Designing Personalized Interaction of a Socially Assistive Robot for Stroke Rehabilitation Therapy

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***Abstract*— Socially Assistive Robot (SAR) research has a potential to augment and assist physical therapy sessions for patients with neurological and musculoskeletal problems (e.g. stroke). During a physical therapy session, generating personalized feedback is critical to improve patient's engagement. However, prior work on a SAR for physical therapy has mainly utilized pre-defined corrective feedback even if patients have various physical and functional abilities. This paper presents an interactive approach of a SAR that can dynamically select features of assessment on individual patient's exercises to predict the quality of motion and provide patient-specific corrective feedback for personalized interaction of a robot exercise coach.**

I. Introduction

An early and extensive physical therapy session is an effective intervention for patients with neurological and musculoskeletal problems (e.g stroke) to regain their functional ability. However, patients can receive only limited amount of sessions due to the costs and the shortage of therapists.

Researchers have explore the possibility of supplementing health services with advanced computing and a socially assistive robot (SAR) [1]. For instance, researchers envision that a SAR can be integrated into the rehabilitation process by automatically monitoring patient's exercises and providing motivational feedback until patient's next visits to a therapist [1]. Prior work on robotic exercise coaching systems demonstrates elderly or post-stroke subjects can successfully exercise and stay engaged with a robot over a single [2] or multiple sessions [3], [4]. However, in spite of this potential of a robot to monitor and guide exercises, prior work is limited to provide pre-defined corrective feedback on patient's exercise performance (e.g. angular difference with a motion template [3], [4]). Generating personalized interaction and feedback for an individual patient still remain a challenge [4].

In this paper, we present an interactive approach of an assistive robot for personalized post-stroke therapy (Figure I). This approach utilizes reinforcement learning to dynamically select the most important kinematic features of stroke rehabilitation assessment for individual patient's exercise motions to predict the quality of motion [5]. Utilizing selected features and patient's held-out normal motions, a robotic system can analyze which features of an affected motion have been deviated from those of normal motions, and generate personalized corrective feedback on a patient's exercise motion (Figure 1c).

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II. Interactive Approach of a Socially Assistive Robot for Personalized Physical Therapy

This work aims to support transparent and personalized interaction of a robot exercise coach that utilizes a sparse machine learning model with feature selection [6] to predict the quality of motion and generate corrective feedback (Figure 1c) with held-out patient's normal motions.

We represent an exercise motion with sequential joint coordinates from a Kinect v2 sensor and extract various kinematic features similar to [7]: joint angles (e.g. elbow flexion, shoulder flexion, elbow extension, shoulder abduction, the titled angle of head, spine, and shoulder), speed related features (e.g. speed, acceleration, jerk, etc.) on wrist and elbow joints, and normalized relative trajectory (i.e. the Euclidean distance head and wrist and head and elbow).

For feature selection, this paper utilizes reinforcement learning (RL) to dynamically identify salient features of assessment for individual patient's motions [5]. Specifically, we apply Double Q-learning [8] to train an agent that sequentially decides whether another feature is necessary to assess an exercise while receiving a negative reward for requesting an additional feature. Although the classical approaches of feature selection (e.g. filter, wrapper, embedded methods) select a fixed set of features with training data for all patients, our approach of feature selection with RL finds an optimal set of features for individual patient's motions [5]. Thus, we hypothesize that feature selection with RL is beneficial over classical feature selection approaches to generate personalized rehabilitation assessment and feedback.

For a machine learning (ML) model for assessment, we utilize a Neural Network (NN) while grid-searching various architectures (i.e. one to three layers with 32, 64, 128, 256, 512 hidden units) and learning rates (i.e. $0.0001, 0.005, 0.001, 0.01, 0.1$) using *'PyTorch'* libraries [9]. *'ReLu'* activation and *'AdamOptimizer'* are applied, and a model is trained until the tolerance of optimization is 0.0001 or the maximum 200 iterations.

(a) (b) (c)

Fig. 1: (a) Flow diagram of an interactive approach of an assistive robot for personalized physical therapy. (b) the setup of a system with a Kinect sensor, a tablet with the visualization interface, and the NAO robot. (c) An example output of the visualization interface that presents predicted assessment on patient's exercise performance with corrective feedback.

III. Dataset of Three Upper-Limb Exercises

For the evaluation, this paper utilizes the dataset of three task-oriented, upper-limb stroke rehabilitation exercises suggested by therapists: *'Bring a cup to the mouth'*, *'Switch a light on'*, and *'Move forward a cane'* [7]. Fifteen stroke patients with different level of functional abilities (37 $\pm$ 21 Fugl Meyer Scores [10] and four patients with affected motions on their left-side) and 11 healthy subjects participated in data collection with a Kinect v2 sensor (Microsoft, Redmond, USA) that records the trajectory of body joints at 30 Hz. A patient performed 10 repetitions of each exercise with both patient's affected and unaffected sides. A healthy subject performed 15 repetitions of each exercise with the subject's dominant side. Two therapists annotated the dataset to implement our approach and compute therapist's agreement (TP in Table I). We utilize the annotation of a therapist, who evaluated patient's functional ability with Fugl Meyer Assessment [10], as the ground truth.

IV. Results

The machine learning (ML) model with reinforcement learning based feature selection (ML - RL) achieves the good agreement level with therapist's annotation: 0.7973 - 0.8331 average F1-scores on three exercises, which is 0.02 higher average F1-score than therapist's agreement (TP in Table I). In addition, our approach (ML - RL) achieves 0.11 higher average F1-score than the ML model with Recursive Feature Elimination, one of classical feature selection methods (ML - RFE). Thus, we expect that our approach can perform better to generate personalized assessment and corrective feedback. For the interaction with patients, we implement the interface that presents the tracked joints of a patient's exercise motion, predicted assessment on patient's exercise performance, and real-time audio and visual corrective feedback (Figure 1c).

TABLE I: Performance (F1-scores) of our approach (ML - RL), the baseline approach with Recursive Feature Selection (ML - RFE), and therapist's agreement (TP)

	Exercise 1 (E1)	Exercise 2 (E2)	Exercise 3 (E3)	Overall
ML - RL	0.8331$\pm$ 0.0059	0.7973 $\pm$ 0.0867	0.8053 $\pm$ 0.0496	0.8119 $\pm$ 0.0526
ML - RFE	0.6742 $\pm$ 0.0715	0.7628 $\pm$ 0.1708	0.6415 $\pm$ 0.0806	0.6928 $\pm$ 0.1147
TP	0.8120 $\pm$ 0.1458	0.7790 $\pm$ 0.1324	0.7654 $\pm$ 0.1382	0.7854 $\pm$ 0.0195

V. Conclusion and Future Work

This paper describes an interactive approach of a Socially Assistive Robot (SAR) that applies reinforcement learning for dynamic feature selection on individual patient's rehabilitation exercises to assess the quality of motion and generate personalized corrective feedback. According to the evaluation with the annotated dataset of three stroke rehabilitation exercises from 15 post-stroke and 11 healthy subjects, our approach achieves good congruence with therapist's annotation, but also allows to generate transparent and personalized corrective feedback. In future, we will evaluate the usefulness of personalized corrective feedback from the NAO robot (Figure 1b) for coaching post-stroke subject's rehabilitation exercises.

References

[1] M. J. Matarić, J. Eriksson, D. J. Feil-Seifer, and C. J. Winstein, "Socially assistive robotics for post-stroke rehabilitation," *Journal of NeuroEngineering and Rehabilitation*, vol. 4, no. 1, p. 5, 2007.

[2] K. Swift-Spong, E. Short, E. Wade, and M. J. Matarić, "Effects of comparative feedback from a socially assistive robot on self-efficacy in post-stroke rehabilitation," in *2015 IEEE International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 2015, pp. 764–769.

[3] J. Fasola and M. J. Matarić, "A socially assistive robot exercise coach for the elderly," *Journal of Human-Robot Interaction*, vol. 2, no. 2, pp. 3–32, 2013.

[4] B. Görer, A. A. Salah, and H. L. Akın, "An autonomous robotic exercise tutor for elderly people," *Autonomous Robots*, vol. 41, no. 3, pp. 657–678, 2017.

[5] M. H. Lee, D. P. Siewiorek, A. Smailagic, A. Bernardino, and S. Bermúdez i Badia, "Interactive hybrid approach to combine machine and human intelligence for personalized rehabilitation assessment," in *Proceedings of the ACM Conference on Health, Inference, and Learning*, ser. CHIL '20. ACM, 2020, p. 160–169.

[6] O. Biran and C. Cotton, "Explanation and justification in machine learning: A survey," in *IJCAI-17 workshop on explainable AI (XAI)*, vol. 8, 2017, p. 1.

[7] M. H. Lee, D. P. Siewiorek, A. Smailagic, A. Bernadino, and S. B. i. Badia, "Learning to assess the quality of stroke rehabilitation exercises," in *Proceedings of the 24th International Conference on Intelligent User Interfaces (IUI '19)*. ACM, 2019.

[8] H. Van Hasselt, A. Guez, and D. Silver, "Deep reinforcement learning with double q-learning," in *Thirtieth AAAI conference on artificial intelligence*, 2016.

[9] A. Paszke, S. Gross, S. Chintala, G. Chanan, E. Yang, Z. DeVito, Z. Lin, A. Desmaison, L. Antiga, and A. Lerer, "Automatic differentiation in pytorch," 2017.

[10] J. Sanford, J. Moreland, L. R. Swanson, P. W. Stratford, and C. Gowland, "Reliability of the fugl-meyer assessment for testing motor performance in patients following stroke," *Physical therapy*, vol. 73, no. 7, pp. 447–454, 1993.