Tele-rehabilitation of Upper Extremity with GARMi Robot: Concept and Preliminary Results

Xiao Chen ∗ Hamid Sadeghian ∗ Yanan Li ** Sami Haddadin ∗

∗ Munich Institute of Robotics and Machine Intelligence, Technical University of Munich, 80992 Munich, Germany (e-mail: xiaoyu.chen@tum.de, hamid.sadeghian@tum.de, haddadin@tum.de).

** Department of Engineering and Design, University of Sussex, Brighton, United Kingdom, (e-mail: yl557@sussex.ac.uk)

Abstract: The discrepancy between the growing need for rehabilitation and the inadequate availability of facilities and skilled therapists is becoming increasingly conspicuous. To address this problem, a tele-rehabilitation system of the upper extremity with the service robot GARMi is proposed. The system utilizes optimal control and game theory, considering the patient, GARMi and possibly the therapist as the agents who share a common cost function. By adapting the roles of these agents, the proposed system can provide passive, active, and assist-as-needed rehabilitation.

Keywords: Active Rehabilitation, Optimal control, Impedance Control,

1. INTRODUCTION

Rebuilding muscle motor functionality for post-stroke patients can be effectively achieved through rehabilitation. Additionally, geriatric rehabilitation is gaining attention due to the global ageing population (Hoenig et al. (1997)). However, the rising demand for rehabilitation is met with shortages in therapy resources, particularly in rural areas. Patients also report a lack of opportunities to continue their recovery outside of therapy time (Tijsen et al. (2019)). In light of this, robots are poised to play a significant role in future rehabilitation, thanks to their ability to repeat motions and their increasing accessibility. Various robots and exoskeletons have already been developed for rehabilitation purposes (Krebs et al. (2004); Nef et al. (2007); Vitiello et al. (2012); Shen et al. (2019)).

According to patient engagement, rehabilitation is categorized as passive and active mode. The passive mode is used in the initial phase of rehabilitation, in which the impaired limb is totally unresponsive (Proietti et al. (2016)). As the functionality of the motor starts to recover, active participation of the patient leads to better outcomes (Lenze et al. (2004)). To encourage patients’ participation and improving exercise performance, several Assist-As-Needed (AAN) approaches have been already proposed. These algorithms generate robot control commands based on patients’ performance, such as deviation from reference trajectory (Zhang et al. (2020); Guan et al. (2018)) or patient’s joint stiffness (Perez-Ibarra et al. (2018)). Shahriari et al. (2019) used an energy tank to generate robot motion, and the maximum energy limit is adjusted according to the force and velocity applied by the subject. A PD controller with a dead-zone as a tunnel for patient motion freedom is proposed in the work of Asl et al. (2017), which also involves an adaptive feedforward neural network (NN) term to compensate for the unknown dynamics of the system.

In the rehabilitation scenario, the human and the robot can be considered as a two-agent system, which their effort can be resolved based on game theory (Neumann (1928)). Jarrassé et al. (2012) discussed the cost function representation of different types of interactions between two agents and their implementation. In our work, instead of considering the upper-limb rehabilitation as a cooperation task (Jarrassé et al. (2012)), we consider the rehabilitation as a collaboration task. This is because human and robot share the same goal, which is to accomplish the rehabilitation exercise and optimize the consumed energy. The continuous role adaption in a collaboration task between human and the robot using game theory is investigated in Li et al. (2015). Later, they propose a similar idea (Li et al. (2016)), in which the robot estimates the human’s intention and follows human motion. Recently, Pezeshki et al. (2023) proposed the interaction of human and robot in a rehabilitation scenario as a two-player non-zero-sum game. The AAN algorithm is achieved through an adaptive optimal control strategy where the human intention is incorporated in an optimal manner.

Different approaches in bilateral tele-rehabilitation has been presented in several studies to include a remotely located therapist into assistive or cooperative rehabilitation exercises (Johnson et al. (2008)). A nonlinear bilateral impedance controller has been proposed for cooperative tele-rehabilitation using two robot manipulators on both sides in Sharifi et al. (2017). In (Shahbazi et al. (2016), a framework is suggested for robot-assisted mirror rehabilitation, which incorporates adaptive assist-as-needed therapy and involves a therapist in the loop. With this approach, patients can utilize their functional limb to modify the intended trajectory produced by the therapist utilizing Guidance Virtual Fixtures (GVFs). The stability analysis of the bilateral system, in the presence of physical interaction and uncertainty in communication channel, has been extensively studied (Nuño et al. (2011)). The results can also be applied for tele-rehabilitation scenarios in which the therapist and the patient need to be in physical interaction through their interfaces. A passivity based approach has been proposed in (Atashzar et al. (2015)) to ensure safety of system subject to injecting energy from the therapist in assistive tele-rehabilitation.
In this paper, we follow an optimal control approach for a rehabilitation scenario, in which the robot can provide assistance while the patient is performing the exercise. The rehabilitation exercise is shared between different agents: patient, robot and possibly a remote therapist. The rehabilitation can be performed in passive or active mode. In the passive mode, the therapist design a customized trajectory based on the needs of the patient. This trajectory is then executed by the robot to guide the patient’s hand. The trajectory can be designed (for instance, by through dynamic movement primitives (DMP)) or modified online by a remote therapist through a teleoperation control interface (Fig. 1). Compared with the existing AAN approaches, the main features of the proposed approach are as follows: i) human motion target and weight of the task contribution can be simultaneously estimated, so the robot trajectory and the weight of task contribution can be correspondingly adapted; ii) it is straightforward to assign different roles to the involved agents, i.e., therapist, robot and the patient, according to the nature of a task.

The rest of this paper is organized as follows. A shared control algorithm is introduced in Section 2. Section 3 shows the evaluation of our approach in both simulation and experiment on a real robot. The discussion and conclusion with possible future work direction are finally given in Section 4 and Section 5.

2. SHARED CONTROL APPROACH

2.1 Problem Formulation

The robot dynamics in the Cartesian space with the coordinate $\mathbf{x} \in \mathbb{R}^m$, and in contact with human hand through the end-effector is given by

$$
\mathbf{M}_C(q)\ddot{\mathbf{x}} + \mathbf{C}_C(q, \dot{q})\dot{\mathbf{x}} + \mathbf{g}_C(q) = \mathbf{u}_c + \mathbf{f}_h \tag{1}
$$

where $\mathbf{M}_C$, $\mathbf{C}_C$ and $\mathbf{g}_C$ are the inertial matrix, Coriolis/centrifugal matrix and gravity vector in the Cartesian space, respectively. $\mathbf{u}_c$ and $\mathbf{f}_h$ are control command and human force in the Cartesian space which are related to the joint space variables through the Jacobian matrix $\mathbf{J}$ as $\mathbf{u}_c = \mathbf{J}^T \mathbf{u}_c$ and $\mathbf{r}_h = \mathbf{J}^T \mathbf{f}_h$.

The command $\mathbf{u}_c$ can be used to realize a desired impedance behavior with inertial matrix $\mathbf{M}_d \in \mathbb{R}^{m \times m}$ and damping matrix $\mathbf{C}_d \in \mathbb{R}^{m \times m}$, toward a desired trajectory $\mathbf{x}_{des}(t)$ as

$$
\mathbf{M}_d(\mathbf{x}_{des} - \mathbf{x}) + \mathbf{C}_d(\mathbf{x}_{des} - \mathbf{x}) = \mathbf{u}_c + \mathbf{f}_h \tag{2}
$$

with an intermediate control $\mathbf{u}$ which is further exploited to assist the patient. This dynamics is linear and thus the high level controller $\mathbf{u}_c$ needs the full model of the system as well as force/torque sensor in the task space (Sadeghian et al. (2013)). Moreover, the inertia of the system is now reshaped to a desired diagonal inertia $\mathbf{M}_d$. In this work, we assume that the human is in interaction through the end-effector and thus the human force $\mathbf{f}_h$ is the only measurable force at the end-effector.

2.2 Shared Control

In rehabilitation, the patient usually follows a certain motion to activate the muscle motors and prefers to minimize his/her metabolic energy in repeated motion. The robot control command consists of two parts, i.e. $\mathbf{u} = \mathbf{u}_l + \mathbf{u}_r$. The remote therapist station applies force $\mathbf{u}_r$ and it is directly transferred and applied through the torque interface of the robot. The next part denoted by $\mathbf{u}_l$ is the share of the local robot which is applied autonomously to assist the patient. Without loss of generality, let’s assume that the share of the remote station is zero and thus $\mathbf{u} = \mathbf{u}_l$. Let’s assume that human and robot have a common cost function

$$
J = \int_0^\infty \left( (\mathbf{x}_{des} - \mathbf{x})^T \mathbf{Q}_1 (\mathbf{x}_{des} - \mathbf{x}) + \mathbf{x}^T \mathbf{Q}_2 \mathbf{x} + \mathbf{u}^T \mathbf{R}_1 \mathbf{u} + \mathbf{f}_h^T \mathbf{R}_2 \mathbf{f}_h \right) dt \tag{3}
$$

where the weights $\mathbf{Q}_1, \mathbf{Q}_2 \in \mathbb{R}^{m \times m}$ are positive semi-definite and $\mathbf{R}_1, \mathbf{R}_2 \in \mathbb{R}^{m \times m}$ are positive definite.

Let’s first consider a constant desired target ($\mathbf{x}_{des} = \mathbf{0}$ and $\dot{\mathbf{x}}_{des} = \mathbf{0}$), such that the equation (2) can be rewritten with the state variable

$$
\mathbf{z} = \begin{pmatrix} \mathbf{x}_{des} - \mathbf{x} \\ -\dot{\mathbf{x}} \end{pmatrix} \tag{4}
$$

with the state dynamics,

$$
\dot{\mathbf{z}} = \mathbf{A} \mathbf{z} + \mathbf{B} (\mathbf{u} + \mathbf{f}_h) \tag{5}
$$

and,

$$
\mathbf{A} = \begin{pmatrix} \mathbf{0}_{m \times m} & \mathbf{I}_{m \times m} \\ \mathbf{0}_{m \times m} & -\mathbf{M}_d^{-1} \mathbf{C}_d \end{pmatrix} \tag{6}
$$

$$
\mathbf{B} = \begin{pmatrix} \mathbf{0}_{m \times m} \\ -\mathbf{M}_d^{-1} \end{pmatrix} \tag{7}
$$

With the new state $\mathbf{z}$ in (4), the cost function is rewritten as

$$
J = \int_0^\infty \mathbf{z}^T \mathbf{Q} \mathbf{z} + \mathbf{u}^T \mathbf{R}_1 \mathbf{u} + \mathbf{f}_h^T \mathbf{R}_2 \mathbf{f}_h dt \tag{8}
$$
where
\[ Q = \begin{pmatrix} Q_1 & 0_{m \times m} \\ 0_{m \times m} & Q_2 \end{pmatrix}. \]  

(9)

In (8), the first term minimizes the error between the actual and desired robot positions. The second and third terms indicate the contributions of human and robot. The optimal solution for this cost function is
\[ u^* = -\frac{1}{2} R_1^{-1} B^T \hat{P} \dot{z}, \]  

(10)

\[ f^*_h = -\frac{1}{2} R_2^{-1} B^T \hat{P} \dot{z}. \]  

(11)

where \( \hat{P} \) is the solution of Riccati equation (12) with the estimated values. Considering the human gain as \( K = \frac{1}{2} R_2^{-1} B^T P \) in (11) and its associated value in (15) as \( \hat{K} \), the error between the measurable human force and optimal force (15), i.e. \( e_f = (\hat{f}_h - f_h) \) is proposed in Li et al. (2015), to update the desired human position as well as the human gain,
\[ \dot{x}_{des} = -\gamma e_f, \]  

(16)

\[ \dot{\hat{K}} = -\gamma e_f^T. \]  

(17)

where \( \gamma \) is the update rate. This update rule pulls the \( x_{des} \) towards the human force direction. Moreover, (17) ensures that the optimal \( \hat{f}_h \) always follows the human force. This can be later used to update \( \hat{R}_2 \) which is an adjustable weight.

The convergence of the above update laws can be shown by Lyapunov function
\[ V = z^T \hat{P} z + \dot{z}^T \hat{P} \dot{z} + \frac{1}{2} (\dot{\hat{K}})^T \hat{K}^{-1} \hat{K} (\dot{\hat{K}} - \hat{K}) \]  

(18)

\[ + \frac{1}{2} tr((\dot{\hat{K}} - \hat{K})^T (\dot{\hat{K}} - \hat{K})). \]

where \( tr(.) \) stands for trace of matrix. \( \hat{K}_1 \) is the first partition of \( \hat{K} \), i.e. \( \hat{K} = [\hat{K}_1 \hat{K}_2] \) and is assumed to be positive definite because the human tries to minimize the trajectory tracking error. Note that this provides a true Lyapunov function of the system compared with the one proposed in Li et al. (2015). The time derivative of this function along the dynamics of the system is obtained as
\[ \dot{V} = -\gamma e_f^T e_f - z^T \dot{\hat{P}} z - \dot{z}^T \hat{P} \dot{z} < 0. \]  

(19)

To reach that, the equality,
\[ e_f = (\dot{\hat{K}} - \hat{K}) \dot{z} + \hat{K} (\dot{\hat{K}} - \hat{K}), \]

(20)

has been used.

Equation (19) ensures asymptotic convergence of \( x_{des} \), and \((\cdot - \hat{K})\) to the desired value of human and to zero, respectively.

Finally, considering \( \hat{R}_2 = \hat{r}_2 I \) with \( I \) as identity matrix, the time derivative of \( \hat{K} \) can be related to the time derivative of \( \hat{R}_2 \). This relationship is given in appendix.

3. SIMULATION AND EXPERIMENTAL STUDIES

In this section, we evaluate the above approach in a two-dimensional planar task space. In our rehabilitation scenario, the human holds the end-effector of the robot, thus robot position and human position in Cartesian space are identical. In this section, the robot position also indicates the human position.

3.1 Simulation - Point Reaching

We firstly verify the capability of the approach to follow a human to reach his goal. The closed loop dynamics (2) is simulated for a planar case. The human force is modeled as a spring-damper system towards a desired planar position, i.e.
\[ f_h(t) = k_h(x_{des}(t) - x(t)) - d_h \dot{x}(t) \]  

(21)

where \( k_h = 2 \) and \( d_h = 2 \). And for the motion point reaching, we set a constant goal of human as \( x_{des}(t) = (2, 3)^T \) which is unknown to the controller.

Fig. 2. Human force with variable \( r_2 \). With same desired motion, the human need to exert more force with lower \( r_2 \). Note that considering cost function (8) for human, it is assumed that human force is optimal, i.e. \( f_h = \hat{f}_h \). On the other hand, in the above analysis, the desired regulation point \( x_{des} \) is assumed to be known for the robot. While these two assumptions are invalid in practice, \( x_{des} \) and \( R_2 \) in (3) need to be replaced with the estimated values \( \hat{x}_{des} \) and \( \hat{R}_2 \) respectively. Replacing \( x_{des} \) with the estimated value in (16),
\[ \dot{x} = (\hat{x}_{des} - x). \]  

(13)

Considering these estimated values, the optimal solutions are now referred with \( \dot{u}^* \) and \( \hat{f}_h \) and obtained by (10) and (11). Substituting the estimated values,
\[ \dot{u}^* = -\frac{1}{2} R_1^{-1} B^T \hat{P} \dot{z}, \]  

(14)

\[ \hat{f}_h = -\frac{1}{2} R_2^{-1} B^T \hat{P} \dot{z}. \]  

(15)
We used similar parameters as Li et al. (2016), 
\[ M_d = \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix}, \]
\[ C_d = \begin{pmatrix} 1 & 2 \\ 2 & 5 \end{pmatrix}, \]
\[ Q_1 = 200I_{2\times2}, Q_2 = 20I_{2\times2}, R_1 = 2I_{2\times2}, R_2 = 20I_{2\times2}, \] and \( \gamma = 1 \).

Fig. 3. Position in point reaching motion. The dashed lines are human desired goal, the dashed-dotted lines are robot estimated human goal, and the solid lines are robot position. Red lines below denote \( x_1 \) and blue lines above are \( x_2 \).

Fig. 3 shows that both the simulated and estimated position converge to a constant goal of human.

### 3.2 Simulation - Trajectory Tracking

Although we have the assumption that \( x_{des} = 0 \), in the rehabilitation scenario, the patient usually moves slowly, thus this approach still works when \( x_{des} \) is small.

We set the desired trajectory as a circle

\[ x_{des}(t) = r \left( \sin \left( \frac{2 \pi}{T} t \right) - \cos \left( \frac{2 \pi}{T} t \right) \right) + x_{cen} \]  

\[ T = 20s \] indicates a slow motion, \( r = 1 \) is the radius of the circle and \( x_{cen} = (0, 1)^T \) is the center of the circular trajectory. The simulation time is 10s.

Fig. 4 shows the simulated robot position and the human desired trajectory. Because of extra robot dynamics, the human is not able to follow the desired trajectory (Fig. 4(a)). And the force applied by human (Fig. 5(a)) is larger than that with the assistance (Fig. 5(b)). With the assistance \( u \) from robot, the human can follow his trajectory more precisely.

### 3.3 Rehabilitation with GARMi Service Robot

To validate the performance of the above approach, a rehabilitation scenario with GARMi is devised. The humanoid service robot GARMi is designed to assist elderly people at home or care centers Tröbinger et al. (2021). The proposed scenario is GARMi holding one hand of the user and performing a rehabilitation exercise at home. GARMi displays a user interface, showing the desired trajectory (the blue circle), the point to chase (the red point), the current human position (the green point), and the human trajectory history (the yellow line) (see Fig. 1). In the rehabilitation process, the patient’s and GARMi’s left hand are trying to chase the red point in the horizontal plane.

A feasibility experiment is conducted with a healthy human without and with GARMi’s help. With the robot support, human needs less force to track the trajectory.

Fig. 6 displays the trajectory and measured human force with or without and with robot help. With robot help, the human shows better tracking performance. Red dashed line is the human desired motion, and blue solid line is the human actual trajectory.
without robot help. It is clear that human applies smaller force when robot helps. However, he feels that tracking trajectory without the help of a robot is easier since the human can adjust his arm stiffness more easily.

4. DISCUSSION

The proposed tele-rehabilitation system using service robot GARMI has the strength of providing assist-as-needed rehabilitation through adaptation of the agents’ role. The therapist can remotely supervise the patient’s performance and adjust the parameters of the rehabilitation exercise through the user interface. Additionally, the therapists can also use a Panda robot arm to superimpose their force on the GARMI, adding a level of control and assistance in the rehabilitation process. This system should also enable the therapist to adjust the rehabilitation motion on-the-fly remotely if needed. The algorithm proposed in (Dimeas and Doulgeri (2020)) is a promising solution for this adaptation. One of the major challenges in tele-rehabilitation systems that involve intensive human-robot interaction is ensuring system stability, particularly when using non-ideal communication channels. The author of this paper has investigated the stability of tactile robots in teleoperation under various commercialized communication networks, including 5G, LTE, and WiFi, as reported in Chen et al. (2022). As part of our future work, we aim to address the challenge of maintaining system stability in tele-rehabilitation systems using these communication networks.

5. CONCLUSION

In this paper, we propose an approach to assist a patient in a tele-rehabilitation exercise. An optimal control approach is used to model the human and robot as two agents in collaboration. By proper parameter selection in the cost function, the assistance of the robot during the exercise can be adjusted. Note that the interaction between the patient and the remote therapist station is the same as the interaction between human and local assistance by the robot, i.e. the remote physician can also get a weight to assist the human.

As this approach has the ability to estimate human intention and help with human motion, it can also be applied to human power augmentation for example in activities of daily living or in factories, either with collaborative robots or exoskeletons.

ACKNOWLEDGMENT

We gratefully acknowledge the funding of the Lighthouse Initiative Geriartronics by LongLeif GaPa gGmbH (Project Y). The authors acknowledge the financial support by the Federal Ministry of Education and Research of Germany (BMBF) in the programme "Souverán. Digital. Vernetzt." Joint project 6G-life, project identification number 16KISK002.

Appendix A. THE TIME DERIVATIVE OF \( \dot{R}_2 \)

The time derivative of \( \dot{K} \) can be related to the time derivative of \( \dot{R}_2 \) following the same way as in Li et al. (2015)

\[
\dot{K} = \frac{\partial \dot{K}}{\partial R_2} \dot{R}_2
= \left( \begin{array}{ccc}
\frac{1}{2} B^T & -1 & \frac{1}{2} \frac{\partial \dot{P}}{\partial R_2}
\end{array} \right) \dot{R}_2.
\]

To obtain \( \frac{\partial \dot{P}}{\partial R_2} \), we take the derivative of equation (12) with respect to \( \dot{R}_2 \):

\[
A^T \frac{\partial \dot{P}}{\partial R_2} - \frac{\partial \dot{P}}{\partial R_2} A - \frac{\partial \dot{P}}{\partial R_2} B^{-1} B^T \dot{P} - PB^{-1} B^T \frac{\partial \dot{P}}{\partial R_2} - \frac{1}{\dot{R}_2} \frac{\partial \dot{P}}{\partial R_2} BB^T \dot{P} + \frac{1}{\dot{R}_2} \frac{\partial \dot{P}}{\partial R_2} BB^T \dot{P} = 0.
\]

This equation (A.2) can be rewritten as

\[
\dot{X} = A \dot{X} + \left( BB^T - \frac{1}{\dot{R}_2} BB^T \right) \frac{\partial \dot{P}}{\partial R_2} = 0,
\]

by denoting

\[
X = A - \left( BB^T + \frac{1}{\dot{R}_2} BB^T \right) \frac{\partial \dot{P}}{\partial R_2}.
\]

Then we have

\[
\frac{\partial \dot{P}}{\partial R_2} = - \frac{1}{2} Y X^{-1}.
\]

Thus by updating \( K \), the value \( \dot{R}_2 \) is also updated as (A.1) indicates.

Appendix B. STABILITY PROOF

Given the Lyapunov function in (18), for convenience, we split it into two parts:

\[
V = V_1 + V_2
\]

\[
V_1 = z^T P z + \dot{z}^T \dot{P} \dot{z}
\]

\[
V_2 = \frac{1}{2} (k - z)^T K^T K (k - z) + \frac{1}{2} tr((k - K)^T (k - K)),
\]

considering equation (12), the time derivative of \( V_1 \) is

\[
V_1 = 2 z^T P z + 2 \dot{z}^T \dot{P} \dot{z}
= 2 z^T P (Az + B(\dot{u} + f')) + 2 \dot{z}^T \dot{P} (\dot{A} z + B(\dot{u} + f'))
= 2 z^T P (Az - B(\dot{R}^{-1} B^T P z + \frac{1}{2} R^{-1} B^T P z))
+ 2 \dot{z}^T \dot{P} (\dot{A} z - B(\dot{R}^{-1} B^T P z + \frac{1}{2} R^{-1} B^T P z))
= z^T P A z + \dot{z}^T \dot{A}^T z - \dot{z}^T \dot{P} (\dot{R}^{-1} B^T P + R^{-1} B^T z) z
+ \dot{z}^T \dot{P} \dot{z} - \dot{z}^T \dot{P} B(\dot{R}^{-1} B^T P + R^{-1} B^T z) z
= -z^T Q z - \dot{z}^T \dot{Q} \dot{z}.
\]

using \( K_1 (x_{des} - x_{des}) = K (k - z) \), along with equation (20), the time derivative of \( V_2 \) is

\[
V_2 = (x_{des} - x_{des})^T K_1^T \dot{x}_{des} + tr((k - K)^T k)
= -\gamma (x_{des} - x_{des}) \dot{K}_1^T e_f - \gamma tr((k - K)^T e_f z^T)
= -\gamma (k - z)^T K^T - \dot{z}^T (k - K)^T e_f
= -\gamma (k - z)^T K^T - \dot{z}^T (k - K)^T e_f.
\]

This leads to equation (19) when using \( V = V_1 + V_2 \).

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