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Cognitive and Learning-based Control: Applications in Robotics

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Abstract: In control arena, one of the most important issues is to effectively control the robot motion and force and in the meantime, the robots must safely respond to contact forces while interacting with people. Another issue is that how to handle uncertainties that are occurred during the process of interacting with environment. Human beings can control ourselves' motions (e.g. control arms to move, legs to move, whole body to move) perfectly. This partly attributes to the fact that human control system is based on millions of neurons that are receiving and sending signals to each other, and partly attributes to the fact that this control is formed by our initial learning. This paper reviews the most recent development on the brain and cognitive intelligence based control used in robotics. Some future research recommendations are proposed. It is concluded that the final goal is how to combine neuroscience, AI, and robotics so that we can make robots have more human-like performances.

Keywords: Adaptive control, Cognitive intelligence, Learning control, Robotics, Human-robot interaction.

1. Introduction

In 2000, the humanoid robot ASIMO is developed by Honda research group, and the robot can walk and climb stairs etc., but the robot cannot have physical interaction with humans [1-2]. Recently, the Boston Dynamics research group together with Google developed a humanoid robot Atlas, surprisingly it is not heavily based on artificial intelligence but motor control and learning through the state space model, and it is by far the most agile robot on the market [3-4]. However, the Atlas robot was not designed to have physical interaction with human beings, so it cannot really have physical interaction with human beings. Similarly, the recent developed humanoid robot Sophia that is largely based on artificial intelligence developed by Hanson Robotics research group can have verbal interactions with human beings, but not too much physical human robot interaction.

Before proceeding further, it is noted that biologically inspired robots have been developed in the past decades [5-9], in which researchers are trying to simulate and copy biology organisms to make robots more intelligent and accomplish complicated tasks. What about simulating and copying human behaviors (human nervous system) instead of animals behaviors? Since the most reliable and intelligent control system ever encountered is the human internal control system.

Human beings can control ourselves' motions (e.g. control arms to move, legs to move, whole body to move) perfectly. This partly attributes to the fact that human control system is based on millions of neurons that are receiving and sending signals to each other [10-12], and partly attributes to the fact that this control is formed by our initial learning [13-14]. It is noticed that when we were babies, we learned how to control the motions over and over again, and gradually formed the perfect control of movement.

Some of the traditional control systems (e.g. PD control) mimic the spring and damper system, as briefly illustrated in Fig. 1. Traditional control systems (used in robots) that are mainly geared to the industrial manufacturing purpose are no longer effective in human-robot interaction, e.g. one of the applications is eldercare. As serving an elderly people requires more complicated motions and safety issues need to be taken into consideration as well while the robot is interacting with elderly [15-18]. The robot requires more than just a position control, motion control, force control, or a trajectory planning [19-21]. It also involves with combination of above and unexpected motion control [22-24]. For example, in the process of assisting an elderly to walk around, if an elderly accidently falls, the robot needs to handle this unexpected motion and help to pick up the elderly.

A learning control system inspired by human brain and cognitive intelligence system seems to be a good candidate to address the above problem, i.e. how to design a human-nervous inspired learning control algorithm for assistive robots to help elderly people in their daily lives, for example, help to pour a cup of water and deliver it to the elderly, help to assist elderly to walk around, and help to clean the house. All these tasks need a robot and an advanced control algorithm. One of the most important issues is to effectively control the robot motion and force and in the meantime, the robots must safely respond to contact forces while serving an elderly people [25-27]. Another issue is how to handle uncertainties that are occurred during the process of, for example, serving an elderly people [28-30]. The development of physical assistive robots is not a main issue here, the main issue is to develop an advanced control algorithm to control the robots to execute an unexpected tasks in the process of assisting elderly people [31-33].

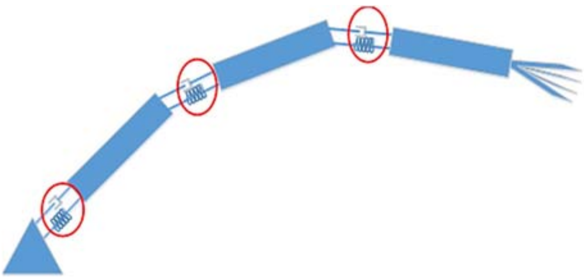

Fig. 1. PD control analogy.

Here, the most recent development of brain and cognitive intelligence based control are reviewed and the human-nervous-systems-based learning control algorithm for robots is discussed in order to further summarize and improve the methodologies in this field. This paper is essentially the extension of previous paper presented in the 1st IFSA Winter Conference on Automation, Robotics & Communications for Industry 4.0 (ARCI'2021) [34].

2. Cognitive Based Control in Robotics

In [35], the author studied how human beings control arms' movements by looking at the patterns of electrical activity in neurons when a person moves his or her arm through combining artificial intelligence and neuroscience, and then apply such skills to robots. The studies show that how artificial intelligence and neuroscience can help each other in order to advancing both fields.

Very similarly, artificial intelligence, computer programs, and brain organization are compared and investigated together in [36], and it came to the same conclusion that AI and brain organization are helpful to each other. The output of brain organization might be useful in better modelling and simulating of AI. In [37], a deep neural network is identified and trained by computational approaches in order to study the patterns of electrical activity of a monkey neurons in the process of recognizing an object. The deep neural network was modelled based on the human brain hierarchical architecture, and it is acknowledged that generally neural networks perform supervised learning. In [38], a "brain-like" control technique is used in the visual servo control of a redundant 7-DOF robotic manipulator for the tele-robotic operations application to remove the image-feature extraction and tracking requirements. However, the technique requires installation of advanced sensing systems and reconfigurable base. Furthermore, the force control is not considered and also safety issue is one of the major concerns when applying above approach. Precisely speaking, the above brain-like control technique can actually be considered as non-vector space control.

In [39-40], the intersection of computational neuroscience, cognitive science, and artificial intelligence are reviewed. It shows that by using Bayesian cognitive models, complex cognition will work in some cases, such as the way human minds model the real world by optimally combining previous experience. However, the study did not specify how we can apply such approach to robots.

In [41], a "learning nonlinear model predictive control" (MPC) policy is developed to minimize path-tracking errors by employing, for example, learning for the mobile robot path tracking problem. The robot is mainly used in the off-road terrain. The developed control policy employs a theoretically vehicle model and a disturbance model, and the authors modelled the external disturbances as a Gaussian process. The process is then further improved contingent on the experience that is collected during the earlier tests. However, the question of how to balance the covariance estimates provided by the Gaussian process model is still a challenge work. In [42], a new learning-based control structure, which makes the robot operate as a "social motivator" through providing assistance and motivation, is proposed for a socially-assistive robot that is able to make individuals involve in cognitively stimulating activities. The authors used a hierarchical reinforcement learning technique for the purpose of providing the robot to learn assistive behaviors based upon the activity structure. The result indicates that the developed learning-based control policy can effectively determine the best assistive behaviors of the robot, for example, over a game interaction.

In [43], the authors discussed how to build and make robots that learn like people. The article presented and illustrated two major challenges in the process of robot learning: image and character recognitions, and learning how to play a video game. The authors argued that the combination of neural network modeling and learning-based artificial intelligence could result in much better result and more human-like learning abilities than that of single artificial intelligence system. Furthermore, it also concludes that deep neural networks learning together with psychological ingredients could lead to a much higher level of cognitive control. The challenging problem and of course the next step of work seem to be that how to build the bridge between deep neural networks learning and psychological ingredients.

There are also numerous of recent studies focusing on the deep learning and neuroscience [45-51], but the studies did not specify how exactly to connect deep learning and neuroscience to robot controls.

In [52], a "recurrent emotional cerebellar model articulation controller neural network" is presented for vision-based mobile robots to handle complex nonlinearities in the dynamic equations so as to achieve accurate positioning tasks. The developed control neural network combines a recurrent loop with an emotional learning system and therefore generate a "cerebellar model articulation" control system, which is acted as the main piece of the control system module. The developed control system contains three parts: a sliding surface, the recurrent emotional "cerebellar model articulation controller", and a compensator controller, and the control system is designed based on the Lyapunov stability theory and therefore, the stability of the overall controller is guaranteed. However, the designed control network has certain limitations where the control network can only be used in target tracking due to the fact that lacking of self-organization mechanism in the overall control system. In [53], the authors proposed an approach by training machine learning regression algorithms to anticipate slippage related to individual wheels in mobile robots that are used in off-road conditions. The novelty about that study is that the machine learning regression is employed rather than classification to detect slippage and related uncertainties. The interesting part is that the slippage is considered as a random variable. The MIT single-wheel equipment is used as a demonstration, and the result shows that the Gaussian process regression leads to a trade-off among computation time and precision. Using deep learning approaches to model slippage as a discrete variable will be interesting to look at in the future.

In [54], a general structure of exploring the consciousness nature in cognitive robots has been developed, and the issue of how to create a humanoid robot that learns to conduct works based on imitation learning is discussed. It is pointed out that the above humanoid cognitive robot can be achieved by copying and following human-provided demonstrations (i.e. the so-called "learning from demonstrations") instead of pre-programming the robot. However, the potential issue is that the robot is very limited to generalize to a completely new set of circumstances where the robot needs to use different actions to execute the same intention, because the robotic system does not understand the demonstrator's intentions. In [55], the development of neuroscience inspired human–robot interaction is briefly reviewed, and some challenging issues are brought up. The study reviewed the above topic from the following two different perspectives: the development of social behaviour in robots, and human social perception. Nevertheless, it was concluded that we need to integrate different research areas to make significant progress in controls of human-robot interaction.

In [56], a framework for coordinating stimulus sport interaction scenarios with robots is developed based on motivational instruction patterns. It is shown that by employing a structured way of assessing multiple interaction configurations and robot platforms, one can obtain a deep understanding in psychological concepts that shape human-robot interaction. However, the study is still preliminary in terms of scenarios presented.

In the beginning of the century, people are looking at the adaptive control to handle the situation where parameters in the dynamic equation change with respect to time. Adaptive control still replies on models and it is a type of model-based control. Later, many research groups investigated the model-free control, particularly the deep reinforcement learning in robotics [57-68]. The challenging problem we are facing is that how to make robots deal with uncertainties and make corresponding decisions, and how to make robots truly achieve human-like intelligence.

In [69], the authors investigated the human–robot cooperative tasks by looking at the needed individual, based on affordance analysis and perspective-taking. The context is that robots and humans are put in a common space, and humans and robots exchange information mainly via verbal communication and social observation, and the robot is then anticipated to carry off interactive object manipulation by considering the human's intentions, skills and beliefs. The study presented is till preliminary. It does not consider cases where different beliefs might appear between the robot and human. Moreover, the study is only limited at the spatial and temporal situations, where a context selection consists of retrieving one monolithic set of beliefs rather than single one belief. In another interesting and similar study [69], a coordinated speech-based humanoid robot is developed that can follow human commands and produce poems, receive audiences feedback and thereafter display corresponding emotional responses, and produce body language movements accordingly.

The dialogue capabilities of the robot yet needs to be further improved in order to allow an active learning for extracting and organizing knowledge from human.

In programming arena, for example in Java, we have the concept of modularized programming [45], where one lengthy program is reduced to one main method and several blocks of sub-methods. Each of these sub-methods is one module, and each module does its own work and returns the result to the main method which utilizes the returned result. A Java example is shown here in Fig. 2 for the purpose of an illustration. Furthermore, it is argued that our human body does not only have one controller, but rather multiple controllers that are working together with the central nervous system, which is our brain and spinal cord. When humans control bodies, not all controllers are working at the same time. For example, when human humans grab an object, the only control system working might be the arm controller and other related controller, the controller that controls our facial expression might not be working. Or as another example, when human beings lay on the bed and relaxing, we still have all the controllers but most of the controllers are not performing to control any movement.

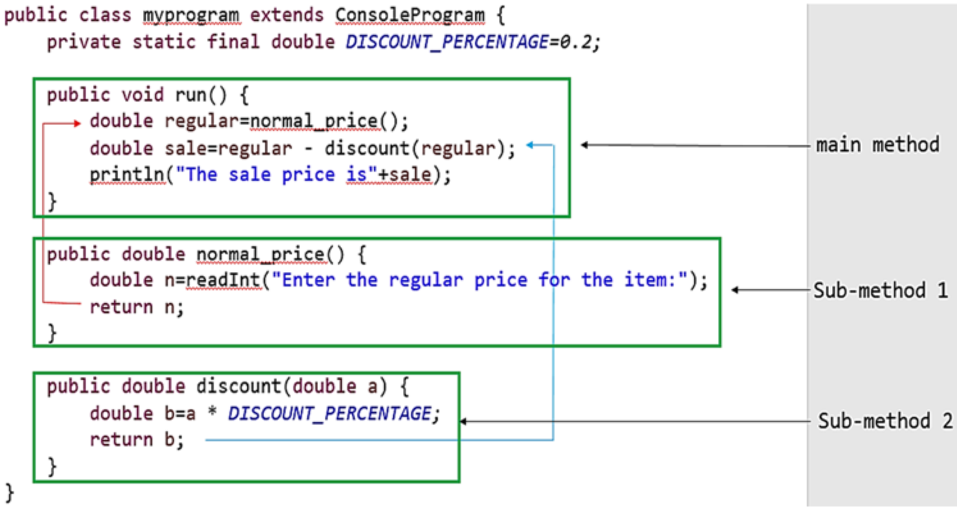

Fig. 2. A Java program example – modularized programming concept.

It is similar to the idea of under-actuated robotics [70-71], where the number of controllers is less than the number of joints, for example, in robotic manipulation. Many complicated robot motion, for example, robot walking, robot running, balancing an inverted pendulum, are achieved by under-actuated situation. Most of the robots in factory floors, e.g. assembly robots in car manufacturing, are fully actuated, where the number of the controllers equal to the number of the joints, and they can be achieved to have the adaptive control functions because of the fully actuated situation.

There are lots of control strategies currently, for example, optimal control [72-73], adaptive control [74-75], model predictive control (MPC) [76-77], etc. As a side note, the optimal control mainly focuses on how to control, for example, a robotic arm with minimum energy and quickest fashion. Adaptive control focuses on how to control, for example, a robotic arm with unknown dynamic parameters to make the robotic arm move as if the unknown parameters were known.

The idea of the multiple controllers working independent and together with the central control system might be one of the future research directions we can take to handle robot control in order for robots to accomplish more complex and delicate works, as conceptually demonstrated in Fig. 3. We can build a model to represent such hierarchy concept and apply such control to robots.

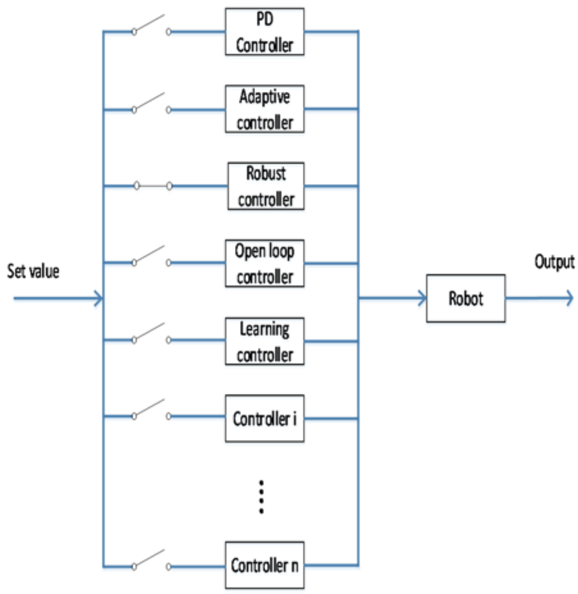

Fig. 3. Multiple controllers work together and independently to control a robot.

3. Discussion

The general approach as a future study that we are going to take for designing cognitive based control for robotics or human-nervous-system-based learning control algorithm is to build a mathematical model to resemble and represent human nervous system based on the structure and function of the nervous system, and then apply such model to robots.

As mentioned earlier, one of the main reasons that human can control and coordinate arms, legs, and whole body perfectly is that we have the initial learning. For example, if you are asked to write a sentence with your foot with a pen stuck in between the toes, you probably will have a very hard time to control such motion and write a sentence. This is because we did not have any initial learning on how to write a sentence with our feet instead of hands. Similarly, if you are asked to write a sentence with your left hand (if you are right hand side writer), you probably still will have a hard time to control such motion and write a sentence, again, the reason is that we did not have any initial learning on how to write a sentence with your opposite hand. But if you are trained or taught how to do that, and after practice over and over again, you then will have an easy time to control such unexpected motion as described above.

The following states how we are going to achieve human-nervous-system-based learning control algorithm in details: in the designing of such human-nervous-system-based learning control algorithm, the initial idea is to make the human-nervous-system-based learning control system have two major sections. The first section contains the learning control algorithm. A basic learning control concept is illustrated in Fig. 4.

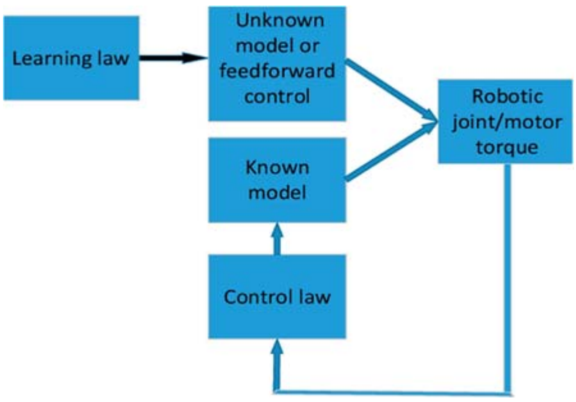

Fig 4. A learning control concept [59].

The learning control algorithm can be designed based on the artificial intelligence by simulating the human learning approach (learning over and over again) and modelling a deep neural nets model. After that, maybe we can add a block that is very similar to the structure of neurons that are receiving and sending signals to each other to the above learning control algorithm, and this forms the second section, which will be one of our future works. The purpose of the first section (the learning control algorithm) is to store enough "correct move" and "wrong move" information, it's very similar to initial learning, as described above. The purpose of the second section (the neurons alike structure) is to utilize the first section's information to communicate with the robot. Fig. 5 briefly illustrates the overall plan for designing a human-nervous-system-based learning control algorithm used, for example, in a socially assistive robot. The key problem that needs to be solved is the human-nervous inspired learning control algorithm instead of building a robot.

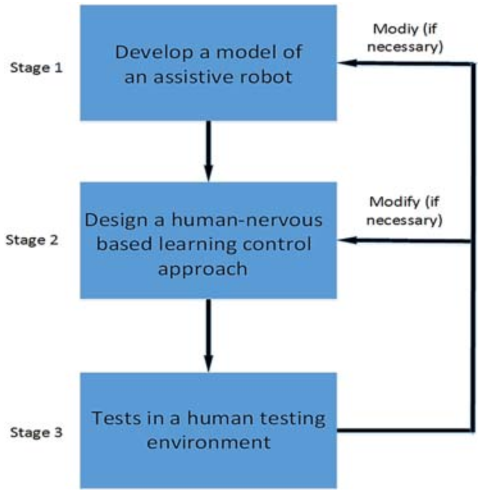

Fig. 5. Example of human-nervous inspired learning control algorithm design overall plan.

4. Potential Applications

Robotic systems have been used in many industrial areas, but its development in the human-robot interaction, for example, socially-assistive robots in eldercare, is still in the infant stage [79]. It is estimated that by 2030, there will be over 1 billion elderly people who are over 60 years old around the world. Young people will not be able to stay at home and serve their older parents often as they have to go to work. Thus the use of assistive robots in eldercare will become necessary in the near future. There are few robots being designed in the last decade where the robots can do some basic tasks for elderly, but mainly on the communication and entertainment level [80-82], not actually having physical interactions with elderly. The significance and potential impact of the cognitive based control research are summarized as follows:

1) By 2030, it is estimated that 20 % of world's population will be over 60 years old. The development of socially-assistive robots will greatly assist elderly people in their everyday lives;

2) The development of human-nervous inspired learning control algorithm will further push the development of the automatic control theory to a new

level and introduce a new concept of control, which can potentially be used also in advanced manufacturing. Manufacturing plays a crucial role in today's economy responsible for about 16 % of global gross domestic products. In current manufacturing industries (e.g. in manufacturing assembly lines), robots are working independently and not working with human operators. In order to improve the productivity and adapt to the rapid changes in production, current assembly robots are very limited in satisfying those needs. Whereas robots working with human operators is an effective approach to meet the needs of rapid changes in production.

5. Conclusions

The author here reviewed the most recent development of the brain and cognitive intelligence based control used in robotics in order to further summarize and improve the methodologies in this field. A human-nervous-systems-based learning control algorithm design framework for assistive robots is briefly illustrated and discussed. Some future research recommendations are proposed. It seems the final goal is that how to combine neuroscience, AI, and robotics so that we can make robots have more human-like performances.

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