Control Strategies and Artificial Intelligence in Rehabilitation Robotics

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■ *Rehabilitation robots physically support and guide a patient's limb during motor therapy, but require sophisticated control algorithms and artificial intelligence to do so. This article provides an overview of the state of the art in this area. It begins with the dominant paradigm of assistive control, from impedance-based cooperative controller through electromyography and intention estimation. It then covers challenge-based algorithms, which provide more difficult and complex tasks for the patient to perform through resistive control and error augmentation. Furthermore, it describes exercise adaptation algorithms that change the overall exercise intensity based on the patient's performance or physiological responses, as well as socially assistive robots that provide only verbal and visual guidance. The article concludes with a discussion of the current challenges in rehabilitation robot software: evaluating existing control strategies in a clinical setting as well as increasing the robot's autonomy using entirely new artificial intelligence techniques.*

As robotics moved from industrial to service applications, engineers began looking for new tasks that could be automated with robots. Industrial tasks had been a perfect candidate for automation since they are physically exhausting and require high precision. Motor rehabilitation seemed like a similarly appropriate robotics application. In the course of rehabilitation, the patient must exercise by performing limb motions thousands of times, and the therapist must physically support and guide the patient's limb during these motions. Since therapists inevitably get exhausted, a rehabilitation robot could support and guide the limb instead.

Numerous rehabilitation robots have been designed for both the upper (figure 1) and lower limbs (figure 2). The two most famous arm rehabilitation robots are the MIT-MANUS, now sold as the InMotion ARM (Interactive Motion Technologies, USA) and the ARMin, now sold as the ArmeoPower

 ISSN 0738-4602

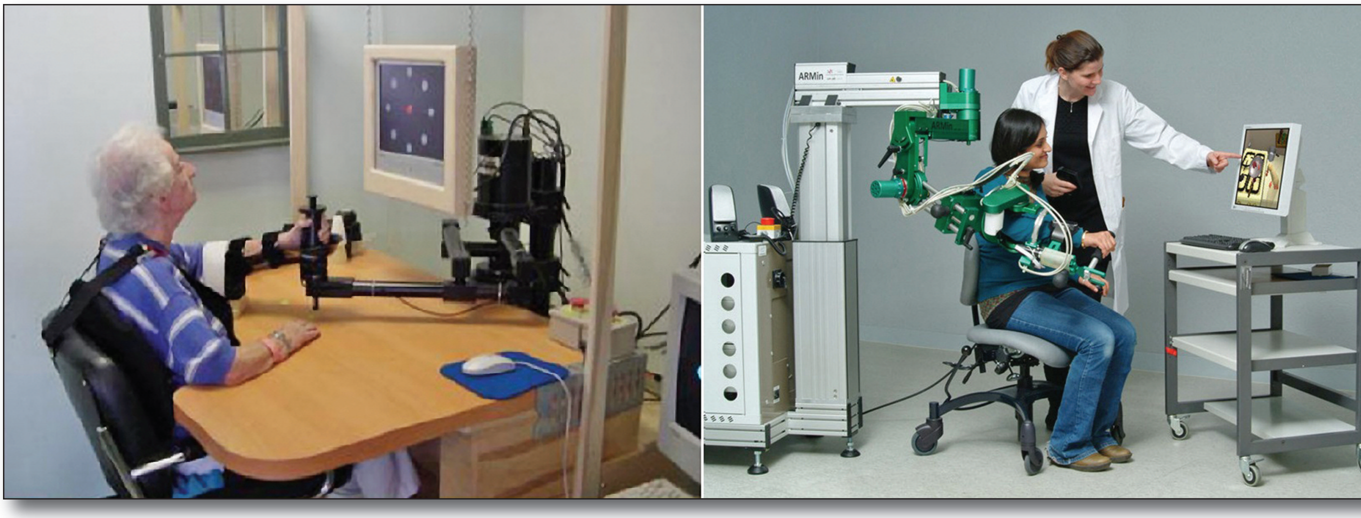

Figure 1. The MIT-MANUS and the ARMin.

MIT-MANUS (left); ARMin (right). MIT-MANUS photo courtesy of H. I. Krebs, Massachusetts Institute of Technology.

(Hocoma AG, Switzerland). The most famous leg rehabilitation robot is the commercially available Lokomat (Hocoma AG, Switzerland), with another notable example being the Gait Trainer (Reha-Stim, Germany). All of these, and many other robots, were developed in order to support and guide the patient's limbs. However, appropriate hardware is not enough; both therapists and robots need to intelligently adapt their support to ensure proper exercise. Mistakes should be corrected, but the patient should exercise actively and intensely, so the support should not be excessive.

The first rehabilitation robot controllers did not adapt their support to the patient at all. They were very stiff, and essentially guided the patient's limbs along a predefined trajectory with little care for what the patient was doing or wanted to do. Clinical tests found that patients put significantly less effort into robot-aided exercise with such controllers than into therapist-aided exercise, and frequently just let the robot move their passive limbs without actively participating in the motion (Israel et al. 2006, Ziherl et al. 2010). This "slacking" process leads to slower neuromotor recovery (Casadio and Sanguineti 2012). To avoid it, the robot needs to adopt a control strategy that assists the patient only as needed: a cooperative control strategy.

Help Me Help You: Cooperative Assistive Control

Assistive controllers are the dominant control paradigm in rehabilitation robotics, and are used in the majority of commercial systems. They operate on the level of the individual motion, helping the patient complete a motion within a desired time while correcting any major errors (such as large deviations from an optimal trajectory). The main characteristic of modern assistive controllers is that they only help as much as it is necessary for the patient to complete a motion, an approach called patient-cooperative control (Riener et al. 2005). This is similar to the work of therapists in rehabilitation: they manually move the patient's limb to accomplish a desired motion, but let the patient move on his or her own whenever possible.

As summarized by Marchal-Crespo and Reinkensmeyer (2009), many rationales have been given for such assistive controllers. Aside from allowing patients to perform more movements in a shorter amount of time, they interleave active effort by the participant with stretching of the muscles and connective tissue, they provide novel somatosensory stimulation that helps induce brain plasticity, and they may help teach patients to perform demonstrated patterns. Although most of these rationales have not been extensively clinically verified (Marchal-Crespo and Reinkensmeyer 2009), assistive control algorithms remain dominant, particularly impedance-based control.

Impedance-Based Assistance

The cooperative principle of impedance-based controllers is as follows: while a patient is moving along a desired trajectory, the robot does not intervene, but it corrects deviations from this trajectory by applying a force to the patient's limb. This correcting force is generated with a mechanical impedance. The first, simplest controllers provided proportional position feedback: as the patient's limb moves farther from the

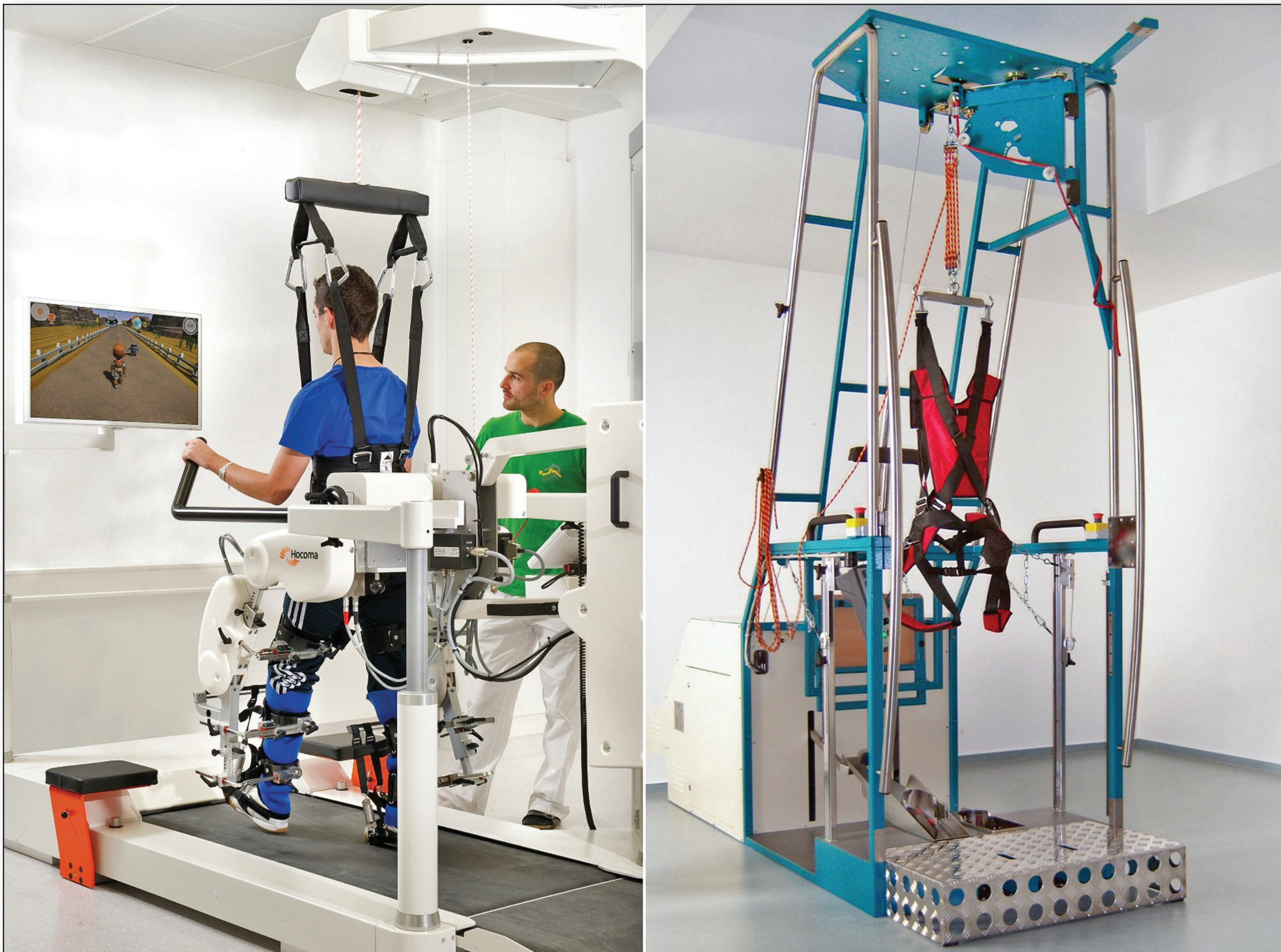

Figure 2. Lokomat and Gait Trainer.

The Lokomat (left) and Gait Trainer (right) leg rehabilitation robots. Photos courtesy of Hocoma AG, Switzerland, and Reha-Stim, Germany.

desired trajectory, the robot applies a proportionally stronger force to the limb. Such force feedback is often combined with visual feedback that informs the patient how he/she should move instead. This generally also requires a deadband around the trajectory so that the patient can make small deviations without being disturbed. The end effect feels somewhat like a tunnel that the patient needs to follow. An additional assistive force, sometimes dubbed a "moving wall" or "flow force," can push the patient along the trajectory if he/she is too slow (relative to a desired velocity profile), providing another type of assist-as-needed control. An example of such assist-as-needed control is shown in figure 3 for arm rehabilitation.

A major problem with such reference trajectories is that they are difficult to adapt to an individual patient. Several algorithms have been developed to adapt reference trajectories automatically (Jezernik, Colombo, and Morari 2004) or to make the trajectories of certain limb joints more compliant than those of other joints (Stauffer et al. 2009). Furthermore, alternative impedance-generation techniques have been investigated, such as virtual objects (Ekkelenkamp et al. 2007). These are shapes generated by the robot's haptic interface; if the patient attempts to move a limb into the physical space where the virtual object is, the haptic interface will push the limb back, creating the illusion of an object. Such virtual objects can thus physically support the patient in reaching a goal.

Movements in rehabilitation should also be self-initiated for better motor learning (Lotze et al. 2003). Many impedance controllers, therefore, employ triggered assistance: the robot is entirely passive until the

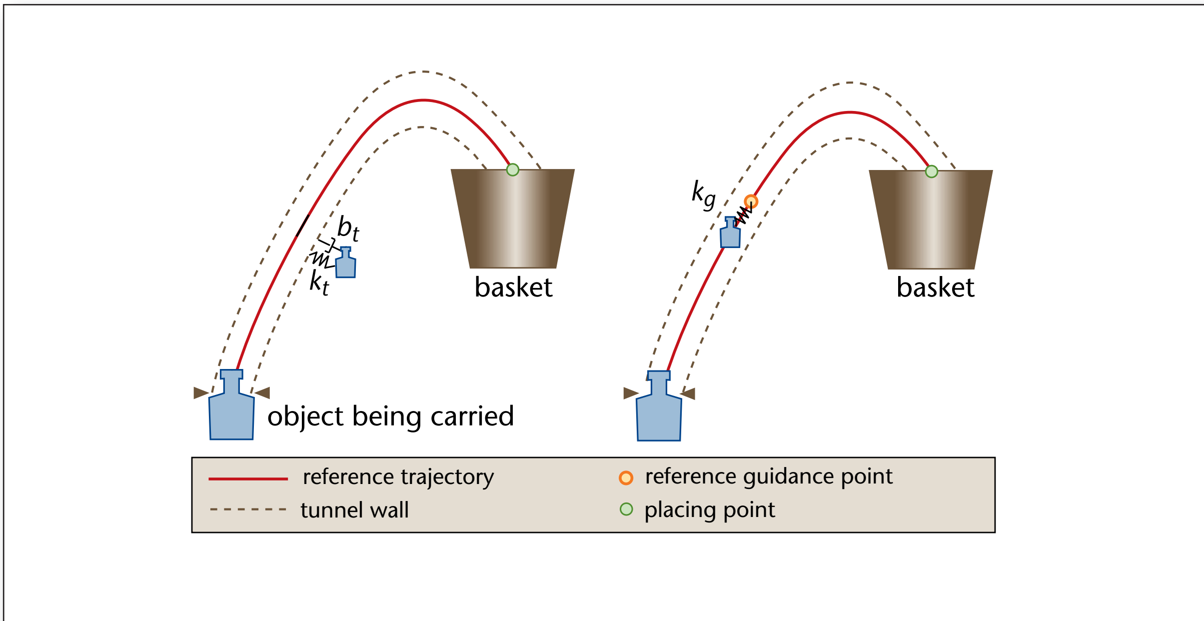

Figure 3. The Virtual Tunnel and Moving Wall in an Arm Reaching Task.

A spring-damper system prevents the patient from deviating from the reference trajectory (left) while a second spring-damper system (right) leads the patient along the trajectory (adapted from Mihelj et al. [2012]).

patient has started moving the limb. Once a motion has begun, the robot uses an assistive force and pushes the patient's limb toward the desired position, but only if the patient is not moving sufficiently quickly or smoothly on his/her own. If the patient's own movement is adequate, the robot becomes passive again. A more complex possibility is the assist-as-needed paradigm where the assistance parameters (for example, robot stiffness, assistive force gain) are adapted over a continuous interval based on recent motor performance (Wolbrecht et al. 2008). When performance is high, assistance is gradually decreased due to a forgetting factor in the control algorithm. Such assist-as-needed control has been found to significantly improve motor recovery compared to classic impedance-based control (Cai et al. 2006) or conventional therapy (Reinkensmeyer et al. 2012).

Electromyography-Based Assistance

Surface electromyography (EMG) is the measurement of a muscle's electrical activity from the surface of the limb. By measuring the activation of different muscles, a robot could provide precise assistance to different parts of the limb. The first implementation was EMG-triggered assistance, where the robot begins providing assistance once sufficient EMG activity is detected (Krebs et al. 2003). A more advanced cooperative control approach is to augment the activity of individual muscles: for example, have an exoskeletal robot apply torque to a joint proportionally to the EMG of the muscle used to control the corresponding joint of the human limb (Song et al. 2008, Stein et al. 2007). This avoids the problem of reference trajectories, which are difficult to adapt to an individual patient and may thus constrain him/her: since EMG-based assistance augments the patient's own movements, it does not provide any constraints.

This lack of constraints, however, presents a different weakness. Patients in motor rehabilitation do not only exhibit voluntary motions, but also pathological movements such as tremor and spasms. Pathological EMG is not easily separated from voluntary EMG, leading to potential augmentation of pathological motions. For this reason, some authors have suggested that EMG may not be a suitable control signal with patient populations such as stroke (Cesqui et al. 2013). Other studies, however, have demonstrated significant benefits of training with EMG-controlled robots (Song et al. 2013). It is likely that the use of EMG in rehabilitation is appropriate for some pathologies and muscles but not others, and this should be investigated further.

Assistance Based on Other Information

Impedance-based controllers provide assistive forces based on motion of the impaired limb while EMG-based controllers provide them based on muscle activity on the impaired limb. However, assistance

Figure 4. Bimanual Training with the HapticMaster Robot.

Photo courtesy of Matic Trlep, University of Ljubljana.

can also be provided based on information from other parts of the body: the motion of the unimpaired limb, the eyes, and even brain activity related to movement. The exploitation of this information is sometimes referred to as intention detection, though the term remains contested. It remains largely experimental, but has great potential for future rehabilitation robots.

Complementary Limb Motion Estimation

Complementary limb motion estimation (Vallery et al. 2009) is an approach mainly used for the lower limbs. Essentially, since human gait is a coordinated cyclic process, it should be possible to predict the motion of one leg based on the motion of the other leg. If only one leg is impaired due to hemiparesis, the healthy motion pattern for the impaired leg could also be extracted from the motion of the unimpaired leg, and a rehabilitation robot can then provide impedance-based assistance based on this estimated healthy pattern.

In principle, since the entire body is coordinated during gait, the motion of the rest of the body can also be used to more accurately generate a motion pattern for the impaired leg. A recent study has thus

Figure 5. EEG Combined with the ARMin Rehabilitation Exoskeleton.

Photo from the authors' joint research with José del R. Millán and Tom Carlson, Ecole Polytechnique Federale de Lausanne, Switzerland.

used sensors embedded in a walking cane to control a mobile leg exoskeleton with such complementary motion estimation (Hassan et al. 2014).

Bimanual Training

The motion of both arms is generally not as coordinated as the motion of the legs during gait, so complementary limb motion estimation cannot be directly transferred to the arms. However, if both arms are used to manipulate the same object (for example, lift a box or turn a steering wheel — figure 4), the motion again becomes coordinated. In such bimanual training, it is then possible to apply cooperative control by measuring the forces applied to the object by the unimpaired arm and replicating them on the impaired side using a rehabilitation robot (Lum et al. 2006). The gains achieved in such bimanual training have been shown to transfer to other, unimanual motions, though at least some motion of the impaired arm is necessary for training (Trlep, Mihelj, and Munih 2012).

Electroencephalography

If the patient's arm is completely paralyzed, there is no way to perform cooperative control using motion measurements. While the robot could simply move the patient's arm to achieve some passive exercise, this does not achieve efficient motor learning; it would be much better to perform self-initiated movements. Luckily, even completely paralyzed patients can think about moving their arm, even if no motion is achieved. If we can detect these thoughts, we can trigger the robot to move in response, achieving self-initiated exercise.

While reading thoughts may sound like science fiction, brain activity can be noninvasively measured using electroencephalography (EEG): measurements of the brain's electrical activity along the scalp. Since it is known which regions of the brain are responsible for motor planning, increased EEG activity in these regions would indicate that the patient wants to perform a motion even if he/she is completely paralyzed. While EEG does not allow precise motor intentions to be identified, it has been used to provide triggered assistance: once the rehabilitation robot detects increased EEG activity, it activates assistance along a predefined trajectory. An example photo of EEG in an arm exoskeleton is shown in figure 5. Such EEG-triggered assistance has actually been shown to lead to significantly better rehabilitation outcome than equivalent amounts of robotic assistance applied at random times (Ramos-Murguialday et al. 2013).

Advanced prototypes of rehabilitation exoskeletons have combined EEG triggers with additional sensors that indicate the type of motion to be performed. For example, the approach of Frisoli et al. (2012) uses an eye tracker to measure what object the patient is looking at. Once increased EEG activity is detected, the robot begins assisting a movement toward that object. However, the use of EEG has met with some skepticism in the rehabilitation community due to a relatively long setup time and perceived unreliability of brain activity measurements, and more studies are needed to show that the clinical usefulness of EEG outweighs its drawbacks.

Challenge-Based Control

Assistive control algorithms have been criticized by studies that suggest that physically guiding the motion during a task can actually reduce motor learning, a phenomenon referred to as the guidance hypothesis (Marchal-Crespo and Reinkensmeyer 2008). While severely impaired patients definitely require physical guidance, patients with a lower level of impairment may benefit more from control algorithms that provide a greater challenge, forcing patients to adapt to more and more complex situations. This is similar to training in sports: while beginners need to be shown how to perform basic moves, experts improve by overcoming increasingly challenging opponents and obstacles. This has led to the development of alternative control algorithms where the robot challenges rather than assists the patient.

Vive la résistance: Resistive Control

Resistive control algorithms, as the name suggests, generate forces that constantly resist any movements that patients try to make, forcing them to apply a larger force in order to perform the motion. In sports, an analogous approach would be weight lifting: the weights generate a resistive force. Such resistive training has been proposed for a variety of arm and leg rehabilitation robots (Lam et al. 2008, Lambercy et al. 2007), but until recently did not achieve widespread use in commercial robots. However, this is likely to change, as a recent multicenter clinical study (Klamroth-Marganska et al. 2014) has shown that better strength training is sorely needed in arm rehabilitation robots — a perfect opportunity for resistive control.

It's Not A Bug, It's A Feature: Error Augmentation

Unlike resistive control, which aims to improve strength, error augmentation aims to improve coordination and precision. It does this by identifying and magnifying the subject's deviations from a desired movement trajectory. This can be done by having the robot push the patient with a disturbing rather than assistive force, requiring him/her to overcome the disturbances to achieve the goal (Patton et al. 2006). Alternatively, the visual feedback given to the patient can be distorted by, for example, introducing a rotation between physically performed and visually displayed movements (Patton et al. 2013). This forces the patient to learn the mapping between physical and displayed movements by trial and error.

Error augmentation and visual distortions in particular may seem counterintuitive at first, as it is not immediately obvious how forcing patients to overcome such additional challenges is helpful for rehabilitation. However, error-driven learning has been emphasized as crucial to learning skills in human motion. Furthermore, a similar principle of error-driven learning is seen in artificial learning systems such as neural networks. Studies with healthy subjects have indeed shown that error augmentation leads to better, more robust movement patterns than assistive control (Patton et al. 2006). Improved coordination has been shown to persist even when the error augmentation is removed.

Until quite recently, most error augmentation studies had been done with healthy subjects or in a single session, limiting their acceptance in therapy. Now that multisession studies with patients have confirmed the usefulness of error augmentation (Abdollahi et al. 2014), it is likely to become a standard feature of the next generation of commercial rehabilitation robots.

On a Higher Level: Exercise Adaptation

The controllers in the Cooperative Assistive Control and the Challenge-Based Control sections work on the level of each individual motion, changing their assistance or challenges during the motion based on how well the patient is performing at that moment. But we can go a step farther and adapt the difficulty of the overall exercise depending on how well the patient has been doing over the course of the exercise.

Performance-Based Adaptation

The principle of performance-based exercise adaptation is simple: if the patient is performing well with respect to a certain performance criterion, make the exercise harder to perform by increasing the motion complexity, required range of motion, required velocity, and so on. Conversely, if the patient is largely unsuccessful at achieving motions, make the exercise easier by decreasing the above parameters. This should ideally ensure an appropriate moderate challenge for patients and increase their motivation to exercise. An early implementation was demonstrated by Colombo et al. (2007), and increasingly more complex strategies were proposed later (Cameirão et al. 2010; Chemuturi, Amirabdollahian, and Dautenhahn 2013). However, most of these strategies have only been tested over a single session; for the greatest benefit, they should be able to guide the patient over multiple sessions, gradually shaping therapy.

A new, interesting challenge for performance-based exercise adaptation has recently arisen in the form of multipatient exercise games where patients compete or cooperate with each other in order to achieve a goal (Novak et al. 2014). The exercise parameters must then be adapted to suit each exercising patient even though different patients may have different needs. Several adaptation algorithms have been suggested for such games (Caurin et al. 2011, Maier et al. 2014), but are so far relatively basic and have seen very little testing with patients.

Blood, Sweat, and Tears: Biocooperative Control

Just because a patient is successfully performing the exercise does not mean that exercise difficulty should be increased; he/she may be already overloaded and struggling just to keep up. Alternatively, a patient who is failing at the exercise may be enjoying the challenge and could get annoyed if difficulty were decreased. To obtain additional subject-specific information, we can measure the patient's physiological responses such as heart rate and skin conductance, which reflect both physical and mental workload. The use of such measurements in rehabilitation robotics is known as biocooperative control.

Physiological responses can be directly fed into a controller that adapts exercise parameters to, for example, keep heart rate close to a desired value (Koenig, Omlin, et al. 2011). Alternatively, machine-learning algorithms, such as neural networks or discriminant analysis, can be used to infer workload from multiple physiological responses and adapt the exercise difficulty accordingly. Such analysis of physiological responses has been shown to effectively complement performance measurements in both upper (Guerrero et al. 2013, Novak et al. 2011) and lower (Koenig, Novak, et al. 2011) extremity rehabilitation robots, though it is still unclear whether physiological measurements provide enough additional information to offset the sensor costs and additional preparation time.

Socially Assistive Rehabilitation Robots

Finally, an entirely different type of rehabilitation robot should be mentioned: those that do not physically support the patient, but instead demonstrate motions to be performed and provide simultaneous verbal guidance, acting as an exercise coach. These are relatively rare in motor rehabilitation and have mainly been studied by the group of Maja Mataric for healthy older adults (Fasola and Mataric 2012). They utilize artificial intelligence techniques that allow them to deliver appropriate verbal instructions at the right time as well as, for example, switch between different personalities — one patient may prefer caring gentle guidance while another may prefer a military drill instructor robot that brooks no argument (Tapus, Tapus, and Mataric 2008).

While socially assistive robots are unlikely to see broad use with populations such as stroke or spinal cord injury, where physical support is crucial, they have provided several lessons that also apply to motor rehabilitation robots, such as patients' subjective preferences for different types of guidance and encouragement. Researchers have now begun adapting elements of socially assistive robots for classic rehabilitation robots, creating robots that give verbal instructions as they provide impedance-based assistance (Mihelj et al. 2012).

Discussion

Large multicenter clinical studies of rehabilitation robots have shown that robots can deliver effective rehabilitation with several advantages over manually assisted therapy (Klamroth-Marganska et al. 2014, Lo et al. 2010). However, the biggest studies focused only on impedance-based assistance; other control strategies such as error augmentation have gained limited clinical acceptance and are rarely seen in commercial robots. One major challenge will be to determine how different control strategies can be combined over the course of rehabilitation. For example, it may be beneficial for patients to progress from assistive control to resistive control and error augmentation as their motor skills improve. As another example, some patients might benefit from EEG- or EMG-based assistance while others should avoid it entirely. However, these two examples remain educated guesses at the moment. A major step forward would be to create a set of guidelines (based on clinical evidence) for how different control strategies should be combined in order to achieve optimal rehabilitation outcome.

These guidelines may not be only used by therapists; they could be built into the rehabilitation robot itself to give it a greater level of autonomy. At the moment, it is always the therapist's task to adapt the exercise and switch between different control methods. In the future, the rehabilitation robot could perform such adaptation autonomously based on the patient's diagnosis, impairment level, and performance. The robot's autonomy could be further enhanced by teaching it to detect compensatory motions: motions where the patient, for example, compensates for the inability to lift the arm by lifting the shoulder instead (Cirstea and Levin 2000). Such motions must be corrected by therapists because they impede the recovery process, create additional health problems, and lead to permanent adoption of pathological movements. However, the artificial intelligence methods needed to detect and correct them are beyond the current generation of rehabilitation robots, and may also require additional sensors such as cameras.

A combination of autonomous exercise adaptation and detection of compensatory motions would enable rehabilitation robots to be more efficiently used in settings such as home exercise, where no therapist is present, or group exercise, where a single therapist supervises multiple patients and cannot fully focus his/her attention on one patient. While the robot will always lack a certain human aspect, elements of socially assistive robotics could partially compensate for this weakness, creating an intelligent and affable robotic therapist.

Conclusions

Several control strategies have been developed for rehabilitation robots, from very simple assistive control to complex error augmentation methods and task difficulty adaptation based on physiological responses. However, these strategies need to be further evaluated to determine how they can be most effectively used and combined in clinical practice. Furthermore, rehabilitation robots themselves need to be augmented with higher-level decision making so that they can operate more autonomously in home or group settings. In the future, this combination of new artificial intelligence methods and better knowledge of existing control strategies will increase the therapeutic advantage of rehabilitation robots and lead to their widespread adoption in many different settings.

Acknowledgments

This work was supported by the Swiss National Science Foundation through the National Centre of Competence in Research (NCCR) Robotics and by the Clinical Research Priority Program "NeuroRehab," University of Zurich.

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