# Capturing and Modeling a Tool Dynamics for Adaptive Task Practice in Stroke Rehabilitation

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Although it is becoming largely accepted that the most effective way to improve functional outcomes in patients with stroke-related disability is to increase significantly the amount of meaningful task practice, the high cost of skilled rehabilitation often prevents the patients to receive such therapy. A possible method to increase the amount of practice for the rehabilitation of upper extremity functions in individuals with strokes in a cost-effective manner is to supplement the patient's one-to-one interaction with a therapist with sessions on a robotic system. Although robots have been used with some success in the rehabilitation of arm movements after stroke, these systems do not parallel the role of the therapist in setting up functional tasks that require the subject to actively engage in challenging manipulation of physical objects. Our long-term goal is to develop such a robotic system that will engage the patient intensively and actively in manipulation tasks by presenting a number of tools whose dynamics will depend on the initial impairment level of each patient, and will vary during therapy as the patient's performance improves.

Here, we explore the implementation of realistic functional tasks on a general-purpose robot to be used for the rehabilitation of upper extremity functions. Although we could simply mount real functional tools on the robot end-effector, doing so would not able us to adapt the task difficulty to the patient's performance. We thus need a model of the dynamics of each tool, such that the difficulty can be manipulated, by increasing stiffness for instance.

To achieve acceptable realism of our functional tasks, we need to model accurately the forces felt by the patient as she interacts with the tools. Because the force profiles of tools such as such as knobs, switches, keys, levers, etc., typically vary with the state of the system, simple parametric dynamics model with constant coefficients (inertia, viscosity, stiffness, and friction) cannot be used. Colton and Hollerbach (2005) modeled the dynamics of a linear spring in a quasi-noise free environment using a general linear model with Exponentially-Weighted Least Squares (EWLS). In EWLS the user specifies *a priori* a number of fixed-width rectangular basis functions (or "receptive fields"). Thus, a EWLS-based model with a large number of basis functions (such as that used by Colton and Hollerbach) can suffer from poor generalization if the noise level is high. To address this limitation, we propose here to use Receptive Field Weighted Regression (RFWR) (Schaal et al., 1998) to learn the unknown dynamics of common tools. We assume that the local dynamics of general 1DOF nonlinear mechanical devices can be represented by:

$$\tau = I(q,\dot{q},\ddot{q})\,\ddot{q} + V(q,\dot{q},\ddot{q})\,\dot{q} + K(q,\dot{q},\ddot{q})\,q + F_0(q,\dot{q},\ddot{q}) \qquad (1)$$

where $\tau$ is the torque due to interaction with the subject, $q$ the angular position, $\dot{q}$ the angular velocity, $\ddot{q}$ the angular acceleration, $I$ the inertia, $V$ the damping, $K$ the stiffness, and $F_0$ the static force. In this context, RFWR incrementally constructs multiple local linear models (receptive fields) from input (position, velocity, acceleration) and output data (torque). The receptive fields are created adaptively when more accuracy is needed and deleted when the model is over-fitted. The dynamics of the tools is then approximated by weight-averaging multiple local linear models. Thus, RFWR can model tools dynamics with non-constant parameters with an optimal number of basis functions.

In this preliminary work, we captured and modeled the dynamics of a readily commercially available doorknob (Figure 1). A magnetic motion monitor system measured the doorknob angle, and the torque/force sensor equipped for the robot controller was used to measure the interaction torque while a subject was manipulating the tool at various frequencies and amplitudes (the robot was positioned not to move).

Our results show that the RFWR-based model correctly models the doorknob dynamics with only 2 receptive fields (Figure 2 and 3). Analysis of the model parameters showed that stiffness and damping varied as a function of position, but little as a function of velocity and acceleration; furthermore, inertia and static force were quasi-constant (Figure 4). In future work, to replay the dynamics of the functional tools, we will disabled the motion mechanism of the tool, attach this disable tool to the robot end-effector, and the robot will simulate the tool. One of the model's parameters (presumably stiffness) will be then manipulated adaptively based on performance, such that the task become increasingly difficult as the patient recover.


## Acknowledgement

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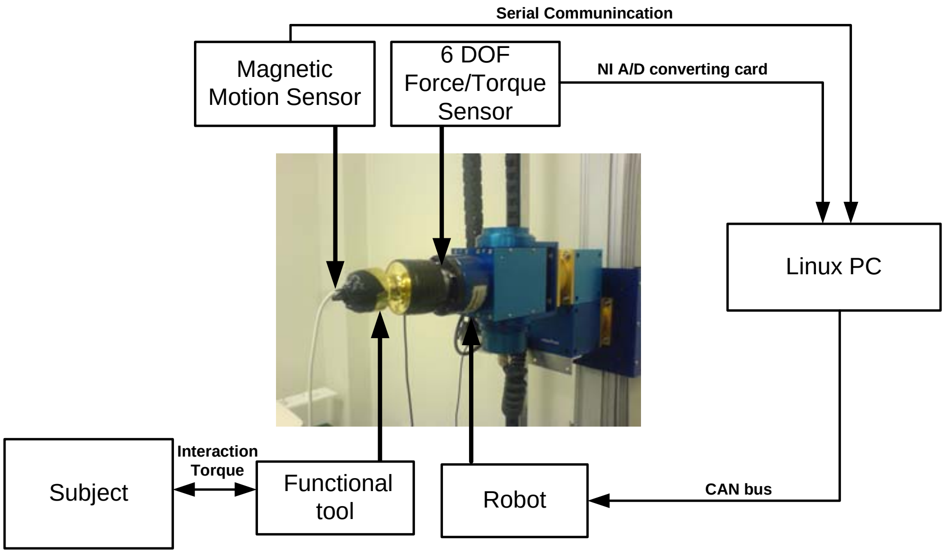


**Figure. 1**. Capturing the dynamics of a doorknob. The robot here is not activated (breaks on). In future development of the system, the robot will replay the dynamics of the tool adaptively, such as the task difficulty progresses as the patient's performance improves.

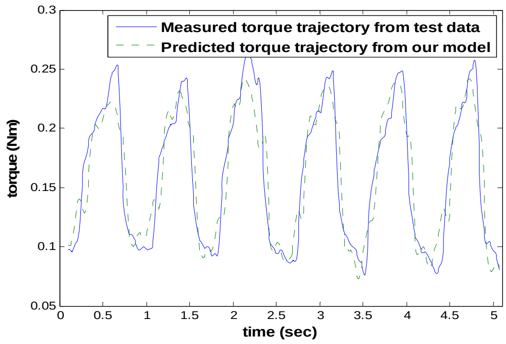


**Figure. 2**. Measured (blue line) and predicted (green dash) torques.

(a) (b) (c)

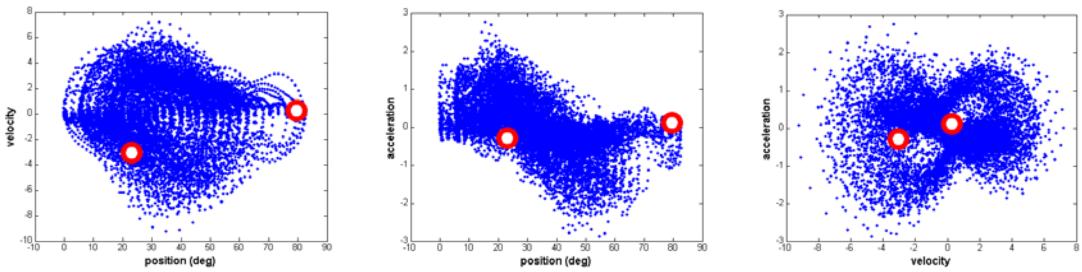


**Figure. 3.** Training data (blue dot) generated by a subject manipulating the doorknob for 3 minutes, and center points (red circle) of the two receptive fields generated by RFWR. The center points are far apart in the position dimension. but close to each other in the velocitv and acceleration d

(a) (b)

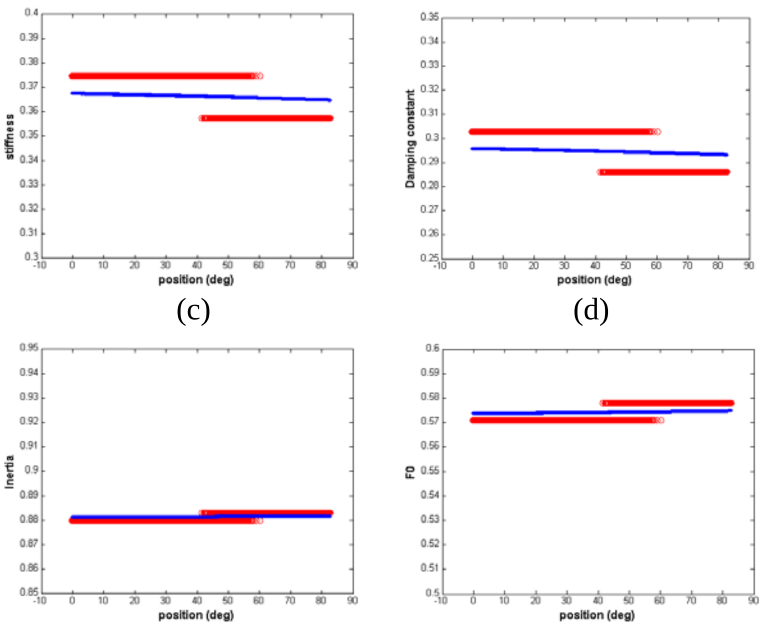


**Figure. 4**. Parameters of the doorknob dynamics as a function of position. The parameters (blue line) are computed by weight averaging the two linear models (red dots) for each position. The stiffness coefficient *K* (a) and damping coefficient *V* (b) decrease as position increases, while there is almost no change in the inertia *I* (c) and the static force $F_0$ (d) as a function of position.

## References


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