Rehabilitation as a game: ‘assist as needed’ reaching movements as Nash equilibria

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***Abstract*— In stroke rehabilitation, tailoring assistance to individual needs is crucial for more effective training. This study investigates the control architecture of an artificial partner (AP) inspired by game theory. The AP modulates assistance in a planar reaching task using adaptive control strategies. We compare AP performance in “lazy” and “generous” conditions. Results show that the AP adjusts its assistance effectively based on game-theoretic principles. This approach shows promise for enhancing robot-assisted rehabilitation through personalized therapy. Future research will explore the long-term effects of these policies and refine the AP’s sensory system and state observer for improved precision.**

I. Introduction

In individuals with neurological impairments, rehabilitation aids functional recovery. In stroke rehabilitation, tailored assistance maximizes recovery and promotes independence [1]. Robots can deliver high-intensity, repetitive exercise, shown to improve upper limb function and daily activities in stroke survivors [2]. When a robot assists a human in performing a movement, the human behaves as a greedy optimizer by reducing their active participation [3]. This phenomenon, referred to as ’slacking’, can hinder recovery. Therefore, it is crucial to only provide ’assistance as needed’ [4]. Adaptive control methods that tailor assistance show promise in improving movement therapy and encouraging active participation [5]. Neuromotor rehabilitation, viewed as joint action, can be understood using differential game theory [6]. Recent studies show that control architectures combining differential game theory and adaptive control lead to stable and effective interactions, allowing robots to adapt precisely to the users’ control strategies [7] and to develop joint coordination [8]. These same paradigms may find application in the rehabilitation domain. Here, we propose an ’assist as needed’ control model where the robot initially starts with a “generous” approach, offering significant help to the user, and gradually shifts to a “lazy” approach, reducing support as the user improves. This interplay can be viewed as a Nash equilibrium, balancing user effort and robot assistance, potentially resulting in more effective and personalized exercise scenarios.

II. Materials and Methods

A. Assistance as needed as Nash Equilibrium

In a game-theoretic framework, robot-assisted exercise can be seen as a coordination game, where the ”assist as needed” paradigm can be interpreted as a Nash equilibrium. The behavior of the robot agent is defined by an objective function (J_R) which depends on the actions of both the patient (u_H) and the robot (u_R):

$$J_R(u_H, u_R) = \tfrac{1}{2}\omega_p \left|x_T - x(T)\right|^2 + \tfrac{1}{2}\omega_v \left|\dot{x}(T)\right|^2 + \tfrac{1}{2} r_R \sum \left|u_R(t)\right|^2 \tag{1}$$

where x is the hand position vector and x_T the target position; ω_p and ω_v are the weight coefficients for the task constraints. Parameter r_R controls the cost of robot effort. A higher r_R means the robot contributes less. It will contribute more if r_R is small. The patient is assumed to have an objective function with the same structure. If both agents aim to minimize their costs, they end up in a Nash Equilibrium (NE), where neither has anything to gain by changing their actions. The robot must be lazier than the patient to reduce slacking behavior. NE-based robot control strategies may be effective assist-as-needed forms of control.

The control architecture models the robot as an ’artificial partner’ coordinating with the human through an optimal feedback controller and state observer. The observer predicts the patient’s action and informs the controller, enabling adaptive control; see Fig. 1 (left).

We modeled the interaction between the partners as a “hard” mechanical coupling, in the sense that we treat robot and human as a single rigid body:

$$M \cdot \ddot{p} + B \cdot \dot{p} = f_H + f_R \tag{2}$$

where p and $\dot{p}$ are the hand position and velocity, M is the inertia matrix, B is a viscosity parameter, and f_H and f_R are the forces (motor commands) generated by the human and artificial partner, respectively. The artificial partner has a synthetic sensory system that perceives the position and velocity of the end effector. It is described as $y_R = H \cdot x + v_R$ where H maps the state vector x to the sensory output y_R adding a sensory (Gaussian) noise v_R.

The state observer block combines sensory information and dyad dynamics to predict the dyad’s next state and the past human motor command. The latter is estimated by combining sensory information with a model of the temporal evolution of the human command, modeled as:

$$u_H(t+1) = A_u \cdot u_H(t) + \varepsilon_u(t) \tag{3}$$

where $0 < A_u < 1$ and $\varepsilon_u(t) \sim \mathcal{N}(0, \Sigma_{\varepsilon_u})$, (3) corresponds to the prior belief that the partner’s input is a low-pass filtered Gaussian noise. The posterior estimate of partner action is incorporated into the feedback controller that will be used

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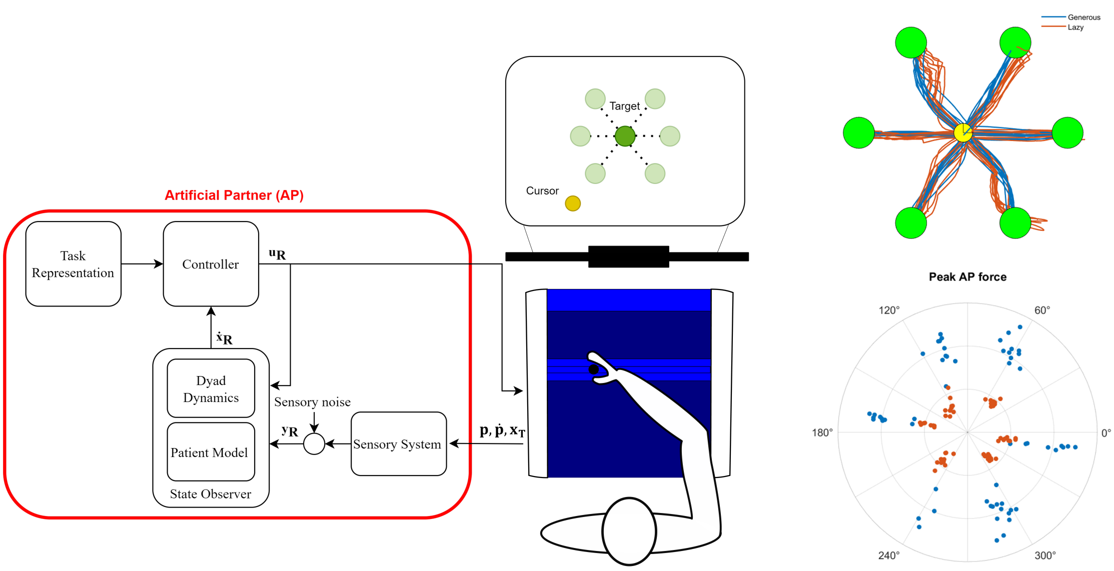

Fig. 1. Left: The artificial partner (AP) architecture comprises a task representation module, a controller, a dyad dynamics model, a patient model, a state observer, and a sensory system. The AP interacts with a human partner (HP), represented in the schematic as a person interacting with the H-MAN (2-DOF) device. Right: Movement trajectories to different targets (green dots), in red the "lazy" ($r_R = 10$) and in blue the "generous" condition ($r_R = 0.1$)(up). Force generated by the AP (bottom).

in the next trial. This way, the AP continuously modifies its behavior to adapt to the human partner. The process converges to the NE.

B. Experimental protocol

We tested AP behavior in a planar point-to-point reaching task while interacting with a healthy human. Movements were performed from a central start point to one of six targets (d = 0.1 m), with an assistive force from the AP. Two conditions were tested: "lazy" AP ($r_R = 10$) and "generous" AP ($r_R = 0.1$). Each experiment involved 60 trials, organized into 10 epochs of 6 trials. The study was approved by the University of Genoa Ethics Committee.

III. Results

The trajectories and forces exerted by the AP during the reaching movements in the two conditions are depicted in Fig. 1. In the "generous" mode, dyad movements are almost straight and quite regular, while in "lazy" mode, they appear more irregular and curved – see Fig. 1 (top right). In the "lazy" condition the robot generates smaller forces and thus minimal assistance; forces are greater in the "generous" condition; see Fig. 1 (bottom right).

IV. Conclusion

The proposed artificial partner (AP) effectively modulates assistance using adaptive game-theoretic control strategies. Unlike other "assist-as-needed" methods, the joint action nature of robot-assisted training is explicitly accounted for. In this context, slacking is not merely a hindrance but the optimal behavior achieved by the human during interaction. Rather than relying on heuristic adjustments, our approach dynamically adapts the assistance in real time based on both robot and human actions. This may potentially lead to a more personalized and efficient interaction, encouraging active user participation and possibly promoting better motor recovery outcomes. Future work will explore the long-term effects of these adaptive strategies and further refine the model to enhance its applicability across various movements and patient groups.

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