The Role of Haptic Interactions with Robots for Promoting Motor Learning

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Abstract

Robot-assisted haptic training has the potential to facilitate motor learning and neurorehabilitation for a diverse number of motor tasks, ranging from manipulating objects with unknown dynamics to relearning walking using robotic exoskeletons. In this chapter, we provide an overview of current haptic methods evaluated in motor (re)learning studies with the goal to discuss implications for the design of rehabilitation technology. We highlight the challenge point framework as a unifying view on how to guide the design of haptic training paradigms, based on the initial skill level of the learner and the characteristics of the task to be learned. Future work on robot-aided haptic training strategies should focus on adaptive training algorithms, providing more naturalistic congruent multisensory feedback that resembles out-of-the-lab training, and conduct long-term studies to assess the efficacy of haptic training on learning not only the trained task but importantly, on skill transfer to real tasks.

Keywords

Motor learning · Neurorehabilitation · Robots · Haptic interfaces · Robot-assisted training · Augmented haptic feedback

12.1 Introduction

Humans go through a continuous process of acquiring new motor skills. Some skills are crucial to meet fundamental needs such as ambulation, nourishment, and self-care, and others involve more skilled movements that bring joy and sense to our lives, including playing sports, music, and dancing. We never stop learning new skills or brushing up on already gained skills. Despite their lower motor performance, elderly people still learn new motor skills [1] although at a slower rate [2, 3]. We might also encounter detrimental situations that demand us to relearn lost functions or learn other motor strategies to circumvent the loss of motor control through intensive neurorehabilitation, after suffering a brain injury. It is thought that motor learning and neurorehabilitation can be optimized by providing intensive meaningful movement training that

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promotes multi-sensory input to the central neural system (see Chap. 3). Given the impact on people's lives, topics of motor learning and relearning of lost functions, and specifically how robotics can be employed to stimulate neurorehabilitation, have been extensively studied—see reviews in [4–6].

The possibility of using robotics to stimulate neurorehabilitation and motor learning is attractive because robots can provide controllable, repeatable, and intensive training paradigms while ensuring patients' safety. Robots are generally used to assist the learner by physically guiding their limbs during movement training (haptic guidance) toward a physiological movement or task goal, thus alleviating physical strain on therapists/trainers. Alternatively, robots could also be used to challenge the learner (haptic disturbance) to improve their task performance, by for example stimulating the exploration of novel training environments or novel movement strategies [4]. In addition, robots can provide haptic feedback, combined with other sensory modalities such as auditory and visual feedback, to stimulate motor learning [4, 5, 7].

While evidence is accumulating that haptic training could benefit the motor recovery of stroke patients [8, 9], the efficacy of robot-aided motor (re)learning in particular for healthy or less-severely impaired persons is not fully established yet. Although haptic guidance is often used in motor training to provide the central nervous system with sensory input from physiological movements, there is currently little evidence that robotic guidance is more beneficial for human motor learning of healthy participants than unassisted practice [10, 11] or to a different form of guidance, such as auditory or visual feedback [4, 5]. Several studies have confirmed that only physically guiding movements to reduce performance errors does not aid motor learning and may, in fact, hamper it [12, 13]. Indeed, research in motor learning has stated that the learners' effort and performance errors are crucial elements to drive motor learning [14, 15] and neuroplasticity [16]. Therefore, new haptic training methods have been proposed that make motor tasks more challenging, suggesting that enhancing or inducing errors, rather than reducing them, could be beneficial to some learners [17, 18].

Although the effectiveness of haptic training methods has been investigated by a myriad of motor learning studies, results remain inconclusive. A potential rationale might be due to the diversity of the selected motor tasks to be learned, study protocol designs, selected haptic training methods, and the learners' skill/disability level across studies. In this chapter, we provide an overview of current haptic training strategies and their effect on an individual's motor learning. We end with the implications for robot-aided rehabilitation paradigms and possible research avenues.

12.2 Haptic Training Methods

Williams and Carnahan categorized the different haptic training methods into two main groups: performance-enhancing (haptic guidance) and performance-degrading (haptic disturbance) methods [11]. Performance-enhancing methods are commonly explored in robot-based therapy and encompass the haptic training methods that: (i) use a robotic device to **haptically demonstrate** the desired tasks' kinesthetic characteristics while the learner remains passive (e.g., [19]); (ii) provide **haptic cueing** through tactile actuators to signal the correct time to initiate an upcoming desired movement (e.g., [20]); (iii) use a robotic device to provide **haptic assistance** to guide a learner's movements while the learner actively executes the motor task (e.g., [21]); and (iv) promote a participant's motivation (e.g., [9, 22]). Haptic assistance methods are derived from traditional physical and occupational therapy, in which therapists manually apply physical assistance to aid patients in accomplishing their intended movements.

Several different robotic controller designs can be found in the literature to provide haptic assistance, depending on which task features the experimenter is interested to teach (e.g., spatial, temporal, and/or spatiotemporal features). Among the most used controllers, we find classical feedback controllers such as *proportional and/or derivative controllers* that apply forces depending on the difference between the desired and actual position and/or velocity of the limb [23–26]. *Path controllers* are used to restrict the limb's movement to an area around the desired trajectory by correcting the movement with forces that prohibit the limb to go outside of the predefined boundaries, providing safety while allowing for free movement [27, 28]. Other controllers apply a position-dependent velocity profile [29], enforce pre-recorded force profiles (*haptic guidance in force)* [30, 31], or match the frequency of a limb's motion with that of a robotic device [32].

While haptic guidance generally aims to reduce movement errors, research on motor learning has emphasized that errors are fundamental signals that drive motor adaptation [33, 34]. Robotic strategies that deteriorate the learners' performance during task execution are likely to increase effort, energy consumption, and attention [18, 19]. Thereby, researchers have proposed **haptic disturbance** methods that apply forces to degrade the performance during training rather than enhance performance (e.g., [14, 35]). One of the first haptic disturbance methods studied in literature aimed at amplifying the learners' movements errors while they were executing the task (*error augmentation)* by applying forces to push learners away from the desired movement trajectory [17, 36, 37]. Other approaches used *haptic resistance* to the participant's limb movements during exercise, or force fields that required specific patterns of force generation [38, 39].

Not only the magnitude of the movement errors but also the history of the experienced errors drive motor learning. Variability in task execution, often assessed as variability in experienced movement errors, has also been shown to predict motor learning in unassisted reaching movements. Participants with higher task-relevant motor variability improve faster their task performance compared to participants with lower motor variability [40]. Motor variability is believed to originate from noise in our motor system, in which a distinction is made between *planning noise*, originating in the brain, and *execution noise*, emerging from the periphery (e.g., muscle activation noise, noise in neuronal transmission) [41]. Higher planning noise results in higher learning rates, while execution noise reduces learning rates; humans seem to optimally tune their learning rate to the planning and execution noise [42]. Yet, the causality of motor variability and motor learning still has to be fully established.

Importantly, it is not well understood how motor variability, particularly motor variability stemming from planning noise, can be successfully stimulated by externally applying haptic forces. Some studies applied unexpected disturbing forces (*haptic noise*) during training [18, 35]. Other approaches aimed to hinder the participants' natural motor variability as little as possible while still providing assistive forces when needed (minimal intervention), for example through using model predictive controllers [21].

In the majority of the aforementioned haptic training strategies, the controller parameters do not change during training (referred to as *fixed guidance/disturbance*). Fixed haptic training strategies often rely on manual tuning by a therapist or teacher to adjust the haptic assistance/resistance to account for interpersonal differences in skill and progress. Moreover, a learner's performance and learning state evolve over time, warranting training strategies that adapt accordingly. A learner might initially benefit from haptic assistance that ensures movement with safety boundaries while exploring the task, and haptic disturbances to improve performance in later learning stages. This modulation can be achieved by adapting the controller's parameters (e.g., the impedance) or applied haptic forces based on the online measurement of the learner's performance (*performance-based adaptive haptic training*) [43–45]. Controller parameters can also be modulated based on the progression of the training, independent of the learner's performance [28, 46, 47].

12.3 Assessing Motor Learning

Motor learning refers to permanent changes in performance in a motor task, together with a reduction of physical and mental effort, as a result of training [48]. Because the general aim of haptic training is to enhance a learner's performance in the long term, the evaluation of their learning progress should only be performed by assessing the learners' performance before (*baseline*) and after (*retention*) the haptic training, when no assistance or resistance from the robot is applied. As a general guideline, retention tests should be performed at least 24 h after training to ensure the memory consolidation of the acquired skill, i.e., to assess long-term learning [11, 49–51]. Retention tests performed right after the training only assess short-term learning.

As important as getting skilled in the trained task is to transfer the acquired skill to untrained altered versions of the trained motor task (*generalization*). This is especially important in neurorehabilitation, in which acquired or recovered skills and functionalities during robotic rehabilitation are desired to be transferred to better function of activities of daily living, beyond the tasks trained during the rehabilitation sessions (e.g., [52]). Despite the importance of skill transfer in motor learning, only a few studies on haptic training methods have evaluated long-term skill transfer using a modified albeit similar version of the trained tasks [18, 32, 53], and even fewer studies assessed the skill generalization to real-life tasks [54, 55].

Different outcome metrics can be selected to evaluate motor learning depending on the movement aspects to be mastered. Performance metrics can be based on deviation from the desired movement path (**spatial** aspect, e.g., in [56]), the timing of an action (**temporal** aspects, e.g., in [57]), or a combination of temporal and spatial aspects, such as velocity error or movement smoothness (**spatiotemporal** aspects, e.g., in [31, 58]).

A common approach to quantify learning is by comparing average task performance before and after training. However, depending on the task, average task performance can be similar between highly skilled and lowly skilled learners. Task performance variability—e.g., the standard deviation of movement errors with respect to a movement goal at the beginning of a training period and at the end of a training period—could then be indicative of motor learning. Highly skilled learners often show lower task performance variability compared to higher task variability in lower-skilled learners, e.g., in [26, 59, 60].

The listed haptic training strategies might have contrasting effects on the learning of different movement aspects. For example, several studies have shown the benefit of haptic guidance in learning to reproduce the temporal—but not the spatial—characteristics of complex spatiotemporal curves [24, 61]. Schmidt et al. also highlight the importance of measuring physical and mental effort [48], as less physical and mental effort are expected in the final stages of motor learning [62]. However, measurements of physical and mental effort are hardly conducted in motor learning experiments, probably because the objective measurement of physical effort (e.g., using electromyography [19]) and mental effort (e.g., brain activation [63]) is cumbersome.

Along with mental effort, there are other relevant psychological factors that might have an effect on motor learning. The OPTIMAL theory states that trainees' motivation and attention enhance motor learning, possibly due to the release of dopamine [64]. Motivation has been shown to have both indirect (e.g., by increasing the number of movement repetitions) and direct (e.g., improving memory consolidation) positive effects on learning [9, 65]. Other psychological factors, such as the sense of agency—i.e., the feeling of being in control over our own movements [66], or personality traits are less studied in the motor learning literature, yet might play an important role in motor learning [21, 67].

12.4 Current Evidence of the Effectiveness of Haptic Methods on Motor (Re) Learning

Several factors might play a role in the effectiveness of robot-based training, making it challenging to compare the results from studies in which similar haptic training methods were employed for different tasks or different strategies for similar tasks. It is generally accepted that the learner's initial skill level might play a crucial role in the effectiveness of robotic training methods [4]. This finding is in line with the **challenge point framework**, which states that motor learning is enhanced when the difficulty of the motor task to be learned is matched with the learner's skill level (Fig. 12.1) [68]. Skill is defined as the ability to perform a task "*with maximum certainty and minimum outlay of energy, or of time and energy*", which progresses as a result of task practice [69, 70]. This learning progression has been proposed to follow three stages: a first cognitive stage (novice), a motor/associative stage (advanced), and a final autonomous stage (expert) [62]. The majority of studies on robot-aided motor learning have been conducted with novice learners during the cognitive stage, while the number of studies on advanced learners and experts is scarce [4].

Although task difficulty has been studied in a large number of motor learning studies (e.g., [71, 72]), a definition of the term has not yet been explicitly stated. Instead, three different but interconnected concepts are employed when talking about task difficulty: nominal task difficulty, functional task difficulty, and conditional task difficulty.

Nominal task difficulty can be defined as the objective and inherent challenge of the task to be learned due to the task's spatial, temporal, and spatiotemporal performance requirements regardless of the differences between learners' initial skill levels. In their recent review [4], Basalp et al. proposed a task classification taxonomy—an extension of the motor task organization introduced by Schmidt and Wrisberg in [70]—to categorize motor tasks depending on

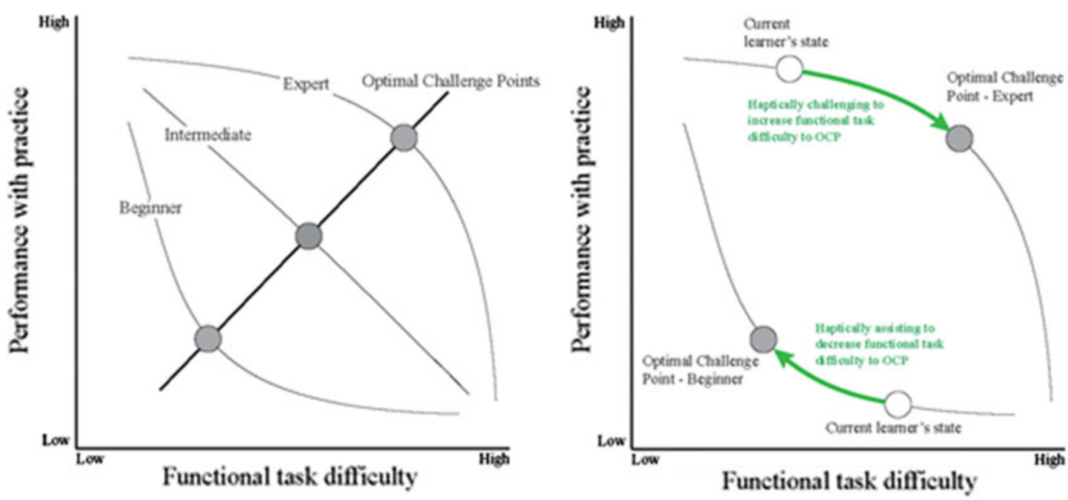

Fig. 12.1 Haptic training methods can help match the functional task difficulty to the learners' skill level. Left figure: schematic representation of the optimal challenge points (gray circles) in relation to the learner's skill level and functional task difficulty. According to the challenge point theory, motor learning is enhanced when the functional task difficulty is matched with the learner's skill level, defined as their optimal challenge points. Right figure: examples of how haptic training methods can help adapt the functional task difficulty through modulating the conditional task difficulty such that the optimal challenge point (OCP) for a certain skill level is reached. For example, beginners can benefit from haptic assistance to decrease the functional task difficulty, and experts can benefit from haptic methods that challenge the learner. Figures adapted from [68]

their continuity (discrete vs. continuous), rhythmicity (single execution vs. rhythmic), and complexity—related to several factors, e.g., demands on attention, memory, and/or processing capacity, or number of degrees of freedom, among others [7, 72]. Different motor task types, e.g., those that incorporate single task execution (e.g., pressing a key) versus rhythmic/repetitive motions (e.g., rowing or walking) have been shown to involve distinct control primitives/actions [73] and activate distinct brain areas [74]. Thus, haptic methods that support learning of one type of motor task might not be suitable to also support the learning of another task category [56, 75].

The **functional task difficulty** depends on the initial skill level of the learner. It is related to how challenging the execution of the task itself is perceived by the—novice, advanced, or expert—learners during training. Importantly, providing haptic guidance or disturbance during training may change the challenge presented to the learner by modulating the amount of task-relevant information conveyed by the haptic training strategy (Fig. 12.1), which is referred to as the **conditional task difficulty**. Robots can adapt the conditional task difficulty, for example by modulating the task environment—e.g., changing the simulated water density in a rowing task (e.g., [76])—or by haptically assisting/challenging the learners (e.g., [27]).

Current evidence supports the idea that the (lack of) effectiveness of state-of-the-art haptic methods can be explained by the challenge point framework. In particular, the effectiveness of haptic training seems to depend on: (1) the nominal task difficulty; (2) the task-relevant information conveyed by the haptic training method (conditional task difficulty); and (3) the initial skill level of the learner (functional task difficulty).

When learners face the training of tasks with low nominal difficulty, for example, simple motor tasks such as steering a virtual car without dynamics [35] or synchronizing between leg movements [19], it was observed that the learners' initial skill level was adequate to successfully learn the task. Thus, training with haptic methods did not promote motor learning in particularly simple tasks. Learning benefits of haptic methods over training without haptics were observed when learning tasks with higher nominal difficulty, e.g., steering nonholonomic vehicles [23, 28] and tracking of letters [31].

However, when haptic training was compared to training with other forms of feedback—e.g., *visual feedback* provided in virtual environments [47] or *terminal feedback* (i.e., knowledge of results and performance after the task is performed [5], no evident differences in motor learning were found between feedback modalities. Thus, for a general sample of healthy learners, providing task-relevant information (conditional task difficulty) by other sources of feedback (e.g., visual or auditory) might promote motor learning at the same level as haptic methods. Nevertheless, when other sources of feedback are not available and/or when the initial skill/disability level of the learners is too low to perform the task by themselves in a safe and motivating environment, the employment of haptic training might be effective to enhance learning.

Indeed, performance-enhancing haptic methods seem to be especially promising in promoting motor learning in initially less skilled (novice) healthy participants [57, 77], children [46, 78], and in brain-injured patients [9, 79]. Healthy novices seem to benefit from performance-enhancing haptic methods to learn the spatial (e.g., reducing the spatial error during path tracing tasks [39, 80]), temporal (e.g., timing turning in curves [23, 78]), and spatiotemporal aspects of the tasks (e.g., learning velocities [26]). This enhanced learning is probably due to the robotic assistance reducing the conditional task difficulty, and thereby, optimally challenging novices. The studies conducted with children, who usually adapt at slower rates [81], further support these findings [46]. Studies performed with neurologic patients seem to be in line with these findings, especially in the learning of the task's temporal aspects [9, 79].

Performance-degrading haptic methods, on the other hand, might provide a more optimal task challenge to advanced learners, by increasing the learner's effort and attention [18, 19] and by promoting the exploration of more advanced movements to achieve the task more efficiently [26]. Although only a few studies with rather small sample sizes have been conducted with advanced and expert learners, initial findings suggest that performance-degrading haptic methods are especially beneficial for learning spatial aspects of the tasks, but not temporal nor spatiotemporal aspects, in initially more skilled participants. The limited effectiveness of haptic disturbance methods to improve temporal and spatiotemporal aspects might be due to the design of these methods, as most error augmentation methods have been designed to only augment spatial errors [37, 55].

Haptic error augmentation and haptic noise increase movement variability and—although results are still inconclusive—could benefit advanced learners more than novices [18, 57]. Haptic error augmentation methods have also been found to be more effective than conventional repetitive training (e.g., [17, 82, 83]) and performance-enhancing haptic methods (e.g., [17, 84, 85]) for re-learning motor tasks' spatial aspects in neurologic patients. Yet, caution should be put when designing performance-degrading methods, as in some cases, the performance degradation might result in a decrease of the learners' perceived competence, hampering learners' motivation [26], and therefore, potentially hindering motor learning [64].

12.5 Implications for Rehabilitation Technology Design

12.5.1 The Personal and Temporal Nature of Motor Learning Highlights the Need for Adaptive Haptic Training Paradigms

As outlined earlier, current evidence highlights the essential role that the learner's initial skill level plays in the effectiveness of the different haptics methods on motor learning. As stated by the challenge point framework, motor learning can be maximized when the difficulty of the task to be learned matches the current learner's skill level [68]. Thus, adapting the haptic methods to adjust the task difficulty to match the learner's ongoing performance may have direct positive effects (i.e., by providing the optimal amount of information to enhance the performance and prevent slacking), and indirect effects (e.g., by enhancing learner's motivation and agency) on motor learning.

Although recent efforts have been made to develop adaptive algorithms (e.g., [43, 45, 86–88]), those have not yet been extensively investigated in motor learning studies. Most studies assess adaptive algorithms for haptic assistance over short time periods, ranging from hours to a few days, likely for practical reasons. Yet, learning is a long-term process that typically starts at a cognitive stage when the learner is still a novice and ends in an autonomous stage as a skillful performer or expert [62]. So, the requirements for haptic training paradigms depend on the learning stage over extended periods of time, in which the haptic training could be used to appropriately challenge the learners to promote their learning. Systematic studies showed that different learners need different types and levels of assistance, and adaptive paradigms need to appropriately account for these differences across individuals and time.

The majority of the adaptive haptic training paradigms focus on isolated aspects of motor learning, including cognitive and/or physical states, yet due to the interdependence of the factors governing motor learning, there is a need for holistic approaches that combine the insights gained in haptic training studies. Recent artificial intelligence (AI) approaches for therapy personalization have yielded promising results [89–91]; however, there are raising concerns about the interpretability and trustworthiness of opaque-box algorithms [92–94]. Furthermore, previous research only employed single metrics (i.e., single performance metrics, e.g., ongoing tracking error), which are, given the complexity of an individual's recovery process, inherently a poor descriptor of the overall patient characterization.

These limitations might be mitigated by developing novel therapist-in-the-loop personalization approaches that combine machine learning to learn and identify meaningful features that define the current cognitive and motor status of the patient from large amounts of high-dimensional data—e.g., biomechanical and physiological metrics—with the possibility to explicitly model the therapists' reasoning (e.g., using symbolic AI) to provide explainable, trustworthy, and interpretable therapy recommendations, such as the level of challenge for the learner, for example by adapting the task difficulty.

12.5.2 Appropriate Delivery of Task-Relevant Information Provided by Haptic Training Methods is Key to Enhance Motor Learning and Transfer

As (re)training functional motor tasks involves physical interaction with tangible objects, haptic training methods might impede motor learning if the haptic feedback hinders the learner's perception of task-relevant information. Such task-relevant information includes somatic (proprioceptive and tactile) information from the interaction with the environment (e.g., tangible objects) which is crucial for fine motor control [95, 96] and motor (re)learning [97–99].

The corrupted perception of task-relevant information during robotic training might be behind the observed (poor) transfer of learning from the virtual training environment to real-life tasks [7]. Current rehabilitation robotics does not support patients in regaining the functional movements needed to perform their activities of daily living and achieve their independence [100, 101]. Despite the crucial role that physiological sensory information plays in motor learning and neurorehabilitation (see Chap. 3), current haptic strategies rely on rather abstract visual feedback while meaningful somatic information from the interaction with virtual tangible objects/environments is neglected [98, 102]. Only a few studies have incorporated haptic rendering—i.e., the simulation of the interaction forces between humans and tangible virtual objects/environments—into motor learning studies [21, 56, 76, 99]. This is probably due to the limitations of the used robots, especially the bulky and heavy exoskeletons employed in clinical settings, as they suffer from low transparency, which limits their capability to haptically render these informative interaction forces.

The learners' perception of the haptic rendering might also be hampered because the forces from the haptic rendering and the assistive/resistive haptic forces are provided from the same actuators. Several efforts have been made to provide these different forces in a way that the interference is minimized. For example, Power and O'Malley evaluated the effect on motor learning of separating the assisting forces from the task rendered haptic forces (a spring-damper dynamic system) spatially (i.e., using different robotic devices), or temporally (i.e., by the sequential provision of the assisting and haptic rendering forces [56]). None of these strategies was found to be effective in learning the dynamic task, which the authors attributed to the difficulty to interpret the feedback designs. More recent attempts to disentangle the assistive from the haptic rendering forces include solutions that employ robots to provide the task-relevant kinesthetic haptic rendering, while assistive guidance is provided through cutaneous skin stretch devices [103].

It is also important to take into account whether the learner perceives the haptic training forces as intended. Several studies suggest that human force perception, both magnitude and direction, is impacted by uncertainty (random errors) and systematic errors (biases). Systematic errors in force magnitude perception often manifest in incorrect force reproductions: humans typically reproduce higher forces than the presented force, indicating that we overestimate externally applied forces, such as an interaction force [104–106]. For low force levels (<10 N), humans seem to rely more on position sensory feedback than on force sensory feedback [107]. In addition, humans are inaccurate in estimating the direction of an applied force [108] and reproducing the direction and magnitude of the applied force [109]. Hence, the question remains: how accurately the learner perceives and subsequently interprets the information provided by the haptic training forces, in particular when these forces can change in direction and magnitude quickly? Also, how should this knowledge be taken into account when designing haptic training methods?

Finally, the haptic training strategy may also alter the learners' perception of the intended goal of the task to be learned. For example, in a virtual tracking task, researchers found that participants trained with error amplification—with repulsive forces that systematically pushed them to the opposite direction of the correct movement—got used to their low performance instead of trying to improve their tracking skills [36]. In addition, when the assistive forces do not align with the learner's own goal or how to reach that goal, conflicts between the learner and robot controller can occur. Interaction conflicts can impact learning and can even lead to disuse of the haptic training [110]. Therefore, when designing haptic methods, the task goals should be clearly established, communicated, and reachable.

In short, the provision of more naturalistic congruent visuo-haptic feedback might grant a more optimal training environment that might promote motor learning, and importantly, the transfer of skills gained during robotic training to real-life activities [7, 111]. Besides providing more realistic interactions with tangible virtual objects [99], providing a more naturalistic visualization of the learners' movements within the virtual environment might enhance motor learning and transfer [7]. To this date, most motor learning studies have provided a rather abstract visualization of the performed movements on computer screens, televisions, or projection systems. The reduced depth cues provided by these displays and the visuospatial transformation from the movements performed in the three-dimensional space to their two-dimensional visualization on conventional screen are far from being natural, realistic, and might enhance the trainees' cognitive load, and thus, negatively impact learning [112]. New off-the-shelf virtual or augmented reality head-mounted displays offer the possibility to provide a more naturalistic virtual representation of the trainers' movements, for example by employing an avatar from a first-person perspective, that might reduce the cognitive load, enhance the sense of agency, and importantly, result in higher motivation [113].

12.5.3 Long-Term Effects and Generalization of Learning of Haptic Training Need More Attention

The primary goal of haptic training is to facilitate long-term learning and generalization of motor skills. However, most haptic training paradigms are only assessed on short-term learning with retention tests right after the training is finished, possibly under- or overestimating their benefits. Therefore, in future studies, researchers are encouraged to conduct long-term transfer tests, along with the delayed retention tests (at least 24 h after training is finished), for a more thorough investigation of the effectiveness of haptic training methods.

12.5.4 More Research is Needed to Understand How Haptic Trainings Could Modulate Motor Variability to Stimulate Motor Learning

Research on unassisted human motor learning found evidence that motor learning rate is positively correlated with the learner's motor variability [40], specifically the planning noise originating from the brain [42]. Some studies attempted to increase task-related motor variability through haptic forces (e.g., haptic noise or force disturbances) in order to modulate a learner's motor variability to subsequently stimulate learning [36, 114, 115]. However, it is unclear whether and how externally provided haptic forces can indeed modulate the learner's internal motor variability to facilitate learning through exploration, e.g., specifically their planning noise as hypothesized by researchers [41, 42]. Hence, despite the accumulating evidence of the impact of motor variability on motor learning in fundamental motor learning research, more research is needed before it can be used to inform the design of haptic training paradigms.

12.6 Conclusion

Current evidence from robot-aided motor (re) learning studies indicates that the effectiveness of the haptic training strategies on motor learning and neurorehabilitation could mainly be explained by the challenge point framework [68]. The functional task difficulty, nominal task difficulty, and conditional task difficulty play central roles in the effectiveness of robot-aided training. Performance-enhancing haptic training methods seem to be especially effective for novice learners and to train the temporal aspects of the task, while performance-degrading haptic methods might be more effective when training more skilled participants, especially in learning the spatial aspects of the tasks.

The findings from studies with brain-injured patients are in line with those from motor learning studies with healthy participants. This is an important observation, as the gained insights from past and future studies with healthy participants could be leveraged to improve current robotic-aided neurorehabilitation paradigms. Although haptic training was found to be as effective as training with other feedback modalities in healthy participants, brain-injured patients might still benefit from the robotic assistance when facing too difficult or frustrating tasks.

Based on the current evidence, we suggest that future research should focus on designing adaptive algorithms that can accommodate the learner's skill, progress level, and learning strategy by identifying and reducing hindrances that could impede learning, or by challenging more skilled learners. Finally, to enhance motor learning and the transfer of the gained skill during robot-aided training to real life, future research should focus on: (1) providing more naturalistic multisensory feedback that resembles out-of-the-lab training and (2) conducting long-term studies including transfer tests.

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