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Literature Review

Overview of some Command Modes for Human-Robot Interaction Systems

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ABSTRACT

Interaction and command modes as well as their combination are essential features of modern and futuristic robotic systems interacting with human beings in various dynamical environments. This paper presents a synthetic overview concerning the most command modes used in Human-Robot Interaction Systems (HRIS). It includes the first historical command modes which are namely tele-manipulation, off-line robot programming, and traditional elementary teaching by demonstration. It then introduces the most recent command modes which have been fostered later on by the use of artificial intelligence techniques implemented on more powerful computers. In this context, we will consider specifically the following modes: interactive programming based on the graphical-user-interfaces, voice-based, pointing-on-image-based, gesture-based, and finally brain-based commands.

Keywords: human-robot interaction, teleoperation, speech-based commands, image-based commands, gesture-based command, brain-computer interface.

INTRODUCTION

In a modern technological sense, the first robots which appeared during the second world war were serial arm manipulators. They were mainly dedicated to telemanipulate objects in hazardous environments such as nuclear plants and to perform simple repetitive industrial tasks. During this historical period, the traditional modes of command and control were telemanipulation, off-line robot programming, lead-through and teach pendant (Low, 2006; Wallén, 2008).

Later on, since the seventies, with the progressive improvement of computer performances, serial robot have proven to be very efficient for various industrial tasks. Moreover, since the eighties, parallel robots joined the domain of industry adding principally more precision and speed compared to serial robots (Ceccarelli, 2001; Gasparetto and Scalera, 2019).

Next, since the nineties, new shapes of robotic systems appeared and continuously evolved in structures, functionalities and performances (Zamalloa et al., 2017). Different robot shapes are experienced such as mobile robots, cable-based robots, flexible robots like snakes, various other animals-like robots, drones, and even humanoid robots (Ramos, 2018). It is a fact that modern robots are becoming popular and proved to be capable of achieving relatively complex tasks in various environments including unknown, hazardous and/or remote areas. Some examples of such systems are space exploration robots as rovers, assistive robots for elderly and disabled people, surgery robots, etc. Humanoid robots are particularly remarkable because of their resemblance to human beings. They are going to be used in social environments with the capability to interact directly with human beings. They will be also used for rescue operations, during wars as soldiers, etc (Ford, 2015).

In the course of this extensive evolution of modern robotic systems, adaptive and smart Human Robot Interaction (HRI) rises unavoidably to be essential for ensuring the success of performing complex tasks and missions. As a consequence, HRI has emerged and stands more and more as a topic of a paramount importance. In the same context, command modes play a fundamental role in any dedicated framework of human-robot interaction as they are substantial features by which communication, interaction, cooperation and expected mutual understanding between humans and robots become possible. In fact, this topic is an essential key for successful development of modern and futuristic HRIS (Sheridan, 2016) and justifies the interest to present this overview about the most used command modes for HRIS.

This paper briefly presents some of the most relevant HRI techniques that are used to generate robot commands. It includes telemanipulation that evolved towards telerobotics, off-line robot programming, interactive-based command, voice-based command, gesture-based command, pointing on image-based command, and brain-based interaction and command.

TRADITIONAL MODES OF HRI

There are actually different techniques through which a human can interact with and command robots. However, at the beginning of the emergence of robotics, there were few elementary interaction and command modes.

Teleoperation

Teleoperation constitutes the first mode of interaction and command that has been employed in teleoperating robotic systems. It started around the 1945 with the first master-slave manipulator designed to manipulate radioactive material in hot cells (Sheridan, 1992). Teleoperation is a manual control performed by an operator who is usually situated in a local site controlling remotely a robot which is situated in its workspace environment. The most common configuration of teleoperation is that of the master-slave where the human operator (master) directly controls the remote robot (slave) by means of a hand controller. Traditionally, the task monitoring was assured by direct vision if possible and by cameras. **Figure 1** illustrates the general organization of a teleoperation system presented in (Sheridan, 1992). On the left side, one can distinguish the human operator (master) who is teleoperating and supervising the task. On the right side, one can distinguish the subordinate (slave) which is executing the received commands.

However, this mode continuously involved the operator’s attention in a direct coupling. It, thus, generated fatigue and a boring feeling during repetitive tasks, leading to cognitive fatigue of the operator. Besides that, other drawbacks can affect teleoperation such as the weakness of sensory feedback, the limited communication bandwidth, the operator's subjective experience and present work conditions. There is also one issue that very seriously affects and reduces the performance of teleoperation and which is hard to address. It is the control instability that is caused by time delays of the feedback signal between the operator and the telemanipulated robot (Lichiardopol, 2007; Sheridan, 1992; Zaatri, 2000).

Thus, to overcome these problems, it was necessary to incorporate a certain degree of autonomy into the system in order to relief the operator. So, with the continuously increasing power processing of computers and IA, the development of traditional teleoperation leaded to telerobotics and to supervisory control systems. These last techniques were developed since the seventies and were enriched with more HRI techniques, smart, adaptive and multimodal user interfaces (Oussalah and Zaatri, 2003; Zaatri and Van Brussel, 1997). The most common techniques which have been used later on to relief teleoperation were: telepresence, teleprogramming, semi-autonomous control, intelligent assistance to support operators and augmented reality (Lichiardopol, 2007; Makhataeva and Varol, 2020; W. S. Kim et al., 1992).

Off-line Programming Mode

Contrarily to telemanipulation techniques where the human operator is fully engaged in the interaction with the robot; for off-line programming techniques, the task execution is fully managed by an automatic controller so that the operator is left almost in an observer role. The off-line robot programming technique is similar to computer programming languages which are usually used for simulation. It consists of writing a textual program (code) that contains the specifications for task execution. The program is a software which is written independently of the robot cell (off-line). To execute the task by the robot, the operator interacts with a computer from where he uploads the program and launches its execution. Once the program starts, the computer manages automatically the task by means of the robot controller according to the program instructions. In the beginning phase of robotics, the operator is left out of the task operations unable to intervene. Nevertheless, while supervising the task execution, he/she can only intervene if necessary by means of an emergency button to stop the task execution by disabling the power supply.

Contrary to traditional teleoperation; textual programming, while it is fully automatic, lacks flexibility for performing complex tasks which require some skills. It is not practical in unstructured environments. Moreover, because of the uncertainties inherent to modelling real environments, robots and sensors. This mode is not applicable at all in unknown and remote environments. It is however well adapted for programming simple tasks (Mitsi et al., 2005; Pan et al., 2012; Yong and Bonney, 1999).

Other techniques: teaching by demonstrating

Beside teleoperation and off-line programming, there are two other traditional methods that were used to facilitate the programming of robots for performing some simple repetitive but relatively complex manipulation tasks. They are based on teaching by demonstration, and they are namely the lead through method and teach pendant method.

"**Lead through method:**" is a method that is also referred to as hand guidance programming method. It is an intuitive method that involves the human operator to demonstrate the task by performing it manually by guiding the robot end-effector. During the demonstration phase, the operator moves by means of his own hands the robot's the end-effector and guides the robot while performing the task. The robot controller stores the trajectory provided during the demonstration. This enables the robot to play back automatically the demonstrated task during the production cycle. The walk through method was usually appropriate for some type of tasks such as spray painting and arc welding (Argall et al., 2009; Eakins et al., 2013; Qi and Zhang, 2009).

"**Teach pendant method:**" like the lead-through method, teach pendant method consists of teaching the robot how to perform the given task, but by means of a teach pendant which is used as an interface tool that serves to guide the robot. The teach pendant is a hand-held device that is used to control the robot without contact and remotely. It is provided in the form of a portable device like a tablet with buttons, switches and dials corresponding to specific functions designed to controlling the robot.

During the teaching or learning phase, the operator holds and uses the teach pendant to drive the robot step by step to any desired locations which are required to performing the task. Thereafter, the relevant poses are stored, and finally, during the production cycle, the robot repeats autonomously the movements and actions that lead to perform the task at specified speed. (Fukui et al., 2009; Joseph, 1998).

The lead through and teach pendant methods involve the human operator in the task, but only during the teaching phase which is performed out of the production cycle. After learning the processes, the robot actions are converted into textual programs which are used thereafter to automatically perform the task (Argall et al., 2009).

INTERACTIVE COMMANDS BASED ON GUI

If we consider the previously presented traditional interaction modes, we notice that there was a need to free the operator from his continuous engagement during full teleoperation and inversely to give him the possibility to intervene when needed during the full automatic task execution of the programming mode. To this end, the interactive control mode, which has emerged around 1995, has provided an alternative for the user to intervene during task execution and even to switch from one command mode to another. It was fostered by the apparition of software interfacing facilities. It has been made possible conjointly with the development of the object-oriented programming techniques and their corresponding languages such as C++, Java, Python, etc. Basically, interactive programming enables to built up Graphical User Interfaces (GUI) on computer screens that contain graphical objects like windows, panels, buttons, sliders, pop-up menus, etc. Each graphical object can be linked to a function that can be executed each time the user activates the corresponding object from the GUI. The generation of functions can be done by mouse clicks on particular widgets, by typing specific character keys of the computer keyboard or by screen touch (**Figure 2**). The GUI enables also the presentation of data in different formats and structures (texts, images, videos) (Appelstal et al., 2018; Myers, 1995).

From the HRI point of view, the introduction of interactive programming techniques was welcomed as it gives the possibility to generate interactively commands via GUI while the robot is even performing operations without necessarily stopping it. It enables also the reflection of feedback information via the GUI.

As shown in **Figure 2**, many needed functions can be programmed and launched via the GUI. Position commands, joint commands, velocity commands, force commands, either constrained or not can be generated interactively. Within this interactive mode, the operator can carry out pick-and-place tasks with robot manipulators or direct a mobile robot to some destination. For instance, to achieve tasks with this mode, the operator directs the robot by a series of clicks on the appropriate buttons.

In addition, this mode enabled to combine pure teleoperation with pure textual programming, providing a way of overcoming their inherent limitations. These modes of teleoperation, off-line programming and interactive programming can be combined and shared to perform tasks more efficiently. This interactive mode has opened many ways for HRI and cooperation (Marion et al., 2017; Zaatri, 2000; Zendoui et al., 2018)

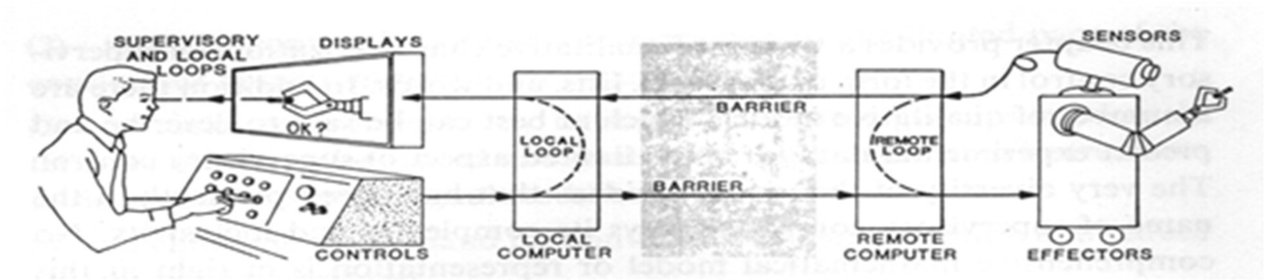

Figure 1. Teleoperation system

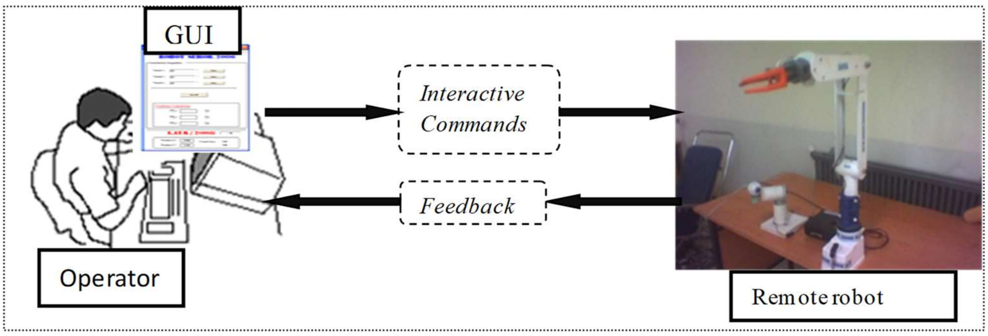

Figure 2. Interactive commands

MODERN COMMAND MODES

Modern command modes make the evolution of the task easier and more efficient. Yet, they require more complex systems to be implemented for they need sensors, relatively fast computers and AI techniques. They need algorithms that process data, extract relevant features and important information as humans do. In the following sections, we present speech-based command, pointing on image-based command, gesture-based command, and brain-based command.

Speech-Based Commands

It is well known that speech is the most natural way to communicate between humans otherwise talking to robots at the earlier age of robotics was like a dream. However, later on with the development of AI, human speech appears to be an interesting mean to command, control and communicate with robots.

Still, using human speech to command robots requires speech recognition techniques, which started in the early 1950s. Of course, early systems had limited vocabulary, but modern speech recognition systems have evolved and are now widely available in many domains. They have gained use with intelligent assistants, such as Amazon's Alexa, Apple's Siri and Microsoft's Cortana, Google's Google Assistant and others (Terzopoulost and Satratzemi, 2020). These systems are enabling speech interaction with computers and other devices. They have capabilities to interpret what is said through speech recognition systems and even may respond to questions or commands across text-to-speech systems.

In particular, automatic speech understanding for generating robot commands is linked to the field of Automatic Speech Recognition (ASR). ASR is intended to convert human speech into written texts. Most Speech-based commands and interaction between humans and robots have been developed with the recognition of isolated words because it is easier to be used as robot commands. Examples of sentences that are used by speech systems to command robots are: go to initial position, find table, move left, etc. However, because of the complex nature of voice signals, ASR still remains in some circumstances a relatively hard issue for robots to understand speech commands.

The principle of speech commands

The principle used for most word recognition systems can be illustrated in **Figure 3** and **Figure 4**. It comprises two phases: the learning phase and the recognition phase. The learning phase consists of creating a list of words which are stored into a dictionary as reference words. The recognition phase consists of identifying any new spoken word to one of the reference words stored in the dictionary.

An example of ASR we have implemented was based on the following procedure: any spoken word which is a continuous acoustic signal is translated by the microphone into an electric continuous signal. This continuous electrical signal is then sampled by a sound card. Some digital operations are then applied such as pre-emphasis, Fast Fourier Transform (FFT), power spectrum, filter bank integration (Mel's Filter), logarithmic compression, Discreet Fourier Transform. The final output is a set of coefficients which are called Mel Frequency Cepstral Coefficients (MFCC) (Muda et al., 2000). MFCC are the main features that characterize a speech signal. They serve to build the dictionary of the robot commands (references) after a training phase of the user. They serve also in the recognition phase to identify any new unknown robot command by comparing it to those stored in the dictionary.

In order to recognize any spoken words considered as possible robot commands, ASR is using various methods of classification such as Hidden Markov Model (Rabiner, 1989), VQ vector quantification (Linde et al., 1980), and learning techniques as Neural Networks (Paul and Parekh, 2011). However, the MultiLayer Perceptron (MLP) is of special importance for acoustic modeling in ASR (Pinto, 2010). As an example in one of our implementation, the role of the classifier is played by the MLP (Zaatri et al., 2015). It selects the closest reference word with respect to the spoken one. The scheme of an ASR is represented in **Figure 4**.

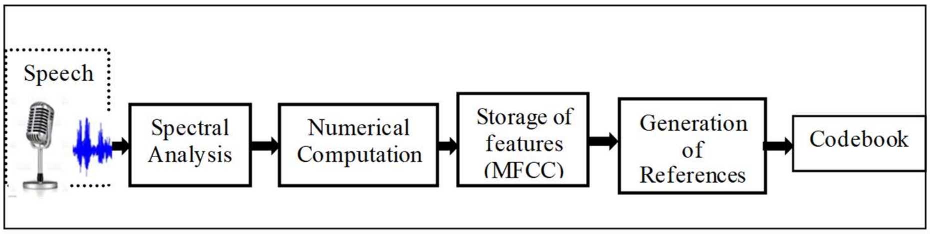

Figure 3. Learning phase

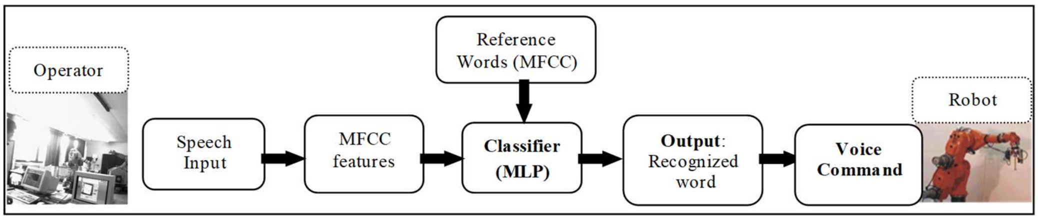

Figure 4. Recognition phase

However, speech-based command is interesting for handicapped people using for instance wheelchairs id the operator's hands cannot be used or if they are busy with some other tasks. With the recent development of personal and humanoid robots, this mode is also gaining more interest. Nevertheless, ARS applied to robotic domain still suffers from many barriers. It is sensitive to hard noisy environments. The results depend on the personal characteristic of the operator that can only be improved by a long training. Efficient success can be obtained with limited vocabulary and cannot match all and new contexts (Oussalah and Zaatri, 2003; Zaatri et al., 2015).

Commands by Pointing on Images (Look-then-Move)

The use of vision to command and control robots is a very important element for enhancing robot applications. Today, many commercial robotics integrating vision systems are available. But because of the sensitivity and complexity of image processing, the efficiency of such systems is mainly limited to static industrial applications. For telerobotics, vision-based control techniques, as stressed in (Sheridan, 1992), make a powerful set of tools for robot interaction and control especially in unstructured and unknown environments. These techniques do not require pre-knowledge or models about the objects to work with. With these techniques, the human operator designates the objects or locations of interest from the received images; afterwards the system extracts their corresponding features and heads towards them in real space. In all these techniques, the supervisor's role, as observed in (Sheridan, 1992) "is limited to conception and pointing, and the tele-robot do the rest".

In general, vision-based robot command systems can be divided in two main folds regarding the applied control system architecture. The earlier technique is named look-and-move and the other one is visual servoing.

Image-Based as Look-then-Move Commands

Because real-time image processing was relatively slow, the earlier vision-based systems were principally designed for applications of type "look-then-move" which are usually dedicated to static environments. They were also referred sometimes as point-and-click or image-based commands (Kim and Stark, 1989; Oussalah and Zaatri, 2003). From the control system viewpoint, their control architecture is an open loop one without continuous image processing feedback.

These systems include stereovision systems to capture images. They work as follows (**Figure 5**). A scene is selected by the operator which inside which the object of interest appears in both stereovision cameras. The operator selects this object in one image by pointing on it with a pointing device such as a mouse click. The stereovision system grabs automatically the left and right images. Then a stereovision algorithm proceeds these images in order to extract the corresponding 3D coordinates of the selected object of interest in the real word. Once, these 3D coordinates are estimated, they are sent as a position command to the robot for heading towards this location or this object. In fact, the robot executes this command by performing "blind" movements which assumes that the environment remains static after the robot has started to move. It is an open-loop approach of a type fire and forget (Wang, 2016) . By repeating this process, the operator can direct easily the robot to perform manipulation tasks and/or navigation.

However, while this technique is simple, it enables high level commands. It represents an efficient way to generate look-then-move robot commands for static environments.

A successful implementation of an automatic image-based (look-then-move) commands named click-and-move, has been developed for six DOF manipulators. It has been described in (Oussalah and Zaatri, 2003; Zaatri and Van Brussel, 1997). It has also been extended to mobile manipulators (Zaatri, 2000) and to parallel cable-based robots (Bouchemal and Zaatri, 2014). All our experiments have proven that it is a very powerful technique for various types of robots in the range where calibration of the cameras has been performed.

Visual Servoing Control

With the increasing power of image processing, it becomes possible to apply machine vision to dynamic systems acting or moving in a non-static environment and capable of tracking moving targets. This technique, known as vision-based control or visual servoing appeared in 1979 (Corke, 1994; Hans, 2018). Visual servoing is distinguished from look-then-move since it enables to control the robot's motion using real-time feedback based on vision sensors (Vahrenkamp et al., 2008).

Gestural-based Commands

Gesture-based robot command is a technique that uses the movement of some body parts in order to interact and command robots. Gestures can be of any type of body movements: head movement, hand gesture, anybody movement and even facial expressions. Also, tools moved by a human operator such as pencils, flags, sticks, etc. can be used to interact and command robots.

As the many modern modes of robot command, gesture-based command has been studied, designed and implemented by many authors. A survey concerning gesture-based interaction is presented in (Galván-Ruiz et al., 2020; S. Mitra and T. Acharya, 2007). Technically, in most applications, gesture-based interaction requires detection and identification of gestures as intended robot commands. Actually, detection and identification of gestures are mainly based on object recognition and tracking approaches involving CCD camera sensors. As for visual servoing, several image processing methods are used for image recognition such as features-based, appearance-based, gradient-based, learning methods, etc. (Baker and Matthews, 2004; Bonci et al., 2021; Lucas and Kanade, 1981; Nearchou, 2011).

Principle of Gesture-Based commands

The principle of gesture-based interaction systems is simple. It requires sensors that capture sequences of images during the movement of a human body part or of any tool moved by the operator. These sequences of images are then analyzed by an image processing software in order to track the motion of some detected elements of interest. Once a significant movement is detected and tracked; the final configuration of the gesture is identified. It is interpreted with respect to a code that links detected movements with corresponding robot commands. This identification of the gesture is finally sent as a corresponding robot command. Lastly, the robot performs the intended action or task. **Figure 6** summarizes the principle of gesture-based robot command showing the sequence of the designed and implemented main operations (Zaatri, 2021).

Applications of gesture-based robot command are numerous and can be adapted and extended according to many needs and contexts. Gesture expressions can be employed in regions where the speech is useless. This can happen, for instance, in noisy places, in underwater areas, and in empty space where the medium cannot convoy the voice waves as with astronauts (Liu et al., 2016). It can be also used for learning by demonstration and for imitation as reproducing operations in medical care or tele-surgery (Staub et al., 2011). This command mode is also interesting in some military activity to communicate and direct remote teams, autonomous and unmanned systems (Elliott et al., 2016). Moreover, it can be used in assistive robotics for supervising deaf people, for surveillance of disabled people, etc. (Bouchemal and Zaatri, 2013).

In addition, the gesture-based interaction can be designed with contact or without contact. Examples of gesture interaction with contact are used for teaching on blackboards, tables and other supports. In these situations, markers and colours can be employed to facilitate the tracking of elements of interest (Bouchemal and Zaatri, 2013; Nearchou, 2011; Sigalas et al., 2010). Moreover, with the event of Covid-19 pandemic, gesture-based control without contact is gaining a special importance by avoiding touch and contact with contaminated people and objects like door handles, machines, etc.

This command mode offers the advantage of freeing the operator from the contact with the computer. Nevertheless, some difficulties which are related to image processing and environmental issues can limit the capabilities and performances of this command mode.

BRAIN-BASED INTERACTION AND COMMANDS

Beside the variety of existing human-machine interaction and command techniques, these last decades, biological ones have opened new unprecedented perspectives towards very interesting and promising innovative researches. Indeed, bio-mechanical actions, myo-electric and bio-cybernetic techniques can be used for interaction, command and control of dynamical systems such as robots, wheelchairs, and even paralyzed body parts of human (Berna-Martinez, 2011; Martinek et al., 2021; Rechy-Ramirez and Hu, 2015).

In this context, the mastering of the brain activity of human beings for interacting and commanding systems reveals to be a very attractive topic. Indeed, brain activity is the prime source for generating command signals. In the past, understanding mind thoughts and detecting intentions were considered as a kind of telepathic capability which only exists in science fiction. However, with recent advances in neuro-sensing technologies, this belief is finally turning into reality (Nam et al., 2018). As a result, the field of human-robot interaction has been significantly enriched by the brain-based interaction and command techniques. It is actually possible for a subject, by means of Brain Computer Interfaces (BCI), to detect or generate commands that can be used to manipulate virtual or real systems according to intentions through the brain activity (Nicolas-Alonso and Gomez-Gil, 2012).

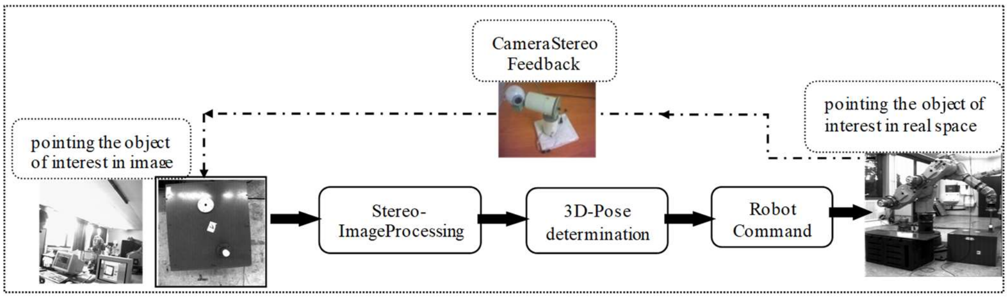

Figure 5. Look then move commands

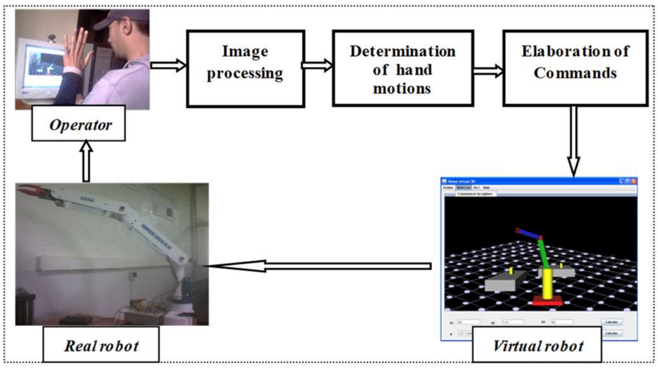

Figure 6. Look then move commands

Principle of Brain-Computer Interfaces

Crow It is well established that human brain activity consists of emitting waves with certain patterns as a result of external stimuli or mental states (Buzsaki, 2006; Doelling and Assaneo, 2021). BCIs are specific devices which are capable of capturing and measuring brain activity, then extracting interesting features, and finally converting these features into outputs to interact with and command dynamic systems. Thus, BCIs enable users to interact with computers and other devices by means of brain activity only (Afonso et al., 2014; Afonso, 2013; Yonck, 2002). They provide a unique way of communication between a human and a machine (or device) without any neuromuscular intervention (Abiri et al., 2017; Wolpaw et al., 2002). More generally, Brain–Machine Interfaces (BMIs) are devices that translate neuronal information into commands capable of controlling external software or hardware such as computers, wheelchairs, prosthesis, and robots. **Figure 7** shows a scheme of a BCI interfacing and converting brain activity of a user into command signals with possible feedback (dotted lines) to the user.

The design principle of BCIs is similar to most other interfaces such as speech-based, image-based, gesture-based ones. It consists of converting basic signals into commands by means of a set of processing operations: detecting the primary user's signals, processing it in order to extract relevant features, classifying the obtained features in order to decide to which predefined command it is supposed to have been issued; then this command is sent for execution (see **Figure 8**).

BCI techniques

Different techniques are used to measure brain activity for BCIs. Most BCIs use electrical signals which are detected using sensors placed invasively or non-invasively. There are several techniques for noninvasive BCI, such as EEG (electroencephalography), MEG (magnetoencephalography), or fMRT (functional magnetic resonance imaging: tomography) (Ferreira et al., 2008). Electroencephalography (EEG) is a physiological method to record the electrical activity generated by the brain via electrodes placed on the scalp surface. The signal amplitude is usually under 100 μV and the frequency band of normal EEG signals is usually above DC up to 50 Hz (Martinek et al., 2021).

In invasive techniques, special devices are inserted directly into the human brain by surgery. In Semi-invasive, devices are inserted into the skull on the top of the human brain, or directly on the cortex (called Electrocorticography – ECoG); the surface of the brain (signal having about 1- 2 mV of amplitude (Ferreira et al., 2008). In general, non-invasive techniques are considered as safest, of low-cost type of devices and then easiest for studies. However, the captured a human brain signals are weaker compared to invasive techniques which are in direct contacts with neural cells (Ferreira et al., 2008; Steyrl et al., 2016).

Applications and Perspectives of BCIs

From the beginning, most applications of the biological and physiological control techniques were oriented towards the assistance of handicapped and disabled people. The progress in developing BCIs is providing a lot of hope for this community, especially for those without muscular capability. What is remarkable concerning the BCIs is that most applications dedicated to medical applications can involve the user at the same time as a commander and as a subject.

After a training period, the user can learn how to generate commands by thoughts, to control and activate prosthesis members or his own body parts such as paralyzed members (Baniqued et al., 2021; Mane et al., 2020). **Figure 9** present an operator wearing a BCI for controlling a mechanical system.

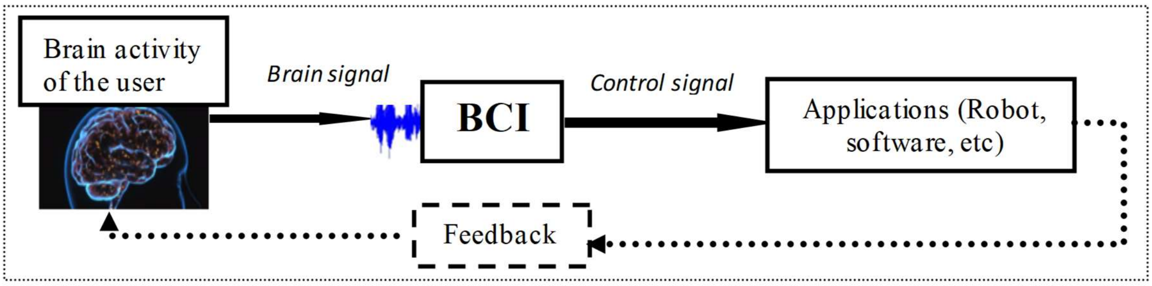

Figure 7. BCI interfacing brain activity to systems

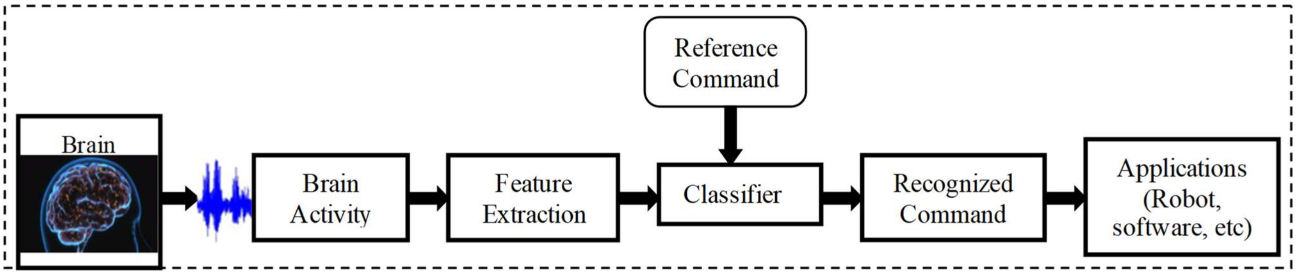

Figure 8. Global organization of BCIs

Figure 9. Operation with BCI commanding a mechanical system

BRIEF SUMMARY ABOUT AI AND HRI

Since the emergence of the first theories and approaches of AI, there was a hope to infuse these techniques in particular to robots for improving their adaptivity and smartness. The flow of techniques provided by AI such as symbolic computations, genetic algorithms, neural nets, fuzzy logic, and machine learning, has served and still serves to attempting to solve and overcome many issues that limit robotic applications. Actually, AI has fed robots by numerous capabilities with more or less satisfying success. Some remarkable fields are speech understanding, object recognition based on vision, autonomous navigation, manipulation tasks, interactions with humans and other entities, cooperation, and so on (Perez et al., 2018; Semeraro et al., 2021).

But following the increasing complexity of robotic systems designed to autonomously perform tasks and missions in various environments; specific control architectures for intelligent systems requiring high level flexibility and adaptivity was proposed and implemented. One popular example of such architecture is the three layered one which combines reflexive and reactive behaviors as well as deliberative capabilities (Arkin, 1998, p. 199; R. Brooks, 1986; S. Garcıa et al., 2018).

However, concerning the contribution of AI to the particular domain of HRI, some authors have analyzed and discussed many relevant applications, challenging issues and potential promising perspectives (Feil-Seifer and Mataric, 2009; Lemaignan et al., 2017; Semeraro et al., 2021; Sheridan, 2016). In fact, the most challenging goal for AI related to HRI is still how to design robots that can understand and interpret human behaviors and intentions in dynamic and possibly unpredicted situations in order to take appropriate decisions?

To this end, continuous efforts are spent on researching techniques and designing join cognitive architectures to improve HRI by trying to allow robots gaining more knowledge and autonomous development as human beings do. Efforts are oriented to developing robot mechanisms to enable developmental learning and capability for acquiring skills (Lemaignan et al., 2017; Nicolescu and Mataric, 2005; Semeraro et al., 2021). Beside supervised and unsupervised learning, reinforcement learning, deep learning; developmental autonomous learning is a very important and challenging approach. It is a kind of a self-learning competence where the robot attempt to acquire knowledge and skills by continuous observation and imitation of people and other intelligent systems. As with humans, it requires observing events and situations, classifying and organizing them, extracting relevant features and inferring rules and understanding situations and partner's intentions (Arents and Greitans, 2022; Nicolescu and Mataric, 2005).

Among the issues and perspectives is the need to make more natural the interaction and the understanding between humans and robots as between humans themselves. This request constitutes also one main objective of the 4th industrial generation which intends to establish natural cooperation and collaboration between humans and smart robots named sometimes "cobots" in order to achieve common tasks and missions (Arents and Greitans, 2022; Chakraborti et al., 2017; Javaid and Khan, 2021; Zamalloa et al., 2017).

Moreover, the actual and futurist development of different kind of intelligent robots and their various possible interactions with humans is pressing towards a homogeneous representation of Human-Robot control architectures. There is a serious need to develop a unified control architecture for HRIS that elevates the cognitive competencies of the robots to approximate the level of humans and eliminates therefore the distinction between humans and artificial intelligent systems when working together as team members (Harriott and Adams, 2013; Krämer et al., 2012; Zaatri, 2021).

CONCLUSION

This paper has briefly described the most command modes involved in HRIS. This includes the traditional interaction and command modes which are namely tele-manipulation, off-line robot computer programming and learning by demonstration (lead-through and teach pendant). It then introduces the modes which have been fostered later on by the conjunction of robotics with the emergence of artificial intelligence techniques and the provision of powerful computing machines. The following modes were considered: interactive commands based on GUI, voice-based commands, pointing on image-based commands, gesture-based commands, and finally brain-based commands. In addition, some relevant and challenging issues corresponding to some command modes have been briefly discussed.

One can notice that the generation of robot commands follows almost the same process: detecting the intended command signal generated by the operator by means of specific sensors; then analyzing and identifying this command w.r.t a dictionary; and finally ordering the robot to executing this command. The constitution of the dictionary that contains the references are usually constituted through a learning process.

Its perspectives on the short and mean terms, there is a need to improve the command modes to make them more flexible and user friendly. These modes can also be combined under a multimodal operator interface to provide more flexible interaction and control of robots. There is also a need to use techniques of artificial intelligence to enable a human-robot cooperation and coordination as partners. On the other hand, BCI is taking more attention for the capability it offers to controlling virtual as well as real dynamic systems. Probably, the most important domain in the near future is the applications of BCI in order to help handicapped and disabled people using their paralyzed limbs, wheelchairs, prosthesis, and service robots.

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