Cognitive Products: System Architecture and Operational Principles

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***Abstract*—Future commercial products and product assemblies could greatly benefit from recent developments in machine learning, providing the foundation of cognitive products equipped with sensors and actuators and embedded into tangible objects operating in the real world. This paper identifies key challenges in the related fields and provides motivation for further advancements particularly in the domain of resource-constrained distributed and embedded Artificial Intelligence. Enabling cognitive capabilities, such as perception, reasoning, learning and planning, could result in higher reliability, adaptivity and improved performance, however it would require an increased involvement of non-technical disciplines like cognitive neuroscience. We propose a generic top-level cognitive architecture providing a reference to various research areas involved in this multifaceted field. Conceptual prototypes of two cognitive products, targeting real-world industrial environments, are presented and discussed.**

***Keywords*–cognitive systems; ambient intelligence; embedded systems; distributed intelligence; cognitive components.**

I. Introduction

Humans have developed skills to survive in a complex world by evolving adequate information processing mechanisms well suited to deal with ill-structured problems involving a high degree of uncertainty. The human brain, however, cannot compete with machines on tasks requiring massive computational resources. Machines are faster, more accurate and stronger than humans. However, humans outperform machines in many tasks, which require flexible, reliable and adaptive control. Since these abilities are currently beyond the reach of state-of-the-art Artificial Intelligence (AI), much of the inspiration for implementing future intelligent machines needs to be taken from cognitive sciences that study computational models of human perception, attention and motor control. The ultimate goal is to turn machines into ones that can reason using substantial amount of appropriately represented knowledge, learn from its past experiences in order to continuously improve performance, be aware of its own capabilities, reflect on its own behavior and respond robustly to surprise [1]. Such a high level intelligence should be complemented by low level cognitive abilities provided by reactive models. This would enable a major leap in the quality of interaction and cooperation with humans.

Therefore, the aim of ongoing research in this field is to develop efficient computational mechanisms for artificial cognitive systems, which consolidate and benefit from findings about the structure and functional organization of natural cognitive systems, while taking into consideration the differences in their characteristics. For example, sensorimotor loops of humans and machines differ significantly in sensing accuracy, actuation precision and internal processing latency, implying different cognitive abilities. Therefore, while following the basic principles of human cognition, certain deviations in the realization of Artificial Intelligence systems can be expected.

Cognitive products are created from a combination of mechatronic systems equipped with artificial sensors and actuators and advanced software algorithms. They integrate cognitive functionality, such as perceiving the environment, learning and reasoning from knowledge models. This field is still in its infancy, however the time is ripe for laying down the foundations of basic system architecture and operational principles, which are key challenges for the research community towards developing future cognitive products.

The main contribution of this paper is the introduction of a generic system architecture and the description of the key operational principles of future products with cognitive capabilities. For illustrative purposes, we provide two conceptual examples of tools incorporating generic cognitive components and building on the notion of embedded AI. Furthermore, we raise key open research questions, which need to be addressed in order to enable the integration of advanced AI into a broad range of future commercial products.

Integrating cognitive capabilities such as perception, learning, reasoning, planning and action into future robots, manufacturing systems, autonomous vehicles, etc. requires the orchestrated effort of various scientific fields, i.e., Cognitive and Neuroscience, Control and Information Theory, Artificial Intelligence and Engineering. In recent years, disciplines concerned with cognitive systems have cross-pollinated each other in various ways. The interdisciplinary research in this area includes two major subfields, Cognitive Science, which develops 'human-like' computational models of cognition, perception and action, inspired by recent advances in neuroscience and sensorimotor control, and AI, which explores algorithms

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realizing cognitive capabilities building on advanced methods of machine learning and Bayesian reasoning.

In Section 2, we briefly review the related scientific fields. Section 3 introduces the concept of cognitive products and identifies the key challenges to be addressed by the AI community in order to enable human-like cognitive functions in machines. Section 4 presents a top-level generic architecture for cognitive products and describes its key elements. In Section 5, we introduce two concept devices, building on a set of generic cognitive features. Section 6 sums up key aspects of cognitive products and production systems of the future.

II. Background

Cognitive neuroscience and Artificial Intelligence have a long relationship, dating back to McCulloch's, Turing's, Neumann's and Hebbian era [2][3], when the theoretical foundations of computing and AI were laid by defining basic principles interwoven with neuroscience and psychology. Since then both fields grew tremendously and evolved into full-fledged disciplines, having some collaboration at the periphery, but not mainstream. However, it is a prime time to intensify the interaction within this relationship again [4][5]. Furthermore, the growing empirical evidence of Bayesian decision processes in human sensorimotor control, reasoning and learning mechanisms [6] has triggered an enormous research effort in cognitive psychology. Neuroscientists investigate cognitive control of multi-sensory perception-action couplings in dynamic and rapidly changing environments, which provide important insights for neurocognitive models used in technical system implementations [7]. Research on perception provides mechanisms allowing to capture information, which is relevant, by attention focus and context understanding.

Better understanding biological brains could play a vital role in building intelligent machines. Recent advances in AI have been inspired by studies of neural computation in humans and other animals. Neuroscience could provide a rich source of inspiration for new types of algorithms and architectures, independent of and complementary to the mathematical and logic-based methods and ideas that have largely dominated traditional approaches to AI [4]. Recent studies attempt to discover mechanisms by which the brain implements algorithms with the functionality of backpropagation. Such developments illustrate the potential for synergistic interactions between AI and neuroscience. Leveraging insights gained in neuroscience research could expedite progress in the field of AI. Earlier research in cognitive science followed the approach to reasoning, which uses behavioral rules based on rewards and punishments and is inspired by Behaviorism [8], and have recently refocused onto the Connectionist approach [9][10].

Data science continually makes rapid advances particularly on the frontiers of deep learning, which provide opportunities for a variety of applications [11–13] stretching deep into sectors of economy that have stayed on the sidelines thus far. The volume of available data is growing exponentially, more sophisticated algorithms are being developed and computational power and storage are steadily increasing. The convergence of these trends is fueling rapid technology advances and business disruptions. However, modern AI generally provides solutions fine-tuned to crunch large complex data sets enabling only rudimentary context awareness.

Artificial Neural Networks (ANN) [14] have become very popular recently due to advancements in computing power, availability of big data and developments in deep learning techniques. The great success of Deep Neural Networks (DNN) built largely on the power of GPUs for massive parallel computing. Deep learning derives its power from computational models composed of multiple processing layers able to learn representations of data with multiple levels of abstraction [15][16]. This makes it naturally fit for pattern recognition problems where learning is about discovering features that have high value states in common [10]. More recent advances in deep learning are moving beyond object recognition and towards scene understanding [17][18]. Yet, current deep learning methods excel in recognition [19] rather than understanding tasks, and furthermore are not able to draw causal relationships between objects. Complex scene understanding requires core knowledge about physics [20], compositions and relationships of objects and causality between them [10]. To understand causal relationships between interacting agents in a scene, their intentions and goals, we need core knowledge from social psychology. The mechanism of learning and thinking needs to be local and incremental, based on a generic approach, which starts from a clean slate and evolves over time. A more principled approach to cognition builds models to understand the world [10], as the key to human intelligence is its capability to explain nature, rather than classify or recognize phenomena.

Several concepts for cognitive architectures have been proposed in the past, namely ACT-R [21], Soar [22], ADAPT [23], PSI [24], however the common shortcoming of all is the lack of general design methodology. These approaches lack modeling of cognitive information processing from the ground up. Examples of basic information processing functions are acquisition, processing and transferring, while more abstract and complex ones are analyzing and classification [25]. Other cognitive functions, such as observe, recognize, encode, store, remember, think, problem solving, motor control and language show that beyond formalizing they also combine new information with existing internalized knowledge representation [26].

III. Cognitive products

Cognition implies the ability to understand the underlying nature of things, not only at present but also in the past and in the foreseeable future, and to take this into consideration in decision-making. For this purpose, humans require sufficient, usually not too extensive information, experience, and profound knowledge on the matter as well as an estimation of the consequences of alternative actions. Transferring these capabilities to digital systems could enable new levels of innovative functionality depending on the scale of particular applications, with systems ranging from local man-machine interaction to shop-floor or factory-wide man-to-machine (M2M) communication to management of inter-organizational production processes. This requires the creation of tangible, durable objects consisting of a physical carrier

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system with embodied mechanics, electronics, microprocessors and software, and equipping them with cognitive capabilities enabled by flexible control loops and cognitive algorithms [27].

In contrast to products operating with deterministic control methods, cognitive products do not only act autonomously, but they do so in an increasingly intelligent human-like manner [27]. Cognitive products could maintain multiple goals, perform context-sensitive reasoning and make appropriate decisions based on complex and uncertain information, which makes them more robust in their adaptation to dynamic environments than other products. Coping with such intelligent, flexible and robust behavior would emphasize the importance of the human factor in smart factories and at the same time could put the human operator into a better position when adapting to highly customized dynamically changing manufacturing processes as compared to fully automated mass production systems. On one hand, the increasing specialization of products and processes requires guidance in task execution, while on the other hand industry requires a continuous, detailed assessment of data in order to optimize product specifications and production processes.

A. Can a machine think?

While the notion of Artificial Intelligence has been around for decades, recent advances in algorithms and processing power combined with the exponential growth in available data are enabling the creation of machines with unprecedented capabilities. While these technologies might not redefine what it means to ‘think’ they are starting to perform activities long thought to be the sole purview of humans – sometimes at higher levels of performance than people can achieve. Although in some tasks AI outperforms human counterparts [28] machines are still far from general human-level intelligence, which relates to qualitative cognitive aspects of human learning and thinking, such as intuition, inference, imagination, imitation, learning to learn, prediction and planning.

As opposed to narrow (weak) AI, typically developed for a specific application such as object or speech recognition (e.g., IBM’s Deep Blue and Watson, Google’s AlphaGO [29]), general (strong) AI possesses an understanding of the world and has human-like cognitive abilities. When a general AI is confronted with a new problem it can find a solution based on experience with similar problems by applying, e.g., transfer learning [30][31] or abstract association or based on its understanding of the world independent of the particular task. Knowledge about the world may be simply related to objects size, location, co-occurrences, properties, but also more abstract insights like physical laws, social behavior, and causality. An ‘ultimate’ test for assessing general intelligent behavior of an AI based on its distinction from a human when inquired by a human observer was proposed already in [32].

Technologies like Cyber-Physical Systems (CPS), Internet of Things (IoT), Industry 4.0 and autonomous vehicles operate in self-contained, distributed and localized manner utilizing resource-constrained devices, which creates scalability issues for deep learning techniques. Therefore, besides flexibility and adaptivity, efficiency becomes a key criterion for future systems. We need a computational cognitive foundation for things that think. For a truly human-like thinking and learning the system should possess causal model of the world describing the structure and the causal relationships between the agents and their environment, rather than merely solving pattern recognition problems. Cognitive systems should be able to perform ground learning starting from a clean slate and evolving on top of born-with theories of core knowledge, e.g., intuitive physics [33] and psychology [34]. They should harness the compositionality, i.e., the construction of new knowledge based on primitive elements, and learning-to-learn in order to rapidly acquire and generalize knowledge to novel situations and processes. These features are necessary for achieving a general-purpose AI flexible enough to adapt to previously unseen scenarios and interactions.

B. Beyond state-of-the-art

We are witnessing an era in which the convergence of algorithmic advances, data proliferation, and tremendous increase in computing power and storage have propelled AI from hype to reality. However, in order to develop truly human-like learning and thinking machines there are open key challenges for AI research, i.e., (i) machine learning requires massive resources (computing power and training data), (ii) models do not generalize well, (iii) processes of training and inference most likely differ from human learning and reasoning.

Within the Smart Movement [35][36] products have been increasingly equipped with electronics, enabling the assessment of isolated environmental data and the interpretation of basic contextual information (e.g., wearable activity trackers, smartphones and watches, etc.). However, these products typically have deterministic and predefined behavior and lack the capabilities required for sustainable and autonomous human-like cognitive functions, such as perception, awareness, learning, reasoning and decision-making. Cognitive products are capable of achieving self-awareness, understand their immediate environment including human collaborators, activities and processes, and can perform goal-oriented complex tasks such as human assistance and guidance, as well as integrate higher-level work-flow information related to environmental states into object models.

Cognitive systems exhibit behavior through perception, action, individual or social interaction with the environment, and depend on standardized networks and interfaces for communication and access to information from distributed and embedded systems. The next generation of products and manufacturing machinery suited for batch and continuous process industries with embedded cognitive functions will enable the following capabilities in an autonomous self-organized fashion

- assistive man-machine collaboration enabling appropriate worker support and guidance in complex processes;
- adaptive control of dynamic M2M networks enabling self-adaptation to work situations, material, human resources and environmental conditions;
- embedded data analytics enabling autonomous sensor-based data collection, data mining and real-time predictive and pro-active planning and decision-making;

- embodiment appropriately related to workers and other cognitive systems in the immediate environment;
- synergistic machine-to-machine organization of production systems.

Further advances of cognitive products could include semantic work-flows and tool description models for (i) work-flow alignment, (ii) quality control, (iii) tolerance range assessment, and (iv) skill, task and overall evaluation. This would require the identification of a formal model for an opportunistic multimodal feedback framework based on the optimization of user, tool, material and environmental parameters. Building on a knowledge database of previously applied strategies a reasoning engine could provide guidance even in previously unseen work-flow situations using context and activity recognition.

C. Embedded AI

Rapid developments in hardware, software and communication technologies have facilitated the emergence of Internet-connected sensory devices that provide ubiquitous observations and data measurements from the physical world. The technology of Internet-connected devices, referred to as Internet of Things (IoT) [37], extends the current Internet by providing connectivity and interactions between physical and cyber worlds. IoT continuously generate data with a variety of modalities and data quality and the intelligent processing and analysis of such data is the key to developing smart applications. As the number of commercial and industrial devices proliferates, connecting them in dynamic networks comprised of intelligent individual components is a key challenge for IoT to realize its full potential [38].

An industrial facility might have thousands of sensors monitoring the status of machines and processes, which however often reside in silos that do not communicate. Some AI solutions are centralized on cloud service architectures, where sensor data needs to be collected, correlated with historical performance data and analyzed to provide actionable information for real-time decision-making. However, in many industrial locations sufficient bandwidth or connectivity cannot be relied upon. Therefore, in order to obtain reliable continuous time-critical decisions we need to embed intelligence at the source of sensing. This requires building smart devices on top of edge computing architectures and equipping them with Artificial Intelligence. To this end, some chip companies work on incorporating conventional AI software in their chips, while others are building advanced cognitive AI solutions that can be embedded in off-the-shelf inexpensive chips. Embedding cognitive capabilities such as perception, awareness, reasoning, learning and decision making into products requires addressing constraints in terms of size and weights, real-time computation, limited processing resources (memory footprint and computing power), low power consumption and low cost. Scarcity of resources hinders autonomous real-time execution of conventional deep learning algorithms on embedded devices due to massive computational requirements. We envision that deep learning will have a pivotal role in realizing a flexible and efficient learning platform for embedded AI. However, industrial design and software need to be optimized to simultaneously meet all of the above constraints, while current machine learning methods still require massive computing power, training data and memory footprint. The next generation of machine learning algorithms need to provide flexible, efficient and incremental learning techniques for resource-constrained environments in order to enable future self-organized autonomous systems. Recent advances in deep learning are already moving beyond object recognition and towards scene understanding, which requires core knowledge about physics, compositions, relationships and causality between objects [39]. If the scene includes agents and humans interacting, percepting and acting, then we also need core knowledge of social psychology for understanding their intentions and goals. For realizing a dynamically evolving low foot-print learning framework, deep learning has to respond to these challenges and answer key research questions such as:

1) Can deep neural networks fit cognitive processes of human brain?
2) How can insights in human perception be applied to AI systems?
3) Can DNN transfer knowledge learned in one task to another?

D. Ensembles of cognitive components

Modern smart factories require the integration of flexible cognitive components enabling implicit supply chain management via vertical integration and quality management via step-wise traceability. Building on the approach of opportunistic sensing cognitive components could advertise their capabilities with respect to both sensing and actuation. Upon localizing each other they could form collective ensembles in self-organized manner and exchange structured data. Furthermore, they could jointly sense their shared contextual state and adapt accordingly by preemptively suggesting usage strategies or best practices to users, or by reactively setting operation parameters to suit particular circumstances. Such ensembles could learn from use and/or misuse of individual tools and take proactive steps to avoid hazardous situations and increase their own life-span. Component and production history awareness could enable the fine-grained modeling, organization and optimization of complex production processes. The ultimate goal is to enable the creation of joint cognitive systems [40], consisting of distributed networks of intelligent devices and human operators.

E. Dependability

The accurate operation of cognitive production tools is of utmost importance even in very harsh production environments as tool downtime or malfunction may lead to reduced productivity, waste products or may harm the worker in safety-critical applications. Certain capabilities related to sensing, localization and communication are particularly vulnerable in harsh environmental conditions such as for example strong electromagnetic fields generated by arc welding. Therefore, highly dependable unified solutions need to be devised, integrated and tested in cognitive tools.

Machines equipped with cognitive abilities could provide higher degree of robustness and dependability by learning to perform complex tasks reliably and accurately in various extreme conditions. In order to achieve that they must take into consideration all available sensory channels and utilize the most appropriate ones. Embedded context and activity recognition based on multi-sensor fusion (RGBD video, motion, orientation and pressure sensors, eye-tracking, GSR, HRV, RFID, indoor localization, etc.) could enable advanced context understanding including presence, activities, needs and skills of workers, work-flows, etc. However, current industrial solutions are limited to recording basic information about specific environmental aspects (e.g., temperature, humidity sensing, etc.). True cognitive products need to advance this state-of-the-art by building on adaptive and robust multimodal sensor networks and distributed data processing algorithms.

IV. Cognitive Architecture

Enabling an advanced level of self-organization, which allows machines to accomplish complex tasks in changing and uncertain environments, maintain multiple goals simultaneously, resolve conflicts between interfering goals and act appropriately in unexpected and previously unseen situations, requires a sophisticated design methodology and appropriate cognitive architecture.

For ensuring robust and reliable behavior of cognitive products we need advanced virtual methods for engineering, tools and models providing fully functional simulation environments. Every cognitive product device generates data, which is fed back into engineering and maintenance systems for continuous product improvement and condition monitoring and therefore requires an individual virtual representation reflecting its context of use. In parallel to virtual methods, modeling and controlling single instances and ensembles of cognitive components require a user-centric product development approach, which takes into account ergonomic aspects and human factors. In order to capture the synergistic interdependence between humans and cognitive products in the context of social interaction and collaboration we need to take into account affective, cognitive and social aspects in interaction design, informed by relevant sociological, psychological, socio-cultural, ethical and legal studies.

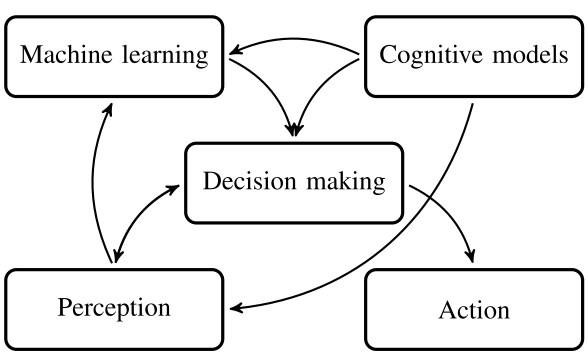

Figure 1. Diagram reflecting the relationships between elements of the Cognitive System Architecture.

A state-of-the-art cognitive system architecture requires a probabilistic approach in order to provide means for integrating perception, learning, reasoning and action in the face of uncertainty. Such an architecture would include a comprehensive repertoire of diverse learning methods capable of generalizing from a very few samples. The acquisition of new skills and activities from little prior experience and a limited number of observations would be facilitated by knowledge representation, learning infrastructure and computational models tailored particularly for low-power sensor-equipped embedded platforms operating in resource-constrained environments.

Cognitive system architectures usually decompose cognition functionally into modules operating in a tightly interconnected mode [41]. The elements describing the conceptual representation of the hierarchical 'human-like' perception–action loop required for realizing cognitive products are shown in Table I.

Creating technical devices that interact with a Human always requires the consideration of the human factor, since the interaction involves two systems that are different by nature, i.e., Biological on one side and Cyber-Physical on the other [42]. Furthermore, enabling a more natural relationship with the user necessitates the integration of sophisticated human-like cognitive functions, such as emotion and intention recognition.

Formal concepts and models of primitive cognitive rules for multi-sensor computational perception, learning and reasoning are inspired by neural processes underlying human cognition and are based on core knowledge theories of intuitive physics and psychology (see Figure 1). They provide a foundation supporting primitives of flexible and efficient learning: descriptive causal model of the world, compositionality and rapid learning-to-learn capability. The aim is to achieve compact representations and optimize inference for execution on embedded devices in real time. Another key criterion is the radical decrease in resource requirements compared to cloud-server based solutions. This requires efficient hierarchical data representations emulating human perception with digital sensors and a new generation of deep learning algorithms and artificial neural networks reflecting the hierarchies of human cognition, distributed and incrementally evolving in nature. Independent cognitive devices would form a network within which they could interact autonomously with each other, providing the basis for the emergence of an even higher intelligent entity.

TABLE I. Elements of the Cognitive System Architecture.

Element	Description
Perception	acquisition of information about the environment and the body of an actor, typically considered in AI an estimation process providing symbolic representation of the world state
Action	process of generating actual behavior in machines in the form of executable control programs derived from precise dynamical system models
Learning	process of acquiring, structuring and reorganizing information that results in new knowledge and leads to behavioral changes, which are measurable and persistent in time
Decision making	process of making inferences and generating representations of conceptual future behavior based on evidence and basic principles using various mechanisms (causal, temporal, spatial, etc.)
Cognitive models	formal models and ingredients of human intelligence reflecting aspects of core knowledge necessary for general-purpose capabilities

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V. Concept devices

In this section we describe a set of specific, yet generic, cognitive features, in the context of two conceptually different prototypes of intelligent production tools. The realisation of these prototypes is ongoing work and therefore their evaluation is not included in this paper. However, with these examples we demonstrate how knowledge transfer could be achieved across a range of cognitive products, ensuring device interoperability and minimizing development costs.

A. Power tool

Let us take the power tool (see Figure 2) as an example of a potential future product with cognitive capabilities. The cognitive power tool is a ubiquitous computing, sensing and actuation device in which sensors are connected in a network, where data analysis is performed in real-time on embedded computing device providing autonomous decision making in a distributed architecture. The cognitive capabilities of the network include state estimation from sensor data, context inference, continuous acquisition, update and use of activity models. The cognitive sensor network has to recognize and understand human actions with respect to tasks and goals, and furthermore estimate and predict user state and future behavior. Certain activities can be performed concurrently and need to be decomposed into primitive actions for classification purposes.

Recent innovations in linear motion and assembly technology enable high-precision measuring systems based on intelligent engineering solutions, opening a variety of opportunities for Industry 4.0 applications. This includes the integration of high-precision digital sensors for torque and angle of rotation acquisition, which provide excellent accuracy, repeatability, durability and process documentation. Both power and control technologies can be fully integrated into the power tool and no external sensors or controls are required during operation. The power tool combines wireless capabilities with state-of-the-art tightening technology, a combination which has the potential to improve efficiency, cycle-times and data collection during the manufacturing process. During each work step the integrated controller monitors the tightening of variable-speed pump drives and transmits the results over wireless channel to a receiving station. Its decentralized intelligence is integrated in the tool and can utilize product variables such as serial numbers to determine the tightening process recipe for execution. Integrating the control of the tightening process ensures the highest level of reliability even in wireless dead zones. Power tool ensembles interconnected in networks could share tightening data and thus optimize production processes and product quality.

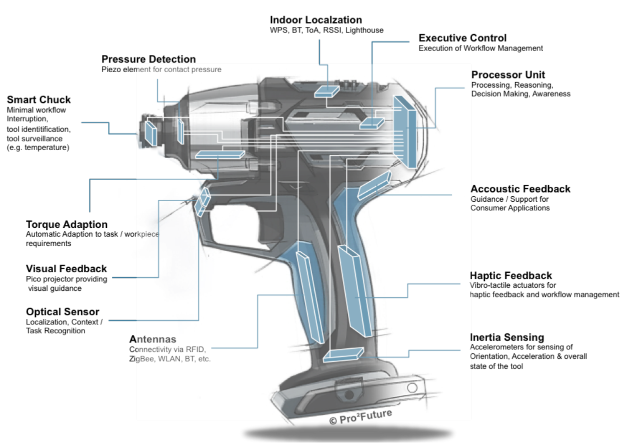

Figure 2. Cognitive components of a conceptual intelligent power tool.

The capabilities of our conceptual cognitive power tool are described in Table II.

TABLE II. Features of a cognitive power tool.

Feature	Description
Pressure detection	piezo element for contact pressure
Smart chuck	tool surveillance (e.g., temperature) for minimal work-flow interruption
Torque adaptation	based on task and work-piece requirements
Visual feedback	visual guidance on pico projector
Optical sensor	high resolution target localization, context and task recognition
Antennas	communication infrastructure (e.g., RFID, Zigbee, WiFi, BT)
Indoor positioning	localization in industrial environmental settings (e.g., WPS, BT, ToA)
Acoustic feedback	advanced guidance in real-time operation
Haptic feedback	vibro-tactile actuators for work-flow management
Inertial sensing	orientation, position and movement tracking
Cognitive unit	context-awareness, intelligent reasoning and decision-making
Control unit	execution of work-flow management

B. Head gear

Recent advances in mobile computing, Augmented Reality (AR) and wearable sensors have had a profound impact on assistive technology supporting daily routines of industrial employees. A great effort is dedicated to exploring the benefits of AR, however more advanced developments are typically restricted to the research community and are not commercially available due to various shortcomings. AR solutions have been developed predominantly on hand-held devices, which constrains user movement and ability to interact with the physical world using hands-free operation. More advanced Head-Mounted Displays (HMD) overcome these obstacles by allowing users to follow instructions in hands-free manner while performing an assembly operation.

Google Glass, arguably the most popular HMD, has been utilized in a variety of settings including agriculture, healthcare, sports, information retrieval and teleconferencing, to name a few. Smart head-wear devices have also been deployed in industrial environments. However, while large scale developments are under way in this field, the potential and the benefits of the evolving HMD technology in real industrial settings are not completely clear yet.

Recent smart head-wear technologies have targeted a number of areas, including

- aviation – helmet-mounted and cockpit-projected solutions primarily used for military purposes with limited commercialization;

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- consumer – home entertainment and daily activity enhancement (Google, Samsung);
- manufacturing – enhancement of process engineering, logistics and field services (e.g., hands-free maintenance instructions, barcode scanning, warehouse navigation);
- medical/Healthcare – telemedicine and hands-free patient information;
- military – reconnaissance with multi-spectral cameras and thermal night vision;
- sports – display salient information such as track trajectory, temperature, altitude and speed in cycling, sailing and motor sports;
- firefighting – object recognition and flow path tracking using thermal vision and edge detection;
- publishing – instant translation.

The field of HMD is still fragmented with respect to the utilized technology. Commercial products use various connectivity methods, a range of operating systems and a number of primary and secondary input/output devices. No single standard solution exists, which could provide all essential features a factory worker might benefit from in a complex industrial environment in order to increase production efficiency. Existing HMD devices lack comprehensive solutions providing a step-by-step guide to assist workers in the completion of a complex assembly task, instead they usually support a prerecorded video playback or a video teleconference access to relevant experts. Typical features of existing industrial HMD solutions include

- presentation of work instructions related to a particular task, which are overlaid on the real-world scene with spatial and temporal relevance;
- superposition of thermal contour of real-world objects frame-overlaid onto a portable display;
- remote asset access and data visualization;
- connected expertise;
- hands-free interaction using voice control.

Reusing many of the cognitive components of the power tool (see Table II), we could imagine a head-wear device equipped with a smart-phone for localized computation and mirrored visual feedback, as shown in Figure 3. Additional components include a world-view camera for monitoring the environment and gesture control, as well as eye-tracking cameras for attention detection, and multi-directional vibro-tactile feedback.

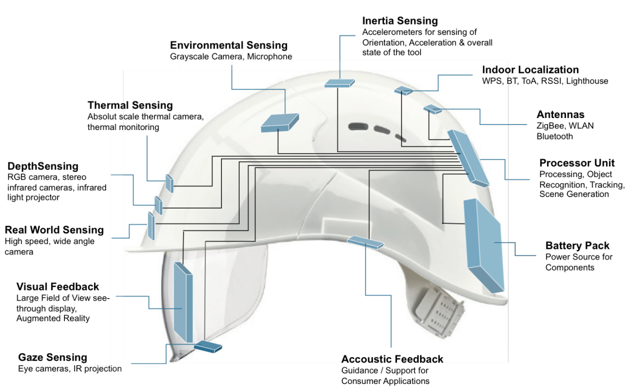

Figure 3. Cognitive components of a conceptual intelligent head gear.

Modern smart-phones are equipped with a variety of unobtrusive embedded sensors (e.g., inertial, infrared, light, proximity, fingerprint, temperature, noise, speech, GPS, etc.), which are widely used for human activity recognition purposes. Data analysis is performed either online in real-time or offline depending on the application and the context. Furthermore, the ubiquity and the significant computational power combined with large built-in memory and low manufacturing cost make smart-phones a very good potential candidate for a head-mounted mini computer, providing a convenient high resolution visual display mirrored in the helmet besides portable sensing and computing resources. Established standards, open source platforms and a variety of connectivity methods make the integration of smart-phones in industrial IT networks easy.

A head-wear with augmented cognitive capabilities could infer the skill or attention level of workers and provide the necessary assistance and appropriate guidance pro-actively. It could anticipate safety critical events and predict human behavior in unstructured and dynamically changing environments, continuously re-training itself also from partial and uncertain information. It could store relevant data locally or remotely and could recall the appropriate piece of information in a timely manner in order to support workers efficiently.

VI. Discussion

In this paper, we have described the basic operational principles of potential future cognitive products, emerging at the intersection of AI, Cognitive and Neuroscience, Control and Information theory, Engineering and Human Factors. Recent developments in AI open up the possibility to advance beyond current standards towards ‘Things that think’, ‘Cyber-Physical Systems’ and ‘Industry 4.0’, which have emerged as keywords for intelligent systems. In this context, we have identified various areas where AI technology could advance the state-of-the-art in cognitive systems. This requires the development of computationally efficient AI algorithms, which could perform real-time inference on resource-constrained embedded devices. We have pointed out a number of research areas, which could provide breakthroughs in this direction such as

- efficient learning from sparse data (‘one-shot’) [43],
- real-time embedded inference,
- advanced perception and scene understanding.

The integration of cognitive functions could enable future products to interact independently with their environment. This would allow self-organized and self-optimized behavior and would increase significantly their adaptivity and robustness. However, achieving such a high level of autonomous intelligence would require a considerable involvement of non-technical disciplines like cognitive science and neurobiology. Considering the multifaceted nature of this area it is necessary that researchers from different fields collaborate more closely in the design and development of future cognitive products.

The ultimate goal is to enable human-like cognitive capabilities in products by supporting multi-sensor perception of complex environments, storing and recalling information, transferring knowledge in the form of reasoning models to

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previously unseen situations, human-like decision-making and continuous learning. This would provide autonomous decision-making, flexible adaptation to new tasks in changing environments and workload capacities. Systems that think, reason, make flexible human-like decisions and sense/adapt to the environment will enable seamless interaction with humans resembling smooth and efficient human-human interaction. Empowering production systems and products to adapt, learn, develop and react human-like would enhance production processes and reduce user frustration. This would facilitate the development of human–machine joint cognitive systems in which humans could teach machines to perform specific tasks.

To support human operators in complex work-flows cognitive devices could benefit from their awareness of

- contextual information offered by other devices and via local sensing,
- state of other tools involved in the production process,
- experience and skill level and work-flow complexity,
- cognitive load and level of attention of human operators.

We envision cognitive industrial systems based on manufacturing machinery connected to world-wide online platforms where machines and tools are added and removed in real-time in plug-and-use or plug-and-produce fashion. In a decentralized system architecture systems, processes and services communicate and interact autonomously and solve problems jointly. Industrial utilization typically triggers the enhancement of production tools with cognitive capabilities driven by their application in particular production environments. However, in specific cases such concept devices can be directly transferred to commercial home appliances as well. Cognitive production tools could bring a competitive advantage for industrial players by providing key benefits such as

- learning from past experience to avoid repetition of errors and continuously improve quality and cost,
- worker guidance and support,
- automated tool configuration and adaptation to current work-flows,
- data collection for detailed modeling and documentation of production front- and back-end processes,
- production task awareness to enable flexible adaptation to variations within a single and across different tasks,
- worker skill awareness to enable compensation for lack of skill or attention,
- collaboration between cognitive tools to provide a resolution for deviations in earlier production steps.

New business models and services could make use of the continuous data streams captured in product utilization and production control, paving the way towards a fully automated product-production ecosystems.

VII. Conclusion

We have proposed a generic cognitive architecture, which could provide the foundation for creating future intelligent products and production systems realizing human-like capabilities such as appreciate, learn and plan. The paper sheds light on the important role AI could play in the design and development of cognitive products, and identifies key challenges to be addressed by the AI community in order to fulfil these high expectations. At the same time, cognitive systems could serve as a suitable environment for leveraging advances in AI research and validating their relevance. The paper presents a motivation for integrated future research, and highlights recent progress opening up the possibility for building the cognitive products of tomorrow. In this context, we have identified a number of research areas where major breakthroughs could advance significantly this field. The aim of this paper is to raise the awareness of relevant scientific fields of such joint opportunities in order to foster a highly interactive broader research community.

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