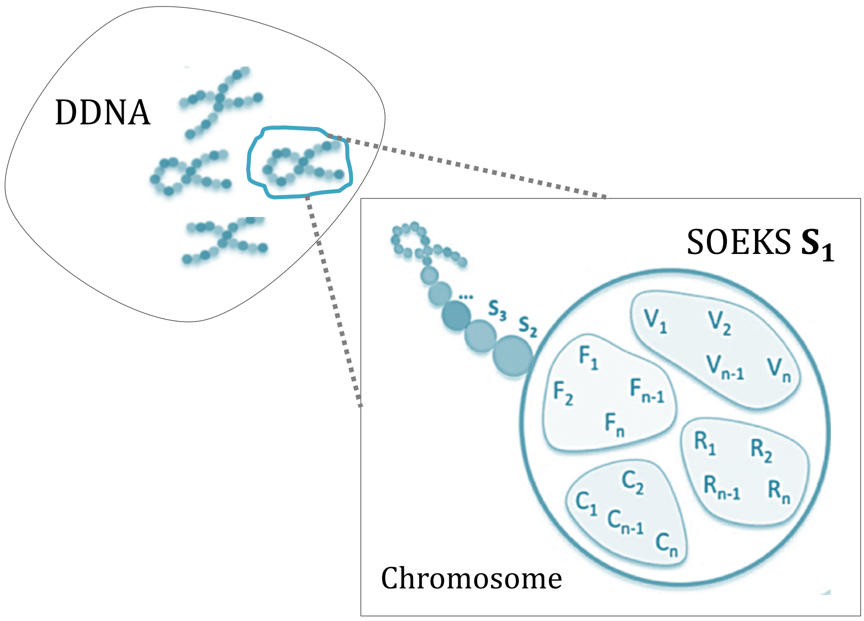

Figure 3: Set Of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA) (Shafiq et al., 2018).

Sanin and Szczerbicki developed SOEKS as a dynamic, standard domain-independent knowledge structure (Sanín & Szczerbicki, 2009). From formal decision events, it captures and stores experiential knowledge in an explicit shape that can be shared across cognitive platforms and architectures, to be later exploited. Such experiential knowledge is accumulated from four basic components: variables (V), functions (F), constraints (C), and rules (R) (Figure 1.4). Variables capture the environment by using an attribute-value language and form the fundamental element of SOEKS. Functions establish relationships among independent and dependant variables. Constraints set boundaries between the environment and its variables. Lastly, rules express relationships among environment states and the actions that should be performed under given circumstances (Sanín, 2007).

Decisional DNA (DDNA)

Combining the above-mentioned basic elements of SOEKS produces distinctive, complex, dynamic and adaptable experiences resembling a DNA structure. Analogously to the combination of the four nucleotides of DNA, the variables, functions, constraints, and rules (four elements), mixed in the unique shape of SOE, then form decisional chromosomes, and then generate DDNA, which are decisional experience fingerprints. In brief, an SOE is an experienced decision result given a set of combined environmental circumstances and can respond to a decisional query presented to it (Sanín et al., 2009). Besides, as experience grows every day in any organization's day-to-day operation, each decision is stored as a decisional gene (SOE), which when grouped become decisional chromosomes and comprise an entire inference tool. Consequently, several decisional chromosomes structured as DDNA assemble the cognitive system's decisional fingerprint.

Decisional DNA has been proven to be an adaptable, efficient, non-domain-dependent knowledge structure in several applications in areas such as Alzheimer's disease diagnosis, financial decision-making, engineering processes, engineering design, deep learning, embedded systems, neural networks, and robot path planning among others (Shafiq et al., 2014). Moreover, DDNA has been shown to solve a system's scalability issues by introducing an experience-based technique that aims to recognize events (defined by the user) using production rules adaptable for different conditions, clients, and situations (Sanin & Szczerbicki, 2007). These proven applications and case studies make DDNA a standard knowledge structure for emerging decision-making technologies, and are used in cognitive systems to gather, discover, store, add, improve, and share information and knowledge – among other cognitive systems, decision makers, and organisations – through collected experience (Sanín et al., 2008).

From Automation to Cognitive Systems

In the early stages of the automation process, machines were an extension of man's physical functions, and designed to compensate for the physical deficiencies/limitations of humans. With the development of microelectronics, machines began to be enriched with smartness and computer systems were able solve complex mathematical problems. The development of techniques in fields such as machine learning (ML) has resulted in significant progress in computer applications, enabling systems to outperform humans in certain tasks. In the field of computer vision, the growth in computational power has resulted in image and video applications gaining processing efficiency as well as real time execution (Pulli et al., 2012).

For many real world problems, solutions can be attained based on mathematical models without the use of tacit knowledge (Andreopoulos & Tsotsos, 2013). Nevertheless, the most common ML approaches involve learning from example, resulting in highly datadependent systems, lacking generalization beyond the training datasets and requiring major adaptations to include new conditions (Ji, 2019). They often cannot match real-world conditions and are not able to estimate unknowns. Consequently, creating robust data-driven models that are immune to noise and deviations; that can perform complex tasks under poorly controlled environments, and do not require excessive amounts of training data to solve unconstrained computing problems became challenging (Meer, 2012).

In parallel to the data-driven approaches, humans have been used as a reference model for excelling under conditions in which machines fall short (Souza Alves et al., 2018). In this context, approaches have been proposed to mimic human intelligence by combining available information and expert knowledge to support decision-making in a knowledge-driven approach (Ji, 2019). In short, Knowledge-Based Systems (KBS) are computer programs that can reason and can use a knowledge base to solve complex problems. When they are able to express some characteristics of human knowledge and expertise to support decision-making, they are also known as expert systems (Durkin, 1990).

The integration of microelectronics, human knowledge, and reasoning through advances in networks has enabled the appearance of cyber-physical systems (CPS), which have moved humans from controlling machinery to controlling processes (or monitoring a self-controlling process). It implies an interface between humans and systems that can go beyond just action–reaction which is usually found in classical KBS (Hollnagel & Woods, 2005). Additionally, the sense that manually encoding all domain knowledge is often impossible has brought doubts if some knowledge should not be learned instead.

In this way, systems could modify their behaviour on the basis of experience, such as humans do (Hollnagel & Woods, 2005).

In this context, Cognitive Systems have emerged as an attempt to mimic in some way human intelligence. Understanding of human biology has contributed to rapid progress in artificial intelligence, endorsing what the human–machine interface has for a long time aspired to be: a cognitive-to-cognitive interaction (Hollnagel & Woods, 1983). Intelligence, in cognitive computing, can be defined as the ability to learn from experience and use the domain of expert knowledge to adapt to new situations (Beheshti et al., 2020). In theory, Cognitive Systems bring together and consolidate the achievements of the fields of knowledge engineering, automatic perception, machine learning, and robotics (Bauckhage et al., 2004). These systems are thought to perform human-like tasks in natural environments requiring perception (e.g. vision) and action (e.g. robots or agents). By combining subconscious processes with processes that humans perceive as more conscious, these systems should be able to not only make predictions, but also to explain their predictions (Gunning et al., 2019).

The Gaps in the Cognitive Interface

To date, the creation of a general-purpose system with the robustness and resilience of human competencies still remains a challenge. In fact, there is no solid evidence to support the idea that systems are developing any kind of consciousness (Signorelli, 2018; Sanz & Aguado, 2020). In reaction, some researchers have shifted the goal of replicating human cognitive functions in a system's design (the ultimate goal of which is the replacement of human cognition by artificial cognition) to attempting to combine biological and non-biological thinking in a way which "supercharges" the human brain

(Griffin, 2015). In this human-in-the-loop cognitive approach, functional (possibly black-box) models are integrated with logical, relational, declarative knowledge-based approaches (yielding hybrid models). The aim is to have systems incorporate some cognitive functions on an everyday basis, just like humans learn from each other – collaboratively. Scientists believe that in the coming era of personal cognitive augmentation, humans and artificially intelligent entities will work together in a natural and collegial partnership, where the total amount of cognition is a combination of human and artificial thinking.

Controversially, on one side, computers are not yet proficient in proceduralizing tacit knowledge in a way to understand and reason about it so as to gain insight into human cognition. On the other side, output from complex models is difficult for humans to interpret and understand unexpected behaviour. This results in a loose connection in which little knowledge is passed to and from.

Therefore, hybrid human–AI coupling can only reach that goal if it can communicate in a way that both parts exchange knowledge. Interfaces may help in establishing a link between the machine representation and the representation that humans can understand. But knowledge must be structured in a way whereby both can gather, interpret, reason, and share. Therefore, knowledge representation as well as other knowledge engineering techniques play an important role in enabling effective coupling. So far as we know, a knowledge representation capable of bridging this gap has not yet been suggested. In addition, a clear set of procedures is necessary to coordinate hybrid–AI knowledge in a way that a system will display fundamental features of cognitive systems – purposeful behaviour, adaptability, anticipation, and extendability (Vernon, 2006).

Smart Knowledge Engineering for Cognitive Systems (SKECS)

The previous sections have briefly introduced the need for applying breakthroughs in emerging technology within the field of KE to support advances in cognitive technologies. The long-term goal of artificial intelligence (AI) is to make machines learn and think like human beings. However, due to the high levels of uncertainty and vulnerability in human life, and the open-ended nature of problems that humans face, no matter how intelligent machines might be, they are unable to completely replace humans – and there is no strong evidence to support the idea that this might happen in the near future. Therefore, to achieve higher conceptual levels of cognition in applications, it is necessary to introduce human cognitive capabilities or human-like cognitive models into AI systems, i.e. to bring the "human-into-the-loop". This results in the development of a new form of AI that carries hybrid-augmented knowledge.

The best way to guarantee success of this coupling is by assuring the availability and high quality of all these knowledge components. Consequently, the SKECS aims at applying breakthroughs in emerging technology to the field of KE to promote advances in Cognitive Technologies by endowing the gathering, representing, sharing, learning, and growth of artificial and human experiential knowledge."

Smart Knowledge Engineering for Cognitive Systems (SKECS) is based on SOEKS and DDNA. Our consideration of using SOEKS and DDNA as carriers for decision making is logically founded on the fact that experience has to be taken into account in order to direct cognitive systems towards wisdom. Wisdom can be considered intelligence in an advanced form, and can be defined as the capacity to perceive and understand, choose, and act successfully under a large variety of circumstances, including in complex environments (Albus, 1991). Intelligence developed from learned experience plays a major role between knowledge and wisdom (Liew, 2013). For that reason, the well-known data–information–knowledge–wisdom (DIKW) hierarchy (Ackoff, 1989) has been slightly reframed, so that knowledge is categorized at the levels of data–information–knowledge stored as experience–intelligence–augmented intelligence–wisdom (or DIK(E)IW), as represented in Figure 5.

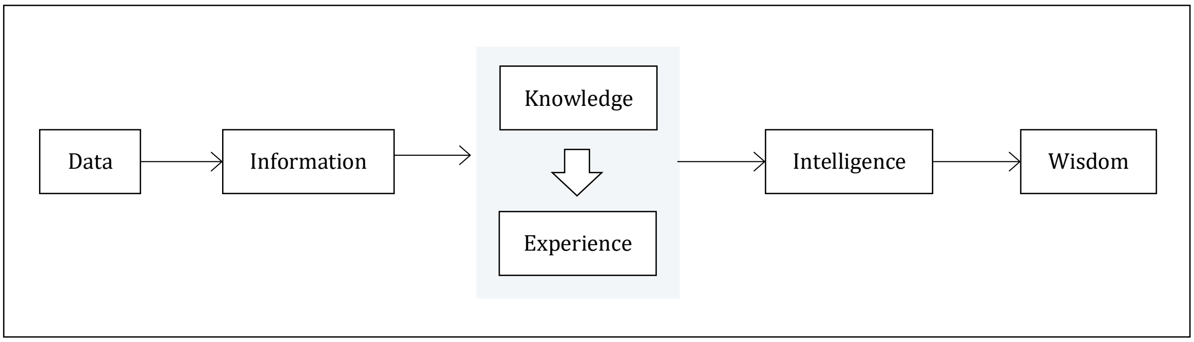

Figure 5: From Data to Augmented Intelligence (Wisdom) – DIK(E)IW.

Experience built from hybrid human–AI knowledge supports the cognitive properties of adaptability, explainability, extendability, and trustworthiness and directed systems towards augmented reasoning capabilities. The next sub-sections of this paper are organized according to the five layers comprising the SKECS: Knowledge Acquisition, Knowledge Formalization, Knowledge Storage/Retrieval, Knowledge Learning and Reasoning, and finally Knowledge Augmentation (Figure 6). The following is a brief summary of technologies that have been considered and are suggested for application in each layer.

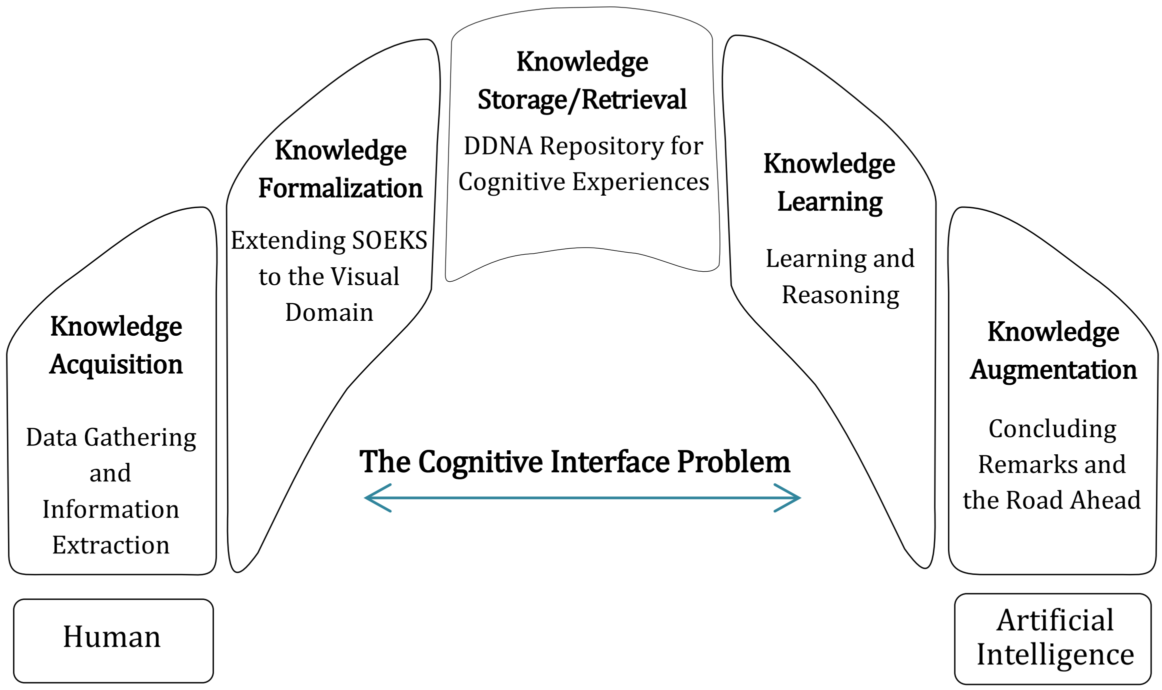

Figure 6. Layers of Smart Knowledge Engineering for Cognitive Systems (SKECS) layers to bridge the Cognitive Interface Gap.

To show how the features of the SKECS could be implemented in practice a case study – the Cognitive Vision Platform for Hazard Control (CVP-HC) - has been investigated (de Oliveira et al., 2018). Practical implementations based on CVP-HC shows that methods, techniques and procedures comprising the SKECS are suitable for advancing systems towards augmented cognition; they also have potential in the field of Workplace Health and Safety (WHS).

The CVP-HC addresses the current limitations of computer vision systems by bridging the gap between top-down and bottom-up approaches and enabling cognitive functions. The result is a scalable yet adaptable system capable of working in a variety of video analysis scenarios with transparency and confidence, while meeting specific industry safety requirements by modifying its behaviour accordingly.

Knowledge Acquisition

Knowledge Acquisition consists of the extraction of knowledge from structured and unstructured sources. It must be in a machine-readable and machine-interpretable format to represent knowledge in a way that facilitates inferencing. As mentioned previously, data and information are much easier to store, describe, and manipulate than knowledge, but the right tools must be chosen to reach that goal. In order to be translated into knowledge, information obtained from data should serve a defined purpose in the problem-solving process (Ameri & Dutta, 2005), and this is not trivial.

To move from data collection to information extraction, range of techniques have been developed over the past few decades. Supervised machine learning techniques are very often used, such as Linear Support Vector Machines (SVM), Adjusted SVM, k-Nearest-Neighbors (kNN), Decision Trees, Random Forests (RF), Extremely Randomized Trees (ERT), Adaboost, Gradient Boosting, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Deep Neural Network (DNN), etc. In this case, the hardest part can be finding the right estimator (or learning algorithm) to solve a proposed problem. Different estimators are better suited for different types of datasets and different issues, and there is no means to precisely predict which one is the most suitable for a given task, and of course no estimator is best for all tasks. Moreover, when operating in real time scenarios, current systems are still challenged by certain characteristics of the elements comprising the scene, such as variation in background, noise, change in illumination, and different camera resolutions (Mosberger et al., 2013).

The main goal of this layer is to call attention to the universe of machine learning methods and algorithms that can serve the purpose of extracting information from the data for the generation of knowledge. Experiments on classification and detection technologies for the purpose of information extraction on challenging data have been conducted over the course of this research to suggest a robust option to integrate CS. Focus has been given to the special case of visual content, as the literature has proven that computers can already outperform humans in many tasks involving vision.

Evaluation of a selected group of methods and algorithms has been done on the prototype CVP-HC. Convolutional Neural Network (CNNs) were found to be the best choice to address classification problems that deal with a dataset composed of a limited number of images of low resolution. However, the choice of a better classification performance for low resolution images had the trade-off of higher model complexity (de Oliveira et al., 2019a).

For detectors, two algorithms (SSD and Faster R-CNN) have been tested for the multi-detection problem. These are considered state-of-the-art detectors (de Oliveira et al., 2019a). In this case, the dataset comprised by classes of personal protective equipment (PPE) extracted from frame-videos of low resolution cameras, which were taken in real life industrial environments (subject to noise, occlusion, change in illumination, etc.). Given the model complexity, and training and detection time, SSD is shown to be a reasonable option to tackle the detection issue for a limited training sample size.

To conclude, the technologies above mentioned comprise the Knowledge Acquisition layer of the SKECS.

Knowledge Formalization

Formalizing knowledge has been a central issue of research in artificial intelligence and related areas. Even before acquiring knowledge, designers and programmers face the representation issue. Computers, unfortunately, are still not capable of forming representations of the world as human beings do, and so simple representations of just formal decision events are needed. In order to make information useful, after it is learned, the knowledge acquired must be represented in an explicit way. The basis for using SOEKS and DDNA as the carriers for decision making relates to the fact that experience has to be taken into consideration to develop better cognitive systems. These technologies include advanced intelligent capabilities for combining tacit and artificial knowledge. They also provide the flexibility required to expand over time as more decision-making events are experienced, being able to escalate the requirements of real time applications. This is another major contribution of this work, as it enables intelligent growth of a system – to the point where it becomes more than just a mere decision support engine, but can augment human–AI coupling in the direction of wisdom. This has only been made possible by the extension of SOEKS and DDNA to the visual domain (de Oliveira et al., 2019b), and its implementation using a decoupled communication model structure through ROS framework to ensure the required scalability and flexibility (ROS Core Components, 2016).

Experiments conducted with CVP-HC demonstrate that, because the status, functions, constraints, and rules of the variables are explicitly represented in a single structure, this enhances adaptability and can explain why a certain output was chosen (de Oliveira et al., 2019b). However, explainability on the ML side is restricted to the evaluation of the status of variables when a response is given, and is therefore limited. Explainable-AI, also known as XAI, may help us to understand and interpret predictions, but it has not been exploited in this research.

SOEKS and DDNA implemented over ROS are included in the Knowledge Formalization layer of the SKECS.

Knowledge Storage/Retrieval

The development of advanced cognitive systems requires a focus on the integration and indexing of hybrid knowledge for retrieval. The interoperation of the architecture (i.e. knowledge representation fields that allow experiences to take part in the process of making similarity judgements) with a non-trivial knowledge base is essential if we want to build systems that "reproduce the entire range of human capabilities".

A repository of cognitive experiences is comprised of visual elements, contexts, and human experience – important components of tacit knowledge – they can all be integrated into a single DDNA IV structure. A DDNA built on SOEKS technology contains fields that allow the experiences to become part of a process of computing similarity, uncertainty, impreciseness, and incompleteness measures, which has been demonstrated through the CVP-HC. These features greatly facilitate obtaining methods to efficiently learn the relevant information in a short time, as well as methods to efficiently match instances of an object in a large collection to provide quick and correct solutions.

For storage and retrieval of these hybrid experiences, a context-aware approach has been investigated to support human judgment and perception to be incorporated into a system's learning and reasoning process. This can be enabled by two means. Firstly, the set of rules embedded in the knowledge representation (Sanin et al., 2019). This is an explicit and proceduralized formalization of expert knowledge, which can be done manually during the configuration process by an expert or produced automatically by rule-mining techniques. Either way involves some extension of human experiential knowledge. The second is by feedback given from time to time during operation of the system. This is a way of aggregating implicit knowledge as the system runs (on the fly) to adjust its unexpected/undesired misperceptions or contradictions (de Oliveira et al., 2020a). Combining these two mechanisms – in addition to the artificial knowledge generated by the output of machine learning algorithms – supports adaptability and trust on the Knowledge Storage/Retrieval layer of the SKECS.

One of the drawbacks of the above mentioned approach is the reduced autonomy of the system's operation. Another point to consider is that software can be fed with tendentious information about specific options in order to increase the chances that a preferred solution be accepted. Therefore, by considering humans as an important part of the cognitive application may also introduce human mistakes/bias into the reasoning process. Auditory data is a required element that that should be considered to reduce those side effects.

Knowledge Learning and Reasoning

The ability to learn and reason about different scenarios and situations is central for the success of decision making. In organizations, decisions or lessons are learned, in general, from previous analogous situations. In addition, experiences gained with time are also used to reason about novel settings. The abilities to learn and reason in diverse circumstances are core desirable elements in cognitive technologies. Lessons learned from past experiences are used to ensure correctness in decision making when similar conditions are encountered and to reason about novel situations. Continuous learning by means of active learning, offers a unique and powerful way of directing the entire intelligence of a system towards wiser decisions (de Oliveira et al., 2018).

The first step towards advancing systems is to improve the continuous learning process, including contextual elements into the learning loop, and to also evaluate this feedback process in terms of trustworthiness (de Oliveira et al., 2020a). Given the costs of training large datasets, and the need for trust by multiple users to be appropriately measured, these issues have not yet been addressed in experiments conducted over the CVP-HC. It is believed that a combination of continuous learning, growth of the platform in terms of experiential knowledge, and feedback auditing would make it possible to augment the entire platform's intelligence.

Moreover, it is has been investigated throughput the CVP-HC the concept of stream reasoning a way to endow cognitive technologies with adaptability and extendability (de Oliveira et al., 2020a). By taking into account new sources of information, it is possible to draw new conclusions and update decisions in real-time. It enables certain goals to be accomplished, even in circumstances which the system was not expected or initially programmed for during the design process. From the point of view of application maturity, at this point the implementation of stream reasoning has been tested only over a few variables, constraints, functions in the CVP-HC; we have learnt that the sytem is able to recognize an unsafe situation from simple rules on the first layer of integration (visual data from a camera and contextual information) and on a simulated second layer with other sensor data.

Knowledge Augmentation

The ultimate goal of the SKECS approach is to allow cognitive systems to augment their intelligence towards wisdom. Augmented intelligence follows a five-function cadence that allows it to learn with human influence. It repeats a cycle of understanding, interpretation, reasoning, learning, and assurance. As yet, the knowledge augmentation layer has been fully explored, but steps have been taken on the road towards that objective. By the continuous learning process proposed in the fourth layer, where the human is placed in the centre, experiential knowledge can be incrementally incorporated (de Oliveira et al., 2020b). This will have an impact on the entire reasoning system, increase its specificity, and generate more certainty during decision-making. Therefore, the concepts and technologies suggested previously can be used as a pathway in the direction of augmented intelligence in cognitive applications (directing the whole AI–human system towards wiser decision-making).

Conclusion and Future Work

This research gives support for the development of cognitive systems by providing guidelines for effective use of hybrid human–AI knowledge in systems so they can, not approach human intelligence, but augment their intelligence capabilities towards wisdom. From investigation of techniques, methods, and the most recent technologies, significant contributions towards that goal have been made. Although the case-study analysis has been limited to the specific case of a cognitive vision system, it is believed that the findings of this study could be applied to any cognitive technology. Progress in machine learning techniques and reduction in computational costs of web services is also expected to make substantial contributions to KE and therefore accelerate the growth of intelligence in cognitive systems.

Furthermore, advances in biotechnology to understand the human brain better will also enhance the capacity of representing human knowledge explicitly. It will facilitate obtaining methods to efficiently learn relevant information. From the Cognitive Sciences perspective, discoveries will come from a clear idea of not only about what the human brain can learn and comprehend, but also how it learns – this knowledge will make it possible to program machines to absorb and apply knowledge such as humans do.

It is also important to mention that, during the course of this research, some philosophical questions have been raised, and they should be brought into the debate when talking about the future of hybrid cognitive systems, such as the value of human skills, accountability and legal responsibility in system decision, privacy, manipulation, opacity, bias, among others. Therefore, we recognise here the importance of bringing studies of ethics and philosophy into the field of AI.

Finally, I hope researchers will find more opportunities and challenges for future work, other than the ones mentioned in this paper, and make valuable progress towards cognitive systems.

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