Cloud Computing in Social Robotics

[1]*Ján MAGYAR (1st year),*
Supervisor: [2]*Peter SINČÁK*

[1,2]Department of Cybernetics and Artificial Intelligence, FEI TU of Košice, Slovak Republic

[1]jan.magyar@tuke.sk, [2]peter.sincak@tuke.sk

***Abstract*—Robots have been successfully used in industry, but they have to meet different requirements as they entered everyday human life where they have to adapt to their immediate environment. This presents a problem due to computational limitations inherent to most robotic systems, which can be successfully overcome through the use of cloud computing. This paper lists some advantages of cloud robotics, the current status of its development, and open issues. It further explores the plausibility and possible benefits of using cloud robotics in human–robot interaction and social robotics, making a case for further research in the area.**

***Keywords*—cloud computing, human–robot interaction, social robotics**

I. Introduction

Robots have a limited computational, storage and battery capacity that hinder their application when they are expected to react to their environment in real time. Computationally heavy tasks cannot be successfully executed on a robot, or the execution time is beyond the acceptable interval. With the emergence of cloud computing, researchers started to offload complex tasks from robots and autonomous systems to the cloud [1]. The idea stems from the mid-90s and originated with the work of Inaba [2], where robots had a radio-linked remote brain still in the vicinity of the robot itself.

Online web robotics started with the availability of the world wide web. The earliest works focused on tele-operation via the Internet [3], further research was done on networked robots with wireless sensor networks and on networked control systems [4]. Benefits of distributed processing in networked robotics along with challenges in communication and synchronization were first described by McKee [5]. In 2010, James Kuffner introduced the idea of cloud-enabled robots [6], igniting the use of cloud technologies in robotics.

Researchers in Singapore constructed the DAvinCi framework, the European Union started the RoboEarth project, and the open-source Robot Operating System (ROS) further accelerated the development of cloud robotics. These systems offer only additional functionality for robots, which correspond to the concepts of Platform as a Service (PaaS) and Software as a Service (SaaS). Du et al. on the other hand introduced "Robot as a Service" by applying service-oriented architecture for robots [7].

II. Advantages of cloud robotics

The growth in the complexity of problems robots had to face in research and application exposed an inherent limitation. Solving computationally heavy problems is only possible with the necessary hardware which results in complex robotic builds that might be counterproductive to the robot's task. A possible solution is to use dedicated servers which alleviate the load on robots. This realization fueled research on the use of cloud computing in robotics with the goal to lower requirements on robotic systems (see Fig. 1 for a general architecture). In the following subsections, we discuss some of the advantages of cloud robotics.

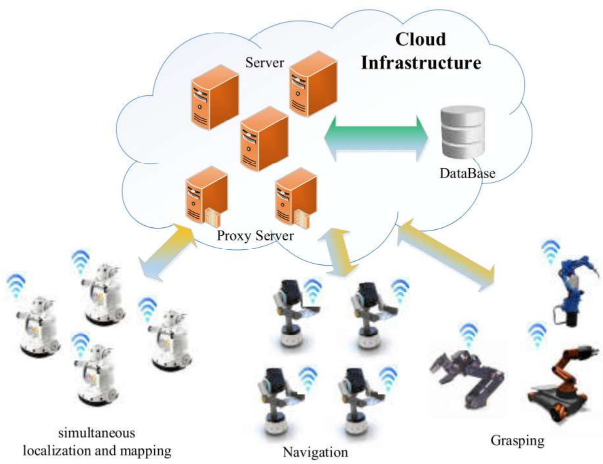

Fig. 1. Architecture of cloud robotics systems with the most common applications listed [8]

A. *Offloading computation*

Cloud computing enables remote computation through massively-parallel computation on demand [9]. Cloud services were first used for web applications, but researchers are increasingly using them for scientific and technical high-performance computing (HPC) applications.

Apart from the implications to robotic system design, cloud computing can speed up computationally-intensive robotics and automation systems applications [10][11]. Rapyuta, the RoboEarth cloud engine, allows computationally expensive algorithms to run in the cloud. In [12], cloud computing was used for sample-based statistical motion planning.

When offloading computational tasks to the cloud, network latency and quality of service must be considered, which is still an active area of research [10]. Remote task execution requires the transfer of real-time sensitive data, what despite the rapid development of wireless communication might still cause network delays [8]. Therefore, an offloading of tasks more related to the robot's immediate actions, such as motion, is still not plausible. Methods used for cloud robotics must also be designed to degrade gracefully when cloud resources aren't available [10].

B. Collective learning

Multi-robot systems are an essential field of robotics, and cloud computing provides a suitable platform for networked robots to share data, process information and facilitate machine learning [1]. Through collective robot learning, the capabilities of robots with more limited computational resources can be enhanced [13], and the overall accuracy of the system can be improved [8].

The "Lightning" framework uses cloud computing for parallel planning and trajectory adjustment [14]. The Ubiquitous Networked Robot Platform manages distributed task execution and supervision [15] by abstracting away from the robotic hardware and offering a generic interface. The MyRobots project envisions a social network for robots to support collaboration. A small scale cloud infrastructure for information sharing among networked robots was presented in [16]. Communication protocols facilitating task offloading and information sharing were proposed in [17]. Collective learning environments for ubiquitous robots were described in [18] and [19]. The Kiva automated Materials Handling System supported collective learning for mobile platforms used to move packages in warehouses [20].

C. Cloud-based knowledge-base

Most robots are equipped with cameras and sensors that collect data supporting decision making. The volume of these data makes it impossible to manage or share them among multiple robots using only their onboard capacities [1]. Large sets of data such as images, videos, maps, sensor networks, etc. can further facilitate machine learning in robots. This has been demonstrated mainly in the context of computer vision [10] (object and scene recognition), path planning, and grasping [21]. Google Goggles, a free image recognition service for mobile devices, has been incorporated into a Cloud-based robot grasping system [22]. RoboEarth (architecture shown in Fig. 2) is also used to gather and provide technical support for robotic navigation and grasping [8].

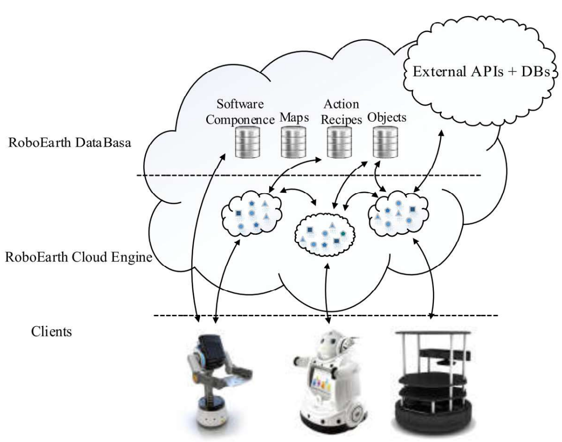

Fig. 2. Architecture of RoboEarth [8]

Although big data on the cloud can hugely improve robotic applications, this poses new challenges for guaranteeing the quality of the datasets and querying data. Datasets collected from distributed sources often contain erroneous, duplicated, or corrupted, so-called "dirty" data. Sampling algorithms can provide approximations to keep running time acceptable. Another challenge is caused by the variety in the representation of data [10], due to the lack of standards [23]. Keeping data in the cloud raises security concerns, especially in the case of sensitive data gathered in private or corporate settings [24].

D. Open source solutions

The development of cloud robotics facilitated the use of open-source solutions for robotic applications. Open-source licenses allow the improvement of the code reuse rate and development efficiency [8] and they provide access to datasets, benchmarks, and simulation tools [10]. The best-known systems for supporting open source in cloud robotics are ROS and RoboEarth. ROS's core part was designed at the Willow Garage research laboratory, and it provides basic tools for distributed computing [8]. A bigger share of solutions is developed and maintained by the international ROS community and includes algorithms, frameworks and hardware drivers. ROS is slowly becoming a standard for robot developers [10]. RoboEarth is more directed at collaborative solutions for multi-robot systems, providing a network database system that is updated dynamically by robots around the world [8].

Besides open source solutions that can be integrated in the working of robotic systems, there are a number of open source simulation libraries available for expediting the development of new systems. The overall availability to datasets and cloud services can also lead to the improvement of robotic system intelligence. While the growing rate of sharing ready-to-use solutions can facilitate the development of cloud robotics, open source presents the same problems as shared datasets, since the quality of code must be guaranteed.

III. Cloud Social Robotics

Although most of the research in cloud robotics has focused on grasping and navigation, the paradigm is gaining attention in the field of human–robot interaction (HRI) [1]. Anzai defined two challenges specific to HRI [25]. The structure of human–robot cooperation must be understood, and based on this knowledge, artificial agents capable of succesful interaction with humans must be developed. Both challenges can be solved only using computationally costly operations (e.g. natural language processing, emotion assessment, speech synthesis). On the other hand, robot design in HRI must be kept simple and easy to maintain, what makes robots with a wide range of dedicated hardware impractical. Therefore, the advantages provided by cloud technologies would be beneficial in social robotics.

A. Application potential of cloud computing in HRI

Social input, such as gestures, emotions, and affect are an integral part of human–human interaction and they provide a communication channel universal across multiple cultures. The observation and processing of these non-verbal cues is natural for humans but are hard to replicate in machines. However, they are essential in human–robot interaction, since an incorrect assessment of a human's emotional state could lead to an inappropriate response from the robot.

In recent years, cloud-based emotion assessment services were made available for inclusion in user applications, such as Google Vision API, Microsoft Face API, Amazon Rekognition, Affectiva Emotion, and Sightcorp F.A.C.E. API. Information about a human's emotional state can also be obtained from speech. First, speech-to-text methods can be used with the transcribed text processed independently. A number of speech recognition services are Google Speech API, Bing Speech API, API.AI, Speechmatics, and Vocapia Speech to Text API, with further services focusing on different languages. Emotion assessment analysis is possible with tools like IBM Watson's Tone Analyzer, Receptiviti Natural Language Personality Analytics API, Alchemy API, and Bitext Text Analysis API. Although the two-step speech analysis method is much more widely used, APIs recognizing emotions in speech are also available, including Good Vibrations, Vokaturi, and Affectiva's Emotion API Speech.

HRI can also benefit from data sharing on the cloud. This has advantages primarily in the personalization of interaction, where data gathered about a person might be too big to be stored long-term on the robot's memory without negatively affecting the robot's performance. Data sharing can also help collaboration between robots. One robot can share data about an environment or a human's preferences, with other robots copying the already learned functionality.

B. Uses of cloud social robotics

Most of the current research in HRI focuses on observing, processing, and replicating social input. A cognitive system presented in [26] detected humans' gestures and speech to produce an accurate robotic response. In [27], automatic speech recognition was used to improve the HRI experience. Human motions data was used to predict intent from gestures in [28]. Through data mining, the connection between motion and intent was determined, and the results were provided as a service.

Another part of research in HRI deals with the use of robots to gather data about users to improve the quality of a service. Such a system was described in [29], where a physical therapy robot collected patient information. Rehabilitation robots used cloud technologies in the work of Dogmus et al. [30], the gathered data were used in improving the quality of human–robot interaction.

Manzi et al. in [31] describe a robotic system called KuBo supported by cloud services. The KuBo robot is based on the youBot from KUKA, which has low computational capability. The robot's functionality was provided through software modules implemented in ROS, relying on cloud services (the system architecture is shown in Fig. 3). The resulting system could find information using web resources, remind the user of commitments and appointments through the Google Calendar API, monitor a smart environment via connection to external sensors and stream audio to support telepresence. Robot operation was enabled via speech commands by using Google Cloud Speech API, while speech synthesis was enabled using Acapela Voice as a Service API. The authors pointed out that time-senstive functionality cannot be successfully implemented through cloud services, confirming the findings of [17].

IV. Future work

As presented in the previous section, human–robot interaction is a complex process. Cloud services can support some of its steps, mostly in the processing of social input and generating robot responses, but the appropriate selection of responses still presents a problem. Due to the number of influencing parameters, action selection cannot be described

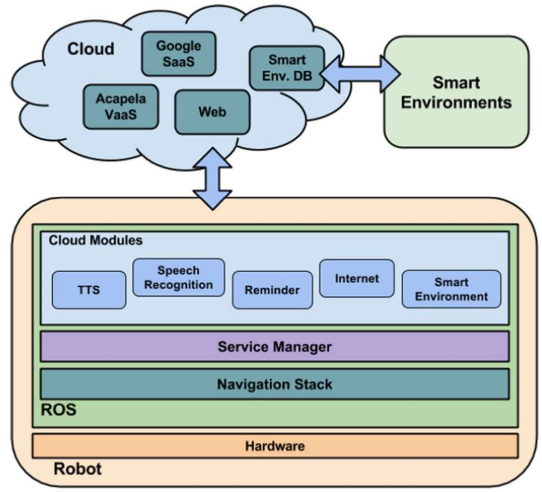

Fig. 3. System architecture of the KuBo robot system[31]

by simple rules, and so teleoperation is often used: a human controls the robot, although the robot seems autonomous to the interacting partner (Wizard of Oz methodology). A drawback of this approach is that interaction becomes monotonous to the teleoperator, which can have a negative effect on the quality of conversation.

In recent years, systems that support learning from teleoperation through reinforcement learning emerged. Reinforcement learning assigns rewards to all actions, the action selection algorithm tries to maximize the rewards during HRI. After a correct action selection, the teleoperator can assign a higher reward to the action, reinforcing its selection. Although this approach proved to be useful in making action selection more autonomous, the learning systems were specific to each problem and no service exists to generally support learning from teleoperation. The author of this paper proposes a cloud service that could fill this gap.

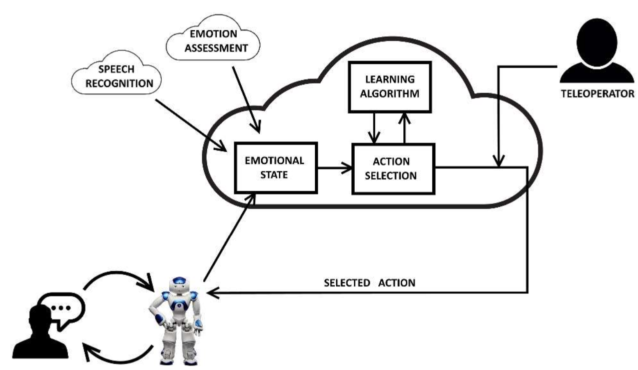

Fig. 4. Architecture of proposed system

This service can be used in systems supporting HRI, as seen in Fig. 4. In this setup, the physical robot plays the role of an agent only observing the human parner and then forwarding the observations to the so-called "virtual robot" in the cloud. Speech recognition and emotion assessment are done using existing cloud services, and based on them, an approximation of the human's inner emotional state is calculated. This state then affects action selection, and the proposed action is approved or overridden by a human teleoperator. Based on the teleoperator's input, the learning algorithm cloud service adjusts the rewards associated with the given actions, leading to a more precise action selection in the future. Another advantage of such a system is that it supports multiple robotic platforms, since most of the functionality (such as emotion assessment and action selection) are independent of the robotic platform.

V. Conclusion

Robots operating in everyday human life are expected to solve problems that are computationally heavy, and require dedicated hardware or high storage capacity, resources most robots don't have. Cloud computing offers a viable solution to these challenges, and new trends in robotics – especially in social robotics – point towards the offloading of computation from robots to cloud services. Such trends are supported by the availability of already implemented cloud services, accessibility of the Internet, and increase in connection speed.

Cloud computing offers advantages to robotics, such as executing computationally heavy operations remotely, access to big data, sharing robotic experience, and collective learning. Because of their agent role, robots don't have to be equipped with a lot of computational resources, which makes them lighter, cheaper, and easier to maintain. On the other hand, the use of cloud computing raises new problems, such as data protection, manipulation of big data, sharing computing resources, and network latency.

Cloud solutions are gaining attention in social robotics and will find further application in the future because of the nature of human–robot interaction. Cloud services can pave the way for tackling problems of understanding and imitating non-verbal communication, which are necessary for successful HRI, acceptance of robotic companions, and human–robot cooperation.

Acknowledgment

Research supported by the National Research and Development Project Grant 1/0773/16 2016–2019 "Cloud Based Artificial Intelligence for Intelligent Robotics".

References

[1] B. Qureshi and A. Koubâa, "Five traits of performance enhancement using cloud robotics: A survey," *Procedia Computer Science*, vol. 37, pp. 220–227, 2014.

[2] M. Inaba, "Remote-brained robotics: interfacing ai with real world behaviors," in *Proceeding 1993 International Symposium on Robotics Research*, Hidden Valley, Pa, 1993, pp. 335–344.

[3] K. Goldberg, B. Chen, R. Solomon, S. Bui, B. Farzin, J. Heitler, D. Poon, and G. Smith, "Collaborative teleoperation via the internet," in *Robotics and Automation, 2000. Proceedings. ICRA '00.*, vol. 2, 2000, pp. 2019–2024.

[4] V. Kumar, D. Rus, and G. Sukhatme, *Springer Handbook of Robotics*. Springer Berlin Heidelberg, 2008, ch. Networked robots, pp. 943–958.

[5] G. McKee, *Informatics in Control Automation and Robotics, Vol. 15 of Lecture Notes Electrical Engineering*. Springer Berlin Heidelberg, 2008, ch. What is networked robotics?, pp. 35–45.

[6] J. Kuffner, "Cloud-enabled robots," in *Proc. IEEE-RAS Int. Conf. Humanoid Robot.*, Nashville, TN, USA, 2010.

[7] Z. Du, L. He, Y. Chen, Y. Xiao, P. Gao, and T. Wang, "Robot cloud: Bridging the power of robotics and cloud computing," *Future Generation Computer Systems*, vol. 74, pp. 337–348, 2017.

[8] J. Wan, S. Tang, H. Yan, D. Li, S. Wang, and A. V. Vasilakos, "Cloud robotics: Current status and open issues," *IEEE Access*, vol. 4, pp. 2797–2807, 2016.

[9] M. Armbrust, A. Fox, R. Griffith, A. D. Joseph, R. Katz, A. Konwinski, G. Lee, D. Patterson, A. Rabkin, I. Stoica *et al.*, "A view of cloud computing," *Communications of the ACM*, vol. 53, no. 4, pp. 50–58, 2010.

[10] B. Kehoe, S. Patil, P. Abbeel, and K. Goldberg, "A survey of research on cloud robotics and automation," *IEEE Transactions on automation science and engineering*, vol. 12, no. 2, pp. 398–409, 2015.

[11] L. Agostinho, L. Olivi, G. Feliciano, F. Paolieri, D. Rodrigues, E. Cardozo, and E. Guimaraes, "A cloud computing environment for supporting networked robotics applications," in *Dependable, Autonomic and Secure Computing (DASC), 2011 IEEE Ninth International Conference on*. IEEE, 2011, pp. 1110–1116.

[12] J. Van Den Berg, P. Abbeel, and K. Goldberg, "Lqg-mp: Optimized path planning for robots with motion uncertainty and imperfect state information," *The International Journal of Robotics Research*, vol. 30, no. 7, pp. 895–913, 2011.

[13] B. D. Gouveia, D. Portugal, D. C. Silva, and L. Marques, "Computation sharing in distributed robotic systems: A case study on slam," *IEEE Transactions on Automation Science and Engineering*, vol. 12, no. 2, pp. 410–422, 2015.

[14] D. Berenson, P. Abbeel, and K. Goldberg, "A robot path planning framework that learns from experience," in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*. IEEE, 2012, pp. 3671–3678.

[15] K. Kamei, S. Nishio, N. Hagita, and M. Sato, "Cloud networked robotics," *IEEE Network*, vol. 26, no. 3, 2012.

[16] L. Turnbull and B. Samanta, "Cloud robotics: Formation control of a multi robot system utilizing cloud infrastructure," in *Southeastcon, 2013 Proceedings of IEEE*. IEEE, 2013, pp. 1–4.

[17] G. Hu, W. P. Tay, and Y. Wen, "Cloud robotics: architecture, challenges and applications," *IEEE network*, vol. 26, no. 3, 2012.

[18] A. Chibani, Y. Amirat, S. Mohammed, E. Matson, N. Hagita, and M. Barreto, "Ubiquitous robotics: Recent challenges and future trends," *Robotics and Autonomous Systems*, vol. 61, no. 11, pp. 1162–1172, 2013.

[19] A. Sandygulova, D. Swords, S. Abdel-Naby, G. M. O'Hare, and M. Dragone, "A study of effective social cues within ubiquitous robotics," in *Human-Robot Interaction (HRI), 2013 8th ACM/IEEE International Conference on*. IEEE, 2013, pp. 221–222.

[20] R. D'Andrea, "Guest editorial: A revolution in the warehouse: A retrospective on kiva systems and the grand challenges ahead," *IEEE Transactions on Automation Science and Engineering*, vol. 9, no. 4, pp. 638–639, 2012.

[21] M. A. Moussa and M. S. Kamel, "An experimental approach to robotic grasping using a connectionist architecture and generic grasping functions," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 28, no. 2, pp. 239–253, 1998.

[22] B. Kehoe, A. Matsukawa, S. Candido, J. Kuffner, and K. Goldberg, "Cloud-based robot grasping with the google object recognition engine," in *Robotics and Automation (ICRA), 2013 IEEE International Conference on*. IEEE, 2013, pp. 4263–4270.

[23] E. Prestes, J. L. Carbonera, S. R. Fiorini, V. A. Jorge, M. Abel, R. Madhavan, A. Locoro, P. Goncalves, M. E. Barreto, M. Habib *et al.*, "Towards a core ontology for robotics and automation," *Robotics and Autonomous Systems*, vol. 61, no. 11, pp. 1193–1204, 2013.

[24] R. H. Weber, "Internet of things–new security and privacy challenges," *Computer law & security review*, vol. 26, no. 1, pp. 23–30, 2010.

[25] Y. Anzai, "Human-robot interaction by information sharing," in *Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction*. IEEE Press, 2013, pp. 65–66.

[26] S. Lallée, K. Hamann, J. Steinwender, F. Warneken, U. Martienz, H. Barron-Gonzales, U. Pattacini, I. Gori, M. Petit, G. Metta *et al.*, "Cooperative human robot interaction systems: Iv. communication of shared plans with naïve humans using gaze and speech," in *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2013, pp. 129–136.

[27] R. Gomez, T. Kawahara, K. Nakamura, and K. Nakadai, "Multi-party human-robot interaction with distant-talking speech recognition," in *Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*. ACM, 2012, pp. 439–446.

[28] Y. Ho, Y. Kawagishi, E. Sato-Shimokawara, and T. Yamaguchi, "A human motion recognition using data mining for a service robot," in *Advanced Robotics (ICAR), 2011 15th International Conference on*. IEEE, 2011, pp. 229–234.

[29] T. Yokoo, M. Yamada, S. Sakaino, S. Abe, and T. Tsuji, "Development of a physical therapy robot for rehabilitation databases," in *Advanced Motion Control (AMC), 2012 12th IEEE International Workshop on*. IEEE, 2012, pp. 1–6.

[30] Z. Dogmus, A. Papantoniou, M. Kilinc, S. A. Yildirim, E. Erdem, and V. Patoglu, "Rehabilitation robotics ontology on the cloud," in *Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on*. IEEE, 2013, pp. 1–6.

[31] A. Manzi, L. Fiorini, R. Esposito, M. Bonaccorsi, I. Mannari, P. Dario, and F. Cavallo, "Design of a cloud robotic system to support senior citizens: The kubo experience," *Autonomous Robots*, vol. 41, no. 3, pp. 699–709, 2017.