Cyber-Physiotherapy: Rehabilitation to Training

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Abstract—**Cutting-edge Human-Computer Interaction (HCI) technologies embedded with Machine Learning (ML) will cause a paradigm shift in various domains, including manufacturing and developing facilities and services for professional and personal use. ML implemented HCIs can help people overcome societal challenges brought about by the COVID-19 pandemic. We introduce a system for people to perform physical exercises at home. This system is intended to help a range of demographics, from non-critical physical therapy patients to experienced weightlifters. More specifically, we propose a method to assess the difficulty of an exercise for visual exercise tracking systems. Pose estimation tracks exercises and reinforcement learning provides autonomous feedback to the user (patient/athlete). This information is processed largely on the client side, allowing the application to run smoothly anywhere in the world.**

Keywords—Human-Computer Interaction, Fitts's law, Index of Difficulty, Pose Estimation, Reinforcement Learning

I. INTRODUCTION

The novel Coronavirus (COVID-19) pandemic upended day to day lives across the globe. The pandemic has affected every aspect of life; how we work, learn and interact as social distancing and stay at home to mitigate the spread of the virus, which led to more virtual existence both personally and professionally. In this transition to new normal remote services play a vital part. The telemedicine industry has a rapid expansion during the pandemic, mass migration to telemedicine has taken place with the decline of 80% in in-person visits over the time March and April 2020 [1].

In a non-urgent care setting, virtual visits have demonstrated their feasibility, and cost-effectiveness, while adhering to social distancing guidelines [2]. Rehabilitation treatments and Physical Therapy have introduced and expanded the resources to move into remote services [3]. For in-patients, regular contact with physical therapists ensures compliance and proper form. However, as out-patients, it is more difficult for people with limited mobility to come into the hospital or clinic regularly. Therefore, more patients prefer home-based physical therapy.

There are many video conferencing tools available today which can be used for a wide range of purposes, from remote physical therapy to professional athlete training sessions. Consumers only need a computer or mobile phone to use these tools. Many of these systems use a single RGB camera, which captures limited visual information to track physical exercises. In this paper, we propose an exercise tracking system that accurately tracks exercises and provides efficient feedback using two cameras and machine learning applications.

II. RELATED WORK AND BACKGROUND MATERIAL

Numerous desktop applications [4] and mobile applications [5] are available today to provide this service to people. Most desktop and mobile applications use a video camera to capture visual information from the user's environment. This is more convenient and inexpensive compared to other technologies. Open-source pose estimation libraries such as Posenet [6], OpenPose [7], and AlphaPose [8] ease the development of these applications. Many of these systems do not track the difficulty of the exercise. The difficulty of the exercise should be different from person to person. We present a method to measure the difficulty of an exercise for an individual by extending Fitts's law.

Fitts's law predicts the time it takes to move an object to a specific location based on the distance and the target width. It is often used for Human-Computer Interfaces. According to the Fitts's law, the time it takes to move an object to a target location is a logarithmic function of distance to target and target width. The original Fitts's law formula is shown in equation 1. Shannon's formula is also commonly used and is shown in equation 2.

$$T = a + b * \log_2\left(\frac{2D}{W}\right) \tag{1}$$

$$T = a + b * \log_2\left(\frac{D}{W} + 1\right) \tag{2}$$

Where T is the time to complete the movement, D is the distance to the target, W is the width of the target, and a, b are constants. In equation 2, Index of Difficulty defined as,

$$IoD = \log_2\left(\frac{D}{W} + 1\right) \tag{3}$$

Researchers have used Fitts's law to assess human body movements. Gupta et al. [9] extended Fitts's law to model the movement of multiple joints. Authors defined a concept called atomic movement, which means the fastest joint among other joints used in a task, and they showed that every other joint is a multiple of the atomic joint. Zhang et al. [10] used Fitts's law to quantify the upper extremity movement pattern in patients with stroke. This study shows that movement time is linearly correlated with the Index of Difficulty, and the affected side of the patients with stroke takes more time to move than the unaffected side.

Muscle strength can be determined by One Repetition Maximum (1RM). 1RM is a measurement of the greatest load that can be fully moved (lifted, pushed, or pulled) once without failure or injury [11]. There are numerous equations to calculate 1RM. Many research works show no significant difference in the 1RM predictive equation except Neto et al. have shown that the equation of Lombardi gave the best predicting results in their study [12] [13]. Therefore, we used the Lombardi formula to calculate 1RM.

$$Muscle\ Strength\ (1RM) = Weight * Repetitions^{0.1} \quad (4)$$
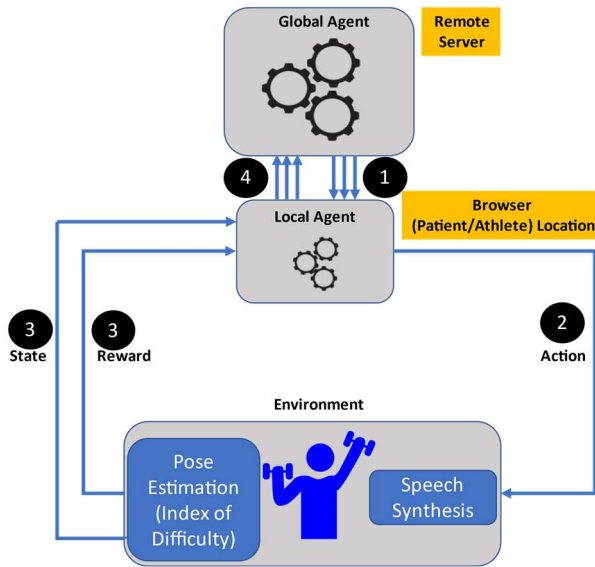
III. METHODOLOGY

A. Architecture

Fig. 1. Reinforcement Learning for Feedback System: (1) Global agent provides its knowledge (stored in Q table) to the local agent. (2) Based on the experience, the local agent performs an action. (3)The state's action is rewarded, and the new state is obtained by the local agent. (4) After an exercise session, newly acquired knowledge is sent to the remote server to update the global agent's knowledge.
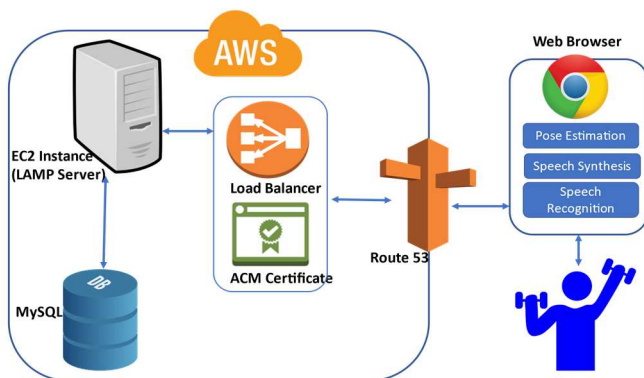

Fig. 2. AWS System Architecture

Given critical goals of cost-effectiveness and ease of use, the proposed framework only utilizes a browser and webcam(/s)-based solution. This ensures that the end-user does not need to make a financial investment to use the system aside from purchasing a webcam. All the users must do to set up the system is to visit the project's website.

The web application is hosted in an Amazon Web Service (AWS) instance. Minification reduces load times and bandwidth usage, making client-side scripts run smoother. An elastic load balancer routes incoming HTTP and HTTPS traffic to the AWS instance. HTTP connection requests are forwarded to HTTPS to secure the connections. The AWS Certificate Manager generates a certificate for HTTPS validation. The system's domain name registration with Amazon's Route 53 and DNS services configure to connect the instance by URL. (fig. 2)

The instance is running an Apache2 web server with PHP capability. The system's database is maintained using MySQL. User-facing pages are PHP files that allow login validation for security purposes and display dynamic user pages.

The "PoseNet" machine learning model is used for pose estimation. This module is implemented in the browser using Tensorflow.js and is utilized in code using the ml5 JavaScript library. p5 text-to-speech functionalities handle voice inputs. Parsed speech is then used to perform certain system functions, removing the need for direct physical interaction that would conflict with exercise performance. The system's verbal feedback is likewise handled with the p5 library's text-to-speech functions.

The proposed framework provides efficient feedback to the user utilizing the Q-learning reinforcement algorithm. There is a local agent for each client and a global agent for all clients in the proposed framework. At the beginning of the exercise set, the global agent provides its knowledge (stored in Q table) to the local agent. At the end of the exercise, the local agent updates the global agent with its newly acquired knowledge. States in the reinforcement learning are defined considering repetition time the accuracy of the body movements, and Index of Difficulty. Actions provided by the local agent are based on its experience. Actions include verbal feedback such as repetition count, encouragement phases, and corrections for incorrect body movements. Visual feedback is used to alert the user of erroneous body movements. The feedback system is rewarded depending on the user's response to the action. (fig. 1)

After completing the physical exercise session, the user receives a report from the web application, which includes starting and ending times of the exercise, the time it takes for each repetition, and a log of mistakes the user made. This information is valuable for a trainer to provide further instructions to users.

B. Repetition Count

Body key-points extracted from the pose estimation are used to measure the relevant body joint angles to count exercise repetitions. For example, to count repetitions of arm curl exercises, the elbow pitch joint (shoulder-elbow-wrist) angle (θ) is captured in each frame. By the "Law of Cosines", the angle θ is calculated using body key-point distances including, shoulder to elbow ($dist_a$), elbow to wrist ($dist_b$) and shoulder to wrist ($dist_c$).

$$\theta = \cos^{-1}\left(\frac{dist_a{}^2 + dist_b{}^2 - dist_c{}^2}{2(dist_a * dist_b)}\right) \quad (5)$$

A high-low threshold algorithm is used based on the estimated angle to count repetitions.

C. Measuring Difficulty of the Exercise

Fitts's law has been used to measure the difficulty of moving objects by many researchers [9] [10]. In arm curl exercises, like in other weight lifting exercises, the goal is to lift a weight from one resting location to another. The users are instructed to move the dumbbell to a target on the screen in the proposed system's user interface. Since the dumbbell weights and muscle strength directly affect an exercise's difficulty, we extended the original Fitts's law equation to our needs [14]. Our extended Fitts's law equation to measure difficulty is:

$$Index\ of\ Difficulty = \frac{Dumbell\_Weight}{Muscle\_Strength}\ Repetition^{0.1} \log_2 \left[\frac{D}{W} + 1\right] \quad (6)$$

Where D is the distance to target, and W is the width of the target. For arm curl exercise, D calculated using equation 7.

$$D = 2 * \pi * l_{elbow\_wrist} * \frac{\theta}{360} \quad (7)$$

l_{elbow_wrist} is the length of the elbow-wrist and θ is the angular displacement of the shoulder-elbow-wrist joint angle. Muscle strength is calculated using equation 8.

$$Muscle\ Strength = Dumbell\_Weight * Repetitions^{0.1} \quad (8)$$

D. User Interface of the Web Application

The user-interface of the web application is shown in Fig. 3. As shown in the screenshot, the interface consists of two videos captured from two cameras at two different angles, real-time tracking information and visual feedback.

IV. RESULTS

The angle taken to count repetitions for the arm curl exercise was plotted against the frames in order. This plot is shown in Fig. 4.
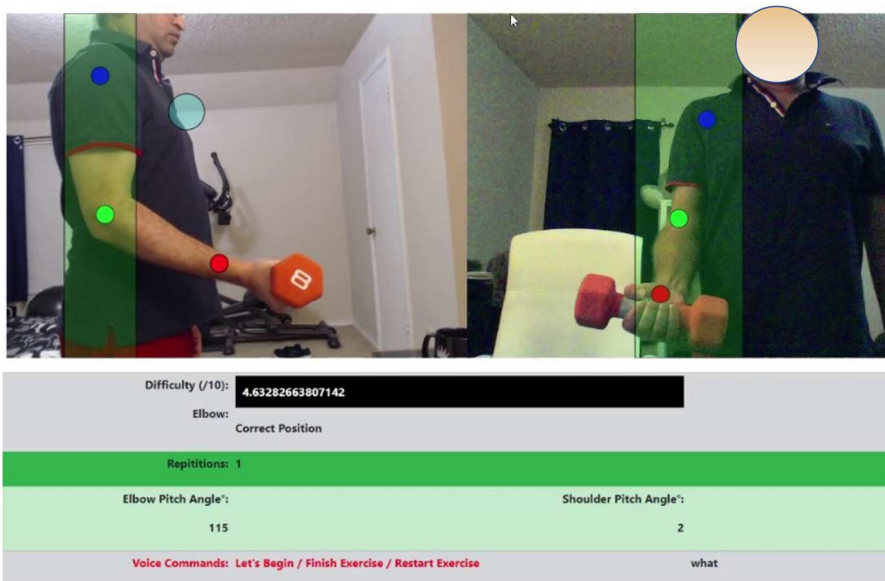

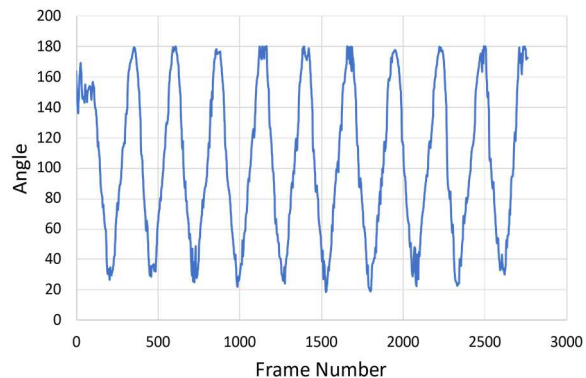Fig. 3. User interface of the web application

Fig. 4. Repetition counting joint angle variation with the time

To evaluate our framework, we hosted an arm curl exercise session with 16 healthy participants. Only 1 participant exercised regularly prior to this session. An instructional video was emailed to participants, and we performed the exercise remotely. The demographics and the 1RM of the subjects are shown in Tables 1 and 2.

TABLE I. DEMOGRAPHICS OF SUBJECTS

Gender	Age Group	Number of Subjects
Female	28-32	8
Male	28-34	8

TABLE II. 1RM OF SUBJECTS

Gender	Minimum 1RM (LB)	Maximum 1RM	Average 1RM ± Standard Deviation
Female	9.57	13.11	10.65 ± 1.18
Male	13.35	41.63	17.72 ± 2.96

We asked participants to perform the arm curl exercise with the heaviest dumbbell they could lift until they were unable to continue. Using our web application, they calculated their muscle strength (1RM) by entering the lifted weight and number of repetitions into the given calculator. We used the Lombardi formula to calculate the 1RM of the participants. After obtaining the 1RM, we instructed participants to perform 10 arm curl exercise repetitions for different dumbbell weights. We suggested the dumbbell weights based on their muscle strength. Muscle strength and dumbbell weight are required to calculate the Index of Difficulty.

The Index of Difficulty (IoD) is calculated for each repetition. Based on the muscle strength, the web application calculates the minimum and maximum IoD and standardize the value between 0 and 10. Difficulty in lifting a certain weight is not the same for all people, and the proposed methodology provides a way to measure difficulty based on an individual's strength. The participants lifted 1LB, 5LB, 8LB,

10LB, 15LB, and 33LB (15Kg) to their comfortability level. Fig. 5, and 6 show the Index of Difficulty variation to repetition for 1LB and 8LB. All 16 participants lifted 1LB and 14 lifted 8LB. Figures 5 and 6, show that difficulty increases with both the number of repetitions and the dumbbell weights. Also, this demonstrate that the difficulty of the exercise is tailored to the strength of the subject.
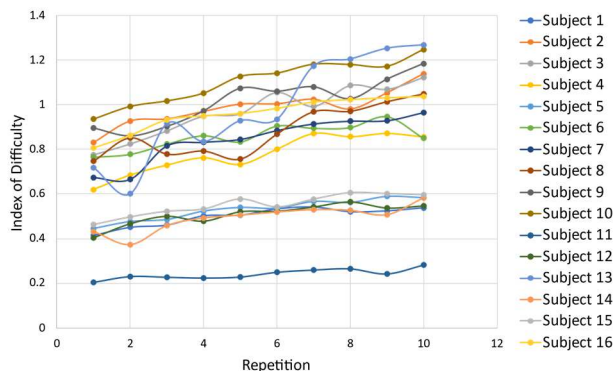

Fig. 5.   Index of difficulty variation to repetitions for 1LB
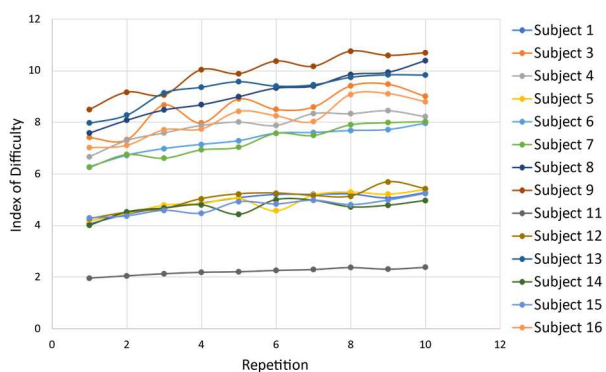

Fig. 6.   Index of difficulty variation to repetitions for 8LB

V.   CONCLUSION

Most exercise tracking applications utilize a single RGB camera to capture body movements. Some important information may be missed due to the limited visual information, and incorrect body movement may go unnoticed during exercises. In this paper, we proposed a physical exercise tracking system that utilizes two cameras and machine learning applications to accurately track and provide efficient feedback.

Too many exercises can lead to exhaustion, muscle soreness, and even injuries. Therefore, measuring the intensity of the exercise is necessary. The intensity will be different from person to person due to variations in muscle strength and endurance. This research study introduced a method to measure difficulty for repetitive exercises based on muscle strength. We extended the Fitts's law equation to obtain an Index of Difficulty (IoD). Our experiment results show that the IoD increases linearly with repetitions and receives the

bigger IoD values when lifting weights close to the individual's muscle strength.

We want to extend this work further and train a machine learning model to generate an automatic workout schedule for individuals based on their previous exercises. Furthermore, we plan to use the proposed architecture to track other physical activities.

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