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Design of Cloud Based Robots using Big Data Analytics and Neuromorphic Computing

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***Abstract*—Understanding the brain is perhaps one of the greatest challenges facing twenty-first century science. While a traditional computer excels in precision and unbiased logic, its abilities to interact socially lags behind those of biological neural systems. Recent technologies, such as neuromorphic engineering, cloud infrastructure, and big data analytics, have emerged that can narrow the gap between traditional robots and human intelligence. Neuromorphic robotics mimicking brain functions can contribute in developing intelligent machines capable of learning and making autonomous decisions. Cloud-based robotics take advantage of remote resources for parallel computation and sharing large amounts of information while benefiting from analysis of massive sensor data from robots. In this paper, we survey recent advances in neuromorphic computing, cloud-based robotics, and big data analytics and list the most important challenges faced by robot architects. We also propose a novel dual system architecture for robots where they have a brain centered cloud with access to big data analytics.**

I. Introduction

It is important to understand the human brain in order to design a robot capable of interacting with its environment. This task may involve combining knowledge of gene expression, synaptic connections, and neuronal microcircuits [1]. In this paper, we look at *(i)* Neuromorphic Computing (NC), *(ii)* Cloud Robotics (CR), and *(iii)* Big Data Analytics (BDA), which together enhance the interactive abilities of robots.

NC describes the use of very-large-scale integration systems containing electronic analog circuits to mimic neuro-biological architectures presented in the nervous systems [2][3][4]. It has evolved significantly in the last couple of decades to bridge computing with neural systems. NC is an interdisciplinary subject that takes inspiration from biology, physics, mathematics, computer science, and electronic engineering, to design artificial neural systems (e.g., vision systems, auditory processors, and autonomous robots) whose physical architecture and design are based on mammalian nervous systems [5].

Cloud computing is the commodification of computing resources, time, and storage by means of standardized technologies to provide elastic on-demand services. Cloud computing has been successfully applied in the smart grid domain to provide the energy management as a service [6]. The term cloud-enabled robotics, or CR, refers to distributed networks combined with service robots to enhance their capabilities [7]. In [8], the authors show that intellectual capabilities of robots could improve significantly when using the cloud.

Currently, the amount of data generated at increasing speeds and frequencies far exceeds the capabilities of traditional data processing. About two zettabytes of digital data is generated every year by physics experiments, retail transactions, security cameras, global positioning systems, etc. [9]. BDA can use predictive tools, machine learning, and natural language processing to ameliorate many of the storage, retrieval, and analytic challenges. Advanced data analytics practiced in business intelligence [10] could augment existing robotic technologies.

II. Neuromorphic Computing

Traditional von Neumann architectures have advantages over the human brain in, for example, precision, indefatigability, logic, and lack of bias [11] but in the realms of pattern recognition and power consumption, a biological system may exceed the capabilities of any traditional computer. Neuromorphic engineering attempts to design brain-like computing devices imitating biological nervous systems that combine classic computation methods and human abilities. For example, SpiNNaker chip models the human brain by simulating thousands of neurons and millions of synapses [12].

A. Architectures using Neuromorphic Computing

Market size of neuromorphic computing is continuously fueled by the increasing demand for cognitive and brain-based computing [13]. Neuromorphic chips, with advantages of cognitive computing, optimum memory usage, high-speed performance, and low power consumption, are projected to drive growth within the robotics industry as well.

Zeroth project integrates a biologically-inspired computer chip with a traditional von Neumann architecture within various devices to provide cloud-like intelligence [3][14]. The Zeroth processor uses electrical impulses to mimic the brain's behavior to let a robot learn via training and feedback rather than by relying on hard-coded instructions. SyNAPSE demonstrates low-power scalable neuromorphic computers matching a mammalian brain in function, size, and power consumption.

A non-von Neumann chip, called TrueNorth, was developed to model biological neural networks. TrueNorth comprises over four thousand cores, utilizes billions of transistors, and integrates one million spiking neurons with millions of synapses [15]. TrueNorth chips are energy efficient and highly scaleable through tiling components into a single large system [16]. The speed and energy efficiency of TrueNorth make it good for processing sensory data in real time.

The Brain Activity Map (BAM) project attempts to understand the functions of neurons and activities of human brains by reconstructing the full record of neural actions across neural circuits [17][18]. The BAM roadmap includes monitoring the neural activity of a simple species, such as a Drosophila brain with thousands of neurons, Zebra-fish brain with a million of neurons, and the entire neo-cortex of an awake mouse.

B. Neuromorphic based Robotics

Neuromorphic robots have computing power to simulate in real-time up to thousands of neurons [19]. The computing power combined with on-board sensory and motor systems are used to implement methods for learning sensorimotor competencies. By briefly controlling the robot manually, it can learn what sensorimotor mapping it should carry.

Data mining tasks (e.g., clustering and classification for real-time tracking) are used with neuromorphic vision sensors for robotic motion tracking in [20], where the algorithm combines clustering space-time events induced by a neuromorphic sensor and a classification procedure. The classifier uses event rates of clusters to determine proper class labels. The robotic motion tracking technique creates collective intelligent multi-pedal robots that utilize neuromorphic vision sensors.

Neuromorphic eye can be used to build a miniature electrically-powered unmanned aerial vehicle equiped with a motion-sensing visual system to follow terrain and avoid obstacles [21]. It includes thrust-vectoring technology for reactive maneuvers and a real-time flight control.

III. Cloud-based Robotics

In a *brain centered* cloud for robots, the brain of the robot can be in the cloud with immense memory and computational power instantly available to robots. For example, RoboEarth [22] and RoboBrain [23] create interconnected knowledge systems perceived as a shared robotic brain. Similar to humans sharing knowledge via online platforms, RoboEarth accomplishes the same for robots by uploading information to a knowledge base accessible by other robots [24]. Once data has been interpreted by a robot and uploaded to the cloud or an internet-accessible storage, other robots can access the already computed information to speed up its processing time [25].

The online database of the RoboEarth cloud engine, called Rapyuta, performs heavy-weight processing in the cloud in lieu of merely querying the database, hence freeing the robot from performing computational tasks locally [26]. Fig. 1 outlines the Rapyuta framework with robots R_1-R_3 having their own computing environments C_1-C_3. All computing environments C_1-C_3 are tightly interconnected and are connected to the RoboEarth knowledge repository allowing them to move heavy computation into the cloud.

Rapyuta achieves its objectives via secure computing environments that are dynamically allocated and interconnected, giving robots the ability to share aggregated information stored in the RoboEarth knowledge repository. RoboBrain employs a similar idea to RoboEarth and Rapyuta with a knowledge engine for robots combining data from various sources and representing them in a format that robots can query [23]. In RoboBrain, the knowledge representation is in the form

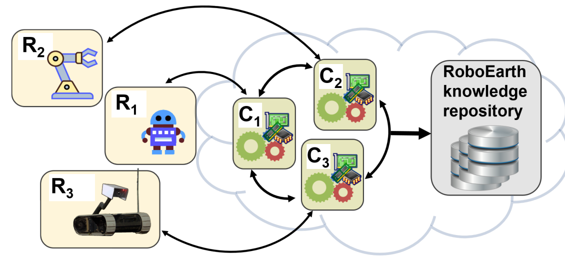

Fig. 1. Rapyuta: an open source cloud robotics framework (adopted from [26])

of a graph that incorporates multiple modalities and is fed by multiple sources. The engine's structure allows a robot to travel through the graph to find information it needs in order to successfully perform a novel task.

IV. Big Data in Robotics

Initially the term Big Data (BD) was used only to denote volumes of large data for visualization [27]. One of the first descriptions of BD was in terms of the *three Vs* with Volume reflecting massive datasets, Velocity relating to real-time data, and Variety indicating different sources of data [9]. More recently, BD is treated as an information asset that demands cost-effective innovative forms of information processing for enhanced insight and decision making. BD analytics may involve learning of labeled data (i.e. classification) [28] or unlabeled data (i.e. clustering) [29]. Noise in collected data (e.g., corrupted training data) is a common problem that can lead to wrong classification results. New sampling methods and noise filtering algorithms provide high quality and clean data, also known as *smart data* [30].

One of the earliest control methodologies for processing large volumes of data in robotics was Sense, Plan and Act (SPA) cycle. Sensing in SPA represents perceiving the robot's environment, which involves clustering of data, while Planning predicts the next position by classifying the data. Robot's actions can incorporate social interactions [31] or Artificial Intelligence (AI) assisted movements [32]. With the current advancement in BDA, the robots SPA steps have evolved into the following three steps: *(i)* descriptive analytics to understand why something happens, *(ii)* predictive analytics to predict what could happen, and *(iii)* prescriptive analytics to suggest what a robot should do in a complex environment.

Big data analytics can help robots to accelerate its self-learning process by using machine learning and computational simulation models in prediction while dealing with adaptive environments. Now robots running algorithms are also capable of learning through a feedback with or without human support to make intelligent decisions (e.g., DeepMind algorithm [33]). Reinforcement Learning (RL) agents interact with their environments by sending short periodic clips of their behaviors to a human operator to determine which paths towards a goal are the best, and the human's choice is used to train a reward predictor, which in turn trains the agent [33].

V. Challenges

In a modern robotics infrastructure, robots should be able to: *(i)* operate in a complex adaptive environment, *(ii)* handle massive amounts of variegated sensor data, and *(iii)* share data analytics among themselves. Providing an interaction platform between experts from various seemingly unrelated communities is crucial to advance research in the area of robotics. For example, for robots to behave flexibly and efficiently, advances in AI, sensors, and propulsion technologies are needed to facilitate efficient and effective decision making [34].

When weighing the pros and cons of traditional and neuromorphic computing with regard to cloud-based robotics, a question arises concerning the optimal application of these technologies. Sharing information between robots has the potential to accelerate their understanding of the environment and speed up decision-making process. Thus, building a common shared database of knowledge and experience is important. The robot's past observations, predictions, and results could be conveniently stored and represented in the cloud.

Continuous influx of information from numerous robotic sensors can generate massive amount of data to be processed. Additionally, each of the sources may follow different internal logic or structure to represent its data, requiring it to be transformed for accessibility and analytics. Since BDA can be computationally expensive for individual robots to timely perform, a cloud environment could provide a viable supporting platform for making computationally expensive predictions. We propose an interdisciplinary approach that combines methodologies from NC, CR, and BDA disciplines to obtain resilient, cost-effective and responsive robotics systems.

VI. Proposed Infrastructure

We propose a dual system architecture combining unique advantages of both neuromorphic and traditional chips on each robot. The robots rely on the cloud computing environment when possible. If a traditional robot is disconnected from the cloud or a command center, its actions are hampered. Our robots include neuromorphic chips, alongside traditional chips, to enhance their machine learning analytics and to let them function without ongoing network connectivity. An on-board neuromorphic chip, with parallelization, asynchronicity, and event-driven mechanisms [35], can enhance vision and motion computations while providing real-time decisions, such that the data collected from the sensors can be timely processed. Since biological systems have energy footprints magnitudes lower than traditional computer infrastructures, relegating specific intelligence to a biologically-inspired neuromorphic architecture results in more energy efficient performance.

In order to control the robot's simple mechanical actions and oversee cloud interactions, traditional von Neumann chips are also used in our system, where these chips control the robot's actions while the neuromorphic architecture manages its local AI. Fig. 2 outlines our robot having NC and traditional chips.

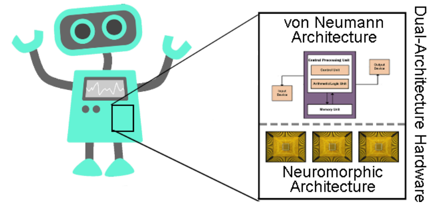

Fig. 2. A structuring of a robot housing dual-architecture hardware

Our architecture extends into the cloud platform offering myriad benefits in the realm of BDA and multimedia processing. When possible, a robot channels information collected from all of its sensors to the cloud that can dedicate enough resources to analyze it. The cloud platform returns precise instructions to each robot and stores historical information for future predictions. As shown in Fig. 3, the cloud infrastructure collects and stores data from all participating robots through the application programming interface (API) and the information lines. By facilitating the deep learning process and performing the BDA on the cloud platform, a global intelligence is obtained which is then distributed to all participating robots' APIs. The services provided by the cloud platform are based on massive historical data impractical to store and process by individual robots.

In order to handle rapidly and unexpectedly changing environments, our robots use local chips and, possibly, knowledge from other robots when the internet connection is intermittent. When the network connectivity is adequate, the robots can rely on cloud infrastructure for heavy and precise analytics. Robots can share knowledge obtained by descriptive, predictive, and prescriptive analytics with other robots directly or via the cloud (see Fig. 3). Our model deals with massive amount of variegated data by using data mining, sampling and noise filtering tools for combining data from various sources to generate smart data.

VII. Conclusion

This paper is an attempt to cover cloud computing, neuromorphic computing and big data analytics to improve the control architecture of robotics. We outline how traditional computers are behind biological systems in terms of pattern recognition, analytics, and power consumption and introduce recent advances in the field of neuromorphic engineering that imitate the human brain by simulating neurons and synapses. Modern robotics is an increasingly interdisciplinary field that could use cloud and big data analytics to facilitate efficient and effective decision making in robots. We present three main challenges in the design of robotics infrastructure. We then address these challenges by proposing a novel dual system architecture (which houses both traditional and neuromorphic chips) where robots have a brain centered cloud with access to big data with analytics. The robots can not only learn from one another by sharing their observation data, experience and knowledge, but can also gain information from cloud-based big data analytics.

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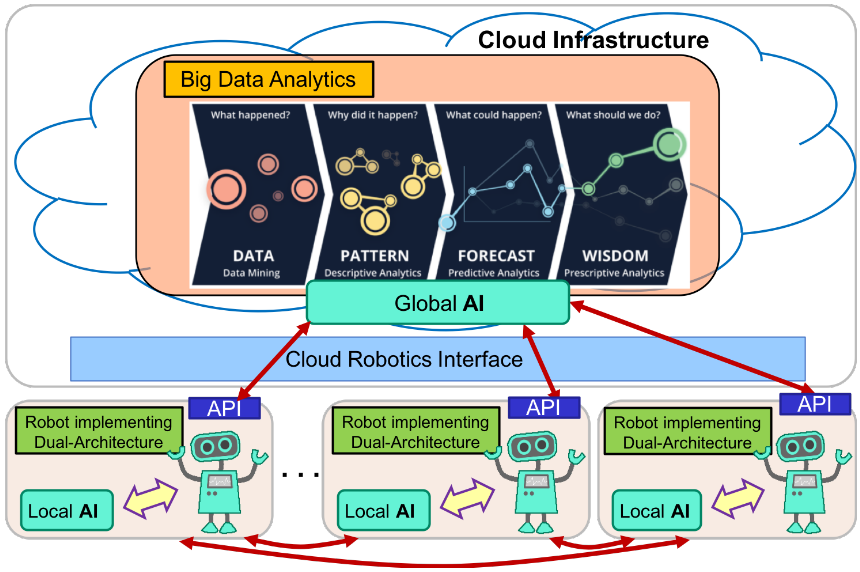

Fig. 3. Cloud-based robot infrastructure combining NC, CR, and BDA

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