A Collaborative and Adaptive Feedback System for Physical Exercises

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***Abstract*—Maintaining motivation to meet physical exercise goals is a big challenge in virtual/home-based exercise guidance systems. Lack of motivation, long-maintained bad daily routines, and fear of injury are some of the reasons that cause this hesitation. This paper proposes a reinforcement learning-based virtual exercise assistant capable of providing encouragement and customized feedback on body movement form over time. Repeated arm curls were observed and tracked using single and dual-camera systems using the Posenet pose estimation library. To accumulate enough experience across individuals, the reinforcement learning model was collaboratively trained by subjects. The proposed system is tested on 36 subjects. Behavioral changes are apparent in 31 of the 36 subjects, with 31 subjects reducing movement errors over time and 15 subjects completely eliminating the errors. The system was analyzed for which types of feedback provided the highest expected value, and feedback directly related to the previous mistake provided the highest valued feedback ($p < 0.0133$). The result showed that the Reinforcement Learning system provides meaningful feedback and positively impacts behavior progress.**

***Index Terms*—Reinforcement Learning, Distributed Machine Learning, Human-Computer Interaction, Pose Estimation**

I. Introduction

In the past few years, technologies have been developed to help people exercise at home. Most of these systems provide schedules and instructions on how to perform an exercise. These applications use video cameras [2], wearable motion sensors [3], and motion capture devices [4] to obtain necessary information from the user's environment, manipulate obtained data to track exercises, and provide feedback via a desktop or mobile application. Numerous desktop applications [5] and mobile applications [2] [3] [6] are available today to provide this service to people.

Verbal/visual feedback is an effective means of encouraging an individual in an exercise situation. Personal trainers provide real-time feedback and encouragement for clients. Many fitness applications offer a customized workout schedule. However, many of these systems lack effective feedback to encourage compliance to an exercise routine. Systems without real-time feedback can even lead to physical injuries due to the system's inability to correct body movements. An efficient and effective feedback system is crucial to maintaining an exercise regime.

Most of the applications that use motion sensors to track exercises provide verbal feedback. The applications that use visual information to track exercise provide either or both verbal and visual feedback. Some researchers use robots to demonstrate the exercise so that the user can mimic the movements [10]. Studies have been conducted to measure the efficacy of feedback methods of remote/virtual exercise guidance systems. Geraedts et al. [11] show that direct remote contact is a good alternative to onsite exercising. Garcia-Vergara et al. [12] conducted an experiment to measure the efficacy of the feedback from a virtual agent that only provides verbal feedback compared to an embodied agent. This humanoid robotic platform can give verbal feedback and nonverbal gestures. The authors demonstrate that visual, embodied feedback required fewer trials to reach an equivalent level of ability.

One of the key challenges of a virtual/remote exercise guidance system is maintaining the person's interest in exercise and encouraging them to start and continue the exercise [13], [14]. When it comes to physical therapy exercise, fear of pain, cognitive impairment, lack of family support, the obscurity of instructions are some of the reasons why patients do not succeed in home-based physical therapy [15] [16]. Rodriguez-Lera et al. [17] proposed a framework to motivate patients during physical rehabilitation using a commercial robot called QT robot. For feedback, the authors used (1) Voice recordings of encouraging phrases, including sentences such as "well done", "amazing", and "You are doing great" (2) Robot hand gestures and (3) Emotions on a screen. This feedback is crucial to increasing their motivation and confidence.

Not all people understand and react to feedback the same way. Ideally, the feedback system should be intelligent and adapt the to users' responses. Researchers have used reinforcement learning to build applications and devices that provide a personalized experience to users. Zang et al. [9] introduce reinforcement learning-based impedance controllers to a robot-assisted rehabilitation system to adaptively adjust the stiffness of the force field according to the subject's performance. Wang et al. [8] used reinforcement learning to find the best time for users to exercise. Tsiakas et al. [7] introduced a multimodal adaptive telerehabilitation system for physical rehabilitation exercising using reinforcement learning. Multimodal data such as speech, facial expression, and body motion was used by the system to select a particular exercise and session difficulty.

Our system provides customized feedback based on the

978-1-6654-1625-2/21/$31.00 ©2021 IEEE
DOI 10.1109/CIC52973.2021.00012

user's real-time performance using the reinforcement learning model. We built an inexpensive virtual physiotherapy system with two cameras using pose estimation technology; prior results show that our current system can accurately count the repetition and detect incorrect posture [1]. This paper extends this system by using reinforcement learning to select appropriate feedback to encourage proper form during exercise.

II. Methodology

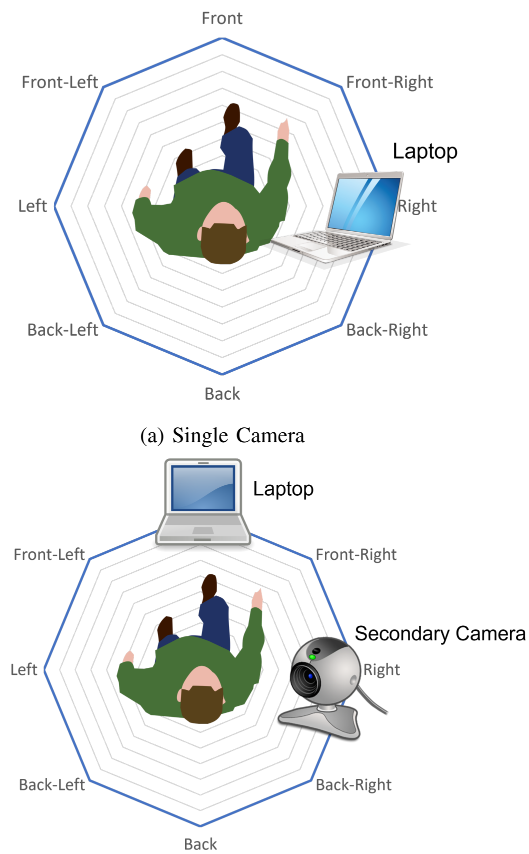
Tracking is performed by two cameras using pose estimation with the Posenet library (Fig 1). Arm curls were tracked in this study. Repetitions of arm curls were counted by observing shoulder-elbow-wrist angles less than 90 degrees then larger than 170 degrees repeatedly. Additionally, during curls, the elbow was considered "locked" properly when the hip-shoulder-elbow angle was never larger than 35 degrees during the movement. For range of motion, "Full" range was indicated for curls greater than 135 degrees, while "Partial" was for curls between 90 and 135 degrees. The introduced framework is also capable of recognizing voice commands to control and navigate web applications. Verbal and visual feedback is provided to patients through this system. At the end of the session, the system generates a performance report of the user that can be saved to the user's computer.

A. *Reinforcement Learning to Provide Autonomous Feedback*

Each repetition of the exercise session provided an episode described by $< s, a, r, s' >$ with each variable explained more thoroughly in the next section. The tuple represents that the user was in state s, the feedback agent provided feedback as action a, the feedback agent received reward r, and action changed to state s'. These episodes are used to train the base reinforcement learning model policy, $Q[s, a]$, and later will be used to train the personalization policy. The reinforcement learning model in this case was Q Learning. In the training phase, we update $Q[s, a]$ in each episode (Fig 2).

1) State Space (S): The state information used to determine the reward provided to the feedback reinforcement learning agent consists of time taken to perform a repetition s_{time}, whether the elbow was locked or not s_{elbow_lock} and the range of motion s_{rom}. The total of repetition time is measured in seconds. The time s_{time} was categorized into 3 intervals [0-2, 2.01-5, 5.01-10]. s_{elbow_lock} is 1 if the elbow is locked properly for the entire repetition and s_{elbow_lock} is 0 if not. If the user performed a partial range of motion (rom), s_{rom} = 0 and for full range of motion s_{rom} = 1. In total the state space consists of $|s_{time}| \times |s_{elbow_lock}| \times |s_{rom}| = 12$.

2) Action Space (A): Possible actions include the verbal feedback options given to the user based on the performed exercise. Action space options consists of reporting the repetition count (a_{count}), reporting how many repetitions remain ($a_{remaining}$) , feedback to correct body movements (a_{elbow_lock}, a_{rom}), verbal encouragement phrases ($a_{encouragement}$) and feedback to change the speed of the exercise (a_{speed}). Hence the action space has $|a_{count}| + |a_{remaining}| + |a_{elbow_lock}| + |a_{rom}| + |a_{encouragement}| + |a_{speed}| = 10 + 10 + 1 + 1 + 5 + 2 = 29$ actions in total.



(a) Single Camera

(b) Two Cameras

Fig. 1: (a) Camera setting position of one camera system, and (b) camera setting position of two cameras system.

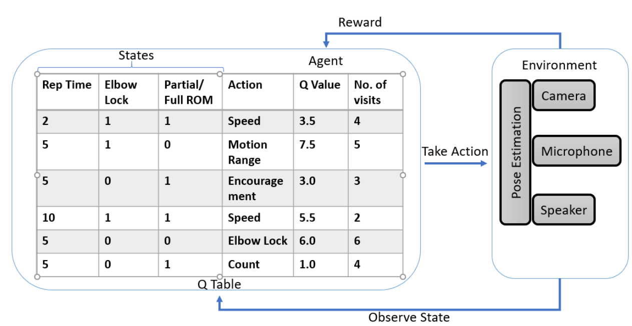


Fig. 2: The Feedback Reinforcement Learning System. Q-Learning is used to track expected future rewards. After the subjects performs a movement, with probability 0.8 the most appropriate feedback is selected as the one with the highest future expected reward, while with probability 0.2 a random feedback was given. The reward for the action was provided based on the behavior of the individual in the subsequent movement.

3) Reward (R): The reward to the feedback reinforcement learning model was assigned based through a function based on user performance on the next repetition. The total reward used to guide the feedback behavior system is provided by the following function:

$$r_{state} = r_{time} + r_{elbow_lock} + r_{rom} \tag{1}$$

r_{state} is reward for state,
r_{time} is reward for time,
r_{elbow_lock} is reward for elbow lock,
r_{rom} is reward for range of motion,

a) Reward for Time: We rewarded the feedback system differently depending on the time taken to perform the arm curl. To establish a baseline, the time taken to perform a single arm curl was measured from two experienced individuals with more than 10 years in personal fitness each. Progressively more negative rewards were given as subjects moves significantly faster or slower than that average time. And additional design goal for the reward function was to be between 0 and -1. The developed reward function for time is as follows:

$$r_{time} = \frac{-|\frac{(time-\mu)}{\sigma}|}{8} \tag{2}$$

Where, μ is the mean time and σ is the standard deviation. Through experimental results on the two experienced subjects we obtained μ as 3585 ms and σ as 433 ms.

b) Reward for Range of Motion (ROM): The reward function for ROM is calculated as follows to provide a value between -1 and +1:

$$r_{ROM} = (max_{reward} - min_{reward}) \times \frac{(angle_{performed} - angle_{min})}{(angle_{max} - angle_{min})} + min_{reward}$$

c) Reward for Elbow Lock: A binary reward is given for elbow lock. If the user maintained the elbow lock for the entire repetition the user is rewarded with +1 reward, otherwise the reward is -1.

B. Collaborative Learning to Tune Model Parameters

Our centralized RL model is initially trained to provide accurate and relevant feedback to the users and allow for tuning based on an individual's behavior. Upon login, the program running on the client's machine receives the joint Q-learning model from the server. Based on the user's response to the feedback provided by the system, the client-side program updates the Q-table. At the end of the exercise session, the client updates the server (Fig 3).

C. User Interface of the Proposed System

Visual feedback is also given for the types of errors that are not easy to correct with verbal feedback alone. For example, not locking the elbow (Fig 4) and not using full range of motion (Fig 5) are errors that are represented both visually and verbally.

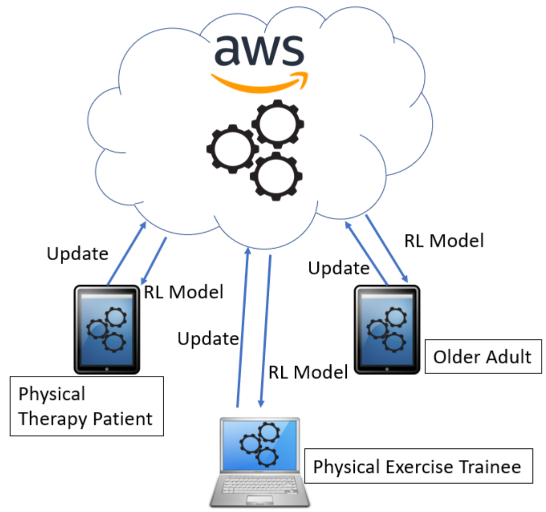


Fig. 3: Distributed Reinforcement Learning framework. The client application can run on any system with a browser and camera. Each client will receive the model from the server which is hosted on AWS. The clients update the server's model after the session ends.

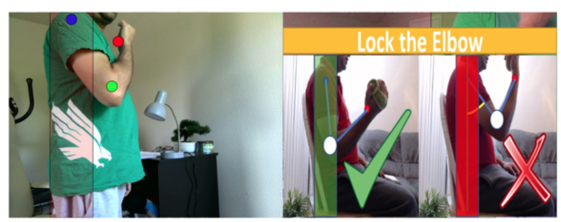


Fig. 4: Visual Feedback on Unlocked Elbow. When the subject performs an incorrect repetition due to poor elbow lock, the system will provide visual feedback including correct and incorrect examples as shown on the right.

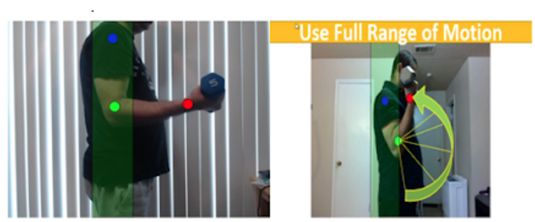


Fig. 5: Visual Feedback on Full Range of Motion. When the subject performs a repetition with limited range of motion, the system provides visual feedback demonstrating an example of full Range of Motion on the right.

III. Results

Subjects performed a series of instructed repetitions of arm curls, with the feedback reinforcement learning system providing feedback after each repetition. The quality of responses were analyzed through observing improvements in user behavior in addition to a more detailed analysis of the relative value of relevant to irrelevant feedback with regards to previous errors that were made.

A. Decreasing error rates

Subjects were asked to perform 3 sessions of 10 repetitions. 36 subjects participated in this study. However, a reward is not assigned to the last repetition since the feedback reward is given by considering the next state of the repetition. Hence, we have only analyzed 27 repetitions from each subject. Fig. 6 shows how the total errors of subjects vary with the trials. With the guidance of the exercise assistant system, 31 out of 36 subjects were able to reduce the number of improper body movements. Fig. 7 shows the total errors of subjects in all three sessions in order. In the last session, 15 subjects were able to perform the exercise without any errors. However, due to the long initial message at the beginning of the exercise set, many subjects took more time than expected, indicating a spike at the beginning of each session.

B. Relevance and value of feedback on errors

An analysis of the state-action values in the learned Q-table can provide insights about the link between relevant and irrelevant feedback. Notably, the system was not biased to provide any particular type of feedback. This includes a goal to provide immediately relevant feedback after a particular error has been observed (e.g. poor elbow lock, poor range of motion, movements too fast/slow, etc.). Does the system bias toward providing more rather than less relevant feedback to errors?

As Q-values in Q-learning provide the estimated intrinsic value of different actions, the relative value of one type of feedback over another for a given state can be readily observed. States of the Q table with clear single errors in elbow lock, range of motion, or movement time were collected. "relevant" actions were those which provided feedback directly related to the error that was made previously (e.g. reporting speed of motion directly after the speed of motion was found to be poor in a preceding trial), while "irrelevant" actions were considered all other types of feedback. The "relevant" and "irrelevant" Q-values for these single-error states were tested for a systematic difference in means using Welch's t-test. The P-value obtained was 0.0133 which indicates a statistically significant difference between the Q-values of relevant feedback relative to non-relevant feedback, with relevant feedback being more valued by the system.

IV. Conclusion

Users make distinct errors and respond differently to feedback, so providing a means of updating feedback based on user behavior is beneficial. It is difficult to design a feedback regiment a priori using personal information such as gender, age, weight, muscle strength as many commercial systems do. In this research study, we proposed a method to adapt the exercise tracking application's feedback using the person's real-time performance. The provided feedback was selected adaptively through Q-learning. Though all feedback was weighted equally in the beginning, relevant feedback for a given error in the previous trial was shown to be more valuable to the system over time. Additionally, 31 of 36 subjects had improved performance with 15 being error-free in the last session. In short, reinforcement learning was used in this virtual exercise assistant to provide useful feedback to improve subject performance in the given exercise task. Improved feedback selection can benefit virtual trainers to make regular exercise more pleasant and effective over time.

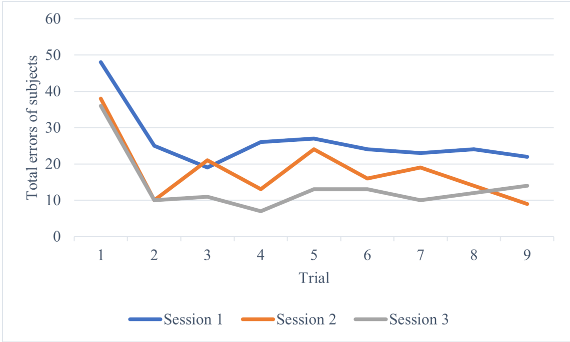


Fig. 6: Total Errors of Subjects to Trials

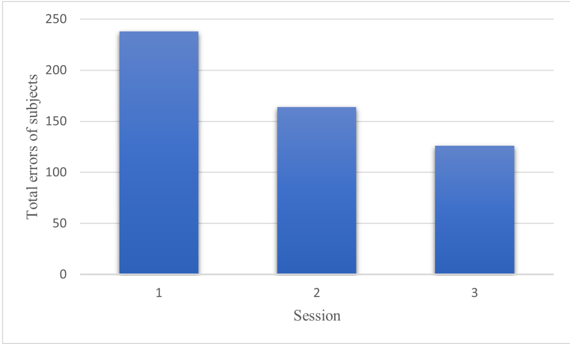


Fig. 7: Total Errors of Subjects in All Three Sessions In Order

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