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INTELLIGENT AUTOMATION: ENHANCING EFFICIENCY AND DECISION – MAKING THROUGH COGNITIVE TECHNOLOGIES

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Abstract*—Automation, particularly intelligent automation, has revolutionized various industries by streamlining processes, improving efficiencies, and enabling accurate decision-making. This topic explores the concept of intelligent automation, which combines artificial intelligence (AI), business process management (BPM), and robotic process automation (RPA) to simplify and scale decision-making across institutions. The integration of these cognitive technologies empowers businesses to analyze structured and unstructured data, develop knowledge bases, and make predictions. By leveraging AI, BPM, and RPA, organizations can enhance production speed, reduce human errors, cut costs, and improve compliance in sectors such as manufacturing, pharmaceuticals, insurance, and more. This discussion delves into the three essential components of intelligent automation: AI for advanced data analysis and predictions, BPM for workflow automation, and RPA for task automation. By leveraging these components effectively, businesses can achieve higher efficiency, better resource allocation, and improved decision-making capabilities

Keywords: - intelligent automation, artificial intelligence (AI), business process management (BPM), robotic process automation (RPA), efficiency, decision-making, cognitive technologies.

1. INTRODUCTION

Intelligent automation (IA), also known as cognitive automation, is the application of automation technology such as artificial intelligence (AI), business process management (BPM), and robotic process automation (RPA) to simplify and scale decision-making across institutions. Intelligent automation has a variety of applications which simplify processes, free up resources, and increase efficiencies. An automotive manufacturer, for example, might use intelligent automation to speed up production or reduce the risk of human error, while a pharmaceutical or life sciences company may be using intelligent automation to cut costs and gain resource efficiencies where repetitive tasks are involved. There really are procedures in place. An insurance company can use intelligent automation to calculate payments, make rate predictions, and meet compliance requirements.

2. THE 3 COMPONENTS OF INTELLIGENT AUTOMATION

Intelligent automation is comprised of three cognitive technologies. The integration of these components to create a solution that powers business and technology transformation.

1. The most critical component of intelligent automation is artificial intelligence, or AI. By using machine learning and complex algorithms to analyse structured and unstructured data, businesses can develop a knowledge base and formulate predictions based on that data. This is the decision engine of IA.
2. The second component of intelligent automation is business process management (BPM), also known as business workflow automation. Business process management automates workflows to provide greater agility and consistency to business processes. Business process management is used across most industries to streamline processes and improve interactions and engagement.
3. The third component of IA is robotic process automation (RPA). Robotic process automation uses software robots, or bots, to complete back-office tasks, such as extracting data or filling out forms. These bots complement artificial intelligence well as RPA can leverage AI insights to handle more complex tasks and use cases.

3. THE QUANTITATIVE HUMAN BRAIN

The human brain comprises with an average weight of 1400 g and a volume of 1350 cm3, the human brain is a remarkable information storage and processing system with an extraordinary computation-per-volume efficiency, contained within an "average" intracranial volume of 1,700 cm3. There are 1,350 cm3 (75 percent) brain cells, 200 cm3 (15 percent) blood, and up to 150 cm3 (10 percent) cerebrospinal fluid in a brief quantification of the brain's constituents and operational parameters. The human brain's raw computational power is estimated to be between 1013 and 1016 operations per second. The functional action potential-based information rate in the human brain is estimated to be 5.52 1016 bits/sec, with a brain power output of 15–25 W and a power density of 1.1–1.8 104 W/m3 at 37.3°C.

When considering the human brain at the regional level, an exceptional component is the neocortex, which has a highly organized neural architecture that encompasses sensorimotor, cognitive, and emotional domains. This cortical structure consists of mini-columnar and laminar arrangements of neurons that are linked via afferent and efferent connections distributed across multiple brain regions. Cortical nanocolumns consist of chains of pyramidal neurons that are surrounded by a “curtain of inhibition” formed by interneurons

Basic Structure of Artificial and Biological (Brain-Controlled) Automation Systems
Although they are based on different concepts in terms of details, artificial and biological (brain-controlled) automation systems have some similarities in terms of their main components.

The starting point in both cases in figure 1 is a "process" that must be controlled. Selected process variables must be observed via appropriate sensors – in one case, technical sensors, and in the other case, biological sensors in the form of physiological receptors – as a result of this process. After that, the sensory data is processed further by a technical processor/controller and the brain/nervous system, respectively. After that, the process variables are adjusted by using appropriate actuators to influence the process (in the case of artificial systems, e.g., via the control of motors, in biological systems, e.g., via the the control of muscles). The sensors can then detect the resulting changes in the process variables, and a new sensing-processing-actuating cycle begins. Although basing on different concepts concerning their details, artificial and biological (brain-controlled) automation systems show common points concerning their principal components

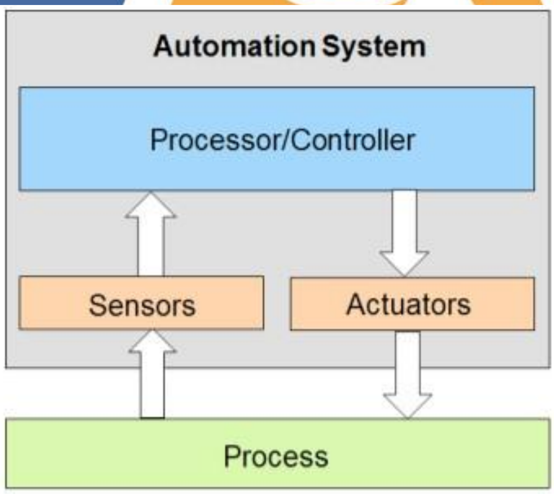

Figure 1. Basic "Components" of Artificial and Biological (Brain-Controlled) Automation Systems

3.2 Basic Idea and Motivation of Brain-Like Artificial Intelligence

The field of Brain-Like Artificial Intelligence as defined in this article is relatively recent and dynamic. It can be considered as belonging to the broader group of bio-inspired technical approaches. As a matter of fact, biological systems and principles have already proven in the past to be valuable sources for technological development. One prominent discipline building on inspiration from biological principles for studying and designing engineering systems is the field of bionics [39]. Here, approaches consider, e.g., the construction of flying machines by studying the flight of birds or the functioning principle of biological receptors for the design of innovative sensors. A further related discipline is the field of cybernetics, which is, amongst others, concerned with the studying of control and communication mechanisms as well as concepts in animals and machines [65]. Another field that could be considered as the most direct ancestor of Brain-Like Artificial Intelligence is the domain of neural networks [48]. Here, the study of the functioning principles of individual neurons led to mathematical models applicable to certain pattern recognition, function approximation, and prognosis tasks. The principal idea and motivation behind the field of Brain-Like Artificial Intelligence as followed in this article is quite straightforward: As outlined in the examples from Figure 1, the dealing with a broad range of tasks in complex environments today still needs human perceptual and cognitive skills. The only system currently successful in processing such multifaceted information is thus the (human) brain. It is unclear, even doubtful, whether a mere further development of the currently employed automation and AI paradigms will be able to change this fact in the coming decades or even century. Therefore, to approach the automation of such challenging tasks, a promising alternative to current (mainly purely mathematic/algorithmic) automation and AI concepts is to investigate in more detail how the brain manages to solve these tasks and to then take over these concepts for the development of technical systems. Evolution has equipped our brains with highly efficient circuits and mechanisms for processing sensory information gathered from millions of sensory receptors, evaluating this information, and making decisions despite numerous possibilities, contradicting aims, and uncertain outcome. Deciphering

Steps of Brain Functioning
1. The starting point for development is, similar as in other domains of automation, a given automation problem and an identification of the requirements.
2. In the classical domain of automation, the next step would now be the elaboration of different potential approaches to solution for the given problem and their comparison. This second step already constitutes the first difference between the field of Brain-Like AI and classical automation. As in Brain-Like AI, brain-inspired concepts are employed, the next step after identifying the automation problem is to evaluate the brain sciences with the aim to determine – as far as known – how the brain manages to solve the given task.
3. Having identified the adequate processing concepts, the next step is the derivation of a technically implementable model based upon these insights. Performing step two and step three is of course far from trivial. A relatively broad body of knowledge is provided from brain sciences concerning the neural level and the functional level. However, between those two levels, a gap exists in understanding how neural activity correlates with cognitive function. The challenge to face in Brain-Like AI for automation is therefore to close this gap in an adequate way in the technical models. (See Chapter 4 for examples of models that are attempting to solve this challenge.)
4. After having developed and implemented the model, the next step is the validation of the model concerning its performed function. In a first instance, this is usually achieved via computer simulations. Particularities concerning this validation process are outlined further in Section 3.4.

5. The next step would then be the development of a demonstrator or – more advanced – the design of the automation system. In certain cases, step 4 a step 5 can also be merged.

6. As a side effect – besides their utility for automation systems – the developed models can furthermore lead to the formulation of new hypotheses concerning brain functioning and therefore contribute to the body of knowledge in brain sciences.

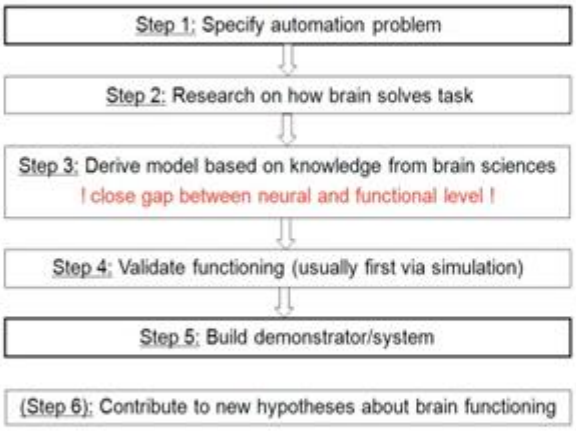

Figure 2. Methodology in the Field of Brain-Like Artificial Intelligence for Automation

4. CONCLUSION

Artificial intelligence in automation has contributed to the businesses by reducing operational cost and vocational costs. It has introduced a new level of accuracy and due to Artificial Intelligence's learning ability, efficiency increases over time. Even though, there is a good advancement in the field of Automation and Artificial Intelligence, both Artificial Intelligence and machine learning are yet to be optimized. Companies have realized that the key to the business success is subjected to machine learning, artificial intelligence and automation. Soon, the companies will be fully equipped with these start systems and would completely change the traditional systems with by yielding significant benefits.

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