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Highly-Individualized Physical Therapy Instruction Beyond the Clinic Using Wearable Inertial Sensors

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ABSTRACT Musculoskeletal conditions, often requiring rehabilitation, affect one-third of the U.S. population annually. This paper presents rehabilitation assistive technology that includes body-worn motion sensors and a mobile application that extends the reach of a physical rehabilitation specialist beyond the clinic to ensure that home exercises are performed with the same precision as under clinical supervision. Assisted by a specialist in the clinic, the wearable sensors and user interface developed allow the capture of individualized exercises unique to the patient's physical abilities. Beyond the clinical setting, the system can assist patients by providing real-time corrective feedback to repeat these exercises through a correct and complete arc of motion for the prescribed number of repetitions. An inertial measurement unit (IMU) is used on the body part to be exercised to capture its pose. In this paper, we present a kinematics data processing approach to defining custom exercises with flexibility in terms of where it is worn and the nature of the exercise, as well as real-time corrective feedback parameters. The system is tested on two exercises perfromed by a healthy individual to demonstrate the feasibility and accuracy of the approach. We demonstrate how it can improve exercise adherence by assisting users in reaching the full prescribed range of motion and stay on the ideal plane of motion and improve hold time. Preliminary results from an ongoing clinical trial are presented.

INDEX TERMS Assistive technology, biomechanics, telemedicine, wearable inertial sensor.

I. INTRODUCTION

Musculoskeletal injury rehabilitation, such as the one used to treat rotator cuff tendinopathy, requires highly individualized intervention to address patient-specific physical limitations such as dressing, toileting, grooming, and occupational demands to return to normal function. The current methods of home exercise instruction do not provide adequate monitoring or flexibility to support individualized patient education programs. When a patient performs home exercises, there is no feedback to ensure that exercises are being performed correctly, which has been identified as a barrier to exercise adherence [1]. Lack of confidence or low self-efficacy has been directly connected to poor exercise adherence and poor treatment outcomes [2], [3]. This issue is further supported from the social cognitive theory perspective, which identifies that in order to change behavior, an intervention has to address issues of self-efficacy to be effective [4], [5]. Extending this concept to rehabilitation by providing exercise feedback beyond the clinic to empower the patient to manage their injury requires a novel approach that introduces automation while maintaining personalization by the rehabilitation specialists for the patient.

In the clinical setting, rehabilitation specialists such as physical therapists, occupational therapists, athletic trainers or physicians (referred to as healthcare providers for the purposes of this paper) prescribe and individualize exercises in order to minimize the patient's pain and address their current level of disability [6]. Throughout rehabilitation, these exercises are constantly modified based on the patient's

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response, symptoms, and physical capacity [7]. The patient is asked to perform the same exercises at home or outside of clinical supervision to facilitate recovery [8]. There are many methods used to illustrate home exercise performance and encourage exercise independence. The most common form is written instruction using static images with arrows. However, clinicians must constantly modify an illustration or rewrite verbal instructions to meet individual patient needs following exercise instruction. This can potentially confuse the patient and reduce their confidence in performing the exercises independently. In addition, treatment adherence with prescribed home exercises is a common concern [1] and is associated with poor patient outcomes [2], [3]. We present a system that extends the reach of the healthcare provider by providing both real-time feedback on individualized prescribed exercises and a less burdensome method to monitor exercise adherence.

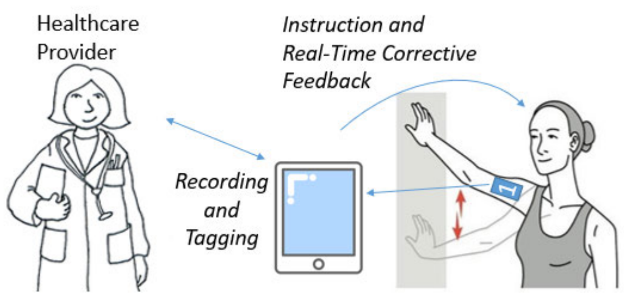

FIGURE 1. RehabBuddy extends the reach of the rehabilitation specialist to the home. In the clinic, the patient is prescribed exercises, which are recorded by the system. Beyond the clinic, the system assists the patient in performing the correct number of repetitions and hold times.

Our approach, named as RehabBuddy, as illustrated in Fig. 1, is based on body-worn inertial measurement units (IMUs) capable of body motion capture outside of a laboratory environment. The devices are attached to the body around the joint being rehabilitated, such as the arm in the case of a shoulder injury. The IMU data is processed to find the three degree-of-freedom (3DOF) rotation of the exercise, as well as other parameters such as the body pose relative to inertial space (e.g., whether the patient is lying down or standing). The current standard of care in the clinic is that the patient is educated by the healthcare provider to perform the exercises correctly. Once the patient is instructed, RehabBuddy will allow the healthcare provider to record prescribed home exercises. With the aid of a mobile application, the RehabBuddy will provide patients with reminders to perform the correct number of repetitions of each exercise, while providing a graphical demonstration of the exercises to help the user to recall them and providing real-time feedback on how accurately they are performing the exercises. These elements are expected to have a significant impact on compliance and ultimately on patient outcomes.

II. MOTIVATION

Healthcare providers incorporate home exercise programs to promote patient self-reliance and improve the patient's functional scale by reducing physical impairments of weakness or inflexibility [9], [10]. The effectiveness of home exercise in improving function, reducing pain, and returning toward normal function is well established and a critical adjunct to clinic-based rehabilitation [11]–[13]. However, two consistent problems arise in treating patients and evaluating treatment effectiveness: (i) objective measure of adherence and (ii) low exercise adherence [2], [14]. Measuring exercise adherence is challenging, as it is currently limited to a self-report diary, which is often an overestimation of activities and burdens the patient [15]. A system that objectively records prescribed home exercises would provide an accurate representation of the exercise dosage being performed outside the clinic. Exercise adherence is commonly poor, with a completion rate ranging from 33–66% in patients with musculoskeletal injuries [16], [17]. Greater exercise adherence improves outcomes [18]. The primary factors associated with low adherence to home exercises in patients with musculoskeletal disorders are (i) discomfort when performing the exercise, (ii) time barriers to performing exercises, (iii) lack of confidence in performing exercises alone, and (iv) dependence on health care provider input to resolve challenges with the patient's disability [1]. These factors, along with the manner in which the healthcare provider provides directions to the patient and the patient's motivation to carry out the treatment intervention, directly affect adherence [19].

Providing biofeedback is beneficial to improving the patient's physical limitations and can be done in many forms [20]. Specifically, inertial sensors have been used to improve the patient's balance and modify incorrect movements and postures in the clinical setting [21]–[24]. While in the clinical setting, patients have input from the healthcare provider when exercising. However, a greater need exists at home for similar input to be offered. RehabBuddy can objectively monitor exercise adherence and can be used at home to provide exercise feedback without the presence of a healthcare provider.

III. RELATED WORK

A. SENSING AND PATIENT MONITORING

Wearable sensor technology used for activity monitoring may be an option to assess data on exercise adherence. The use of inertial sensors for motion capture and analysis is well documented in the literature [25]–[32] and includes commercial fitness activity trackers. Examples related specifically to physical therapy include several projects [33]–[36] designed to track patient activity for the purpose of remote monitoring by the healthcare provider, yet with no real-time feedback component. The primary limitation and challenge with passive monitoring systems is that they are prone to gross false-positive detections because of the large amount of time the devices must be active and the presence of activities of daily living that must be discerned from the rehabilitation exercises. RehabBuddy addresses this by being an interactive system instead of a passive listener as the patient performs the exercises. Our system is started by the patient indicating they are ready, and the system prompts the patient to begin progressing through the exercise poses while monitoring quality and quantity of performance.

B. REHABILITATION REAL-TIME FEEDBACK

Iosa *et al.* published an extensive literature survey on the medical use of inertial sensors in human movement analysis [37]. They identified a wealth of literature on patient monitoring and assessment in post-processing, and concluded that "it is conceivable that in the next few years, wearable inertial devices will allow human movement analysis to go a step further, from assessment to a combined approach including assessment and rehabilitation at the same time."[*45*] Another recent survey of wearables used for upper extremity rehabilitation includes some systems that provide feedback [38]. However, none targets musculoskeletal rehabilitation, which requires patients to exercise targeted muscles by moving and holding precise postures. Rather, the prior work discussed is primarily targeting patients recovering from a stroke, where gross movement is desired, and motivation is the main concern. There is a void in the literature on effective methods for real-time patient guidance and feedback for musculoskeletal rehabilitation is an open research area.

Some emerging rehabilitation systems are based on visual approaches for motion capture, such as using the Xbox Kinect or a similar technology [39], [40]. While there is potential with these approaches, there are limitations, which are overcome using wearable inertial sensors. (i) The use of IMUs is portable and not constrained to a specific location; patients often perform their exercises at the workplace and on the go. (ii) Items used in rehabilitation, such as elastic bands or wheelchairs, are known to interfere with a vision-based motion capture system. (iii) Also, some exercises utilize elements of the environment, such as rolling a ball on a wall to strengthen the shoulder or tying a resistive band to a door handle. It is difficult to guarantee that a vision-based motion capture system such as a Kinect will have a clear view for all types of exercises needed. RehabBuddy overcomes the limitations of visual motion capture systems with the freedom and portability of body-worn IMUs without infrastructure assistance.

Using wearables, a system named PT-Vis uses visualization approaches for a feedback system for knee injury rehabilitation [41], [42]. Through trials with six knee injury patients, they found great utility and promise in using wearable sensors to provide visual and numeric feedback on joint angle and progress to assist with knee rehab. The patients report positive experiences on the usefulness of feedback. However, PT-Vis uses a flex sensor to provide a single degree of freedom (DOF) measurement of the knee angle. Flex sensors and similar approaches such as an optical linear encoder (OLE) [43] would not work for a multi-joint structure with more degrees of freedom like the shoulder. Also, with RehabBuddy, we go beyond providing feedback only on range of motion to also provide feedback on taking the correct pose along the correct plane of motion. This requires sensing in more degrees of freedom, which IMUs provide.

Using IMUs, the Rehabilitation Visualization System (RVS) utilizes two sensors to track knee exercises [44], [45]. RVS provides patients with a demonstration of the exercise and on a separate screen provides real-time feedback on the range of motion for the knee and leg elevation. In a randomized clinical trial, they found improved outcomes for patients who used RVS, which is encouraging for our proposed general solution. Interactive Virtual Telerehabilitation (IVT) is a similar system that also uses IMUs, intended for tele-rehabilitation, and is used to track knee exercises [46]. The third project in this category is the Automated Rehabilitation System (ARS), which also focuses on knee exercises and is intended for use in the clinic where the physical therapist is training several patients at once. RVS, IVT, ARS, and a fourth unnamed similar project [47] are all designed specifically for the knee, with pre-defined exercises but with no ability to tune them (except for ARS) or capability to define custom exercises. They demonstrate the potential and effectiveness of a wearable approach using IMUs. With RehabBuddy, the goal is a general solution to be able to mount the sensor on any joint and prescribe an arbitrary arc of motion. This provides the ability to individualize physical therapy to a patient-centric approach which is key for wide applicability and use.

IV. REHABBUDDY DESIGN

A. SENSING APPROACH

Each wearable sensor node is based on a set of orthogonal inertial sensors, commonly referred to together as an IMU. Pose estimation is done using a sensor fusion algorithm, where the 3DOF orientation/pose of the device can be tracked in inertial space. The sensor suite and algorithm are commonly used in unmanned vehicle control systems to provide stability and are often referred to as an Attitude and Heading Reference System (AHRS). This pose estimator is used to process the raw data (rotation rates, acceleration, and magnetic field) and produce the orientation angles in a world reference frame defined by the gravity vector and magnetic north. The sensor fusion algorithm utilizes knowledge of dynamics to propagate the orientation changes based on the rate gyroscope data and fuses the propagated estimate with the direct orientation estimate based on the accelerometer and compass. This way, the AHRS can tolerate shocks and vibration and maintain a stable estimate of the device's orientation. The RehabBuddy's worn sensors measure and report their 3DOF orientation, typically referred to as "pose". We used off-the-shelf units, Shimmer3 IMU made by Shimmer Sensing.

B. IN THE CLINIC: EXERCISE CAPTURE AND TAGGING

Currently, a patient's visit entails progress assessment and training on a set of exercises that the patient is expected to carry out until the next visit. The prescription is highly individualized and depends on the phase of healing, current symptoms, and functional level. Unfortunately, as previously established, exercise adherence is often low, negatively affecting patient outcomes.

RehabBuddy introduces a new step into the visit, where the healthcare provider instruments the patient with the wearable IMUs at the joint of interest. Then, the mobile application on a tablet is placed in a training mode to allow the healthcare provider to sequentially move the patient through the specific exercise. The tablet user interface is designed to allow the healthcare provider to indicate the beginning and end poses and specify the number of repetitions to be performed each day and hold times for each exercise. These parameters serve as reminders for the patients when they are on their own and are also used to build feedback visualizations.

The core measurement that each IMU along with its sensor fusion algorithm produces is the orientation/pose estimate in three-dimensional space ($\mathbb{R}3$) in the world reference frame. The pose can be represented in several ways, including a Direction Cosine Matrix, Euler Angles, the Eigen Axis and Angle representation, and Quaternions [48]. We note that conversion between these forms of representing pose is a direct calculation. The orientation of an object, like RehabBuddy's worn sensor units, is represented as a rotation in $\mathbb{R}3$ between the world reference frame and the object's body frame. In this discussion, we use Quaternions to represent orientation. An orientation quaternion can be defined as:

$$\mathbf{q} = q_w + \mathbf{i}q_x + \mathbf{j}q_y + \mathbf{k}q_z \tag{1}$$

$$\mathbf{q} = cos\left(\frac{\theta}{2}\right) + \mathbf{i}e_x sin\left(\frac{\theta}{2}\right) + \mathbf{j}e_y sin\left(\frac{\theta}{2}\right) + \mathbf{k}e_z sin\left(\frac{\theta}{2}\right) \tag{2}$$

$$\theta = angle\left(\mathbf{q}\right) = 2cos^{-1}q_w \tag{3}$$

where $\mathbf{q}$ is an orientation quaternion defined by a rotation around the axis $e^{\rightharpoonup} = \left[e_x, e_y, e_z\right]$ by an angle θ. Equation (1) relates the mathematically favorable Quaternion form for orientation representation with the more intuitive representation of orientation, the Eigen-axis ($e^{\rightharpoonup}$) and Angle (θ) representation (2), which represents a 3DOF rotation by a single rotation about an arbitrary axis. The Eigen-axis represents the plane of motion between two reference frames, while the angle represents the range of motion (3).

Toward tracking exercises using a body-worn IMU, we develop an exercise representation. To calculate the exercise arc, we capture the starting and target poses and calculate a difference quaternion that represents the ideal range and plane of motion path that encapsulates the correct form of the exercise:

$$\begin{aligned} {}_{\mathrm{e}}\mathbf{q}_{\mathrm{exercise\_arc}} &= {}_{\mathrm{w}}\mathbf{q}(\mathrm{t}_{\ \mathrm{exercise\ definition\ start\ pose}})^{-1} \\ &\quad \times {}_{\mathrm{w}}\mathbf{q}(\mathrm{t}_{\ \mathrm{exercise\ definition\ target\ pose}}) \end{aligned} \tag{4}$$

$$ {}_{\mathrm{e}}\mathbf{q}_{\mathrm{target}} = {}_{\mathrm{e}}\mathbf{q}_{\mathrm{exercise\_arc}} \tag{5}$$

where ${}_{\mathrm{w}}\mathbf{q}(\mathrm{t}_{\ \mathrm{exercise\ definition\ start\ pose}})$ is the quaternion captured while the user is standing in start pose in the world reference frame, and ${}_{\mathrm{w}}\mathbf{q}(\mathrm{t}_{\ \mathrm{exercise\ definition\ \ target\ pose}})$ is the target quaternion captured while the user is standing in the final end pose, both defined in the world reference frame. We then find the difference quaternion ${}_{\mathrm{e}}\mathbf{q}_{\mathrm{exercise\_arc}}$ which is the difference quaternion between the two, which represents the target pose relative to the start pose as the reference frame. This effectively defines the exercise reference frame and ${}_{\mathrm{e}}\mathbf{q}_{\mathrm{target}}$ as the target pose in that frame which represents the ideal motion of the exercise in a single quaternion.

C. DETECTING PLANE OF MOTION, RANGE OF MOTION, AND COUNTING REPETITIONS

Defining an exercise reference frame allows an account for differences in start position from when the exercise is defined to when it is utilized in tracking the motion during exercise execution. When the user wishes to begin exercising, they need to stand in the initial pose and indicate this on the app to capture the exercise execution start pose:

$${}_{\mathrm{w}}\mathbf{q}_{\mathrm{start}} = {}_{\mathrm{w}}\mathbf{q}(\mathrm{t}_{\ \mathrm{exercise\ execution\ start\ pose}}) \tag{6}$$

$${}_{\mathrm{e}}\mathbf{q}(\mathrm{t}) = {}_{\mathrm{w}}\mathbf{q}\mathrm{start}^{-1}{}_{\mathrm{w}}\mathbf{q}(\mathrm{t}) \tag{7}$$

${}_{\mathrm{w}}\mathbf{q}(\mathrm{t}_{\ \mathrm{exercise\ execution\ start\ pose}})$ is the quaternion that the user sets as the start pose upon beginning to perform the exercise which we define as the start pose ${}_{\mathrm{w}}\mathbf{q}_{\mathrm{start}}$. This new start pose ${}_{\mathrm{w}}\mathbf{q}_{\mathrm{start}}$is used to transform the current pose of the sensor ${}_{\mathrm{w}}\mathbf{q}(\mathrm{t})$ in the world reference frame to find ${}_{\mathrm{e}}\mathbf{q}(\mathrm{t})$, which represents the orientation of the IMU in the exercise execution reference frame. The set start position defined in (6) can be reset if the patient shifts from that position and finds the measurements to be incorrect. To change the frame of reference, the start position (6) is overwritten with a recorded start position from the patient's new frame of reference. This is used to move the exercise from the current world reference frame to the initial world reference frame using (7). This places the target pose and the original saved exercise arc into this new start pose's frame of reference, with result being the exercise is updated to reflect the new frame of reference based on the start pose update.

Next, we calculate the exercise feedback variables. Our method is based on conceptualizing a triangle of quaternions representing (i) the rotation from start pose to target pose ${}_{\mathrm{e}}\mathbf{q}_{\mathrm{target}}$, (ii) the rotation from the start pose to the current sensor pose ${}_{\mathrm{e}}\mathbf{q}(\mathrm{t})$, and (iii) the rotation from the current pose to the target pose ${}_{\mathrm{e}}\mathbf{q}_{\mathrm{error}}(\mathrm{t})$ defined as:

$${}_{\mathrm{e}}\mathbf{q}_{\mathrm{error}}(\mathrm{t}) = {}_{\mathrm{e}}\mathbf{q}(\mathrm{t})^{-1}{}_{\mathrm{e}}\mathbf{q}_{\mathrm{target}} \tag{8}$$

$$\theta_{\mathrm{ideal}} = \mathrm{angle}({}_{\mathrm{e}}\mathbf{q}_{\mathrm{target}}) \tag{9}$$

$$\theta_{\mathrm{current}}(\mathrm{t}) = \mathrm{angle}({}_{\mathrm{e}}\mathbf{q}(\mathrm{t})) \tag{10}$$

$$\theta_{\mathrm{error}}(\mathrm{t}) = \mathrm{angle}(\mathrm{e}\mathbf{q}_{\mathrm{error}}(\mathrm{t})) \tag{11}$$

$$\mathrm{ROM\ error} = \theta_{\mathrm{ideal}} - \theta_{\mathrm{current}}(\mathrm{t}) \tag{12}$$

$$\mathrm{POME} = \theta_{\mathrm{current}}(\mathrm{t}) + \theta_{\mathrm{error}}(\mathrm{t}) - \theta_{\mathrm{ideal}} \tag{13}$$

We calculate the relative pose between ${}_{\mathrm{e}}\mathbf{q}(\mathrm{t})$ and ${}_{\mathrm{e}}\mathbf{q}_{\mathrm{target}}$ to find ${}_{\mathrm{e}}\mathbf{q}_{\mathrm{error}}(\mathrm{t})$ which reflects the error between the patient's current pose and the exercise target pose which the patient should be in as defined in (8).Range and plane of motion information is converted from quaternion representation to the more intuitive angle-axis form. The angle of ${}_{e}\mathbf{q}(t)$ in angle-axis form (10) represents the total angle by which the patient has moved from the start pose, without regard to the axis of rotation. This is the range of motion (ROM) as described by the system. Quaternion ${}_{e}\mathbf{q}_{error}(t)$ is the error in both range of motion and plane of motion relative to the end pose. Translating the quaternion to angle-axis form and taking the angle of ${}_{e}\mathbf{q}_{error}(t)$ (11) represents the total angle by which the range of motion differs from the target pose. It is how many degrees the user must move before they reach the target pose.

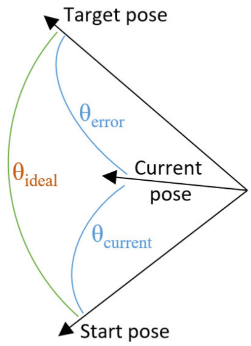

FIGURE 2. Illustration of angle measurements between the start pose, current pose, and target pose. The three are used to estimate the plane of motion error.

Fig. 2 illustrates the angle measurements used to estimate plane of motion error. If the patient moves perfectly in the correct arc of motion, the sum of $\theta_{error}(t)$ and $\theta_{current}(t)$ should equal $\theta_{ideal,}$ being the ROM from start to target expressed in degrees. But θ_{ideal} is the shortest path between the start and target poses along the POM, so if the user is off-plane, the path in degrees from start pose to current pose to end pose will be a longer one than the optimal path. This can be visualized as a triangle between the start pose, target pose and current pose. By subtracting this ideal angle from the angle of the total displacement in degrees, $\theta_{current}$ plus θ_{error}, the difference gives a measure of the error in the plane of motion. This value is reported back to the patient as the error by which they must adjust their current pose to once again be correctly following the ideal path of motion. This is defined as the plane of motion error (POME) in (13).

In summary, with the IMU reporting current orientation at a rate of approximately 50 Hz, the user's progress from their start pose to their end pose and back again can be detected, as $\theta_{current}(t)$ starts at zero at the start pose increases until it matches that of θ_{ideal}. This is programmed using a simple state machine that tracks the user's progress from start pose to end pose to back to start pose.

D. THE REHABBUDDY APPLICATION

There are three components of the RehabBuddy application. First it uses user poses calculated by an IMU and reported as a quaternion over Bluetooth to create a defined exercise. Then, that exercise is used to provide user feedback as they perform repetitions of the defined exercise recorded by quaternions in the same way. Third, the user's pose as reported by the IMUs during exercise is logged to a csv file so that this information can undergo post-processing and the trials can be recreated from the exercise, which is stored as a file during the exercise definition process.

To create the exercise, first the healthcare provider names the exercise and sets the number of repetitions to be performed as well as the length of time the user should hold the start and end poses while performing the exercise. Then, the healthcare provider moves the user into the start pose and presses the record start button, at which point the app defines the start pose by taking the average of the quaternions captured while the patient is holding their arm still in this start pose. Next, the healthcare provider guides the user through the motion of the exercise until their arm is in the stop pose and uses RehabBuddy to record the stop pose in the same way. The application then uses these two quaternions to calculate the ‘‘exercise arc’’ quaternion encompassing the trajectory of the exercise performed correctly as described in Section IV.B. This ideal exercise quaternion is named and saved with the exercise's repetition and hold time parameters. This saved exercise can now be selected from a menu and the user can proceed to a page with a screen containing a line graph of the range of motion path of the exercise and a bar graph depicting the error in the plane of motion.

Fig. 3 shows this feedback system as it is currently designed in the app. The panel in the middle tracks the user's sets and reps and has a countdown timer that helps the user track how long they should hold at the end pose. To the right of that is the guide path that shows the user their current range of motion and guides them to move to their target, the plateau at which they will then hold before following the range of motion path back down to the start pose. Providing reliable feedback about how long they have been holding their poses will encourage users to hold those poses longer. To the right of the guide path is the error bar, which shows the user the magnitude of how far from the plane of motion their current pose is, which helps them adjust their current pose toward the plane of motion. Plane of motion is important as some patients, in particular those who experience pain, may perform exercises incorrectly to avoid pain by compensating with another joint.

E. VERIFICATION WITH A CAMERA-BASED APPROACH

To validate the IMU sensor output, we used an RGB-D camera as a reference sensor, namely the Intel RealSense. The reported images and depth measurements were processed by Skeleton Tracking software developed by Cubemos. This method was utilized to provide us with a secondary reference. The RGB-D camera frames are fed into the pose estimation software. There, each joint in the frame is detected and estimated in 3D space based on human pose inference and reported depth and RGB measurements. The result is a 3D

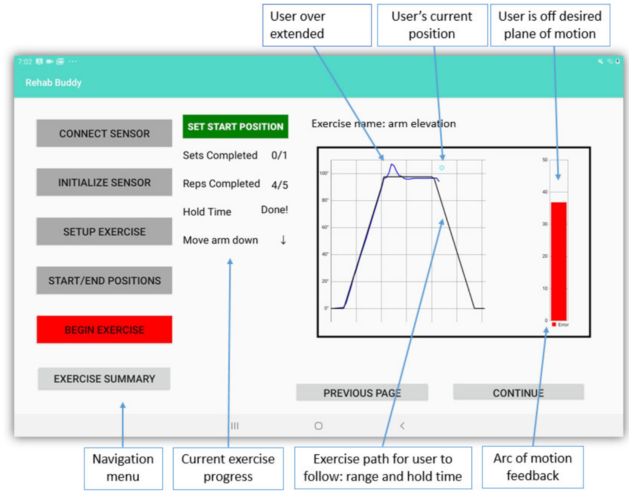

FIGURE 3. RehabBuddy tablet application showing exercise feedback. Exercise feedback system is being tested in a clinical trial.

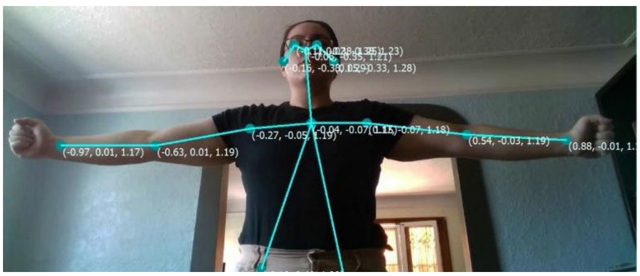

FIGURE 4. Demonstration of camera-based position reference using skeleton inference and an RGB-D camera.

map of the user's position as shown in Fig. 4. This skeleton, composed of reported joint positions, can be transformed into vectors describing the motion of the person at a given frame. Selecting a pair of joints that are of relevance to the exercise in question, a vector estimating the limb is formed. For instance, the forearm is a vector that can be created between the wrist and the elbow joints. By tracking this vector over time, exercise execution performance can be recorded in a way similar to that limb's motion as tracked by an IMU. To capture an exercise using the RGBD data, first the shortest angle between the start vector and the end vector is calculated, denoted as $\theta_{start-end}$. Second, each frame's two joints of interest are used to create a limb vector. Third, the shortest angle between this limb vector and the start vector is calculated, denoted as $\theta_{start-limb}$. Fourth, the shortest angle between the limb vector and the end vector is calculated, denoted as $\theta_{limb-end}$. The range of motion θ_{ROM} is the angle between the start and current moving vector (the limb vector) $\theta_{start-limb}$. The plane of motion error $\theta_{POMerror}$ is the sum of the angles between the start and the current limb position and that limb and the end position, minus the ideal angle between start and end.

$$\begin{aligned} \theta_{ROM} &= \theta_{start-limb} \\ \theta_{POMerror} &= \theta_{start-limb} + \theta_{limb-end} - \theta_{start-end} \end{aligned}$$

The ROM and POME calculated using this alternative RGB-D method is graphed on top of the ROM and POME calculated using the IMU data to get a second reference for comparison. We found general agreement between the pose estimates from the IMUs compared to the RGB-D skeleton inference. Fig. 5 shows an example recording comparing the two methods for five repetitions of an exercise.

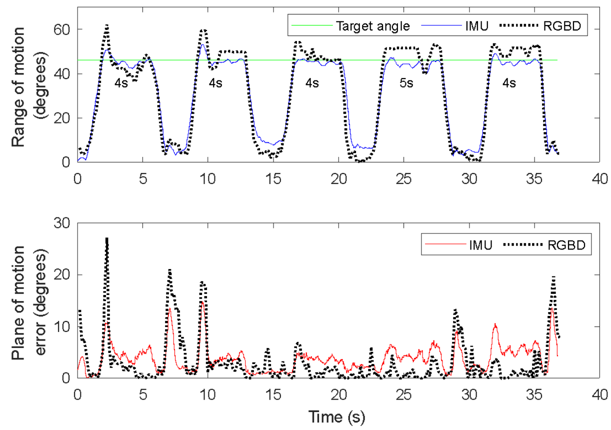

FIGURE 5. Exercise execution performance comparing RGB-D and inertial measurement units (IMU) estimates. The general agreement provides confidence in the IMU-estimate accuracy.

V. EXPERIMENTS

The system was tested in a series of trials to demonstrate the system's ability to guide the user to perform exercises to the correct range of motion and hold times while detecting when they move out of plan. The subject is one of the co-authors, a healthy individual, performing two common shoulder exercises. The purpose for this technical paper is to demonstrate the correctness of the approach and offer preliminary observations on the effect of the feedback on exercise performance. As of this writing, a clinical trial with patients is underway whose results will be published in a future clinical paper.

A. PROOF OF CONCEPT DEMONSTRATION OF THE APPLICATION

Displayed in Fig. 6 is an arm elevated into abduction, a common exercise that is defined by the start pose with the arm at the side and the correct end pose as shown in Fig. 6(b). These are the two poses used to calculate ${}_{e}\mathbf{q}_{\text{exercise\_arc}}$ as described in Section IV.B. The exercise describes a forward elevation of around 85 degrees. For demonstration purposes, Fig. 6(c) and 6(d) also show deliberate incorrect execution of the exercise for demonstration purposes, where the arm is moved out of the desired plane of motion, too far forward, and too far back.

As shown in Fig. 7, the feedback error bar reflects the difference between a correct intermediate pose and an incorrect one and is used as feedback to guide the user to adjust to a pose like that in Fig. 6(b).

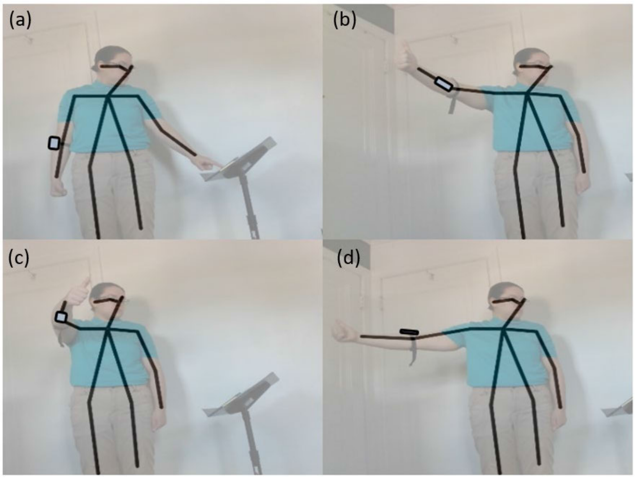

FIGURE 6. Arm abduction exercise, (a) start pose, (b) end pose, (c) arm too far back, (d) arm too far forward.

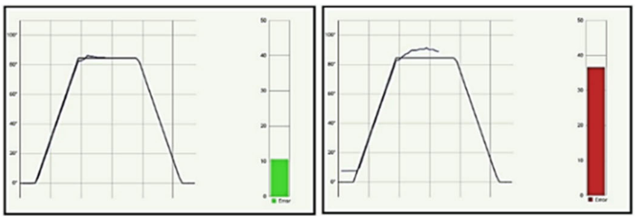

FIGURE 7. Left: App feedback when correctly holding end pose. Right: App feedback (with red bar plot) when arm is held too far back during end pose.

For this demonstration trial, the user performs six repetitions of the exercise highlighted in Fig. 6. The user was receiving feedback for the entirety of the test. The first two repetitions were to be done as close to correct as possible, the second two were done moving off-plane too far back, and the final two were done off-plane too far forward. Fig. 8 shows the resulting ROM and POME plots. The differences in resulting plane of motion errors graphed in red on the bottom plot highlight the difference between a rep following the correct plane of motion and either of the two types of incorrect ones, despite each repetition achieving the same range of motion.

B. TRIAL 1: ARM ABDUCTION

For trial 1, the quaternions were recorded from a trial calculating the ROM and POME while the user followed the exercise with the guide system providing feedback. Then for comparison, the user repeated the exercise again without being given this feedback. The exercise was the same as in the demonstration, a forward flexion of around 85 degrees defined in Fig. 6. Fig. 9 shows the four resulting graphs of 7 repetitions with and then without feedback. The exercise's range of motion is graphed in blue, and the error generated when moving off the plane of motion is given in red.

Table 1 below shows a summary of the results for Trial 1. For the range of motion graphed in Fig. 9, the average, standard deviation, and the percent error are calculated at a per-repetition basis based on the average range of motion when the user is near the end pose for each of the seven repetitions. This is achieved by taking all values above a certain threshold calculated by taking the average of the highest 90^{th} percentile of the range of motion points recorded. When the exercise was done without feedback, the average range of motion was about 10% higher than it was when the exercise was done with feedback. This shows that the 85-degree target ROM was hard to hit and, in this case, the subject routinely overestimated. In cases where over extension could lead to re-tears, this feedback could be helpful.

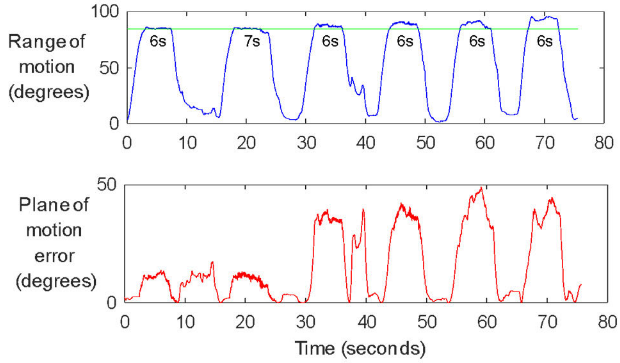

FIGURE 8. Graph of feedback for repetitions: first two were done correctly, subject deliberately moved arm too far back for the second two repetitions, and too far forward for the final two repetitions.

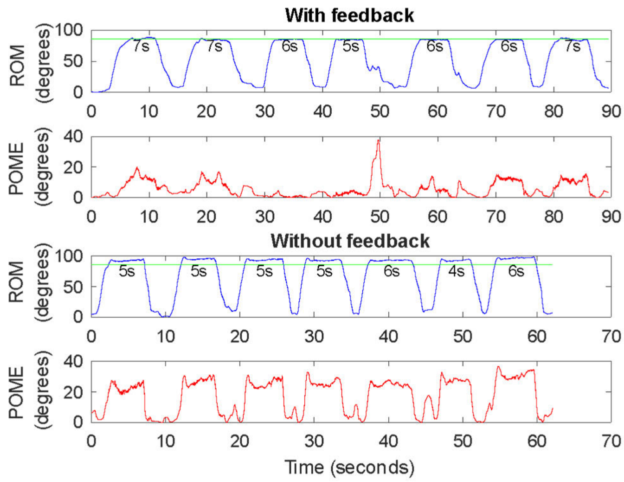

FIGURE 9. Range of Motion (ROM) and Plane of Motion Error (POME) over time during an elevation exercise.

For the plane of motion error graphed in red above, the mean and standard deviation are calculated over the entirety of the exercise. The ideal plane of motion error is zero throughout the exercise. When the exercise was done without feedback, the average plane of motion error was more than double than it was with feedback. This shows that the feedback system does help keep the user closer to the desired exercise plane of motion by helping them gauge their current success.

Average hold time was calculated as well, based on the length of time the user held each repetition's end pose. In this exercise, the outcomes were similar, although the user did hold about a second longer when using the feedback system.

TABLE 1. Results for forward elevation exercise with and without feedback. The feedback prevented over-extension, reduced range of motion (ROM) error, and plane of motion error (POME).

Condition	ROM mean (deg)	ROM standard deviation (deg)	ROM error	POME mean (deg)	POME standard deviation (deg)
With Feedback (84.9° target)	83.42	3.71	1.74%	5.72	5.45
Without Feedback (84.9° target)	93.55	2.73	10.19%	17.16	11.32

C. TRIAL 2: DIAGONAL MOTION

The first trial was a linear exercise of arm abduction which involves along a single plane of motion for the shoulder. For trial 2, we demonstrate the systems capability of allowing clinician use any plane of motion with diagonal proprioceptive neuromuscular facilitation diagonal pattern of flexion/abduction/external rotation. The motion resembles drawing a sword. The exercise's start and end poses are shown in Fig. 10. Again, the quaternions were recorded from a trial calculating the ROM and POME while the user followed the exercise with the guide system providing feedback. Then for comparison this was followed by the user performing the exercise again without being given this feedback.

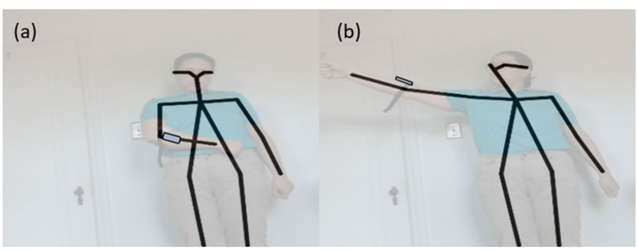

FIGURE 10. Sword draw exercise, (a) start pose, (b) end pose.

Fig. 11 shows the four resulting graphs of five repetitions with and without feedback. Table 2 is a summary of the ROM calculated in the same manner as described for trial 1. This time the user was close to the desired ROM of 146 degrees graphed in green with and without feedback. However, the average hold time was about 50% longer when using the system feedback. For the POME, without feedback, the user had about twice as much average error as they did when they were following the guided feedback reference.

D. TRIAL 3: KNEE FULL EXTENSION

The third trial demonstrates the systems capability of allowing clinician use RehabBuddy on any limb by performing a leg exercise, more specifically a knee extension. The quaternions were recorded from a trial calculating the ROM and POME with and without user feedback in the same procedure as the first two trials. The results are like that of the first two trials, with RehabBuddy lowering both ROM and POME, preventing overextension and keeping the user on the target POM.

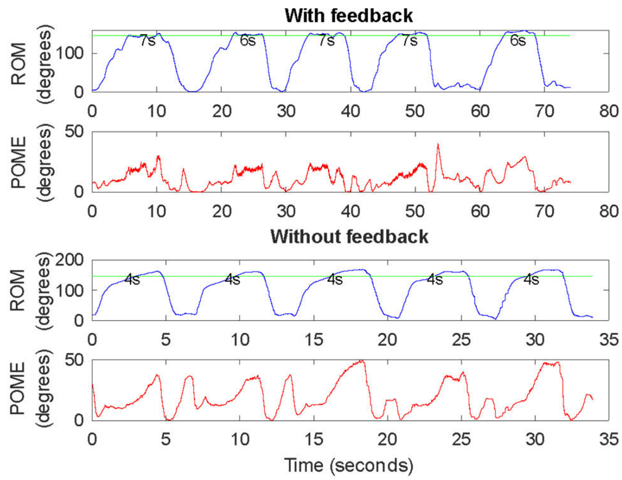

FIGURE 11. Range of Motion (ROM) and Plane of Motion Error (POME) over time during a sword draw exercise.

TABLE 2. Results for sword draw exercise with and without feedback. The feedback prevented over-extension, reduced range of motion (ROM) error, and plane of motion error (POME).

Condition	ROM mean (deg)	ROM standard deviation (deg)	ROM error	POME mean (deg)	POME standard deviation (deg)
With Feedback (146.1° target)	145.6	8.94	0.34%	11.2	7.3
Without Feedback (146.1° target)	148	14.5	1.3%	19.2	13.1

TABLE 3. Results for full knee extension exercise with and without feedback. The feedback prevented over-extension, reduced range of motion (ROM) error, and plane of motion error (POME).

Condition	ROM mean (deg)	ROM standard deviation (deg)	ROM error	POME mean (deg)	POME standard deviation (deg)
With Feedback (80.0° target)	77.2	4.82	3.55%	10.2	8.81
Without Feedback (80.0° target)	95.3	8.72	19.2%	29.8	19.5

E. CLINICAL TRIAL PRELIMINARY RESULTS

RehabBuddy is undergoing a clinical trial. A future clinical paper will outline the outcomes in terms of statistical

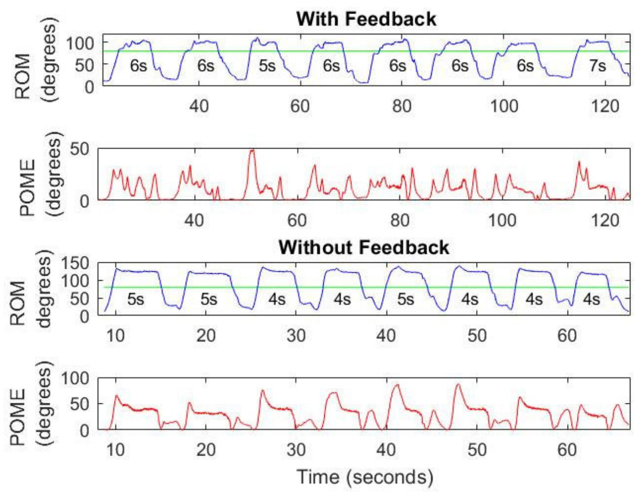

FIGURE 12. Range of Motion (ROM) and Plane of Motion Error (POME) over time during a full knee extension exercise.

significance by clinical standards. However, early results are promising and evidence for RehabBuddy's effect on overextension and POME should continue to grow as more trials are done. Presented below are early results from 21 subjects participating in this study. Fig. 13 shows the average ROM, and Fig. 14 shows the average POME.

The trial designed was given IRB approval on February 19th, 2019 and assigned IRB number 46074. Subjects recruited to the trials are patients attending physical therapy at a University of Kentucky outpatient physical therapy clinic. Compared to Trials 1-3 presented earlier, three conditions are compared here; with feedback, without feedback, and under supervision of a physical therapist as a reference condition. Also, instead of degrees, ROM is measured as a percent of 100, where 0% is the patient at start pose and 100% is the patient at target pose. This is because each exercise had a unique ROM, ranging from 30 degrees to 150 degrees.

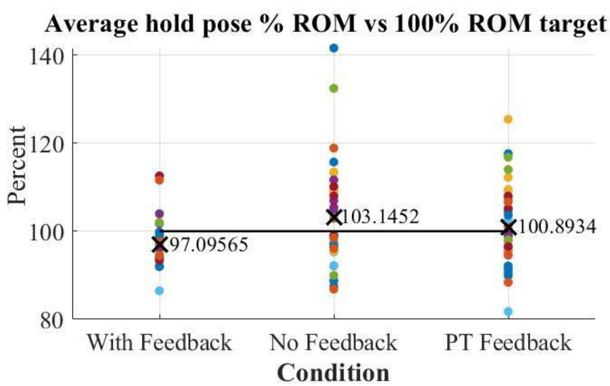

FIGURE 13. Comparison of average patient Range of Motion (ROM) for each exercise compared across all 3 testing conditions: with RehabBuddy feedback, without feedback, and with feedback from a physical therapist (PT) as a reference condition. The overall average is marked by an 'x'.

Figure 13 shows the results of Percent ROM for all three conditions. The average ROM is taken at 80% of the 100% target where everything above this line is counted as being at the hold position. RehabBuddy has the lowest average ROM with a lower standard deviation, indicating RehabBuddy's ability to prevent overextension and improve consistency. Under the without feedback condition, the ROM had the highest (worst) average and the largest spread. With physical therapist feedback, the average ROM was closest, however, with a larger standard deviation compared to with RehabBuddy feedback.

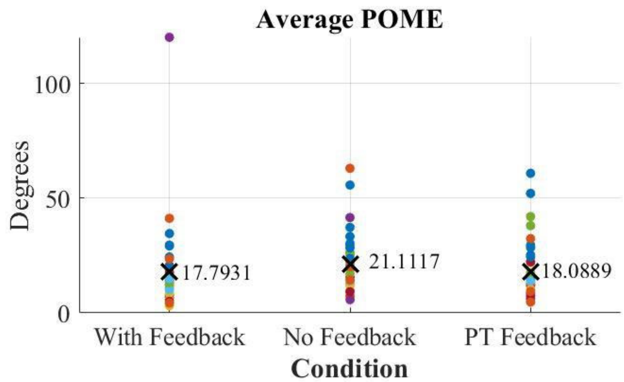

FIGURE 14. Comparison of average Plane of Motion Error (POME) across each exercise trial compared across all 3 testing conditions versus the ideal value of 0 degrees POME. The overall average is marked by an 'x'.

The aggregate POME recorded during each exercise is displayed for each condition in Fig 14. Here RehabBuddy still has a tight cluster and the lowest average error, though PT feedback is close, with both at around 18 degrees.

VI. CONCLUSION

The approach demonstrated above can be extended to be versatile enough to allow a rehabilitation professional to prescribe any limb motion from any posture. This approach allows healthcare providers to individualize the exercise prescription in response to pain and a variety of disabilities. In addition, it removes the need for the standard written illustration that can lead to confusion and non-adherence. Also, the system potentially decreases the risk of further injury by providing real-time feedback to notify the patient that exercises are performed incorrectly in either quantity or quality. The real-time positive feedback when the patient performs the exercises correctly simulates an at-home ''physical therapist'', promising to enhance patient confidence. Correct exercise performance with feedback has improved pain and outcomes [49] while empowering patient independence [10]. Finally, the system can provide an objective record of the number of exercises performed correctly, frequency of performance, and duration of exercise sessions which are valuable as well compared to self-reporting.

The above trials indicate that IMUs can be used to effectively interpret and display real-time user feedback. Providing subjects with this feedback during exercise execution may lead to more accurate ROM adherence, less POME as the exercise is performed, and longer hold times. The system helped both subjects maintain proper form by providing feedback about the POME. When performing the exercises with feedback, the subjects were more capable of correcting these specific issues and offset the effort of simultaneously tracking repetition count, hold time, so that accurately performing the exercise could be the focus of the session.

While this paper focuses on the engineering of RehabBuddy, a future paper will present clinical trial results. A trial is currently underway to demonstrate this system in the clinic, comparing three conditions where patients execute prescribed exercises without feedback, with physical therapist feedback, and with RehabBuddy feedback. Preliminary results from this trial are presented here.

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