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Procedia Computer Science 176 (2020) 3093–3102

Procedia Computer Science

www.elsevier.com/locate/procedia

24rd International Conference on Knowledge-Based and Intelligent Information & Engineering Systems

Human Feedback and Knowledge Discovery: Towards Cognitive Systems Optimization

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Abstract

Current computer vision systems, especially those using machine learning techniques are data-hungry and frequently only perform well when dealing with patterns they have seen before. As an alternative, cognitive systems have become a focus of attention for applications that involve complex visual scenes, and in which conditions may vary. In theory, cognitive applications uses current machine learning algorithms, such as deep learning, combined with cognitive abilities that can broadly generalize to many tasks. However, in practice, perceiving the environment and adapting to unforeseen changes remains elusive, especially for real time applications that has to deal with high-dimensional data processing with strictly low latency. The challenge is not only to extract meaningful information from this data, but to gain knowledge and also to discover insight to optimize the performance of the system. We envision to tackle these difficulties by bringing together the best of machine learning and human cognitive capabilities in a collaborative way. For that, we propose an approach based on a combination of Human-in-the-Loop and Knowledge Discovery in which feedback is used to discover knowledge by enabling users to interactively explore and identify useful information so the system can be continuously trained to gain previously unknown knowledge and also generate new insights to improve human decisions.

Keywords: Decisional DNA (DDNA); Set of Experience Knowledge Structure (SOEKS); Knowledge Management; Cognitive Systems; Knowledge Discovery; Human-in-the-Loop

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10.1016/j.procs.2020.09.179

1. Introduction

The creation of a general-purpose vision system with the robustness and resilience of the human visual abilities is still seen as a challenge [1]. In this context, one of the most recent tendencies in computer vision field to achieve more robust, resilient, and flexible systems is the combination of cognition and vision into cognitive computer vision [2]. Cognitive Vision systems have become a focus of attention when in tasks dealing with complex visual scenes and considerate variation of conditions. The design of such systems usually involves functionalities such as knowledge representation, learning, reasoning about events and structures, recognition and categorization, and goal specification, all of which are concerned with the semantics of the relationship between the visual agent and its environment [3]. The visual information in combination with explicit models of context can direct those systems to an explanatory but purposive behavior allowing them to adapt to unforeseen changes of the visual environment, and anticipating the occurrence of events, which mimics the human brain aptitudes [4].

In theory, cognitive vision applications uses current machine learning algorithms, such as deep learning, combined with cognitive abilities that can broadly generalize to many tasks. However, in practice, perceiving the environment and adapting to unforeseen changes remains elusive, especially for real time applications that has to deal with high-dimensional data processing with strictly low latency. The challenge is not only to extract meaningful information from this data, but to gain knowledge and also to discover insight to optimize the performance of the system. The discovery of new facts that were not previously explicit in data can be crucial to decision-making processes [5].

To address such issue, this paper proposes a framework based on user feedback to discover knowledge by enabling users to interactively explore and identify useful information in a human-in-the-loop approach [6]. This knowledge is incorporated into the system as experience that grows continuously over real time operation and that might enrich the application with smartness, creating its decisional fingerprints (optimization). By processing this novel knowledge, the system might generate new insights, improving human understanding about a specific situation and improving their (re)action/decision. To establish the human-machine interaction and cooperation we make use of a representation that can be assimilated by both humans and machines and which supports mechanisms for storing, reusing and sharing experiences. This unique, dynamic, and single structure is called Decisional DNA (DDNA). DDNA makes use of Set of Experience (SOE), which has been used in numerous different domains and has been recently extended for the use of formal decision events related to image and video [7]. DDNA and SOE provide a knowledge structure that has been proven to be multi-domain independent; thus, suitable for use in Cognitive Vision Systems as well [8-10].

This paper is organized as follows: In Section 2, some fundamental concepts are presented, which includes the general idea of Cognitive Vision Systems, Knowledge Representation and Management applied to them (with special focus on SOEKS and DDNA) and the concept of Knowledge Discovery. In Section 3 Collaborative Knowledge Discovery is described, followed by its application in Optimization of Cognitive Systems in Section 4. Finally, in Section 5 conclusions and future work are provided.

2. Fundamental Concepts

In this section w briefly introduce concepts that have driven the present research in order to provide a broader view of the issue we aim to address.

2.1. Cognitive Vision Systems

The term cognitive vision has recently been introduced as an attempt to attain more robust, resilient, and flexible computer vision system by endowing them with cognitive capabilities [11]. In theory, Cognitive Systems bring together and consolidate the achievements of the fields of artificial intelligence, automatic perception, machine learning and robotics [12]. Rather than only observing its surroundings, a cognitive vision system is capable of communicating and interact with it. The main goal is to mimic the human brain in respect to receiving visual information from the environment and combining them with other sensory information to create perceptual experiences [13].

However, perceptual processes depends on perceiver's expectations, on information available in the stimulus itself, as well as on previous knowledge [14]. Those are features difficult to be incorporated into the system during its design process. To our knowledge, a system able to process a variety of existing information (such as sensor data, visual content from cameras, input signals from machines and any other contextual information available) to characterize setting at the same time as it retrieves past experiences for the creation of perceptions does not yet exist.

One of the main challenges in creation of perceptual experiences is the processing of different sources of information that comes often unstructured, or structured in different representations at once. This matter becomes significantly complex when past information is retrieved to be accounted into analysis of a given situation. Consequently, a knowledge representation which supports the building of a multi-modal space composed of information from different sources, such as contextual, visual, auditory etc., in a form of experiential knowledge would be a very useful tool to manage this process [7].

2.2. Knowledge Management for Cognitive Systems

Selecting a way of standardizing and representing knowledge in cognitive systems may facilitate the process of learning relevant information and obtaining models capable of generating new insights. In the cognitive field, it is a challenging to design a unique standard structure that could integrate image/video modularization and its virtualization, together with contextual information given the complexity of aggregating and representing such varied data.

For us, cognitive systems must be supported by a standard knowledge representation, capable of integrating data of all sorts to so the learning process can achieve similar intelligence capabilities of humans. This structure should allow the scalable expansion of knowledge-based over time when experiencing more decision-making events (learning facilitation), and it should be able to escalate the requirements of real time applications. Aiming to address these issues we have proposed an experience-based technology that allows a standardization of image/video and the entities within together with any other information as a multi-source knowledge representation without limiting their operations to a specific domain and/or following a vendor's specification [15]. Our representation supports mechanisms for storing and reusing experience gained during cognitive vision decision-making processes through a unique, dynamic, and single structure called Decisional DNA (DDNA) [16]. DDNA makes use of Set of Experience (SOE) in an extended version for the use of storing formal decision events related to image and video [17].

2.3. Set of Experience and Decisional DNA

The Set of Experience Knowledge Structure (SOEKS) is a knowledge representation projected to obtain and store formal decision events as a form of structured experiences [18]. It is composed by four elements: Variables, Functions, Constraints, and Rules. Variables represent knowledge in an attribute-value form, which follows the traditional approach for knowledge representation and they are the central component of the knowledge structure. Functions, Constraints, and Rules are ways of creating relationships among those variables. Functions create relations between a set of input variables and the respective dependent variable; therefore, SOEKS utilizes functions as a way of creating multi-objective goals by associating those variables. A Constraint is a special type of Function that limits the space of possibilities; i.e., creates a subset of possible solutions, controlling the performance of the system in relation to its desired goals. Finally, Rules are relationships that operate in the universe of Variables and are used to express the condition-consequence connection in a form of "if-then-else". Functions are used to represent inferences (which can be given by a domain expert, for instance), and associate actions with the conditions under which they should be implemented [19].

The Decisional DNA (DDNA) is a structure which has the capability of capturing decisional fingerprints of an individual or organization and has the SOEKS as its foundation. Multiple Sets of Experience can be collected, grouped, classified and organised into decisional chromosomes, which accumulate decisional strategies for a specific area or field. This set of chromosomes consist of what is called the Decisional DNA (DDNA) of the organization [20].

2.4. Knowledge Discovery

Currently, the existence of large amounts of data suggests the use of tools capable of processing them and facilitate the process of finding new knowledge. The discovery of new facts that were not previously explicit in data can be crucial to decision-making processes and it is known as Knowledge Discovery in Databases (KDD) [21].

The knowledge discovery applied to databases consists of processing a large amount of data with the objective of extracting knowledge that can be reused either by an expert in the domain or by a knowledge-based system to solve problems in the domain [22]. It is not a trivial procedure as involves identifying novel, potentially valuable, and ultimately understandable and useful patterns in data [23]. The process can be extended and generalized to non-database sources of data, which may result in even more complexity.

When the information in a repository is structured and contains answers to questions or solutions to problems (decision-making), which can be searched, retrieved, and reused, this repository is called a knowledge-base. Knowledge discovery from knowledge bases is an important problem in the field of data mining as well. Discovering knowledge from knowledge-bases is used to minimize the issue of lack/incompleteness of knowledge, which is a bottleneck in intelligent systems [24].

Knowledge discovery concerns the entire knowledge extraction process, including how information is stored and accessed, how to generate knowledge from it, how to utilize this information/knowledge efficiently, scalable algorithms to analyze gigantic repositories, how to interpret the given results and support decision making, and how to model and support the interaction between human and machine. It also concerns the process of learning and analyzing the application domain [23].

Furthermore, the knowledge discovery process is controlled by an expert, who is in charge of guiding and validating the extraction process. In addition, the system may take advantage of domain knowledge to improve every step of the process in a form for interactive knowledge discovery [22, 25] (Fig. 1).

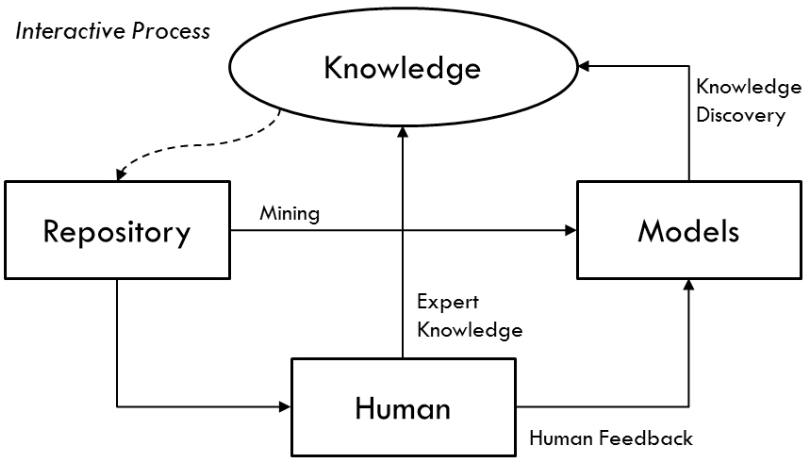

Fig. 1. Interactive Knowledge Discovery.

3. Collaborative Knowledge Discovery

In the past few decades a lot of progress in powerful computational tools have been made by separate communities, bringing Machine learning to focus of attention [26]. Researchers from Machine Learning field tend to believe in the power of their statistical methods to identify relevant patterns - mostly automatic, with no human intervention [27-28]; nonetheless, the dangers of modelling artefacts grow when end user comprehension and control are reduced [29]. In addition, mobile, ubiquitous computing and sensors, together with low cost storage, will accelerate this avalanche of data [30], and there might be a big threat here: drowning in data while starving for knowledge [31]. Subsequently, it is a grand challenge to enable effective human control over powerful machine intelligence to support insight and decision making without the integration and combination of machine learning methods and advanced analytics methods [26].

We envision effectively tackling these issues by bringing together the best of two worlds, but in a collaborative way: A balanced combination of theories, methods and approaches from Human-in-the-Loop and Knowledge Discovery in a Collaborative Knowledge Discovery approach [26]. It is important to point out that our proposed method is based on Interactive Knowledge Discovery [32], but the collaboration form stands for the fact that the systems and individuals will be sharing knowledge and work together in pursuit of a common goal and both are learning and gaining new experiences. In this sense, not only systems is expected to improve in performance by getting them to higher-order thinking like problem solving, but also the human decision making is also improved by bringing the power of numerical computation, information retrieval, statistical reasoning into analysis.

3.1. SOEKS and DDNA to support Learning

Machine learning is one of the fastest growing areas in the computer science field [33]. Machine Learning algorithms are designed to learn patters so they can be used for predictions. Most ML researchers have concentrated their field of study on automatic machine learning, where great advances have been made in the past few years, for example, in speech recognition, recommender systems, or autonomous vehicles, etc. Automatic approaches greatly benefit from big data with many training sets. Though, in many domains, such as health and surveillance, we are confronted with a small number of data set, i.e. rare events, and datasets with high deviance among samples [34]. This may compromises the efficiency of automatic machine learning approaches significantly.

In this context, interactive machine learning may be of help, having its roots in reinforcement learning, preference learning, and active learning [35]. The term interactive machine learning has not yet been well defined, but we assume to be as “algorithms that can interact with agents and can optimize their learning behaviour through these interactions, where the agents can also be human” such as defined by [34]. This “human-in-the-loop” approach can be beneficial in solving computationally hard problems, where human knowledge and perception and their cognitive capabilities may assist the system in adapting to new situations and to handle abstract ideas to change their environment. Moreover, human intervention may help to reduce exponential search space through heuristic selection of samples and reduce problems greatly in complexity in the learning phase [36].

The communication between humans and machines in a way that they exchange knowledge is a key point in interactive machine learning. Interfaces may help to establish the link between the representation of the machine and representations that humans can understand. But knowledge must be structured in a way that both can gather, interpret, reason and share. For this reason we propose the representation of both human experiential knowledge and information collected by a system together in the unique structure of SOEKS that expresses machine-readable semantics of knowledge. SOEKS offers the possibility of representing simple and complex knowledge structure in a standardized way. Fig. 2 shows a representation of SOEKS message configuration, which has been implemented over ROS framework [37], but can be extended to any platform that uses publish–subscribe architecture [38].

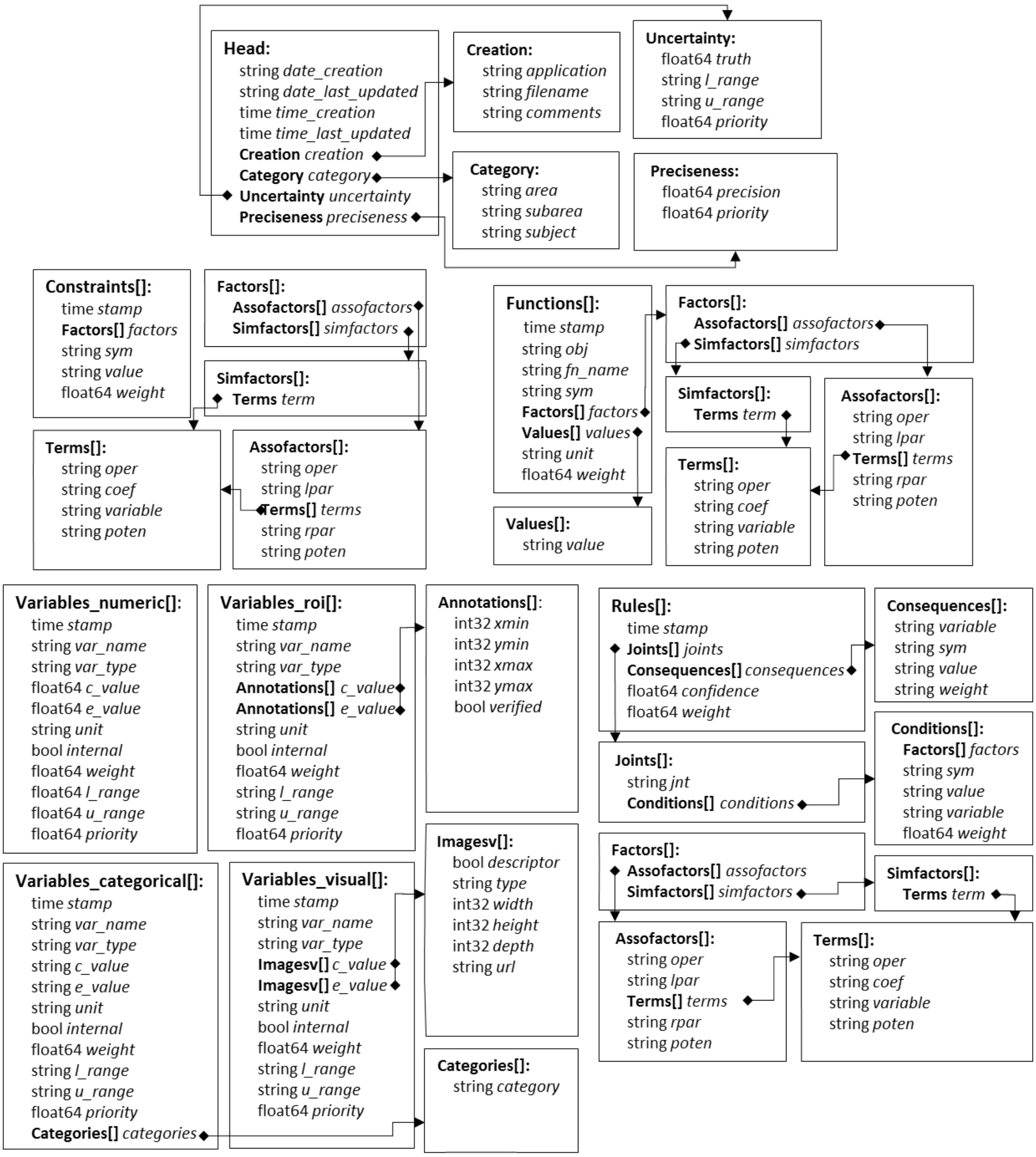

Fig. 2. Example of SOEKS message types implemented over ROS framework.

3.2. Human-in-the-loop and Active Learning

The Human-in-the-loop approach enables end users to interactively find and characterize previously unknown and potentially useful and valuable information/knowledge. It may be defined in the classical sense as the process of identifying novel patterns, with the goal of understanding these patterns [26]. This user may be able to identify, extract and understand them so the system can gain new, and previously unknown knowledge, and also to reduce duplicated or wrong samples [39]. This knowledge may then be used for the system to learning actively and to generate insights.

Active learning is a subfield of semi-supervised machine learning. Its key hypothesis is that if the learning algorithm is allowed to choose the patterns which it learns from, it will perform better with less training [40]. An active learning scenario in a Cognitive System involves evaluating the informativeness of available knowledge, correcting any ambiguity and incompleteness that generates uncertainty, and also incorporating domain knowledge into the learning process [41]. This process is exemplified on Fig. 3.

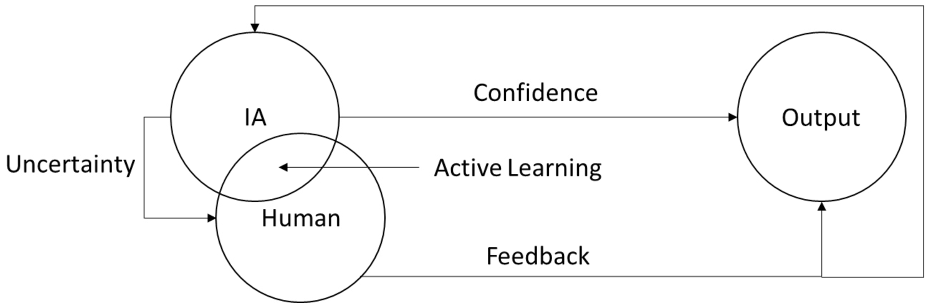

Fig 3. Human-In-The-Loop Approach.

Active learning involve a more rapid, focused, and incremental model updates than the old-fashioned machine learning process. These properties assist everyday users to interactively explore the model space through trial-and-error and drive the system towards an intended behaviour [42]. Moreover, interactive machine learning can facilitate the optimization of applied machine learning, empowering end-users to create systems for their own needs and purposes, increasing its specificity consequently performance.

4. Towards optimization of Cognitive System

Machine learning and artificial intelligence are invaluable for cognitive systems. The standard way to incorporate machine learning and artificial intelligence into a system is to first train a learner to accurately predict output as a function of a set of inputs. Deep learning based design approaches, combined with limited exhaustive searches, have proven to be a potent solver of multi-objective optimization problems by learning this input output relations [43]. However, as mentioned previously, system with some cognitive capabilities, which are able to receive visual information from the environment and combine it with other sensory information to create perceptual experience require large amounts of training data and are not yet able to generalize well for novel databases. For this reason, efforts in development of cognitive systems applications have moved away from generality to accomplish simple tasks for constrained scenarios [44]. Consequently, general-purpose artificial vision system matching the capabilities of the human vision is still to be developed.

In this sense, we believe the creation of a general-purpose system does not invalidate the specificity of the system if it learns as it runs. Therefore, the combination of knowledge discovery with human-in-the loop can be used to enrich the system with useful knowledge, so it can actively learn and be optimized for each scenario/application. The knowledge representation we propose takes in consideration the machines efficiency in numerical computation, information retrieval, statistical reasoning, and almost unlimited storage. Machines can capture many categories of information from the environment through various sensors, such as range sensors, visual sensors, vibration sensors, acoustic sensors, and location sensors [45]. On the other hand, humans have their own cognitive capabilities which includes consciousness, problem-solving, learning, planning, reasoning, creativity, and perception. These cognitive functions allows humans to learn from last experiences and use this experiential knowledge to adapt to new situations and to handle abstract ideas to change their environment [7].

In our proposed approach decision making resulted from the combination of machine learning technologies and human expertise and feedback (Collaborative Knowledge Discovery) is incorporated back into to the system for training purposes and also used to optimize results and improve decision making (Fig. 4). In the hazard control field, which has been our focus of interest, machine learning could be used to train a classifier to detected and flag the presence of any possibly risky activity. The system operator could then apply their knowledge, judgment and expertise to interpret that output, investigate and make any intervention on site is necessary. This decision taken could be fed back into the system, so when a similar situation occurs a recommendation based on experiential knowledge could be given. It not only saves times and operator's effort in case of repetitive situations, but also assists unexperienced operators that are facing that circumstances for first time, augmenting their knowledge about the giving situation and speeding the decision making process. This can be seen as a pathway towards Augmented Intelligence [46].

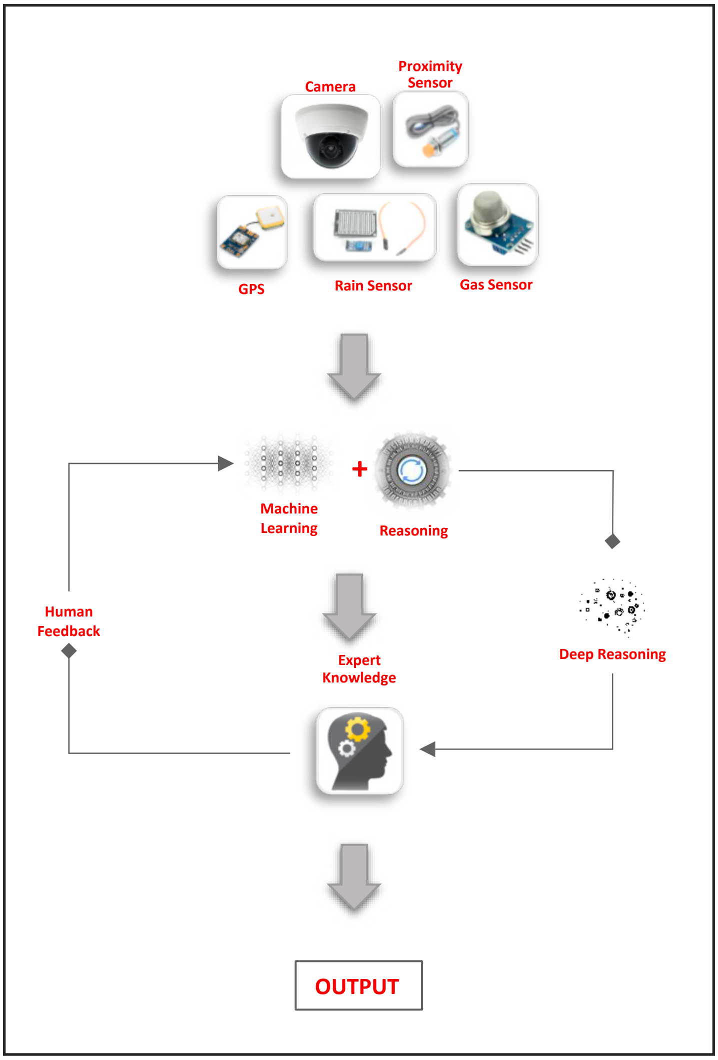

Fig 4. Optimization of Cognitive Systems through Collaborative Knowledge Discovery.

5. Conclusions and Future work

This paper proposes an approach based on user feedback to discover knowledge by enabling users to interactively explore and identify useful information so the system can gain new and previously unknown knowledge. This approach can be used in cognitive systems to extract meaningful information from data, to gain knowledge and also to discover insight to optimize the performance of the system as it runs. In addition, by processing this novel knowledge, the system will be able to produce new insights, increasing human understanding about a particular situation and improving their (re)action/decision.

To enable the interaction between humans and machines in a way that they exchange knowledge in a collaborative way, SOEKS and DDNA is suggested. They can be used to establish the link between the representation of the machine and representations that humans can understand. In this way, knowledge is structured in a way which both can read, interpret, reason and share.

The next step in our research will be the test and evaluation of the proposed methodology through a case study of a Cognitive System for Hazard Control (CVP-HC). This system is being designed to ensure that workers remain safe and compliant with Health and Safety policy for use of Personal Protective Equipment (PPE) and serves as a showcase to demonstrate a real operation of a Cognitive System and technologies involved to enable its functioning.

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